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Development of an optimization methodology for an industrial user in Smart Grid applications

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DECLARATION

I hereby declare that this submission is my own work and, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at University of Florence or any other educational institution, except where due references are provided in the thesis itself.

Any contribution made to the research by others, with whom I have been working at the University of Florence or elsewhere, is explicitly acknowledged in the Thesis.

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Fabio Esposito

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To my family, love and friends.

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PUBLICATIONS

1. F. Esposito, A. Dolci, G. Ferrara, L. Ferrari, E. A. Carnevale – A case study based comparison between solar thermal and solar electric cooling – Energy Procedia (in press)
2. A. Chesi, F. Esposito, G. Ferrara, L. Ferrari – Experimental analysis of R744 parallel compression cycle – Applied Energy 135 (2014) 274-285

SYNOPSIS

The increasing World population and the growth of once-developing economies are two of the major challenges that the present energy system needs to face. The increment of energy request is difficult to be supplied with traditional fossil fuels. Indeed, on the one hand although new reserves are found every year, they are usually more expensive to extract. In addition, the impact of global warming and climate change on our everyday life will soon be stronger and more expensive to be handled if there will be no change in the current energy mix. Nonetheless, shifting the current energy system from fossil-fuel based towards a renewable energy based is difficult. Some of the Renewable Energy Sources (RES), like geothermal, hydroelectric or tides, are predictable and can be adopted for a planned energy generation, required to match the request at any given time. However, the locations where they can be exploited are limited and their overall potential is not enough to supply the World energy demand. Other RESs, like Sun radiation and wind, present a greater potential in terms of power and energy that they can supply but feature also an intermittent and unpredictable behavior. This ultimately limits their application in the current energy system, designed to host a few, big, centralized power generation plants. The unpredictability of Solar and Wind power generation is an expensive issue for the current energy system because their potential lack of production requires on the one hand that backup generators are ready to feed energy into the grid, on the other hand the grid management increases its complexity. Indeed, the average Solar or Wind power generation plant is of small to medium scale, and they are numerous and distributed on the territory. Thus, the electricity grid changes from a one-way conduit to a network where several generators of different size are connected.

A possible solution to allow a greater penetration of RESs in the power system, by means of a reduction of the detrimental effects caused by their unpredictability, is offered by the Smart Grid. With the original Smart Grid is meant every technology or practice aiming at achieving improvements in the electricity grid in terms of: economy of operation, environmental friendliness, security and quality of supply. Because of their broad definition, the Smart Grid concept can be applied at different scales and to several components of the energy system. Not only the electricity grid itself, but also district heating and even the transport system. At its smallest scale, the Smart Grid features intelligent users, which adapt their power generation and usage depending on several inputs. Some of these inputs are external, e.g. the weather forecasts and energy prices, some other are internal, e.g. the energy request of an activity or process that is fundamental for the daily operation or comfort of the users. The lack of experimental data on Smart Grid in the literature is due to the complexity of performing tests on large-scale systems that involve several different stakeholders and to the intrusiveness of these tests on the everyday operation of the users of the power system. Nevertheless, on the smallest-scale actor of the Smart Grid, called in this Thesis work, "Smart User", it is possible to carry out the tests required to validate the viability and effectiveness of the newer paradigm of energy system provided by the Smart Grid concept.

This work focuses on the Smart User, in particular on its design and control, with the objective of providing an opportunity for a broader diffusion of RESs, a greater participation in the energy market of the small energy producers and a more convenient, secure and reliable supply of energy for the final user. The core of the Smart User designed is a co-generation unit (CHP), an internal combustion engine of 25 kW rated electric power output, placed in an actual facility. The facility of choice for the installation of the plant is Pontlab, a laboratory carrying out research and tests for several industrial partners. The choice of this user as test-bench for the Smart User resides in the possibility of having different energy requests, both in qualitative terms (electric, thermal, cooling) and in quantity. Indeed, the loads profile assured by this peculiar user are extremely variegated, because they depend on the type of tests that are led during each day. Moreover, Pontlab offers loads with different priority, thus allowing the chance to test Demand Side Management (DSM) strategies, a key aspect of the Smart Grid. The CHP is backed up on the thermal side by a conventional boiler and on the cooling side by a compression chiller. Furthermore, in the facility are installed also Photovoltaic panels with a power output of half the CHP one and a small Wind Turbine. Two thermal storages are fitted in the facility, one for cooling, the other for heating purposes; an electrical storage is going to be implemented as well, whereas at the moment it can be simulated thanks to the dedicated electric interface of the Smart User with the main plant grid. Because of its unique set of generators and manageable loads, Pontlab proves to be a versatile user that can be operated in several possible ways. The thermal layout of the plant is a compromise between the existing one and the ideal layout of the Smart User, where all the generators are in parallel to their respective storage. This latter configuration allows a greater flexibility of operation, which is desirable for the Smart User, but is also more complicated to manage and expensive to build. Thus, for this first test case it was avoided in favor of a more traditional and reliable configuration, which could always be switched to standard operation mode whenever desired by the owner of the facility. The most important device of the Smart User is what makes it “smart” i.e. its control system, composed of several temperature sensors and energy meters, a Programmable Logic Controller and a Supervisory Control And Data Acquisition (SCADA) system. Inside the SCADA run three algorithms: the Day Ahead Algorithm (DAA), the Advanced Dispatching Algorithm (ADA) and the Real Time Algorithm (RTA). The first two perform an optimization of the system management pursuing three possible objectives: the minimization of costs of operation, of primary energy consumption, or of carbon dioxide emissions. Conversely, the last algorithm serves as a link between the optimized solution, defined as a series of generator and load set points and the control in real time of the system. This is carried out in a semi-automated way for the thermal plant, which is controlled by the temperature of intervention of the auxiliary units and the temperature of the fluid exiting from the storages. On the other hand, the RTA itself performs the electric balance of the electric loads and generation.

All the algorithms have been developed ad hoc during this Thesis project and present novelties compared to those currently used in the literature for the optimization of energy system operations. The DAA and ADA are alike in terms of structure although they act at different times: the former performs a first attempt of optimization of the operations of the plant considering the weather forecasts, energy prices and activities for the following day as they are known one day before operation. Along with the first optimized solution, the DAA provides also a power exchange profile with the grid that will be granted during the following day, despite of a possible change in load or weather condition. The latter has the important role of upgrading the optimized operation considering the updated inputs such as more reliable weather forecasts for the present day or possible load and price inputs variations. This allows the system to reduce the influence of errors in the weather or load forecasts, refining the optimization; in addition, it provides an instrument for the controller to answer to possible price input variations for ancillary services. Because of the need for this upgraded solution, the ADA runs once every fifteen minutes and dictates the maximum computational time allowed for the optimizers to reach convergence on an optimized solution. Finally, the RTA ensures not only the balancing of the electrical loads and generation, but also, by means of a dedicated small electric storage, the respect of the grid exchange profile promised the day before.

The optimization algorithms are based on two different optimization strategies: genetic algorithm (GA) and shortest-path optimization. The first performs, for each time step and possible loads combination derived from the storage usage, the optimization of the set points of the generators and the modulation of the loads. The employment of GA allows the controller to take into account non-linear aspects of the energy system, such as the CHP efficiency at partial load, in a fast and computationally light manner. Moreover, the limited number of variables optimized at the same time ensures that the solution found is close to the global optimum. On the other hand, the Shortest-Path optimization defines the best possible sequencce of system states (i.e. storage usage) to achieve the daily optimization of the energy system management. The daily optimization of the plant is indeed a higher level of optimization compared to the one that can be achieved considering one time-step at a time and optimizing each single step regardless of the value that the inputs assume during the whole day. Using the GA and the Shortest-Path algorithm in symbiosis it is possible to achieve an accurate and almost globally optimized solution within the fifteen minutes mark, which is essential for the ADA.

In order to evaluate the solutions proposed by the optimization algorithms and assess the potential of the approach followed, two series of input sets were defined to test the algorithms offline. The first series of inputs were designed ad hoc to test the algorithms in specific conditions where a daily optimization would take greater advantages compared to the single step one. The inputs are therefore very specific, so to be able to know in advance what an appropriate management of the plant would be like. Moreover, they are simple, allowing a better readability of the results. In this first case, the grid exchange profile required is the virtual-island. The second series of inputs, conversely, takes advantage of the data acquisition system on the actual plant. Four summer days and five winter days were selected as typical days for the analysis of the algorithm performance on a real test case. With typical days, two scenarios are evaluated. The first is the present scenario, where there is no imposition of a grid exchange profile and the algorithms' performance can be judged with respect to the present standards in CHP operation and management. The second scenario is a future one where, according to Enel S.p.A., the Distribution or Transmission Service Operators will require to adapt the power exchange profile with the grid following a given a set of rules. These tests allow for the evaluation of the true potential of the algorithm when applied to a power system operating in an energy framework where the RESs penetration in the grid can be improved compared to the present situation. The RTA algorithm is tested on two different conditions. The first is an actual day where both the forecasts and the real time measured values come from the same day. The second is a fictional case created with the aim of stressing the RTA in harsh conditions, i.e. when the forecasts are considerably different from the real time values that the SCADA registers.

The Thesis is composed of six chapters. The first chapter introduces the present energy framework, with an overview of the problems related to energy supply and climate change, thus providing the basic motivations for the research on Smart Grid topics. The second chapter presents a review of the state of the art regarding Smart Grid. First, the Smart Grid, Micro Grid, Virtual Power Plant and Smart User concepts are discussed, along with the proposed control strategies for the management of the grid, referring to the works presented by many authors in the literature. Then, the focus is moved to the optimization algorithms and their implementation in energy systems. The third chapter describes the Smart User plant in Pontlab, providing the specifications of each device that it includes and the thermal and electric layouts of choice among the possible alternatives. In addition, it treats the sizing of some components and the different approach required for their application within Smart Grids framework. The control algorithms are described in detail in the fourth chapter. The modeling of the system, the constraints set, the different techniques adopted and the benefits or downsides of each approach followed are discussed. The fifth chapter presents a detailed description of the input sets employed for the algorithm tests. The motivations behind each test performed are made clear in advance and then each valuable result is presented and discussed in respect to the goals set. Finally, the conclusions are drawn in the sixth chapter, along with a brief listing of the future developments of the project.

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NOMENCLATURE

Latin Symbols

a	generic adjacency matrix coefficient
c	specific heat capacity
C	costs
e	number of subdivisions for the electric storage
E	energy
l	number of levels of charge / levels in DOE
m	mass / maximum number of edges to evaluate
n	number of time-steps / number of experiments
p	number of parameters in DOE
P	power
t	number of subdivisions for the thermal storage / time
T	temperature
V	total number of system states
Y	DOE function

Greek Symbols

η	efficiency

Abbreviations

2DS	2°C average temperature increase scenario
ABC	Artificial Bee Colony
AC	Alternating Current
ACOA	Ant Colony Optimization Algorithm
ADA	Advanced Dispatching Algorithm
AEEG	Authority for Electric Energy and Gas
AMFA	Adaptive Modified Firefly Algorithm
ASM	Ancillary Services Market
BESS	Battery Electric Storage System
CAR	Cogenerazione ad Alto Rendimento

CCHP	Combined Cooling Heating and Power
CHP	Combined Heat and Power
CM	Capacity Market
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
COP	Coefficient Of Performance
CPP	Critical Peak Pricing
DAA	Day Ahead Algorithm
DBB	Demand Bidding/Buyback
DC	Direct Current
DER	Distributed Energy Resources
DG	Distributed Generation
DIEF	Department of Industrial Engineering of Florence
DJ	Dijkstra-based Shortest Path Algorithm
DLC	Direct Load Control
DMS	Distribution Management System
DNO	Distribution Network Operator
DOE	Design Of Experiments
DR	Demand Response
DRS	Demand Response Strategy
DSM	Demand Side Management
DSO	Distribution Service Operator
EDR	Emergency Demand Response
EGA	Elitist Genetic Algorithm
ELF	Electric Load Following
EMOO	Evolutionary Multi-Objective Optimization
ESS	Electric Storage System / Energy Storage System
EV	Electric Vehicle
FC	Fuel Cells
GA	Genetic Algorithm
GHG	Green House Gasses
GME	Gestore Mercati Energetici
HV	High Voltage

ICE	Internal Combustion Engine
ICS	Interruptible/Curtailable Service
ICT	Information and Communication Technologies
IEA	International Energy Agency
ILP	Integer Linear Programming
IPEX	Italian Electricity Market
LCA	Life Cycle Analysis
LP	Linear Problem
LV	Low Voltage
MG	Micro Grid
MGCC	Micro Grid Central Controller
MGT	Micro Gas Turbine
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MV	Medium Voltage
NPV	Net Present Value
O&M	Operation & Maintenance
PES	Primary Energy Savings
PHEV	Plugin-Hybrid Electric Vehicle
PLC	Programmable Control Logic
PQR	Power Quality and Reliability
PSO	Particle Swarm Optimization
PUN	Unified National Price
PV	Photovoltaic panels
RES	Renewable Energy Source
RTA	Real Time Algorithm
RTP	Real Time Pricing
SA	Simulated Annealing
SCADA	Supervisor Control And Data Acquisition
SG	Smart Grid
SLS	Stochastic Local Search
SO	Standalone Operation

SS	Single Step
SU	Smart User
TEE	Titoli Efficienza Energetica
TLF	Thermal Load Following
TOU	Time Of Use
TSO	Transmission Service Operator
VPP	Virtual Power Plant
V2G	Vehicle-to-Grid
VSO	Virtual Standalone Operation
WT	Wind Turbine

Subscripts

abs	absorption chiller
adim	non-dimensional
c	cooling
CHP	co-generator
e	electric
L2	modulable loads
ne	non-exploitation
O&M	operation and maintenance
pr	primary
strg	storage
th	thermal

1 INTRODUCTION

The energy system of the whole World will soon face the need of a change. Because of many factors, such as the growth of population, wealth in developing countries and the effects on the atmosphere due to human activities in the last two centuries, the old paradigm of energy system is no longer functional nor feasible both energetically and environmentally. In this introductory chapter, the present power system and the challenges that the industrial and scientific sectors need to face are presented.

1.1 Present environmental and energetic framework

The present energy system has developed following the idea of centralized generation. This concept is in accordance with the tendency to produce electric energy far from cities and populated areas, or at least where the landscape favors the operation of power plants, like near major rivers. The exploitation of scale factors allows these power generators to be more efficient than smaller ones. In addition, the emissions of large-scale power plants is monitored and treated in a more effective way. Moreover, it is easier to manage a national electricity grid with a small number of big power plants rather than several smaller ones. For all of the above reasons, since when the electricity began to be a commodity diffused among the population, the national power production evolved in the power system that we know today.

When electricity began to be produced, engineers, technicians and industrial men, developed various system and ideas to bring power to factories, public buildings, and, later on, to the population. It is not surprising to notice that most of the technologies that we see today moved their first steps during the early period of electrification. Depending on the most available resource in a precise area, different ways to produce electricity were experimented. Indeed, in the beginning, there was no grid and the electricity was produced where the early adopters would use it. The first national grids came only afterwards, in the first decade of the 20th century.

Electric energy production has always been strictly connected to the price of available resources, and therefore the energy mix of each nation, meant as the different natural resources that are exploited for the production of electric energy, depends on what is available at the lowest price. Thus, the development of technologies for power production also follows the same rule. Until the first power crisis in the '70, fossil resources were cheap to extract and use as fuels for power generators. At the same time, not much effort was placed towards the research of efficient generation solutions or differentiation of power technologies. The fuels of choice were oil, gas and coal. This led to the construction of big fossil fuel powered plants, located in industrial areas, far from city centers in order to avoid the emissions affecting the surrounding population. The effects on the atmosphere and the global costs of this behavior were rarely considered and facing these expensive issues was delayed to a future time. The energy demand kept growing along with the development of the economies and production capabilities of the most industrialized Countries. Energy was so cheap, that it was not even convenient to meter it, but rather let the users pay flat rates, depending on the nominal power of their connection to the grid. This did not help to promote a social awareness of both the economic and environmental costs of electricity production, until now.

1.1.1 Today's energy system paradigm

The present energy system is based on the concept of "centralization": big isolated power generation facilities that distribute the electricity produced by means of high voltage (HV) grids to several areas. The HV grid is required to transmit the electricity over long distances without incurring in excessive energy losses. The electricity reaches transformation stations where the voltage is lowered to medium voltage (MV) and then it is dispatched directly to final users or low voltage (LV) transformation stations. The grid must always balance the production with the demand. In a centralized scheme, this is done exclusively by adapting the production to the demand in real time. The system is well represented by a one-way communication where there is no involvement of the demand in the management of the system itself. There are a few exceptions to this general rule, because, for some countries (e.g. Denmark and Norway) the territory and natural phenomena allow to produce most of the energy required by means of natural renewable resources which are often distributed on the territory. In a large system, such as the national grid of industrialized Countries, the contribution of a single user, as large as it can be, is irrelevant to the system operations themselves. A centralized scheme enhances this barrier between "actors" and "spectators" of the power system. The tariff schemes adopted reflect this separation: the typical tariff for electricity for centralized systems is fixed price per kWh consumed.

Although being easier to manage and operate compared to distributed energy systems, centralized power plants have some drawbacks. They:

- Require long time to start, warm-up and connect to the grid;
- Do not operate at high efficiency during partial load;
- Cannot follow highly variable loads;
- Feature high investment and operation costs, therefore are sensible to scenario modifications.

In the last 5 years, the situation began to evolve and differ with the diffusion of Renewable Energy Sources (RES) and especially those that since then had little fortune because of their high costs and unpredictability (i.e. Wind Turbines (WT) and Solar Photovoltaic Panels (PV)). Until 2009, the only RES actually exploited in the power system were the hydroelectric and the geothermal. Indeed, among the different RES these two offer a great advantage, they are as clean as the other renewables but they also feature a steady and predictable power-output, at least in the medium term.

1.1.2 Energy Crisis and Climate Change

The increase of energy consumption in the World today is dominated by the high rate of growth of developing Countries (i.e. China, India and South-East Asia most of all). There are two important aspects to consider regarding the increase in energy consumption: the first is how the energy is produced, i.e. which are the reserves of fossil fuels and what alternatives are viable; the second is the impact on the environment related to this increase in demand. The World Energy Outlook 2013 from OECD/IEA [1] presents the expected primary energy demand in 2035 and the share of global growth in energy consumption for each area of the World, see Table 1.

Table 1 - Energy demand growth in the World divided by area

	OECD	Eurasia	Latin America	Africa	Middle East	Non-OECD Asia
Primary energy demand in 2035 [Mtoe]	4340	1370	480	1030	1050	6600
Share of global growth (2012-2035) [%]	4	5	8	8	10	65

From the data reported it can be observed that energy supply in the near future is going to be a critical issue if the energy system is managed as it is now. The once developing Countries will then lead the worldwide energy demand. Indeed, with greater wealth and the adoption of an western lifestyle, the energy demand will rise in Non-OECD Asia by 65% compared to 2012 values.

Fossil fuels, such as coal, oil and natural gas, on which the current system is based, are a feasible solution only for a limited amount of time and are featured by energy prices that depend on their extraction cost. For a summary of global fossil fuel reserves, divided by fuel type, see Table 2, from the World Energy Council 2013 – World Energy Resources: A Summary [2].

Table 2 - Global reserve of fossil fuels

	Reserves 1993 [Mt]	Reserves 2012 [Mt]	Production 1993 [Mt]	Production 2012 [Mt]	2011 Reserve/Production ratio
Coal	891530	10131610	7520	4474	>100
Crude Oil	223454	140676	3973	3179	56
Natural Gas	209742	141335	3518	2176	55

Therefore, even if theoretically there are enough fossil fuels to fulfill the whole demand for at least half a century, this is not a feasible nor economical solution for two main reasons:

- Although new reserves are discovered regularly, the amount that can be extracted at today's cost is marginal. Thus, as the reserves deplete, there are other energy supplies that become convenient economically;
- Fossil fuels are not a clean energy solution, there are technologies that can limit emissions, but it is very unlikely that relying on them only or for the major part, will not have a great impact on the environment and ultimately in everyday life.

Climate change is something that has been debated for a long time by the scientific community. The major points of discussion were whether there was climate change, and if it was due mostly to human activities rather than natural phenomena. Nevertheless, in the last years some consensus grew at least on the first point, mostly thanks to different independent studies providing data on the average temperature of the atmosphere and other indirect observations that imply global warming. A single Celsius degree of increase of average temperature of the atmosphere indicates the presence of much more "energy" in the atmosphere itself. This can lead to stronger weather phenomena such as hurricanes, droughts, local hot and cold temperature spikes, whose costs are great on the communities and the nations but are rarely considered as costs associated to energy development strategies. This is because of the difficulty of prediction of these atmospheric phenomena and because they act on a global scale. Therefore, it is hard to associate a single nation's energy strategy to phenomena taking place in the same area. The scientific community defined a limit value of average temperature increase that should not be crossed, and it is 2°C. If that limit is surpassed, the chances to invert or to slow down global warming would be reduced greatly, unless at very high expense to redesign the whole energy system.

The emissions of pollutants and Green House Gases (GHG) are being reduced by most of the industrialized Countries trying to comply with agreements such as Kyoto Protocol (cite) and the European Horizon 2020 targets. However, the targets set, although relevant, will prove inadequate if the entire World will not reduce significantly GHG emissions. If the developing Countries rely on the same energy mix that today is used in Europe or USA, then the amount of CO_2 in the atmosphere will be too high to avoid reaching the 2°C limit. Thus, even if a consistent improvement has already taken place, greater efforts must be made by the scientific community, industrial system and World population in general to redefine the way we satisfy our energy needs, both thermal and electrical.

All this considered, the present scientific and industrial interest in RES development and implementation in the national grids is justified.

1.1.3 The diffusion of Renewable Energy systems

Since the early 2000s, renewable energy technologies other than hydroelectric and geothermal began to be introduced. According to studies such as Jacobson S. and Johnson A. (2001) [3] the diffusion started with the introduction of dedicated policies and thanks to environmental factors. The RES considered as "new" are WT, PV, solar thermal collectors and new types of Biomass. These technologies helped to diffuse RESs in the energy markets. Indeed hydro-electric and geothermal plants can be built only where the features of the landscape or of the underground generate favorable conditions, and although in developing Countries there is un-exploited potential, still it is not enough to cover the energy needs of the population. Wind and Sun on the other hand have a greater potential in terms of installed capacity but, as was mentioned above, they lack predictability and are expensive, and they struggled to find a place in an energy market dominated by "cheap and reliable" fossil fuel. A few studies, such as the one from Leijon M. et al. (2010) [4], define important parameters to evaluate RES like their degree of utilization and consequently the cost per kWh produced. The authors assert how WT and PV, due to their intermittent behavior, are consequently not suitable for energy production. The importance of RES for a sustainable development is stressed by J.P. Painuly (2001) [5], according to whom their potential to provide clean energy is not important only for industrialized countries, but also for developing ones, which can adopt them to supply with clean energy rural or isolated areas. Nonetheless, the growth rate of China and India pushed towards the installation of more traditional solutions when RES started to diffuse in OECD countries. A trend that is now changing, with Non-OECD countries that have been leaders in the installed capacity of RES in the last two years.

The IEA Tracking Clean Energy Progress report (2014) [6] provides useful data on RES diffusion from year 2000 to now, along with projections for the next 5 years and targets for the 2DS Energy Technology Perspective scenario. This scenario is related to an energy system that could give at least 50% chance of limiting the average global temperature increase to 2°C, other scenarios considered are 4DS and 6DS, which respectively consider an average temperature increase of 4°C and 6°C. The data reported in Figure 1 demonstrate the diffusion of RES in the global energy sector. In the diagrams, for each RES the current status compared to the 2025 targets is highlighted. It is worth noting that by the end of 2013, over 100 countries presented a backing scheme for RES support, which helped to create a spot market as well as increase their development with a consequent reduction of costs.

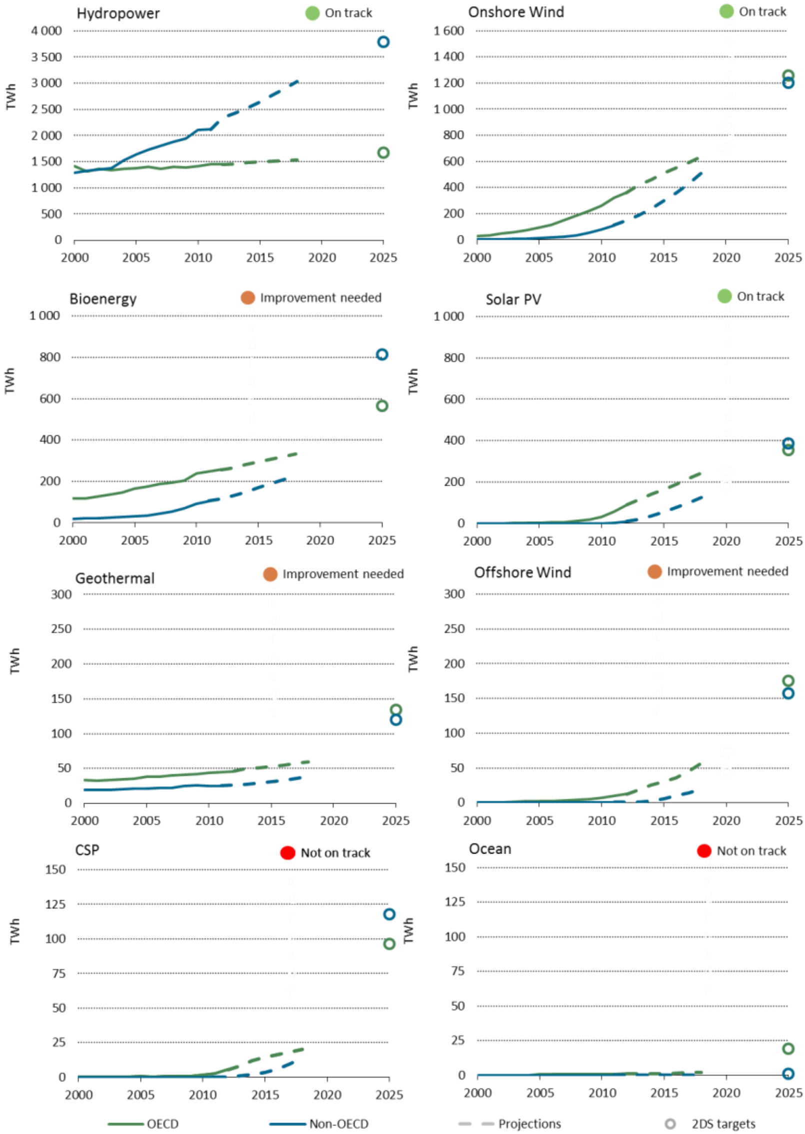


Figure 1 - RES productivity compared to the goals set for 2DS scenario - source: IEA Tracking Clean Energy Progress report

The energy price that can be achieved with a given technology is one of the greatest drivers for its diffusion, in Figure 2 the present price, projections and targets for different energy production technologies is presented.

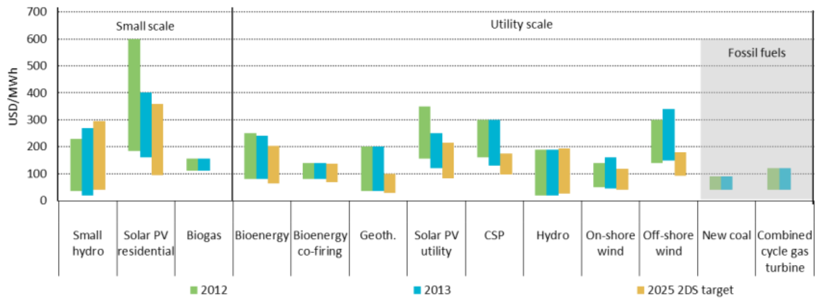


Figure 2 - Leveled energy price for RES compared to coal and combined cycle gas turbine technologies

The study carried out by IEA involves also other sectors of the energy field, both in terms of production and usage, as well as in terms of management. They review the present status compared to the 2DS target, along with policies recommendation for each sector: RES, nuclear power, gas-fired power, coal-fired power, carbon capture and storage, buildings, industry, transport, electric vehicles (EV), biofuels, cogeneration district heating and cooling, smart grids. According to this study, the only sector on track with the goals assigned is the diffusion of RES, which still needs dedicated policies but complies with the objectives set. Of the other sectors, some have seen improvements but are urged to increase their effort, like: gas-fired power, industry, transport, EV, co-generation and Smart Grids. On the contrary, the remaining sectors are far from their targets and actions are required in order to put them back on track. Regarding the Smart Grid sectors, IEA's study notes a steady growth in research activity but also a lack of actual deployment data, deployment that is considered as insufficient. Therefore, they suggest policies that help to support the development of international standards in order to accelerate research, development and deployment, new electricity regulations to enable a practical sharing of Smart Grid costs and benefits and finally promote the development metrics, national data collection and international data co-ordination.

In 2011, the share of renewables generation was 20% on World scale. As can be noticed in Figure 1, the RES energy targets for 2DS scenario are well over twice today's value for all but hydro-electric technology in OECD countries. This means that in order to meet the targets a higher share is required. The present power system is not capable to accept distributed and unpredictable power generators. Thus, new challenges need to be faced and a new concept of energy system is required.

1.2 Current research challenges and goals

In the last decade, several studies and researches have been carried out to address the impact of RES on the power system and, on the other hand, the benefits that they can bring. The first studies focused on small, isolated power systems, such as those of islands where high penetration of RES could be reached with a reasonable installed capacity. In most of the papers, the RES considered are WT and PV, with a power output strictly dependent on weather conditions. Some studies, like Duić N. and da Graça Carvalho M. (2004) [7] describe these so-called "renewable islands" case studies, islands where the RES are economically competitive ways to satisfy the energy demands. According to the authors, the issue of RES intermittency can be solved, at a relatively high cost, with hydrogen energy storage. In the paper, the model defined by the authors was tested on Porto Santo island data for two different cases: demand peak-shaving and 100% renewable power system with two possible configurations, WT alone or WT and PV mix. The results show that for peak shaving a mix of wind and solar energy is more effective whereas the only wind solution is preferable in case of 100% RES power supply. It is evident that the results of this kind of studies often depend on the peculiar location and energy system analyzed. Within the same framework of the program “Renewislands” a similar study was presented in Chen F. et al. (2007) [8], with details of the work tasks and activities required to develop a RES, Fuel Cells (FC) and hydrogen storage infrastructure aiming to promote RES penetration in isolated power systems such as those of islands. The main results of each part of the activity are reported in the paper. Interest on the RES potential to supply clean energy to islands is proven also by the paper proposed by Oikonomou E.K. et al. (2009) [9]. The authors developed a methodology called EMERGENCE 2010 that allows them to improve the RES contribution in terms of regional sustainability thanks to the tools that it provides to different stakeholders to evaluate projects and plan their actuation. Still on the topic of RES potential in rural or isolated areas, Akella A.K. et al. (2009) [10] show the social, economic and environmental impact of RES for a case study in India consisting of a region with remote villages. This research proves several benefits of RES applied to the case study, among which: tangible reduction of emissions, clean development mechanism that favors sustainable development, in both India and other developing Countries and communities, reduction of end-users’ dependence on fossil fuel, a better power quality ensured by the deep connection between load and generator. Similarly, Praene J.P. et al. (2012) [11] present the status, achievements, policies and future objectives for the energy independence of Reunion Island.

One of the key issues related to WT and PV diffusion in the grid is that the present energy system is not capable to fit them at high percentages of the total productive capacity. The fact that these RES can modify rapidly and in a difficultly predictable way their power output requires the power system to adopt reserve power that can quickly act as back up when for example the wind decrease its speed or the clouds shade a PV field. This is very expensive for Distribution Service Operators (DSO) and

Transmission Service Operators (TSO). The grid itself is not designed to fit a great number of electricity injection points in different areas and at different tension levels. The major problem is the lack of real-time communication among the energy producers and the DSO, which ultimately leads to difficulties in balancing services and risks of poor power quality. Hammons T.J. (2008) [12] presents shortcomings and issues of the present distribution grids and regulations in Europe. The effects of a high percentage of RES in the energy system are investigated by studies such as Brouwer A.S. et al. (2014) [13] who quantify the effect on the present-day power system of increasing Intermittent Renewable Energy Sources. It is found that at 20% penetration of wind power, the increase of the primary reserves is 0.6% of the installed wind capacity, whereas the size of all the other combined reserves grows up to 10% of the installed wind capacity. At the same time thermal generators are affected by a 4% efficiency reduction for an overall cost of the system associated to this equal to 1-6 €/MWh (i.e. almost 10% of electricity wholesale price). A similar research was performed by Nikolakakis T. and Fthenakis V. (2011) [14] for the test case of New York State grid and loads request. They determined which is the highest percentage of penetration of renewables in the grid itself, before serious energy dumping must be performed. It was found that the combination of both PV and WT allow the grid to accept a higher percentage of renewably produced energy compared to the option with WT alone. Nevertheless, the latter solution is still more economical even with the curtailment of a large fraction of the energy produced. According to the authors, the situation might change in the future due to the fast paced lowering of PV costs. The same analysis is carried out by Krajačić G. et al (2011) [15] who take into account the Croatian energy system as case study. The authors present a novel approach in the planning of the power system with a focus on the integration of a high share of RES in the system itself. A great interest is placed on the storage capacity of the system and the benefits that it can allow. A total independence of Croatia in the energy sector could not be achieved in the simulation (performed on one-year time span) but the amount of RES still reached over 78% with important emission savings. The ultimate limit to RES penetration in the grid is envisioned by Battaglini A. et al. (2009) [17] who propose a roadmap towards a European and North African SuperGrid of 100% Renewable Energy Sources by 2050 as an effective and reasonably expensive way to address global warming and fluctuating renewable generation issues together.

The potential of RES to reduce the impact of human energy supply activities on the climate is examined by Nagl S. et al. (2011) [17], with a feasibility study of a 95% reduction in GHG emission within 2050. Several scenarios are defined and the cost of such a shift towards renewable and/or clean solutions is evaluated. Although the cost for this transformation seems reasonable and makes it feasible, a few major conditions for success are indicated: an extension of the European electricity grid, an international climate protection agreement and a coordinated European policy on renewables. A similar research is proposed by Ludig S. et al (2011) [18]. In this case, the analysis performed by the authors on the long-term climate change mitigation allowed by RES in eastern Germany features a greater temporal resolution in respect of other studies. This results in a greater accuracy in the evaluation of costs and a reduction of share of inflexible technologies that can be admitted in the energy market. The time resolution used is 2 hours, whereas in the case of 1 hour the higher complexity of the simulation is not justified by the results, which are almost identical. In the paper are also presented a series of outlooks and points of interests onto which the future research needs to focus. The effects on the electricity market produced by RES is the focus of a research carried out by Schleicher-Tappeser R. (2012) [19] who considers the fast-paced innovation and disruptive change that renewable resources-based power technologies can introduce in the electricity market, regardless of it being ready for such a major change. The author suggests several modifications to policies and market initiatives to be adopted rapidly.

How to integrate new RES in the power system is vital for the solution of the energy crisis and climate change issues discussed above. A possible solution is the definition of a new concept of transmission grid, where not only electricity but also information is shared among producers, users, and “pro-sumers” (i.e. those who produce and consume energy at the same time). Such a grid, managed in an optimized manner, has the potential of both allowing a greater share of energy in the system from RES and to enhance security of supply and power quality. This grid, for it is designed and managed in an intelligent way, has been called the “Smart Grid” and will be discussed in the following section.

2 THE STATE OF THE ART IN ENERGY PRODUCTION AND MANAGEMENT OPTIMIZATION

The new proposed paradigm for the energy system, in contrast to the present centralized system, is Distributed Generation (DG) also referred as Distributed Energy Resources (DER) in the literature. There is no unique definition for DG, but most of the authors agree with the fact that a thermal or electric generator, in order to be classified as DG, should operate in close relation to the local grid into which they feed the energy.

In the literature there are several works discussing this topic in different fashions and from several points of view. El-Khattam W. and Salama M.M.A. (2004) [20] present a survey of distributed generation types, technologies, definitions, and operational constraints and classify them according to different categories. The DG economical and operational benefits required to support the implementation of the DG in the distribution network are discussed. In Pepermans G. et al. (2005) [21], the authors survey existing small-scale generation technologies highlighting their major benefits. The best definition they provide for DG is "an electric power generation source that is connected directly to the distribution network or on the customer side of the meter". Also Alanne K. and Saari A. (2006) [22] deal with the definitions of DERs and evaluate political, economic, social and technological aspects of regional energy systems considering their degree of decentralization. Distributed energy system characteristics are discussed in the context of their sustainability and the authors conclude that DERs are a good option for sustainable development. Lopes Peças J.A. et al (2007) [23] present a review of the key aspects and issues related to distributed generation. The aspects covered are the challenges to be won in order to increase the integration of DG in the transmission grid, the management policies required and the opportunities related to DG. The presence of renewables in DG is also discussed. The paper focuses on the main drivers for DG growth and on the problems that need to be solved, especially switching from a "fit and forget" approach to an integrated one regarding power system planning and operation. The drivers for diffusion of DERs are divided among environmental, commercial and political such as: limiting Green House Gas (GHG) emissions, avoidance of building new transmission circuits and large power plants, uncertain electricity markets that favor small generation solutions, improved power quality and stability, higher security of energy supply and support for a competitive market. The challenges can be distinguished in technical, commercial and regulatory as well: increased power quality, protection and stability of the power system are a possible benefit of a higher penetration of DG in the main grid, but only if their management and operation follow a new paradigm. In order to support the development of DG, three approaches are possible in terms of commercial arrangements: recover costs of active management directly by means of mechanisms for price control, establish an incentive scheme to reward DG, define a market for electricity and sales of ancillary services related to DG. Nevertheless, the authors identify in the regulation of DG operation and connection to the grid a fundamental requirement for their development. The paper also features a first attempt to value different kinds of ancillary services that could be provided by non-intermittent DGs. The services more likely to take place in the short-medium term are: DNO security of supply, TSO frequency response and regulating/standing reserve. The modeling tools and practices play an important role in DG development. Manfren M. et al. (2011) [24] provide an analysis of the different models currently available for the planning and design of distributed generation aiming at gathering capability to sustain a shift in the energy paradigm of urban energy systems. The authors also define the features that such models should have and still lack, thus providing a guide for future research on the topic. The diffusion of DG technologies relies also on the interest of the energy market on the benefits they offer, Poudineh R. and Jamasb T. (2014) [25] present a market-oriented point of view on the topic. It is clear then that the role of DERs in the future and the methods for their planning and optimization are critical research problems for the implementation of a new grid concept, the Smart Grid [26].

One of the first examples of DG are Combined Heat and Power units (CHP) that supply both electricity and thermal energy to their users. Indeed, the DG concept comprises also isolated or rural energy supplies. Among RES, PV and WT are often installed directly where the electricity they provide is needed. Therefore they are considered DGs and their great growth in numbers in the last years promote interest on the design and operation optimization of DERs. Amor M.B. et al (2010) [27] show a LCA analysis of a distributed generation system including solar panels and wind turbines. Different scenarios (average, below and above average conditions) are evaluated and the outcomes are that although very climate-dependent, DERs show improvement for Northeastern American power grid when compared to centralized production.

Distributed Generation can be considered as the hardware of a new model for the energy system. However, the hardware alone will not be sufficient to tackle the energy and climate issues. Communication between the different actors of the system is required, as well as an in-depth optimization of each component of the grid, from the smallest building-scale up to the regional one. Ruiz-Romero S. et al. (2014) [28] analyze the results of DG integration in the electricity distribution network evaluating its effects most of all in terms of power quality. This demonstrates to be highly affected by DG. Therefore, the authors stress the importance of the development of a two-way communication infrastructure as well as hierarchical and distributed architectures to adjust and synchronize the voltage regulation of the distributed energy resources. Once these control and communications systems are ensured, RES can be optimally integrated into the distribution grid. Some studies try to investigate the scenario of a 100% decentralized worldwide renewable-based energy system. Pleßmann G. et al (2014) [29] simulate the hourly electricity demand and renewables productivity of over 160 countries. To ensure the matching of loads and production in each hour, three different storage technologies are considered. The results of the study are a global average cost for electricity of 142 €/MWh which is considered enough to make the shift feasible.

2.1 The Smart Grid

The concept of Smart Grid has been discussed and defined in several ways in the literature but a standardized definition is still missing. Nevertheless, considering the various definitions proposed it is possible to identify the Smart Grid as any combination of hardware and software technologies, as well as practices, meant to enhance the efficiency, security, economy of operation and environmental friendliness of the present energy system. The fundamental objectives of the Smart Grid can be listed as:

- Allow the shift towards DG with a greater penetration in the power system of RES, thus achieving a reduction of the GHG emissions, see Phuangpornpitak N. (2013) [30];
- Increase the global energetic efficiency of the system with greater Primary Energy Savings (PES) compared to the centralized grid;
- Reduce the costs of operation and maintenance for all the stakeholders of the energy systems, from energy service suppliers to DSO, TSO and final users as well;
- Promote a greater participation of small energy producers and final users in the energy market and balancing services;
- Enhance the security of energy supply and system reliability;
- Improve the power quality of the energy system.

To achieve these goals, the SG relies on several concepts, tools and components. The first important feature is its modular structure: the SG operates on a wide scale, i.e. national; it can be considered as composed of smaller, but still “smart” modules. From the largest to the smallest scale there can be identified energy hubs, Micro Grids (MG), Virtual Power Plants (VPP) and finally Smart Users (SU) or Smart Homes. Each component shares with the Smart Grid concept the same fundamental objectives. However, at different scales, the actual design and operation of the system may differ. In any scale considered there are three levels onto which the control system of the SG components operates: generation, demand and storage. Some authors extend the SG concepts to district heating, like in Lund H. et al. (2014) [31], where the authors believe the SG and Smart Thermal Grid to be complementary, an aspect which is also important for the research presented in this Thesis. Moreover, with the advent on the automotive market of an increasing number of Electric Vehicles (EV) and Plug-in Hybrids, researchers focused on their possible role and integration in the SG, Sousa T. et al (2012) [32], Hota A.R. et al. (2014) [33]. Research on SG is expanding rapidly in industrialized countries such as USA, Europe and Japan but, as demonstrated by reviews such as Fadaeenejad M. et al. (2014) [34], also in China, India and Brazil, Countries that are investing in the improvement of their national grids and recognize the strategic importance of SGs.

Hereafter, for each scale and each operational level of the SG, a description along with references from the state of the art will be proposed.

2.1.1 A smart system composed of smart components

As mentioned before, the Smart Grid concepts are infused in all of its components. Different aggregation levels require the optimal management of different energy vectors. For instance, on the greater scale it is un-realistic to exploit the thermal energy, both at high or low temperature because of the long distances that the thermal vector fluid would need to travel, therefore dissipating most of the energy it transports. Whereas, at a lower scale, like in cities, it is possible to consider district heating as one viable solution to pursue the goals of the SG. At building scale, even single loads can be taken into account into the optimization process. On the other hand, the greater scales allow the optimization of the whole generation system, considering the power production and requests of several smaller grids and the centralized power plants together. Mancarella P. (2014) [35] provides a review with a holistic approach on the SG components and possible tools for optimization.

2.1.1.1 Micro Grids

A Micro Grid can be defined as a network of generators and loads, typically with a high grade of DG presence, which can be operated in a twofold way: grid-connected, i.e. exchanging electric energy with the national grid, or, in isolated mode, disconnected from the main grid. They usually include both LV (≤ 1 kV) and MV (1-69 kV) tension levels and are a step towards SG implementation considering they act as the link between centralized generation and DG. Jiayi H. et al. (2008) [36] and Ustun T.S. et al. (2011) [37] present an overview of concepts, technologies and ongoing-research on MGs.

In order to be able to operate both in island mode and grid connected, MGs require several tools and components. In terms of generation capabilities, a MG usually implements several generators of different kinds, whose sizing must take into account the possible operation of the MG isolated from the grid. Intermittent RES, such as PV and WT, can be deployed along with fossil or bio-fuel-alimented prime movers like Micro Gas Turbine (MGT) and Internal Combustion Engines (ICEs); innovative solutions and some case studies in the literature include Fuel Cells (FC) as well. Combined Cooling Heating and Power (CCHP) solutions are often very valuable within MG, for they offer the possibility to satisfy both electric and thermal loads and thus increasing the system efficiency and PES, Wei G. et al (2014) [38] present a comprehensive review of the modeling, planning and energy management of the CCHP microgrid. The power range of these technologies is usually between 10-100 kW_e, especially because of the flexibility of operation and fast time of response that are required in order to follow the load demands during island mode. Storage technologies, especially the electric ones, play a fundamental role inside MGs. Those featured by a quick response time and high power allow the management of quick transient phenomena occurring when the disconnection/connection from the main grid is actuated. On the other hand, slower storages featuring greater capacity, can improve greatly the penetration of RES among the DG mix of the MG. Palizban O. et al. (2014) [39-40] analyze the principles of MGs design that allow them to participate in active network management. The authors propose the application of IEC/ISO 62264 standards to both MG and VPP along with providing a review of MGs in terms of: advanced control techniques, energy storage systems and market participation during both island and grid-connected mode. The authors stress the importance of island-detection methods, providing also a discussion about each method's advantages and shortcomings.

Thanks to the fact that it can be operated in island mode, the MG is a valuable asset of the SG. Indeed, from a grid perspective the MG can be considered as a single entity, a distinct producer or consumer of electric energy. This means that the grid itself does not need to balance loads and generators inside the MG but only among MGs. Because of this and the fact that the major part of the power generation is done within the MG boundaries, there is less need of energy transmission in the main grid, which implies that power losses and also the investments for the upgrade of the transmission grid are reduced. MG, being a smaller system, is easier to be controlled and managed and therefore there is the opportunity to improve also the Power Quality and Reliability (PQR) of the energy system. Nonetheless, in order to be operated in island mode while guaranteeing PQR and balance within grid standards, MG must include three levels of operation optimization and controllers, each one maneuvers within different boundaries:

- Local micro-source controller and load controller, which is in charge of controlling the voltage and frequency during transient conditions based on local information only. This controller interfaces the smaller scale optimizers and operation management devices with the MG;
- Micro Grid Central Controller (MGCC), its roles span from monitoring the active and reactive power of the several generators interconnected to the optimization of the operation of MG. The control is performed sending set points to both generators and controllable points. It can be considered as the main controller of the MG;
- Distribution Management System (DMS), which, conversely, interacts with the upstream network, i.e. the greater-scale system.

At each level, an optimization system is required in order to instruct the controller in the best operation to adopt. Each level of optimization shares similar goals, which are the same proposed by the SG concept: economy of operation, lesser emissions, greater power quality and reliability of the system. Furthermore, an optimization of the design of the MG itself is often required, e.g. how many generators and storages are required, their ideal size and so forth.

In the literature can be found several researches concerning MGs. Baziar A. and Kavousi Fard A. (2013) [41] developed a modified Particle Swarm Optimization (PSO) used to solve an optimization problem regarding MG systems including RESs and storage devices. An example of the optimization of a generation system connected to a MG is provided by

Malakar T. et al. (2014) [42], who performed the optimization of a wind-pumped storage hydro plant connected to the MG by means of an Artificial Bee Colony (ABC) algorithm. This heuristic algorithm is used to determine when it is better to charge or discharge the storage in order to maximize the profits or at least reduce the unscheduled interchange penalties that are applied following a frequency based pricing mechanism. A penalty applies when a deviation from the scheduled feeding of electricity in the MG is registered. The results of the simulation show that the algorithm not only reduces the penalties but can also be used to maximize the efficiency of the hybrid system. Zhou K. et al. (2014) [43] focus on the models for the optimization of load distribution in MGs. The authors reviewed several models, pinning their shortcomings. They state that traditional optimization methods are unsuitable for this kind of problem because they do not take into account important constraints, e.g. storage size, whereas genetic, particle swarm and bee colony type of algorithms are more promising. In their paper the authors propose a model, of generic type, which can lead to more effective and efficient solutions of the optimal load distribution problem compared to the models reviewed. This optimization results from a compromise among different aspects that need to be taken into account at the same time with a multi-objective optimization problem including six different functions: total operating costs, total emissions, interruption costs (reliability), total power line loss, power quality costs and power generation efficiency.

In order to address correctly the problem of the optimization of both the design and management of the MG beforehand, it is useful to define several scenarios that are likely to occur during the operation of the MG itself. This is especially true for the design optimization, which in the present work is not performed by means of automated algorithms. Responding to this research quest, Mohammadi S. et al (2014) [44] propose to investigate the effects of uncertainty on the optimal operation management of MGs. The method consists of two phases: a first one where several scenarios (both likely and unlikely to happen) are picked for the analysis by means of the optimization algorithm based on the Adaptive Modified Firefly Algorithm (AMFA), then, the actual optimization is performed. The results of the simulation demonstrate that the method applied to the MG with different types of generation units (WT, PV, Micro-Turbine, FC and storages) is satisfactory in terms of capability to investigate the different scenarios and thus reduces uncertainties.

The new concept of local grid that is suggested by MGs opened the road for the discussion over established technologies and practices. In their paper Sechilariu M. et al. (2014) [45] define a multi-layer supervision control for a grid operating in Direct Current (DC), conversely to the standard Alternating Current (AC) ones. According to the authors, the main advantage of a DC grid, is that the different sources of electricity can operate together without any issue in terms of phase-matching, the transformation to AC being performed only at the connection with the main grid, therefore the system is generally simpler compared to the AC one. Moreover, several loads in urban buildings can be efficiently fed with DC rather than AC/DC converters. The energy system considered in the study comprises PV array and energy storage; in addition, some of the loads can be interrupted in order to ensure the balance along with production curtailment. The optimization of the system is carried out with the definition of a series of IF-THEN clauses, which leads the algorithm towards the most appropriate solution. The strategy adopted allows a very fast, real-time optimization of the system, but on the other hand the level of optimization is poorer compared to other approaches presented in the literature because of its simplicity. The advantages and disadvantages of DC grids are also investigated in Planas E. et al. (2013) [46].

The research on MG is carried out worldwide, and several projects are active in different Countries. Still, the size of the problem and the importance of the systems involved often prevent researchers from carrying out a proper experimentation, thus most of the studies and projects consider real test cases and simulate the behavior of the MG applied to those test cases. A review of the existing projects as well as the most significant simulations of MG networks is presented by Lidula N.W.A. and Rajapakse A.D. (2011) [47] as well as by Planas E. et al. (2013) [46].

2.1.1.2 *Virtual Power Plants*

The concept of Virtual Power Plant has been around for over fifteen years now. The first definition of something similar to a VPP was proposed by Dr. Awerbuch in 1997. He defined the Virtual Utility as *"a flexible collaboration of independent, market-driven entities that provide efficient energy service demanded by consumers without necessarily owning the corresponding assets"* [48]. Indeed the definition of the Virtual Utility matches what is nowadays considered a Virtual Power Plant. VPP aggregate different types of DG units by means of an advanced system of optimization and communication in order to improve the performance of the VPP itself. The VPP concept differs from the MG one for three main reasons:

- It is usually of a smaller scale, from hundreds of kW_e to several MW_e;
- The generators inside the VPP do not need to be on the same local grid nor the same geographical area. E.g. a group of generators distributed in different geographical locations can act as a VPP from an electricity market perspective;
- The intervention on the load side of the balancing equation is more sporadic.

The VPP is still a valuable concept for the deployment of the SG because of its peculiar characteristics of management, control and optimization of the generators it comprises. The benefits of its structure and design can be:

- An increase of primary energy savings and therefore being a "greener" solution compared to a standard operation of the same collection of generators;
- Reduction of energy losses due to transmission and distribution of the electricity;
- Ease the integration of RESs in the power system thanks to a stabilization of their stochastic power output;
- Allow the DSO and TSO to delay investments for grid upgrades, indeed VPPs do not require expensive hardware upgrades in order to be employed;
- Thanks to its smart control system and high flexibility it can provide value-added functions such as ancillary services to enhance the reliability and security of the power supply;
- Increase the participation of small producers into the electricity market, improving market competition and thus economy of energy services.

In order to achieve these benefits the key is to be able to forecast the possible consumption and generation in advance. On the side of consumption one could rely on statistical or measured data for similar conditions, on the other hand for the generation some DG technologies allow the planning of the production and flexibility in operation (i.e. ICE and MGT). Storages as well enable a greater freedom in system operations. Some other DG generators, such as WT and PV have a limited flexibility thus the only way to "plan" their operation is to base on forecasts of their productivity based on meteorological data and models. In Tascikarouglu A. et al. (2014) [49] the evaluation of a hybrid system composed by RES, H_2 and thermal power systems is performed. An economic operation-based dispatching strategy that adapts interactively to the real measured wind and solar power production values is proposed. This strategy allows the authors to overcome the effects of the stochastic nature of wind and solar power generators and thus achieve higher benefits in the electricity market. The results obtained are an increase in the forecasting accuracy for RES productivity and the operation costs for the VPP is halved. If the productivity of stochastic RESs like wind and solar cannot be known in advance, or when the weather forecasts fail to provide a reliable prevision of their productivity, the flexibility of the other generation technologies inside the VPP can be exploited to achieve the goals of the VPP and gain a spot on the electricity market. In Yang Y. et al. [50] the authors take into account the concept of VPP and illustrate a real-time control strategy for dispatching active power among DG units in order to satisfy load variation and RES intermittency. The DG responds to the target determined by the upstream grid. From the simulations carried out, the proposed approach for real time control could achieve the active power control target with ease while reducing the generation costs.

2.1.1.3 Smart Users and Smart Homes

The smallest-scale system of the Smart Grid is the Smart User (SU) or Smart Home. It can be defined as the local system of the end user, comprising either flexible loads only or both generators and flexible loads. Along with the obvious presence of loads to be satisfied and the possibility of self-generation by means of different prime movers or RESs, storage devices of different types are often considered as fundamental for these applications. Depending on the type of plant and its components, the SU can provide several services from a SG perspective. The SU, like every single subsystem of the SG, shares with it its objectives and philosophy of design and operation. Hence, the SU can be defined as a local network of devices and generators, managed by a central controller, which can take into account several inputs, provided by the user itself and/or the DSO along with data acquired by weather stations and other sensors. Typical goals of a SU are:

- Reduction of energy supply costs for the user;
- Greater efficiency of the energy supply and consequently an increase in the primary energy savings of the system;
- Allow Standalone Operation (SO) or Virtual Standalone Operation (VSO), thus increasing the security and reliability of the energy supply;
- Respect an energy exchange profile with the grid, especially when the SU includes intermittent RESs, hence allowing both a greater penetration of RESs in the power system and a reduction of the costs that energy producers, DSO and TSO must bear because of their unpredictability;
- Enhance the PQR of the local network.

If the SU does not feature any generator, the flexibility that it can achieve and therefore the benefits of a smart operation of the system are reduced. Nevertheless, mechanisms like Demand Side Management (DSM), which will be discussed in the following section, can be adopted to accomplish the goals set to some extent. It is easy to see how SUs including generators, renewable or fossil fuel alimented, allow a greater degree of flexibility of operation and eventually greater benefits for the user itself. At the present date, it is hard to foresee what SUs of the future will be like. However, considering the load-only case as a subcase of a more generalized system that includes generators, loads and storages of different kind, most of the works in the literature prefer to analyze this latter solution rather than the simpler one.

The possibility to achieve the proposed objectives is given by the central controller of the SU, which relies on the data acquired by several sensors and smart meters within and outside the SU boundaries. These Information and Communication Technologies (ICT) along with the central controller are the main difference between a standard pro-sumer system, designed and operated according to present standards (e.g. thermal load following operation for a CHP system), and the SU.

In the literature there are a few research papers dealing with what can be considered as a first declination of the SU concept, still, most of them consider rather limited or simple cases, which do not exploit the full potential of the SU. One of the earliest studies related to such systems is found in Al-Ali A.R. et al. (2011) [51]. The authors of the paper present the design, small-scale implementation and testing of an embedded system that integrates RES (i.e. PV) and storage technologies into a smart home. The system schedules and arranges the power flow during the day from the RES or from the grid, achieving a 33% less expense compared to a base-line case. A simulation of a household managed through a Global Model Based Anticipative Building Energy Management System is described in Missaoui R. et al. (2014) [52]. The model developed by the authors is capable of finding a good compromise between economical savings and occupant comfort level taking into account physical constraints of the plant and price inputs. The simulation of the loads and behavior of the house is performed by a Simulink/MatLab© model. The whole system allows the house to save almost 18% of the energy and therefore expenses. A much more detailed and interesting study is the one of Tascikaraouglu A. et al. (2014) [53], which is also one of the very few considering a real experimental case, i.e. not simulated by a model but properly built and operated. The authors of this study investigate an experimental Smart Home as a basic component of the SG. The goal of the study is to address both the DSM issues (related to preserve the comfort of the inhabitants) and to reduce the problems related to the unpredictable generation of renewables, all within a domestic energy management strategy. The idea is to shift deferrable loads in order to avoid them being active during times when electricity is expensive or the production from renewables is limited. The smart meters in the house allow the occupants to know the instant, daily and monthly consumption of each appliance; these data are also stored on a web-based application to allow the remote monitoring and management of the system. The household is featured by various RES and storage systems. The analysis is carried out in terms of in-home energy management, control of appliances and power flow. The control algorithm works from the assumption that better forecasts of the meteorological data allow a better efficiency of the grid-connected smart home, maximizing the local exploitation of the electric energy produced by the renewables installed on the site. The operation of the system is optimized considering both generation and load side, the latter divided in two groups: controllable and non-controllable, taking into account several inputs like time varying tariffs, RESs productivity, desired temperature inside the building, storages' state of charge. The system relies mostly on a Fuzzy Logic decision controller, which is based on a set of rules. House users can override the system if they require one appliance to operate at a given time regardless of the optimization proposed. The algorithm, including the RES forecasting routine based on an Artificial Neural Network, can generate a solution within 28 seconds, fast enough for home appliances management. The improvements are present although not strong (around 3% for the whole year) but, according to the authors, could be improved with a greater network of smart homes.

In conclusion of this brief literature review on the topic of Smart Users it is interesting to cite the work of Balta-Ozkan N. et al. (2013) [54] who present a review of interviews and studies on householders' perception of smart metering and smart home in general technologies. The study allows the researcher to understand which are the prospects of future smart home appliances and tech markets.

2.1.2 Demand Side Management and Generators Management

The Smart Grid requires each of its subsystems to be able to operate in compliance with the objectives that guide its design and operation. Each subsystem must then be able to respond quickly to several inputs, both from within and outside its boundaries. The typical inputs that are taken into account are divided in three categories:

- Environmental conditions: temperature, solar irradiation and wind speed. These are usually considered for the forecast of the levels of thermal loads due to space conditioning and the productivity of intermittent RESs like WT and PV. These inputs are independent from the will of any of the stakeholders involved in the energy field.
- Internal requests: what the users within the boundaries of the subsystem require. In this category can be found for example the electrical and thermal load profiles that result from the activities planned for a given amount of time or obtained from statistical analysis carried out over similar periods of the year. These inputs are a direct expression of the “comfort” of the end-users, i.e. the temperature level set inside a building or the expected production of goods for a factory in a given day.
- External constraints: inputs that are provided or imposed from the outside of the subsystem. An example can be the electricity market prices, ancillary services rewards or power grid exchange profiles. These constraints might be in accordance or in contrast with the ideal operation of the system that the end-users wish.

For each subsystem, every category might include different inputs, or for example, one input that is considered internal from the point of view of the Micro Grid can turn to be external for the Smart User. Nonetheless, these three categories are transversal and can be applied to each subsystem.

All of the inputs concur to define a compromise of operation, which is one of the best possible solutions according to different perspectives e.g. economy of operation, primary energy savings, environmental friendliness and power quality. The core of the SG can be considered its network of communication between several controllers and optimizers. Nonetheless, it is important to stress that they must operate on the hardware of the system in order to apply their suggested operation. In general, two are the sides where the controllers can operate: demand side and generation side. Both of the interventions can take advantage of the presence of storages in the subsystem. Each of the possible control strategies is described in the following sections along with a brief review of relevant researches from the literature on the topic.

2.1.2.1.1 Control strategies for loads

Every form of management of consumer's behavior or any action performed in order to modify the consumptions of a facility can be referred to as Demand Side Management or Demand Response (DR). The modification can occur either from the final user or from an external driver, e.g. the DSO. The diffusion of DSM schemes have already begun in the United States, Europe, China and other countries, although still in a way which is far from unlocking its full potential.

Faria P. and Vale Z. (2011) [55] and Siano P. (2014) [56] all deal with this topic in their research papers. There are two categories of DR programs: price-based demand response and incentive-based demand response. Under the first category falls the modification of the consumption profiles carried out by the end users as response to a change in the price they pay for energy. The participation to such price-based DR programs is voluntary at present. The second category includes those DR programs that allow customers to receive fixed or time-varying incentives in addition to their price of supply. Penalties for customers who fail to comply with a request of their contractor can also be applied, e.g. if a user cannot comply with a request of curtailment of a load because in that moment the load to be curtailed is vital for user's operation. The most common price-based DR programs are:

- Time Of Use tariffs (TOU), according to which, the price of electricity varies during different periods of one day length, depending on the cost for the generation and delivery of the electric energy during the same period;
- Real Time Pricing (RTP), where the electricity price varies once every hour, in direct correlation with the trend of the wholesale price of electricity;
- Critical Peak Pricing (CPP), which is based on TOU but there are high price modifiers during peak hours.

These schemes rely on the actions that the end user will perform in order to exploit favorable conditions and avoid peak hours for its more energy-heavy activities.

On the other hand, the incentive-based DR programs include:

- Direct Load Control (DLC), a program allowing an external operator to switch off or cycle customer's electric loads. This kind of program is offered preferably to small residential or commercial customers;
- Interruptible/Curtailable Service (ICS) where instead of switching off completely a load, the user can take advance of a rate discount on the bill if he accepts to reduce part of his loads during periods of contingencies, whereas he is penalized if he fails to modulate a load when requested to do so. This program suits better larger industrial customers with several big loads

that can be modulated without affecting in a great way the productive process or the activities carried out by the user;

- In Demand Bidding/Buyback (DBB), a program according to which a customer can offer curtailment capacity to the operator for him to exploit it in case of necessity. This program is preferred for large customers compared to small ones;
- Emergency Demand Response (EDR) which can be considered a hybrid between DLC and ICS, is usually exploited by the DSO or TSO when the reserves are insufficient;
- Capacity Market (CM) programs that consist of a customer offering load curtailment as a form of power reserve for the system, thus the customer acts as a virtual producer by reducing the load he would have required;
- Ancillary Services Market (ASM) programs, similar to DBB programs but in this case the customers participate only in the ancillary service market.

Research papers in the literature concerning different possible DSM strategies and contracts have been increasing in number in the last years, as a demonstration of the great interest on the exploitation of their theoretical potential. He X. et al. (2013) [57] present a concept of consumer-centered approach to DR tariffs, stressing the importance of a diversification in contract types. Diversification is required in order for demand response to be appealing to a large number of users. To tailor the contract to the contractor the authors propose the use of profiling criteria that could help to identify the preferences and priorities in loads and services required by each consumer. Goulden M. et al. (2014) [58] define two possible philosophies behind DSM, the first where end-users are strictly managed from the external grid and its operators. The other, where they are conscious of their choices energy wise and they are actively working towards DSM. The study does not expect the two visions to be mutually exclusive but rather that the final DSM will be performed as a mix of both. Nikzad M. and Mazafari B. (2014) [59] propose a demand response model including penalties and incentives assigned to customers depending on their response to network requests. Their study focuses on the reliability enhancement of the system granted by the DR scheme presented. Dupont B. et al. (2014) [60] focus on the assessment of locational dynamic pricing potential, especially applied to residential sector. The authors point towards the definition of the correct amount of costs, which can be associated with every participant in the electricity distribution, final user included, by location and time dependence. According to the authors, once a correct estimate is performed, it would be possible to find a fair tariff as well as a more effective DR from the users themselves. Mahmoudi N. et al. (2014) [61] introduce a new DR scheme for electricity retailers and end-users. The scheme comprises different contracts and options at the same time. Several possibilities are proposed and evaluated on a real case study, with the feasibility of the proposed scheme and augmentation of the energy share coming from DR for the retailers as outcome.

From an operative point of view, there are two actions that the controllers in charge of loads optimization can do in order to exploit DSM benefits:

- Reduce the energy consumption of the user by modulating or switching off low-priority loads;
- Shift energy consumption to a different time of the day;

In both cases the potential of the response and the comfort (i.e. the non-disturbance of the programmed activities) of the user, can greatly benefit from the presence of a storage system. Several studies in the literature propose different solutions for the optimization of the load management problem within the frame of DR, some of these include also prime movers for self-generation and energy storages. Moura P.S. and de Almeida A.T. (2010) [62] developed a multi-objective optimization model in order to reduce the problems related to the intermittent nature of RES and their integration in the power system. DSM and DR are demonstrated to have a major role in the electricity system both for their ability to reduce the need of new intermittent production capacity (while still reducing the emissions of the whole system) and to adjust the consumptions in real-time, therefore adapting them to the actual production. Aghaei J. and Alizadeh M.I. (2013) [63] in their paper aim to apply Mixed Integer Linear Programming (MILP) to a multi-objective self-scheduling optimization problem of a Microgrid including CHP, energy storages and DR scheme. The goals of the optimization are twofold: first, minimizing operation costs and secondly reducing emissions. The model defined was tested on a standard 24 bus achieving a 1.5% reduction of daily operational costs when not implementing the DR scheme and 9.1% when the DR scheme is applied, an evidence of DR optimization potential, along with an emission cost reduction of 4%. In Mahmood A. et al. (2014) [64] the authors propose an algorithm for the optimal distribution of loads over the day for several households. The algorithm allowed reaching a good demand-side peak-shaving result as well as energy cost savings. In Zakeri G. et al. (2014) [65] the authors present an efficient linear programming formulation for the demand response of a consumer who must pay an additional peak demand price for energy supply during peak hours. Caprino D. et al (2014) [66] applied real-time scheduling techniques to the problem of household appliances management. The load features of each appliance considered were modelled in order to meet both timing and service constraints. The peak load is reduced by 8% on average basis, with a maximum of 41% reduction.

The potential benefits of DSM are shared among different stakeholders of the energy system, from the energy service providers to the final user, even if he is not involved in any DSM program himself. The possible benefits are:

- DR program participant's bill savings: those who participate actively to DR programs can take advantage of contingences or price volatility to save on their energy supply bills;
- Bill savings for non-participants: customers not taking part in DR programs can save on their bills thanks to the reduction of wholesale costs of electric energy allowed by both a more competitive market and a general reduction of the operation and maintenance costs for both producers and operators;
- Improved system reliability: undesired shortage and local black-outs can be avoided with great advantages for customers, both in economic and comfort level terms;
- Greater market dynamicity: the presence of more stakeholders on the market enhances the competition and therefore preventing the price from being controlled by a minor part of energy producers;
- Improved choice: customers can tailor their electricity bills on their unique needs, choosing from different tariffs, incentives and penalties;
- System security enhancement: the operators of the system deal with a much more flexible system, which can handle contingencies with more chance to success and lesser costs.

In addition to the short review of papers focused on different approaches to the problem of DR optimization, a few published scientific works that analyze large-scale case studies in order to demonstrate the potential of DSM application are presented hereafter. Pina A. et al. (2012) [67] show the potential of demand side management policies in a system already heavy on renewable power such as the one of Flores Island in the Azores Archipelago. The outcomes of the study are that DSM application allow the operators to postpone investments on the grid and on new renewable resources as well, by 3 or 4 years, depending on the demand scenario considered. Thus, the authors demonstrate how DMS has the double advantage of deferring new investments while making renewable energy more economically viable at the same time. In Moura P.S. and de Almeida A.T. (2010) [68] the authors present a study on DSM strategies to expand wind-power penetration in Portugal's electricity grid. It is found that a 1% reduction in consumption would allow a reduced need of intermittent wind power by 11% with a cost lower than any other RES (0.023 €/kWh) whereas DSM strategies focusing on the reduction of peak load will instead reduce the issues related to intermittent wind power productivity during peak hours.

2.1.2.2 Generation planning and curtailment

The operations of the Smart Grid can be optimized not only by managing the loads that are required by the users at different scales but also by directing the power generation. Indeed, power generators, both the renewable and the fossil fuels ones, provide a further degree of control over the energy system. Fossil fuels generators or non-intermittent RESs allow the manager of the plant to increase or decrease the power output in order to respond to the several inputs that drive the operation and optimization of the grid considered. On the other hand, the intermittent RES generators can only decrease their power output compared to the maximum they can provide in a given weather condition. Moreover, the intermittent RESs usually rely on incentives that reward the energy they produce, thus it is very unlikely that a user might desire to modulate them at any time. Therefore, the possibility of intervention on these generators is very limited. Any other solution, like load modulation or energy storage, is preferred. Conversely, the non-intermittent RES (like hydroelectric, geothermal and biomass) as well as fossil fuel-powered prime movers offer greater margin for intervention. For example, their power output can be modified in order to satisfy local loads when intermittent RES reduce their productivity due to a temporary decrease of wind speed or clouds shading the solar generators. This is true especially for small-scale systems where the size of the conventional power generators still permits quick response times and great modulation capabilities. As the power system scale grows, the same happens with power generators and with their increase in size, thermal inertial effects and lack of modulation become relevant issues. At the regional or national scale, the present energy system cannot be considered flexible. In order to ensure power balance it relies on power reserves and back up plants that are ready to be grid connected when the load grows or the RESs productivity decreases. As has been introduced in the previous section, this limitation can be overcome with DGs, allowing the central power plants to focus on providing the base load and operate at maximum efficiency. Reddy K.S. et al. (2014) [69] present a review about the methods for Integration, Control, Communication and Metering inside a Smart Grid, including some DR programs for operation scheduling of energy sources and loads.

2.1.2.3 Peak Shaving with storages

There is one more degree of freedom to employ for the achievement of Smart Grid goals and it is the time shift between the moment when the energy is produced by the generators and the one when it is consumed by the users. This shift in time can be performed, for example, by using storage devices. Storages can be of different kind and adopt various technologies that ultimately determine their costs and the role in the energy system that better suits them. Depending on the scale considered, thermal and/or electrical storages can be present within the energy system. Usually, thermal storages are implemented in small to medium size systems because it is hard to store a great amount of heat while limiting the thermal losses. Electrical storages on the other hand can span from very small capacities (like capacitors) to medium capacity (like batteries) or very high capacity like water basins at different heights. The rated power obtainable can vary as well, from the relatively low power usually released by lead acid or Lithium batteries, to the high power outputs allowed by the electric capacitors. Some thermal storages like molten salt ones can be adopted in electric power generation. It can be said that the higher the variability over time of the loads and RESs production and the greater is the opportunity to use energy storage. The role of storages in allowing a greater percentage of RES in the power system and their potential as components of the SG is dealt with by Zamora R. and Srivastava A.K. (2010) [70]. In their paper, they present a review of microgrid concepts, projects and optimization with focus on the role of energy storage. A case study simulation is performed and presented, showing the improvement capabilities of the microgrid in terms of grid reliability. Moreover, Denholm P. and Hand M. (2011) [71] analyze the upgrades (in terms of storage capacity, minimum un-flexible generation and curtailments) required in order to allow a greater penetration of RESs in an insulated power grid (i.e. Texas one as considered in their case study). It is found that penetrations of up to 50% can be achieved with curtailments as little as 10% if the must-run base load generators are eliminated in favor of fast ramping-up ones. However, in order to achieve penetrations of 80%+ while keeping curtailments at 10%, storages and load shifting affecting one day of average demand are required. Bussar C. et al. (2014) [72] push the boundaries of storage potential imagining a 100% renewable production of electric energy covering the whole European demand; the authors seek to optimize the type, size and location of the required energy storages. The model used was called GENESYS and it is a Genetic Optimization Algorithm. The outcomes of the study show that for a 2500 GW RES rated power installed in total, the storage capacity required is 240 TWh (6% of the total energy demand). The model defines the preferred RESs and the mix for each Nation, as well as the short-term / mid-term and long-term required.

A different “form” of electric storage, which has been receiving more and more attention in the last years is represented by Plug-in Hybrid Electric Vehicles (PHEV) and Electric Vehicles (EV). PHEVs and EVs are expected to grow in number within the transport systems and car pools of firms.

From the point of view of the energy system, they can be considered as loads and generators, like with every other kind of storage. Their role can be important for two main reasons:

- Unlike other kinds of storage they can move and therefore shift the energy not only in time but also in space (for example from home to office or vice-versa);
- Especially in the case of small households or enterprises, the power they exchange with the system is relevant and the energy stored can be of the same order of magnitude of the whole needs of the user itself.

The correct scheduling of this peculiar type of storage is the focus of the study proposed by Khayyam H. et al. (2013) [73]. The model created by the authors was applied to a realistic case study in order to assess its benefits: vehicle charge-discharge cycle optimization as well as forecast of parking lots and grid load demand. The possible benefits and limits of Vehicle-to-Grid (V2G) concept as a viable option for DSM programs and as energy storage are presented by Mullan J. et al (2012) [74]. The concept is tested on Western Australia's isolated grid, particularly small and with a landscape preventing the adoption of common storage technologies. According to the authors of the study the, V2G is not an economically feasible solution to apply peak shaving and other DSM practices. Other solutions, like battery banking, present overall similar benefits but lower infrastructure costs.

Like with DSM and Generation curtailment, in order to achieve the goals set for the Smart Grid, the operation of storages in the energy system must be accurately modeled and optimized. Some research papers focusing on storage optimization are reported hereafter. Levron Y. and Shilovitz D. (2012) [75] defined a first order approach to the problem by the definition of a graphical analytic method for storage sizing and management in order to achieve the maximum possible peak shaving.

The limits of this approach are found in its simplicity, which is also its strength in terms of computational weight. The model proposed can be adopted correctly only if power losses are minimal compared to the energy stored and power output of the storage system and, anyway, it can optimize only the behavior of the storage system, without considering any other variable at the same time. A simulation of a Battery Electric Storage System (BESS) for five households in different regions of Canada is performed by Leadbetter J. and Swan L. (2012) [76] based on synthetic data. Each household presents peculiarity in terms of loads, therefore different results are achieved for each case. On average, the scored peak shaving potential features values around 42%-49% reached by using small storages (5 kWh/ 2.6 kW). Nevertheless, areas where heat demand is handled mostly with electricity-based solutions, like heat pumps in Quebec, performed worse, with only 28% of peak shaving achieved even when using bigger storages (22 kWh / 5.2 kW). Several algorithms dedicated to peak shaving by means of electrical batteries are proposed and compared by Johnson M.P. et al. (2011) [77]. In this work both the case of lossless batteries and battery losses are taken into account and the model can also suggest, offline, the optimal battery size for system design. Nottrott A. et al. (2013) [78] carry out the optimization of a PV-BESS operation by means of a linear programming routine in order to minimize demand charges of the battery system. The optimization exploits a MILP technique and different kinds of batteries are evaluated. The study demonstrates that Lithium-ion ones are still too expensive to result in an economically feasible solution and highlights the importance of an effective planning of the batteries management and dispatch schedule, which allows an increment of the Net Present Value (NPV) of the system.

All of the studies reviewed demonstrate the importance of storages in SG system and their potential to flatten the power demand. Each one of the proposed strategies represent a step forward towards the goal set by the

SG concept. Nonetheless, their real potential is found only when they act all together. In order to do so, a great effort is required for the optimization of a system with great flexibility such as one that includes quick responding generators, modulation of loads and storages for both electrical and thermal energy. The greater the extension of the system, the higher the number of variables to be considered simultaneously. In the following section the key aspects of energy systems optimization, the issues to overcome and the state-of-the-art of optimization algorithms will be presented.

2.2 Optimization of design and operations planning

The optimization of the design and operation of an energy system is a twofold problem. On the one hand, there is the problem related to the description of the system itself: which equations are chosen for the description of each component, what are the constraints, the linear or non-linear behavior of the system and the time discretization that is considered. On the other hand, there is the optimization of design and/or operation of the system and how to perform this task. These two aspects are deeply interconnected, for example, some algorithms for the optimization of a problem can be applied only if the problem description features some hypothesis, e.g. linearity. Moreover, it is important to determine which depth of analysis of the system and its simulation is required to have significant and reliable results. An overly approximated problem might indeed lead to solutions that are not as good as expected or even completely unfeasible for the actual system. There is not a universal solution or a one-fits-all approach; therefore, depending on the scale, the components, the objectives of the optimization and the level of detail that is required, the best practice can be different. The literature reflects this abundance of concepts, approaches and optimization techniques. Indeed, there are works sharing similarities in terms of problem description and optimization but there are many other unique research works. It is out of the scope of this Thesis to compare every possible approach presented in the literature; nonetheless, it is important to provide an insight on the most used ones, outlining their pros and cons, thus giving solid basis to the present research work.

First of all it is important to define the difference between a linear and non-linear description of the problem, what kind of constraints are non-linear and which components are more influenced by the linearization of a non-linear problem.

2.2.1 Linear problems

Before venturing in a short analysis of the state-of-the-art optimization in the energy field, it is important to provide a reminder about what a linear problem is and some examples of linear problems applied to an energy system.

A linear problem (LP) is represented by a set of linear equations and linear inequalities that bound the feasible solutions of a linear objective function of a given number of real variables. This feasible region, in the case of a linear problem, is a convex polyhedron that represents the space of the solutions of the problem complying with the constraints: each inequality of the constraints set defines a semi-space that limits the extension of the polyhedron itself. One of the most important features of linear problems is that every optimal solution is a global optimum of the problem: this makes the optimization of the variables set much easier compared to any other possible family of problems. Indeed, a methodology or an algorithm defined to search one optimum of a linear problem ends up finding its global optimum.

The standard mathematical definition of a linear problem is:

$$
\begin{gathered}
maximize\ \boldsymbol{c}^{\boldsymbol{T}}\boldsymbol{x} \\
subject\ to\ \boldsymbol{A}\boldsymbol{x} \le \boldsymbol{b}, \\
\boldsymbol{x} \ge \boldsymbol{0}
\end{gathered}
$$

Where ***c*** and ***b*** are vectors and ***A*** is a matrix of real values. The objective function can be either maximized or minimized. The optimization of linear problems is known as *linear programming*. Linear programming has several fields of application, from business to engineering problems.

An example of a linear problem, applied to the energy field, is the optimization of the operation of a heat storage coupled with a CHP in order to satisfy a thermal load.

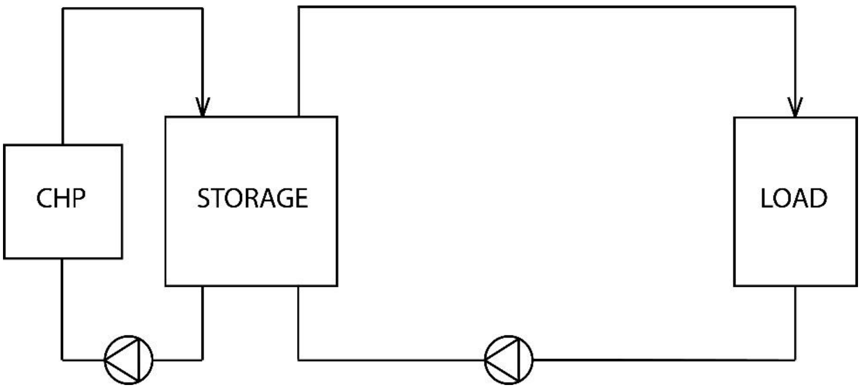


Figure 3 - CHP and Storage simplified plant layout

Let us consider a system like the one depicted in Figure 3. Let us assume for the sake of simplicity that the thermal load can always be satisfied by the CHP thermal power output and that the storage can be charged or discharged at any rate. Let us consider also the storage to be big enough to be operated in any possible way (i.e. no limits on capacity are required) during a single day, composed by three different time-steps of 8 hours each. The function to be optimized can be a cost function for the plant, such as:

$$minimize \sum_{t_i=0}^{2} P_{CHP}(t_i)c_{CHP}(t_i) + P_{st}(t_i)c_{st}(t_i) + P_{th}(t_i)c_{th}(t_i) \qquad \text{Eq. 1}$$

Where c_{CHP}, c_{st}, c_{th}, are respectively the unitary costs of operation of CHP, storage and thermal load, and they depend on time. The power balance of the system, valid for each time step, is described by the Equation 2:

$$P_{th}(t) = P_{CHP}(t) + P_{st}(t) \qquad \text{Eq. 2}$$

Where P_{th} is the thermal power demand, P_{CHP} is the power provided by the CHP and P_{st} is the power provided or accepted by the storage. The thermal power output of the CHP and the thermal power of the storage are the unknown variables that determine the optimized operation of the plant, along with the charge of the storage at each time-step. The state of charge of the storage at time step t is provided by the Equation 3:

$$L_c(\tilde{t}) = L_{c,i} + \sum_{t=1}^{\tilde{t}} P_{st}(\tilde{t})\Delta t \qquad \text{Eq. 3}$$

Where $L_{c,I}$ is the initial state of charge of the storage. If a daily optimization is desired, three time-steps need to be considered and the equation system describing the plant can be written as ***Ax***=***b***:

$$\begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \Delta t & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & \Delta t & 0 & 0 & \Delta t & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & \Delta t & 0 & 0 & \Delta t & 0 & 0 & \Delta t & 1 \end{bmatrix} \begin{bmatrix} P_{CHP}(0) \\ P_{st}(0) \\ L_c(0) \\ P_{CHP}(1) \\ P_{st}(1) \\ L_c(1) \\ P_{CHP}(2) \\ P_{st}(2) \\ L_c(2) \end{bmatrix} = \begin{bmatrix} P_{th}(0) \\ L_{c,i} \\ P_{th}(1) \\ L_{c,i} \\ P_{th}(2) \\ L_{c,i} \end{bmatrix} \qquad \text{Eq. 4}$$

It is clear that the problem has a linear formulation thanks to the fact that the constraints are linear (can be written as ***Ax***=***b***) and the objective function is linear as well.

From the canonical form of a linear problem, depending on the type of variables involved, two different subclasses of problems and optimization can be introduced: Integer Linear Programming (ILP) and Mixed Integer Linear Programming (MILP). An ILP problem differs from the standard LP because all of its variables are integers. MILP problems, on the other hand, accept some of their variables x_i to be non-integer. In order for ILP and MILP to be employed, the objective function and all the constraints must be linear. To solve a MILP problem several algorithms and methods have been developed, which can be adopted depending on some particular mathematical features of the problem itself. Regardless of the method used to solve this type of problem, thanks to their linearity, the algorithms employed to find the solution are very fast and capable of reaching a solution whose distance from the global one is known in advance. Indeed the shape of the solution surface is convex and therefore it features only one optimum solution and this allows the algorithms used to take into account very high numbers of variables and constraints at the same time, up to hundred of thousands, while still being computationally light. The limits of this approach are in the description of the problem itself. Not all the problems can be written in linear form nor be linearized without trading in precision of the solution.

2.2.2 Non-linear problems

A problem becomes non-linear as soon as the objective function or one of the constraints is non-linear. There are several classes of non-linear problems and some of them can be solved with ad hoc algorithms in an efficient manner. As example, if the objective function to be maximized is the ratio of a concave and a convex function and the constraints are convex, then the problem can be transformed to a convex optimization problem by means of *fractional programming* techniques and solved quickly. Nonetheless, typical engineering problems rarely fall under these special classes of non-linear problems. In some cases they can be NP-hard problems (Non-deterministic Polynomial-time hard), and thus require much greater computational effort to be solved. Simple examples of non-linear constraints are polynomial equations obtained by regression methods to describe the experimental characteristic curve of a component and if clauses that are required to describe the different behavior of the system depending on some input values. A system described by non-linear equations and involving several variables can have several local optima, of which, only one might be the global optimum of the problem. Depending on the shape of the solutions surface, the search for the global optimum can be very difficult; moreover, it can be impossible to assess the actual distance of a solution found from the global optimum. There are several techniques and algorithms dedicated to the solution of non-linear optimization problems, these methods can be divided in two great families: analytical and heuristic. The first category includes several programming techniques like: *Newton's method*-based algorithms like *sequential quadratic programming* or *gradient methods*-based ones, like *Interior point methods, Gradient Descent, Ellipsoid Methods*. The analytical optimizers often rely on special characteristics of the objective function or the constraints to find the solution. Therefore, they cannot be applied to any non-linear problem. On the other hand, the heuristic algorithms are less problem-constrained, even though each algorithm can perform better or worse on a single problem, depending on the problem itself. None of the heuristic algorithms can ensure the global optimality of the solution found neither they can define how close to the global solution is the optimum they find. Nevertheless, they trade their accuracy in favor of speed, and they can perform very well when non-linear analytical techniques would fail to find a solution in a reasonable (useful) time. Heuristic algorithms, as the name suggests, are based on experience. The experience they refer to is the knowledge of the solution obtained with previously investigated sets of values for the problem variables. Allen Newell and Herbert A. Simon in their Turing Award acceptance speech, discuss the Hypothesis for Heuristic Search saying that a physical symbol of a given system will repeatedly generate and modify known symbol structures until they match the structure of the solution [79]. Therefore, at any iteration of the heuristic search, these algorithms modify the input variables of the problem in a manner that leads the set of variables towards the problem solution. Heuristic-based optimization algorithms are often inspired by natural phenomena and usually referred to as *Meta-heuristic algorithms*. They can be further categorized depending on the techniques they adopt, e.g. evolutionary processes, trajectory correction, if they are population based or not, whether they have memory of the previous iterations or not and so forth. To cite a few of the most used ones: *Genetic Algorithms* (GA), *Ant Colony Optimization Algorithm* (ACOA), *Particle Swarm Optimization* (PSO), *Simulated Annealing* (SA), *Covariance Matrix Adaptation Evolution Strategy* (CMA-ES), *Stochastic Local Search* (SLS). Each of these algorithms can be further modified starting from the basic concepts underlying them in order to adapt to a particular problem. Indeed, in the literature, it is hard to find the same exact implementation of a Meta-heuristic algorithm twice.

2.2.3 Multi-objective optimization

In a general power plant or energy system, the most common goals are the minimization of: operation costs, emissions, primary energy consumption. Sometimes other aspects are relevant and introduced as variables to be optimized, e.g. power quality, some other times there are specific targets for the optimization process, which may vary from study to study, e.g. the number of switch on/off cycles of a given device. Dealing with more than one objective function at a time requires the implementation of specific strategies, which are referred indistinctively in the literature as multi-objective optimization, multi-objective programming, vector optimization, multi-criteria optimization, multi-attribute optimization or Pareto optimization. These strategies aim at the simultaneous optimization of different objective functions. It is easy to understand that in multi-objective optimization there cannot be a single global optimum, as a set of values improves one of the objectives, it will worsen other ones.

2.2.4 Analytical optimization in energy systems

Considering an energy system, typical objective functions to be maximized or minimized are: economy of operation and design, pollutant and/or carbon dioxide emissions towards the environment, primary energy savings. These objective functions are typically linear, e.g. regarding cost functions, the overall cost for the day is usually composed of the specific costs of operation of each component of the plant (that are constant values), multiplied by the variables describing the operation of the system, like power outputs. The set of constraints on the other hand, depending on the depth of the analysis, can be linear or not. However, the real physics of the energy system or plant is strictly non-linear. Therefore, a linear description of the problem, although being possible most of the time, leads to an error in the evaluation of the problem solutions and, perhaps, to a wrong optimal set of values for the variables describing the system. Nevertheless, LP optimization presents several advantages, which justify, in some cases, the linearization of the problem describing the physics of the real system. For example, for the simulation of particularly large systems, an approach based on energy balances between components is often the most appealing and there are several works in the literature dealing with linear or linearized approximations of grids (thermal or electrical or both) featuring hundreds of components.

In order to model correctly a system heavily influenced by non-deterministic behavior of some of its components, such as intermittent

RES, Handschin E. et al (2006) [80] developed a stochastic extension of a basic MILP algorithm for the optimization of the operation of a DG network featuring also renewable resources. The algorithm itself is computationally hard to solve as a whole; therefore, a decomposition algorithm was defined and applied. This allows the solver to reach a reasonably accurate solution in an acceptable time. Ren H. et al (2010) [81] present a multi-objective optimization by means of linear programming of a DER system. Both economic and environmental goals are pursued, the outcomes of the study point out how considering environmental optimization shifts the generation towards DER equipment. The multi-objective optimization changes the scheduling of the system and gas-engine based DERs are found to be more sensitive to optimization goal change than are Fuel cells. The study carried out shows also that carbon taxes are ineffective in changing the scheduling unless they are very expensive. On the other hand, fuel switching towards biogas has a great effect in terms of both system operation and sensitivity to different optimizations approaches. In another study, Ren H. and Gao W. (2010) [82] present a MILP model to improve the planning and design of a DER system comprising also energy storages. The model defines the optimal mix of generators and their scheduling during each hour of the year. The benefits in terms of annual improvement of costs, emissions and PES are 13.4%, 4.5% and 17% respectively.

Stochastic system analysis along with RESs optimization is important especially when the system is being simulated to address the problem of its design, hence with a very long time-scale. Buoro D. et al. (2014) [83] present a MILP optimized model that seeks the minimization of total annual costs of a CHP plant with district heating as well as solar thermal plant, standard boilers and heat storage. The plant needs to satisfy the requests of nine industrial facilities in northern Italy. The model allows the calculation of both the economic and environmental benefits as well as the share of thermal load demand satisfied by means of renewable energy. The outcomes depend on whether the solar thermal plant is allowed or not in the system. In the first case the savings on the annual costs are 5% whereas without it are slightly lower, 4.5%. The optimal size of the solar field covers 60% of the thermal load and a weekly storage is suggested (4000 m^3). If heat dissipation is not admitted, the ideal size of the storage is greater and reaches the values of seasonal storages. A straightforward MILP optimization is carried out in Omu A. et al. (2013) [84] for a six-building district located in UK and, in Erdinc O. (2014) [85], for a Home Energy Management system that includes PV, Electric Storage System (ESS) and a V2G option. The pricing of electric energy changes on real-time basis whereas the sell price is considered constant. Several test cases are examined achieving economic benefits of 35% compared to the base-line case when adding PV and ESS units. DR strategies aiming to reduce peak power are also applied.

Pandžić H. et al. (2013) [86], who present a MILP model that evaluates different scenarios to address the uncertainties of pricing and RESs productivity, use an approach similar to the one used in Handschin E. et al (2006) [80]. The scenarios are modeled on historical data and the model performs this optimization on a realistic case study in order to draw conclusions. Again, like in the similar study cited, the model is computationally heavy because of its stochastic component, which imposes the evaluation of several cases in order to be reliable. A similar research was carried out by Sowa T. et al. (2014) [87] who model a CHP system as a component of a VPP in order to allow a higher share of renewable energies in the electricity market and provide ancillary services. The operational strategies proposed by the algorithm are evaluated in terms of economic, technical aspects and uncertainties in both generation and load forecast. The optimization technique used is again a stochastic mixed integer linear programming one that takes into account the whole portfolio of decentralized units, comprising in the present case: WT, PV, CHP, ESS, and EV. The stochastic part of the model allow the researchers to consider different possible scenarios to overcome the issues of uncertainties not only regarding RES productivity but also those of market price and load demand. A purely deterministic approach is indeed proved to be worse, compared to the stochastic one. The main reason of the poorer performance of the first approach is the lack of information, which ultimately leads to the proposal of unfeasible solutions, which receive the penalties applied for unfeasibility. Likewise, Zapata J. et al. (2013) [88] perform a research on the possibility to reduce the imbalance created by RESs intermittency as well as load unpredictability by means of a CHP optimized via MILP. Nonetheless, instead of relying on stochastic scenario analysis, the optimizer performs a day ahead guess of operation that is modified (re-scheduling) during the present day in order to guarantee that the imbalance is reduced once the updated weather and load forecasts are known. The optimization method applied is not useful for design purposes, therefore in this case only the operation of the system is taken into account. Two kinds of solutions can be provided: one that maximizes the reduction of the imbalance, whereas the other seeks the best economic solution while reducing the imbalances. For an ICE CHP the authors determined that the economic benefits of reducing imbalance are minimal because of the small efficiency of the prime-mover of choice (25%) and a large heat to power ratio. Thus, imbalance cost reduction cannot cope with the extra primary energy costs. A further example of optimization of a medium-scale energy system is found in Aghaei J. and Alizadeh M.I. (2013) [88]. Their research aims to apply MILP to a multi-objective self-scheduling optimization problem of a MG including CHP, ESSs and DRS. The goals of the optimization are, in order, minimizing operation costs and secondly reducing emissions. According to the researchers, the novelties of the work compared to the previous literature are MILP optimization of the self-scheduling problem of a CHP-based MG, the presence of two contrasting objectives (maximization of MG benefits and minimization of emissions), the use of lexicographic optimization and hybrid augmentedweighted ε-constraint method to solve the multi-objective optimization problem. All the non-linear equations of the problem are linearized and two distinct objective functions are defined for costs and emissions. Both consider a one-day period and the model allows to find the optimized operation for the whole day. Even though the research tries to perform a proper multi-objective optimization of the system, one of the disadvantages of the approach adopted is the non-optimization of the range of the objective function over the efficient set. Another disadvantage is the absence of guarantee to find a pareto-optimal solution efficient or non-dominated[1]. The model defined was tested on a standard IEEE 24 bus achieving a 1.5% reduction of daily operational costs when not implementing DRS and 9.1% when DRS is applied. Conversely, the emission cost reduction is 4%. In Wakui T. et al. (2014) [90], the optimization of the design and operation of a multiple CHP system for a residential building is investigated. The target for the energy system is to satisfy the loads of a MG of residential CHP without feeding electric energy to the grid. MILP optimization model was used for operations planning, nevertheless the hot water distribution network and the piping design are non-linear problems. Thus, the authors introduced a linearized approximation that allows them to implement the MILP solver for the optimization of the system. The results show the energy-saving effect achievable with power interchange and that the savings reduce with the increase in the number of residence units connected through the hot water supply network. The problem of linearization of system behavior description in order to exploit MILP is faced also by Bischi A. et al. (2014) [91] whose research relates to a state-of-the-art MILP model for the optimization of the operations of a CCHP system. The model can take into account different prime-movers, variable price of the electricity, tariffs

[1] A solution is called non-dominated, Pareto optimal, Pareto efficient or non-inferior, if none of the objective functions can be improved in value without degrading some of the other objective values.

and ambient conditions. The authors identify also two different approaches to the energy problem. The first is a data-driven black box approach where each component is described by its performance curve obtained by real data interpolation. The second is a first principle thermodynamic approach where the energy system is divided into simple elements whose performance curves are known and mass/energy balances are imposed to the optimization problem to define the plant best operating conditions. The model was tested on several plant test case and proved to be fast and reliable enough, although achieving only sub-optimal solutions because of the approximation introduced by using a linear set of equations instead of the required non-linear ones. The objective function is the sum of all the costs associated to each component for maintenance, operation and for energy sold/bought to and from the grid. The total time span is daily and each day is divided in 24 smaller periods of analysis of one hour each. The problem size reaches at maximum 6000 variables and 4227 constraints. With 20 intervals of piecewise linearization of non-linear functions the execution time is in the order of 10 minutes.

When the linearization of the problem cannot be performed without losing the physical soundness of the outcome, or there is a need for a more accurate solution, the MILP technique cannot be used. Before the advent of meta-heuristic algorithm, the only option was to adopt MINLP approaches. Although they lose most of the benefits of the MILP techniques, such as the capability of analyzing a high number of variables at the same time with very low computational times, they are still used in the literature, also for energy systems optimization.

An example of MINLP optimization is proposed by Tveit T.M. et al. (2009) [92], who, in their study present a MINLP model for the analysis of long-term thermal storage investment along with CHP solutions. The model proposed can take into account non-linear behavior of the system but due to its non-convexity it is prone to find local optima if it is not solved many times with variable starting values. The limitation of MINLP is evident in this study and the size of the system considered cannot match those listed above because of the long time required for a complete run of the algorithm. An approach analogous to the one of Zapata et al. (2013) [88] but featuring MINLP is performed by Ghadikolaei H.M. et al. (2012) [93]. The study deals with a two-stage optimization of DG operation in order to minimize costs and CO_2 emissions penalties. The first stage is a day-ahead optimization performed by means of a MINLP optimizer with the aid of Benders decomposition method. The second stage has an hour-ahead time frame which takes as inputs the scheduling suggested by the first-stage optimization and operates on the spinning reserve in order to ensure the power balance. The proposed method was tested on two fictional yet realistic case studies with acceptable results. Pruitt K.A. et al. (2013) [94] present a MINLP optimization of the sizing and operation of a CHP system for a large hotel case study. A comparison with a MILP procedure on the same test case is performed as well. The difference between the linear and non-linear (solved with heuristic techniques) in terms of time to optimize the operation of the system considered as test case, is huge: 2 seconds compared to over 10 hours. Nevertheless, even if the linear approach grants a proximity to global optimality (of the linear problem) below 1% and the non-linear one is at 10% from its own global optimum, the global optimum is still better than the local one, both in terms of performance of the plant and feasibility of the solution. The study allows researchers to understand in which cases the simpler optimization is enough and in which it is not satisfactory. A mixed approach is adopted by Fazlollahi S. and Maréchal F. (2013) [95], who, in their article present a novel method for the preliminary design of an integrated urban energy system. The optimization involves several periods of 24 hours, each representative of different typical days and both the economic and environmental aspects are considered in the multi-objective analysis. The optimization model used relies on evolutionary algorithms and MILP at the same time. With this paper, the researchers propose to fill the lack in the literature providing a simultaneous consideration of a multi-period and multi-objective optimization of an energy system design. This is done with a MILP model along with a multi-objective evolutionary algorithm (EMOO). The procedure proposed evaluates the total costs and CO_2 emissions at the same time, decomposing the model into a master and slave optimization. The energy system analysis is divided into two main steps: sizing and design optimization goes first, whereas operation optimization is performed afterwards. The master optimization algorithm (the evolutionary one) provides a set of decision variables (type and size of equipment). Then, a thermo-economic simulation model generates the inputs for the MILP optimizer for the system operation, which ultimately feeds back the output to the master optimizer again until a Pareto set of solutions is found. A distinctive feature of the evolutionary algorithm of choice is that it works with continuous variables, not binary genes as is usually done. The time span of the optimization is one year. The assumptions made for the linear part of the problem are those common in the literature when solving the optimization problem with MILP techniques (e.g. no partial load consideration). Moreover, distribution network constraints both for heat and electricity are not considered.

To conclude this brief review of analytical methods for energy system analysis, the importance of taking into account non-linear phenomena is evident when considering the quality of the solution that the optimizer finds. If the linear approximations of the problem are relevant, as proved by some of the authors cited, the solution can turn out to be completely unfeasible for the actual system. Moreover, in many of the works described, the physics of the actual system tends to be hidden by the requirements of the equations that should describe the system in order for these optimizers to actually work. From an engineering point of view, this is a relevant aspect because it makes it harder to keep contact with the real system. Indeed, optimization methods should always be “aware” of the actual needs of the system they describe. When considering an energy system it is important to understand not only which are the actual specifications and performance of its components but also how they are managed in the real system, e.g. considering whether they can be controlled directly or their operation is semi-automated. Nonetheless, due to the complexity of a deterministic analysis of non-linear phenomena, the linear approach can be very valuable when the size of the system, or total number of variables considered is particularly high. For example, with the simulation of entire districts, especially if the analysis carried out is a preliminary one and thus it does not require high levels of detail. Solving in an analytical way a non-linear problem becomes hard in terms of both problem description and computational time with ease.

2.2.5 Meta-heuristic algorithms in energy systems

The meta-heuristic algorithms are an alternative and very attractive solution for energy system analysis when the modeling of non-linear phenomena must be considered. As introduced before, they lack the precision of the deterministic approach. Still, if the problem proves to be highly non-linear, they are faster and more reliable than their analytical counterpart. Several authors in the literature adopted them for the optimization of energy systems. It is rare to find applications to large systems or for long periods (i.e. yearly or monthly optimization) though. This is reasonable considering that non-linear systems are definitely computationally heavier than linear systems to be optimized. Some of the authors performed comparisons among different algorithms in order to assess the best for the case considered. It is worthy to notice that the performance of meta-heuristic algorithms are strictly related to the tuning of their parameters and it is realistic to believe that there is no algorithm performing better than all the others in every possible situation. Actually, in many cases, the differences are marginal.

Recurring meta-heuristic algorithms in the literature, in several forms, are Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Silva M. et al. (2012) [96] present a GA for the assessment of the optimized short-term scheduling of a distributed energy resources power system. Three time-frames for the ahead scheduling are considered: day ahead, hour ahead and five minutes ahead, each time the reliability of the wind speed forecasts increases and therefore the value and quality of the solution proposed. The model is tested on a 33-bus distribution network with high penetration of renewable generation and consumers with demand response contracts. One of the key aspects of the algorithm is its fast run-time, which allows adapting the solution in a brief period and thus reacting to updates on forecasts. In Shi R. et al. (2011) [97] the authors performed a comparison study on a distributed Micro-Grid case study between Elitist Genetic Algorithm (EGA) and PSO. EGA and PSO performed better than the original GA with EGA scoring just slightly better than PSO. Chanda S. and De A. (2014) [98] as well adopted a PSO algorithm for the purpose of their study: an optimization model to enhance both social welfare and improve the dynamic stability of power markets where Smart Grid concepts are applied. The model was tested in the IEEE 30 bus system and compared to standard curtailment-based optimization methodologies, achieving promising results. The model operates on market clearing price in order to find the solutions with better results. The simulations results demonstrated that the proposed model and methodology is effective. In order to correctly plan the expansion phase of the distribution network it is vital for operators to be able to evaluate both costs and reliability indexes of the choices taken. Gitizadeh M. et al. (2013) [99] developed a hybrid algorithm (including both PSO and Shuffle Frog Leap (SFL)) to achieve the simultaneous optimization of both aspects (costs and reliability) and confronted the results obtained with those of standard PSO and SFL algorithm. The hybrid algorithm designed behaved better both in terms of quality of the solution and computational time compared to the single algorithms alone. In Motevasel M. et al. (2013) [100] the authors presented an Intelligent Energy Management System to find the most economical and environmentally friendly way to operate a CHP-based microgrid including renewables and storages. The scheduling of the plant and each of its generators productivity is based on the optimized outputs provided by a Modified Bacteria Foraging Optimization algorithm. Its results are compared then to those provided by a GA and a PSO and found to be better both as value and variance of the solution. The thermal storage operation is scheduled considering that if the heat recovered is more than the thermal load demand then the storage is charged. Conversely, if the heat recovered is lower, then the storage and the boiler will compensate. The modeling of the system is strictly connected to the plant itself. However, in this way, the operation of the storages is not optimized for the whole period but rather for the single time-step considered. Having a multi-objective optimization the model seeks a pareto-front of optimal solutions. As could be expected, the weighted sum of different objective functions is not a very efficient way because it needs a great number of runs to find non-dominated solutions. The best solution is chosen by means of a fuzzy satisfactory method for multi-conflicting objectives. Soares J. et al. (2012) [101] proposed a modified Particle Swarm Optimization (PSO) approach called Signaled PSO. The goal of the authors was to address the optimization of a great number of variables (thousands) in a short time. In Evolutionary PSO the start values, like inertia, velocity limits, memory and cooperation weights, are modified during the simulation. This allows a greater exploration of the search space. The optimization algorithm was tested against a MINLP technique and other heuristic algorithms such as GA, PSO, EPSO and New-PSO on a short-term energy resource-scheduling problem. For the MINLP competitor in the algorithm comparison, the objective function minimizes the cost associated to dispatching and energy production in each time-period, therefore not performing a true optimization along the whole period but rather the sum of optimized time-steps. MINLP execution time is 20 times more than GA and 35 more than Signaled-PSO with comparable fitness with the latter and slightly better than GA. MINLP discharged all the storages within the first hour, demonstrating to be unable to effectively optimize the operation of the system for the whole period considered. According to the authors, the algorithm presented performs well both in terms of results and execution times making it an optimal candidate for large number of variables optimization.

3 A REAL TEST CASE

The Smart Grid concepts, since their definition, have been tested only little on real systems. The reasons are the difficulties and potential risks of such tests on large, expensive plants, which, most of the time are not property of a single owner but rather tens, hundreds or thousands, depending on the size of system considered. The systems involved in the tests always need to ensure their performance in terms of power balance, control of tension, frequency and reactive power management at all times, also during experimental tests. This is not an easy task, especially for large systems, where it is greatly impractical and expensive to carry out such activities, if not unfeasible. Therefore, it is hard to find in the literature records of experimental campaigns meant to address the concrete capabilities and performance of the Smart Grid concepts on the actual power grid. As was pointed out in the previous section, dedicated to the review of the state-of-the art of the SG in all its aspects and scales, most of the analysis executed so far are either simulations, on realistic systems modeled on software or experimental tests made on micro-scale simulacra of the power systems they should be installed on. One of the closest examples of a real test case is found in Ferrari M.L. et al (2014) [102]. The study involves a distributed generation test rig comprising two prime movers (gas turbine and ICE) for co-generation and a manageable thermal load, although the load requests are fictional and set for test purposes. The plant layout and controlling scheme are similar to those that an actual plant could have. Nevertheless, the scale of the application is likely to be larger than the one experimental rig proposes. Indeed, in the paper, three possible generalized layout for district heating systems are presented, depending on the level of flexibility that is desired.

The double loop layout (i.e. one hot temperature and one cold temperature loop), ideal for large heat distribution networks, is the one of the proposed test rig. Two different software were used to optimize plant operation due to the different goals that are pursued when operating online and offline. The online optimization tool is based on a cost ranking criteria to be fast enough to control the actual energy system in real time. Nonetheless, due to its great dependence on the initial conditions of the system and the speed performance that are required for real-time management of the system, it is not capable of finding globally optimized solutions. The offline optimizer, on the other hand, is based on a GA. It can be used only for prediction but cannot operate the system in real-time and its role is to define an optimized sizing of the system and strategy for its operation. It is interesting to notice how this study shares some similarities with the one proposed in the present Thesis, although being completely independent. For example, in terms of choice of controlling algorithm and their diversification for optimal management of the actual plant, which is something often lacking in those studies not taking into account the actual operation of the physical devices. During the off-line tests [103], carried out hypothesizing a certain industrial load with two thermal peaks during the day, it was found a 6% daily operation costs reduction and the great importance of the role of the thermal storages. In addition, the online optimizer demonstrated that it was capable of reducing daily costs on the actual system, even with the limitations just mentioned. The study demonstrates not only the validity of the SG concepts on the small scale systems like Smart Users and Smart Homes but also the importance of tests performed on tools capable of managing an actual plant in order to shorten the distance between conceptualization and commercial diffusion of the technologies related to SG. The application-oriented and engineering approach to the energy management problem have been always considered fundamental during the research presented in this work, and stand-out from those described in the literature.

The research goal of the activity conducted by the Department of Industrial Engineering of Florence (DIEF) in collaboration with Yanmar Research Europe, Enel SpA and s.d.i. automazione, was not only to propose a possible solution for the adoption of SG concepts on small scale applications but also to demonstrate with tests on a real test case, the real potential of such solution. Thus, the first step of the activity was to analyze several possible users, like farms, commercial and industrial firms of different typology in order to find one that could be suitable for the research activity. The fundamental requirements were the opportunity to have a varied combination of loads, electric, thermal and cooling and the presence of intermittent renewable generators (or the possibility for their installation). Other features of interest were the chance to pay for electric energy with a RTP scheme rather than TOU or CPP and to be able to carry out tests during the normal activity of the firm where the plant would have been installed both managing generators and loads. The ideal test case was identified in *Pontlab* facility, a structure dedicated to research for industrial partners, located in Pontedera (PI), Italy. Pontlab laboratories carry out several kinds of tests, both chemical and mechanical on materials and components. Tests performed span from durability on injectors for automotive to thermal stress evaluation of components, from spectrometry to innovative fuels exploitation in mass transport. The test rigs require mostly electrical energy, which is also used to produce on board the thermal energy needed in several situations. The refrigerating capacity needed for some tests is provided thanks to a cold circuit that satisfies the needs of the whole structure. Electrical energy is also required for illumination and auxiliaries in addition to the thermal and refrigeration energy needed for air-conditioning. The number and different types of test rigs and combination of tests carried out within the facility, depending on the requests of the clients, allows Pontlab to feature an extremely variable set of load profiles. Moreover, the presence of previously installed PV plant and a micro-WT made it a perfect candidate for the purposes of the study.

In this section a description of the plant representing the Smart User in the Pontlab facility will be presented, along with possible layout and specification of its components, its control system and data acquisition. Furthermore, two scenarios of operation will be described: the present one with RTP but no restrictions from TSO/DSO in terms of electricity grid exchange profile, and a future one, were possible constraints imposed by the TSO/DSO are implemented in the analysis.

3.1 Plant description

The installation of the CHP within Pontlab facility has been carried out by DSF group, representing the official dealer of Yanmar micro-CHP in Italy. The Pontlab facility is divided in three floors: basement, ground and first floor. The layout of the floors is presented in Figure 4, Figure 5, Figure 6, Figure 7 and Figure 8. In the basement are located the climatic chambers; at the ground floor there are the workshop, durability test benches, the 3d scanner laboratory and part of the administrative office; finally, at first floor is where the laboratories and remaining offices are located. There is also an external terrace used as technical room for the installation of space conditioning equipment. Because the plant should be able to operate in a conventional manner, if desired, when not required for Smart User tests, the initial projects, both thermal and electrical, were developed considering the option to operate the CHP in either Thermal Load Following (TLF) or Electric Load Following (ELF) modes. Due to the limit that the thermal requirements of the facility are only for room heating, the cogenerator is coupled to an absorption chiller, ensuring a greater exploitation of the CHP for cooling production in the summer period for both space conditioning and loads supply. Indeed, the absorption chiller allows the exploitation of the thermal energy recovered by the engine also during the summer period, when space heating is not necessary. The traditional design and sizing of plants including a CHP is performed to operate it in either TLF or ELF mode. In the first case, the sizing maximizes the use of the thermal energy produced, implying that electricity production is a secondary beneficial effect of CHP operation, which can indifferently be sold to the main grid or consumed by local users. In the latter case, the sizing is carried out maximizing the exploitation of the electric energy, but this is economically and energetically convenient only if most of the thermal energy produced is not wasted. TLF and ELF modes do limit the flexibility of the plant required by the SU concept. Therefore, the conventional layout illustrated in Figure 9 was modified in order to increase the flexibility of operation required by the research activity.

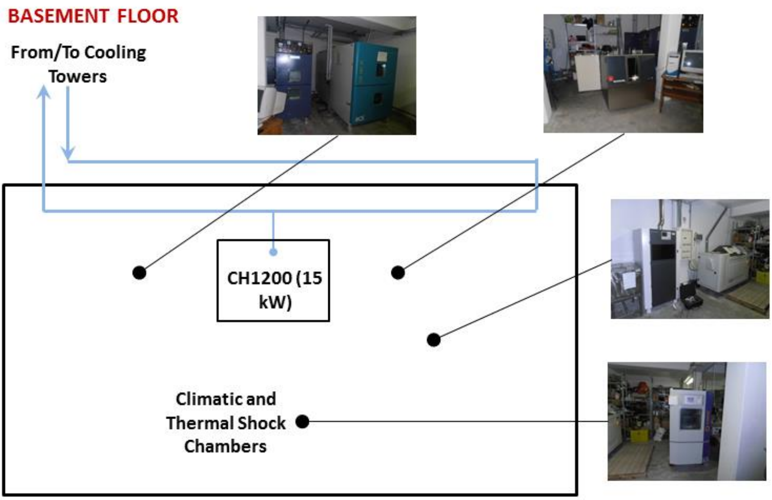


Figure 4 - Cold temperature loop and users in the basement floor

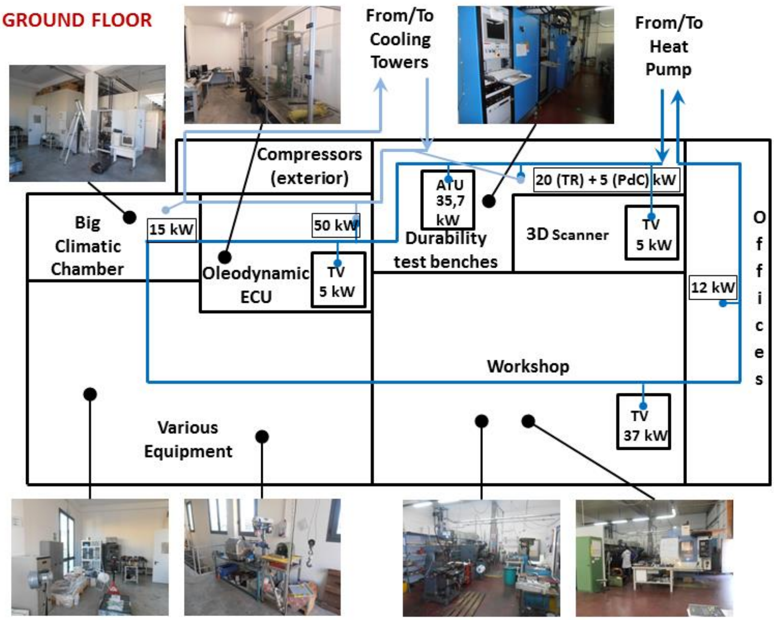


Figure 5 – Cold temperature loop and users at the ground floor

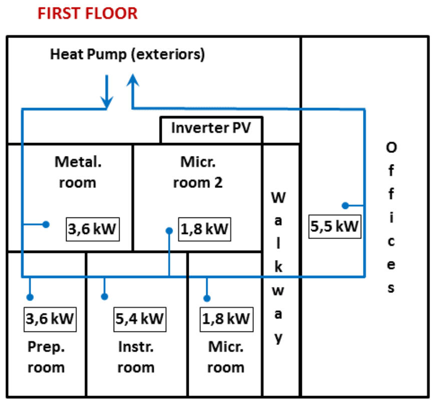


Figure 6 - Cold temperature loop and users at the first floor

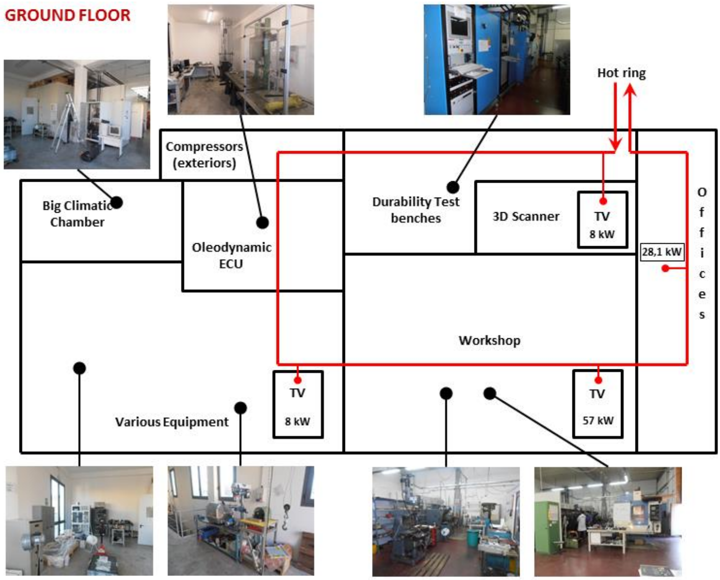


Figure 7 - Hot temperature loop and users at the ground floor

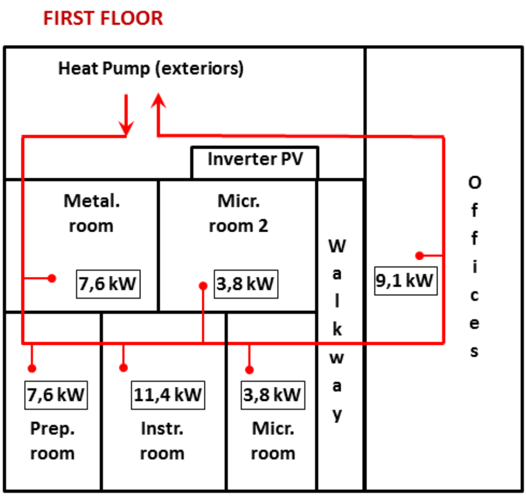


Figure 8 - Hot temperature loop and users at the first floor

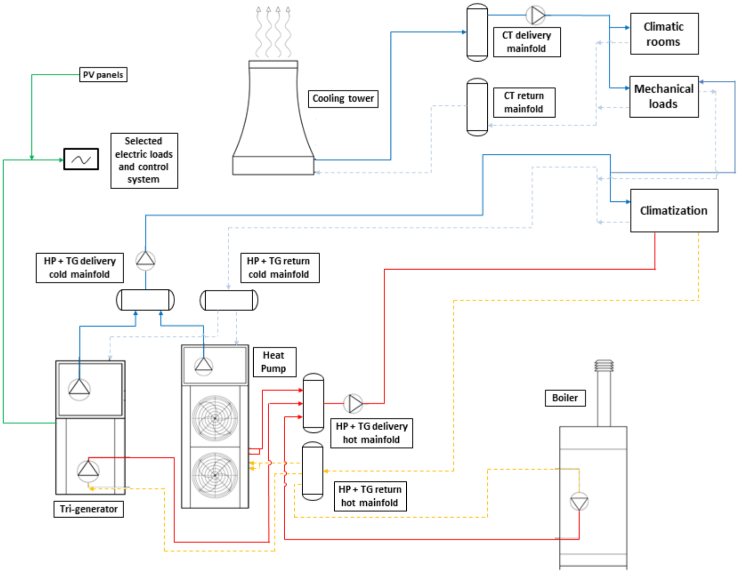


Figure 9 - Conventional Tri-generation Plant Layout

3.1.1 Loads to serve

The loads requests of Pontlab are of three different kind: electricity, heating and cooling. Their variability, granted by the numerous machineries and test rigs involved in every-day activity, as already mentioned, is a very attractive feature of this test case. The electric plant features nine electric panels:

- General panel: located at ground floor, close to ENEL power meter;
- Panel “1”: located at ground floor, close to the general panel, inside which the ampere-meter of the three phases is placed;
- Panel “2”: located at ground floor, to which are connected the machineries in the workshop;

- Panel “3”: located at ground floor, which feeds the large climatic chamber, the oil-dynamic facility and both lights and air conditioning systems of the workshop;
- Panel “4”: located in the basement, supplying energy to the remaining climatic chambers, the ozone-meter, the xenon-test machine and the system for the corrosion resistance tests in salty fog;
- Panel “5”: located at the ground floor, dedicated to the durability test benches, the compression chiller, one of the three air compressors, the air treatment units and the fire alarm system;
- Panel “6”: located next to panel “5”, which supplies electricity to the remaining air compressors and the pumps for the heating and cooling circuits;
- Panel “7”: located at the first floor, dedicated to the equipment in the analysis laboratory;
- Panel “8”: feeding all the offices loads.

A comprehensive list of all the loads installed is presented in Table 3 and Table 4

Table 3 - List of installed machinery and test equipment

Device	*Electric power [kW_e]*	*Heating power [kW_e]*	*Production mode*	*Cooling power [kW_c]*	*Production mode*
Durability Test Benches					
DS1	4.5	0	On-board	0	-
DS2	4.5	0	On-board	0	-
DS3	4.5	0	On-board	0	-
DS4	50	0	On-board	10	Compression chiller
DS5	50	0	On-board	10	Compression chiller
DS6	150	20	On-board	25	Cooling Tower +

					Compression chiller
DS8	50	0	On-board	10	Compression chiller
Climatic Chambers					
CST27/2T	19	0	On-board	n.d.	Cooling Tower
CST157/2T	27	0	On-board	15	Cooling Tower
DCTC600P	2.5	0	On-board	0	
CH1200	24	0	On-board	15	Cooling Tower
SU250	19	0	On-board	0	
Xenon-test	5	0	On-board	0	
Ozone-meter	3.6	0	On-board	0	
Workshop					
Oil-dynamic facility	50	0	-	30	Cooling Tower + Compression chiller
Working Station	10	0	-	0	-
Milling cutter	n.d.	0	-	0	-
Lathe	n.d	0	-	0	-
Drillers	n.d.	0	-	0	-
Laboratory					
DSC	4.5	0	-	0	-
DMA	0.6	0	-	0	-
ICP	4.75	0	-	0	-
TGA	4.5	0	-	0	-
Spectrometer IR	1	0	-	0	-
Chemical imaging	1	0	-	0	-
GC	2.6	0	-	0	-
Microwave oven	3.2	0	-	0	-
Heater	1.5	0	-	0	-
Analyzer C-S	3.45	0	-	0	-
SEM	3	0	-	0	-
Metaliser	1	0	-	0	-

Cutting machine	1.5	0	-	0	-
Polisher	0.3	0	-	0	-
Compressors					
Back-up	5.5	0	-	0	-
Back-up	5.5	0	-	0	-
Operating	17	0	-	0	-

Table 4 - List of all air-conditioning and room heating equipment

Device	*Model*	*Heating power [kW_e]*	*Cooling power [kW_c]*	*Flow rate [m^3/h]*	*Quantity*
Workshop and laboratories					
Workshop Heater	Euroklimat UTK.T L675H	57	37	8000	1
Workshop Heater	Euroklimat UTK.M001	8	5	900	2
Air Treatment Unit	Euroklimat	n.d.	35.7		1
Fan Coil	Ferroli FCS 4T	3.8	1.8		9
Offices					
Fan Coil	Ferroli FCF VBM15	2.4	0.98		1
Fan Coil	Ferroli FCF VBM30	4.55	1.85		6
Fan Coil	Ferroli FCF VBM40	5.45	2.45		2
Fan Coil	Ferroli FCF VBM50	6.6	3.01		2
Fan Coil	Ferroli FCF VBM60	7.9	3.55		1
Water heater		1.5			3

The sum of all the loads show a great unbalance towards electricity, mostly because many test benches, even when requiring heat for their operation, generate the heat by means of electric resistance. Considering the electric-to-heat ratio of the CHP, it cannot be dimensioned in order to satisfy the electric needs of the whole plant. Nonetheless, the plant can be split, electrically wise, in two portions, one that acts as the Smart User and includes the CHP, and the remaining part, which is left unchanged and operated conventionally. The electrical loads included in the SU are listed in Table 5

Table 5 - Smart User electric loads

Device	*Rated electric power [kW_e]*
Test Bench DS3	4.5
Atlas Compressor	7
Electric chiller	25
Climatic chamber CH1200	24
Climatic chamber DCTC600P	2.5
Climatic chamber SU250	7.7
Workshop heater	1.8
Oven	2
Office lights (1st floor)	1.1
Fan coils	1.8

From the point of view of the SU application, each load category, electric, thermal or refrigeration, includes loads that can have three different priorities:

- Privileged Loads: that can be neither modulated nor interrupted;
- Adjustable Loads: that can be modulated but not interrupted;
- Not privileged Loads: these can be further divided in deferrable and interruptible. In the first case, the load once activated must finish its operative cycle; in the latter, the load can be interrupted as long as it operates for a given cumulated time during the day.

Depending on the type of load, and the value of the activity related to its usage, a cost for its modulation or interruption can be determined. This categorization of loads allows the SU to optimize its operation working not only on the generators, modulating their power output when necessary but also on the Demand Side of the loads-generation equation. This is of great importance both in terms of research and SU final application, providing a further degree of freedom for the management of the plant, thus allowing to exploit better the contingent operating conditions.

The next paragraph deals with the generators of choice for the SU and provides insights on their sizing. The topic is relevant but not at the core of the Thesis presented, therefore the level of detail of the description is limited for the sake of brevity.

3.1.2 Electricity, heat and cooling generators of choice

The facility is connected to the electricity grid by a LV electric connection with a maximum power exchange of 180 kW_e. This connection, considered the contemporaneous factor of usage of all the equipment installed, can ensure the satisfaction of the electric loads both before the intervention to upgrade the energy system to SU configuration and in the present SU configuration. Before the modification of the plant, the heating and cooling loads, were satisfied, respectively, by means of a Riello gas boiler with a rated power of 34 kW_{th} and a Euroklimat RAK.E-0262 compression chiller of 61.8 kW_c along with a cooling tower of 25 kW_c. The heat required for air-conditioning is distributed in the building by means of a medium temperature loop. The cold water circuit, on the other hand, ensures the distribution of the refrigerated fluids, the cooling tower can take the water temperature down to 25°C whereas the compression chiller can cool it further to 13°C. Both hot and cold circuits involve two manifolds, one for the delivery and one for the return of the water. Regarding RESs, Pontlab features a PV plant on the rooftop with a rated power of 13.6 kW_e and a micro-wind turbine with a rated power output of 3 kW_e.

The solution sponsored by Yanmar to pursue the goals of the future Smart Grid is to insert a CHP generator along with the RESs in an energy plant. Theoretically, for their quick response time and good efficiency in off-design, CHPs (especially ICE driven of small size) are an ideal solution to counter the effects of RESs intermittency or sudden load change from the foreseen values. On the contrary, traditional large-scale power plants suffer more when asked to regulate in order to address a new load condition. Indeed, in the SG concept, the role envisioned for these power plants is often to provide the base load only, letting the DG deal with the balancing of the system. In the literature, there are examples of similar solutions, where CHP are operated in unconventional modes (not TLF or ELF) in order to provide a stable power profile with the electricity grid [104-106]. In the case of an energy system operating as SU, the sizing of the CHP should take into account more parameters than is done for standard TLF or ELF cases. For example, the rated power of the RESs becomes relevant and should be inferior to CHP potential in order for it to be able to cope with their oscillation. Moreover, in the case where VSO is required, the electric power output of the plant should match the maximum electric power request from the loads. It can be noticed how the sizing of such a system should take into account all of the components together, which cannot be done in a system where most of the equipment is already installed. Indeed, in the test case considered, the electric load is considerably higher than the RESs maximum power output. Moreover, upon request of the Pontlab managers, the CHP should be able to operate in standard mode when tests are not being carried out on the system or if desired for any reason. Hence, even if the sizing of the CHP in a proper SU should follow a dedicated procedure, in this case, a compromise between SU and standard sizing had to be adopted.

Considering the loads during typical days of operation and loads contemporaneous factors, the CHP was sized considering the thermal request duration curve. As anticipated in the previous paragraph, on the basis of the duration curve of thermal loads, it was clear that the CHP should have had a rated power considerably lower than the minimum electric power request of the whole plant, which is rarely below 100 kW_e. If the CHP were sized for the satisfaction of the base electric load, then most of the heat provided by the cogenerator would have been wasted, even considering the installation of an absorption chiller for the supply of the cooling power required. This would have greatly reduced the efficiency of the plant and its economic convenience. For these reasons, the options for the SU plant were to equip it with one or two Yanmar CP25 CHP, with rated electric and thermal output of 25.1 kW_e and 38.6 kW_{th} respectively; the efficiency of the cogenerator are: 31.5% for the electric part and 53.5% for the thermal one. The solution with two CHPs would allow a greater coverage of the electric requests of the SU and during the summer period would be able to grant a greater part of the cooling load. Nevertheless, during the winter period, the thermal energy request is minimal compared to the potential of the two CHPs combined: part of the heat would need to be wasted even considering to switch one of the CHP to summer operation mode and fuel the absorption chiller. All this considered the single CHP solution is to be preferred for it is optimized from the thermal point of view. Furthermore, the electric power output of a single CHP well suits the potential of the RESs installed, making it an interesting solution for the SU sizing and operation. The CHP is currently installed on a skid on the terrace outside the first floor of Pontlab, on the same skid are installed: the absorption chiller Yazaki WFC-SC5 to allow tri-generation, and the Programmable Logic Controller (PLC) for the control and data acquisition from the sensors acquiring data from plant components. In Figure 10 and Figure 11 can be found the skid scheme and photograph.

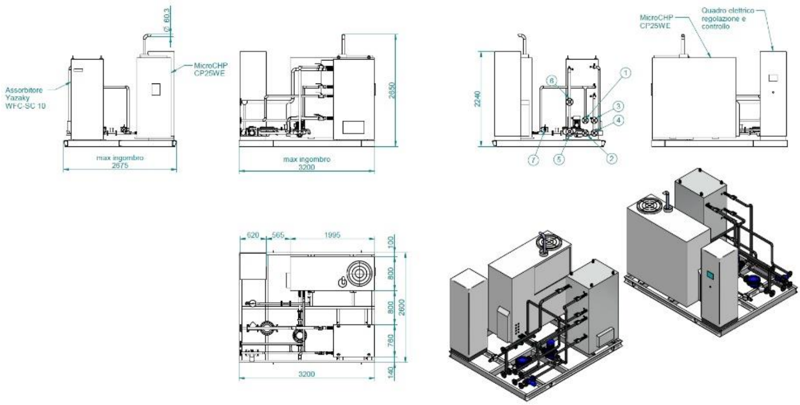


Figure 10 - Skid layout and views

Figure 11 - Skid assembly on Pontlab terrace

The main characteristic parameters of the devices constituting the skid are reported in Table 6.

Table 6 - Specification of equipment installed on skid

Parameter	*Unit*	*Value*
CHP		
Electric power	kW_e	25,0
Output	V/-/Hz	400/3phase/50
Inlet power	kW_{th}	74,6
Natural gas volume flow	Nm3/h	7,77
Natural gas minimum pressure	mbar	15,0
Natural gas maximum pressure	mbar	35,0
Average temperature	°C	15,0
Hot water circuit		
Thermal power	kW_{th}	38,4
Warm water return temperature	°C	78,0
Warm water delivery temperature	°C	83,0
Water volume flow	m3/h	6,6
CHP pressure drop	mbar	25,0
Absorber pressure drop	mbar	90,4
Other pressure drops	mbar	26,6
Overall pressure drop	mbar	142,0
Absorption chiller circuit		
Cooling power	kW_c	66,8
Cooling water return temperature	°C	31,0
Cooling water delivery temperature	°C	34,1
Cooling water volume flow	m3/h	18,4
Cooling tower pressure drop	mbar	20,3
Absorber pressure drop	mbar	85,3
Other pressure drops	mbar	34,4
Overall pressure drop	mbar	155,0
Cold power	kW_c	28,5
Cold water return temperature	°C	12,0
Cold water delivery temperature	°C	7,0
Cold water volume flow	m3/h	4,9
Absorber pressure drop	mbar	56,0
Other pressure drops	mbar	24,0
Overall pressure drop	mbar	80,0
Efficiencies		
Electric efficiency	%	33,5
Thermal efficiency (heating)	%	51,5
Thermal efficiency (cooling)	%	38,5
Overall efficiency (heating)	%	85,0
Overall efficiency (cooling)	%	72,0

3.1.3 Storages

Although in commercial applications of co-generation and tri-generation thermal storages are not widely diffused, they have a great potential in terms of performance and economical improvements on the energy plant and this is demonstrated in several research papers. Haeseldonckx D. et al. (2007) [107] outlined the significant benefits that can be achieved by means of thermal storage together with a CHP system. Indeed, the storage allows a de-coupling of the request and the supply with both economical and system efficiency improvements. The correct sizing technique and the obtainable emissions savings are presented in the paper. Other studies deal with larger systems and the implementation of storages that can span from daily to seasonal size. A year-long optimization of the storage sizing and operation for a large district heating case study, based on MILP technique, is performed by Christidis A. et al. (2012) [108]. The study and optimization performed allowed the authors to prove the effectiveness of heat storages to both enhance the overall efficiency of the system and increase economic savings. A first analysis of the importance of coupling a CHP with a thermal storage when including RESs in the energy system considered is presented by Chesi A. et al. (2013) [109]. In the paper, the authors evaluated the influence of storage size on a Smart User running several generators (fossil fuel and RESs) with a VSO operation towards the grid. The study refers to a plant installed in Navicelli (PI), whose layout differs significantly from the one assembled in Pontlab. The storage allows a de-coupling of loads request and thermal production. Therefore, it is possible to limit the intervention of the auxiliary boiler and increase the exploitation of CCHP system. The system was modeled in TRNSYS© taking as input load profiles from the literature. The outcomes of the study show how the adoption of the storage greatly enhances the flexibility of the system, which is a key requirement for a plant that is meant to be operated within a Smart Grid.

In order to operate within a SG, the SU needs to include several storage devices. Assessing the ideal type of storages or their size is out of the scope of this thesis. Nonetheless, a description of the components installed or whose installation is expected in Pontlab is provided hereafter. Ideally, for greater flexibility of operation, each of the kind of energy required in the power system should be stored in a dedicated storage. Therefore, for the load requests of Pontlab, either three (electricity, hot water and cool water) or at least two (electricity and hot water) storages should be considered. In case of two storages, the hot water can be used either to directly satisfy the thermal loads or to provide the absorption chiller with the heat it requires. Whereas, with three separated storages, the cold water and hot water can satisfy their respective loads directly. The electric storage is important for two main reasons: during operation planning, in order to have one more degree of freedom in the optimization process, and in real-time management, where the storage is in charge for the compensation of sudden load variation from the expected values. In this latter case, the bigger the storage, the slower/less frequent can be the correction of the CHP electric power output in order to respect a given grid power exchange profile. The real-time operation of the system will be discussed in a dedicated section.

In Pontlab plant, two storages are currently installed: the hot temperature storage, used during winter operation mode, and the cold temperature storage, which, conversely is employed during summer operation mode. The electric storage, although being very important for the operation of the system as a proper SU, will be installed in the near future. Nonetheless, at the moment, its presence in the plant can be simulated because the whole SU is connected in a sub-grid whose exchange with the main one of Pontlab is known and the presence of the storage can be simulated at the connection between the two.

The sizing of the thermal storages was carried out by means of a computational model developed with LMS AMESim© software, a 1-D simulation tool based on the bond-graph methodology. The software allows the simulation of transient conditions, whose impact on the performance of the system is relevant considering the thermal inertia of the system. Thanks to a Design Of Experiments (DOE) approach, with the final goal of:

1. Minimize the energy consumption of the plant;
2. Maximize the revenues.

For the scope, several simulations were performed in order to assess the optimal size of the cold and hot storages. The optimal size resulted from the analysis carried out was 3 m^3 for the hot temperature storage and 2 m^3 for the cold temperature one. A detailed description of the approach followed can be found in [110]. The devices chosen for the application are insulated stratified storages, therefore they supply the thermal-vector fluid always at the same temperature, which is the maximum admitted by the CHP in the case of the hot storage, 85°C and the lowest produced by the absorption chiller for the cold storage, 4°C. The storages are provided with thermocouples to measure their temperature. Nevertheless, during actual operation it is hard to verify the perfect stratification of the fluid contained within. Thus, there could be an error in the evaluation of the actual temperature of the fluid coming out of the tank, although in terms of average power in a 15 minutes period, the error does not have a strong impact on the performance of the plant.

3.1.4 Possible Layouts and adopted layout

Here are presented the electric and thermal layout of the SU. In Chapter 2, dedicated to the state of the art on Smart Grids, their components and key technologies, many papers describe possible layouts for applications of different genre. The plant designed, especially the thermal one, is the result of a compromise. Indeed, the SU plant in Pontlab was realized modifying the existing one and some modifications could not be performed because of an excessive discomfort and interference of the procedure with the activities carried out in the facility. Therefore, the ideal plant for the SU, which would require the greatest grade of flexibility of operation, was discarded in favor of a less intrusive and more traditional solution, which would have allowed the plant to be operated both as a "less flexible" SU and in standard ELF-TLF modes. Indeed, some solutions, potentially better performing, had to be modified considering that the plant installed in Pontlab does not represent only a test rig for research, but must be able to operate in a steady, safe and economically convenient way at all times.

The electric layout of the SU, apart from the connection points of the generators, both renewable and fossil, is a standard one. A simplified scheme is presented in Figure 12.

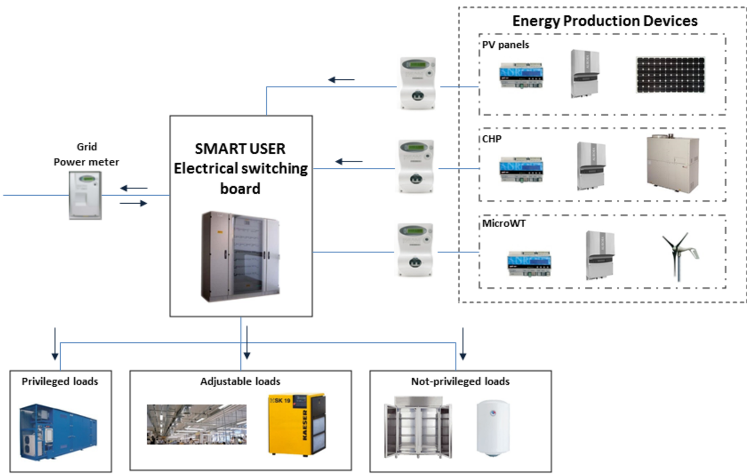


Figure 12 - Simplified Electric Layout

The connection point of the generators were set so that theoretically the plant could operate in VSO, therefore they are all connected inside the local power network. Their meters are interfaced with the SU electrical switchboard along with all the loads included in the SU portion of the local electric grid. The SU electrical switchboard is then connected to the grid power meter and measures the electric energy exchange of the SU with the main grid. According to the common installation practice, all the RESs, except the PV plant, should be connected directly to the main distribution grid so as to benefit of the "Tariffa Omnicomprensiva", the All-inclusive feed-in tariff granted for renewable energy production. On the other hand, the connection point of the PV plant is next to the energy meter in order to take advantage of the "Scambio sul Posto", the Local Energy Exchange incentive that goes along with the Energy Account system for solar electric energy production.

For the thermal layout, three different options can be considered when designing the plant:

1. Two thermal storages, one dedicated to the cooling system, one to the heating system, in parallel with their respective generators (CHP and boiler or absorption chiller and compression chiller) and with the users (Figure 13);

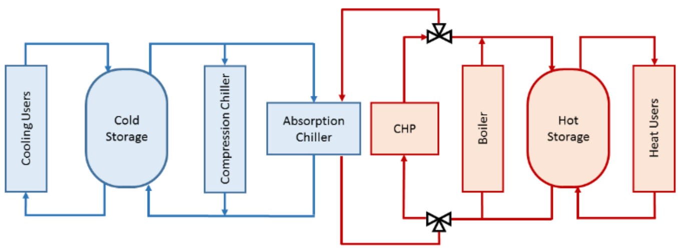


Figure 13 - Parallel Generators Smart User Layout with two thermal storages

2. A single hot water storage, in parallel with the CHP, the boiler and the hot users, connected by means of two three-way valves

to the absorption chiller, which is in cascade with the compression chiller and the cooling users (Figure 14);

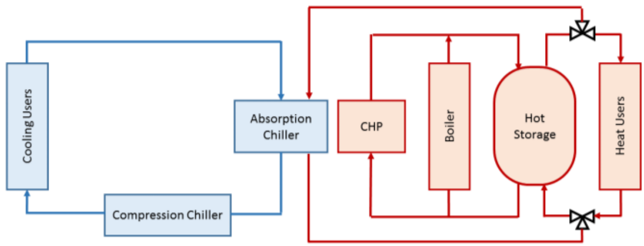


Figure 14 - Parallel Generators Smart User layout with one thermal storage

3. Two thermal storages, one for heating and the other for refrigeration, which can be charged only by CHP and absorption chiller respectively. In this plant the hot storage, the boiler and the heat users are in cascade, likewise for cold storage compression chiller and cooling users. Two bypasses, one for the hot section and one for the cold section of the energy system, allow the fluid returning from the users to go directly to the auxiliary generator (boiler or compression chiller) without entering the storage (Figure 15).

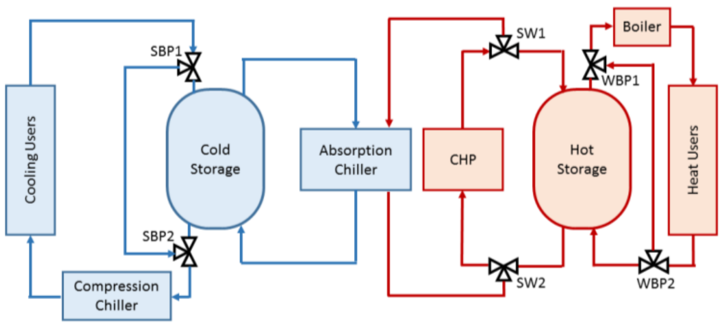


Figure 15 - Auxiliary Units in cascade layout with two thermal storages

Let us examine the advantages and disadvantages of the proposed layouts. The first plant (Figure 13) maximizes the flexibility of operation and it is therefore the ideal solution for the SU. In this case, both the boiler and the CHP, or the absorption chiller and the compression chiller, can charge their respective storage. During winter operation this is not expected to happen frequently, being the CHP and the boiler both fueled with natural gas, and being the CHP much more efficient because of the production of both electricity and heat at the same time. On the contrary, during summer operation, the absorption chiller is supplied with the heat produced by the CHP, hence by natural gas, whereas the compression chiller employs electricity. Therefore, there might be occasions when the CHP should be kept turned off but it is convenient to charge the storage by means of the compression chiller. This solution is therefore of great interest because of the flexibility of operation that it allows. Nonetheless, it presents some drawbacks that ultimately led to the choice of a different one for the plant in Pontlab. First of all the plant is more complicated, and presents more components, thus it was harder to realize over an existing plant. It also requires greater control over the auxiliary units, e.g. if the optimized operation requires the boiler and the CHP to supply different powers to the storage, then there must be a way to control the amount of power. Theoretically, this can be done by modifying either the temperature (very impractical) or the mass flow rate. Moreover, usually both boiler and compression chiller cannot provide the same temperature level as output independently from the inlet temperature. Therefore, even if modifying the flow rate is feasible, it is not easy to ensure in all conditions that the desired power is actually respected. Another issue is the temperature of the storage, indeed the lack of control of the outlet temperature from either the CHP or the boiler might result in the loss of stratification in the storage; unless the fluid injection is performed at the height corresponding to the outlet temperature of the generator. However, this solution is usually expensive. Therefore, the plant might not ensure the desired temperature level to the user, which can be critical for some loads, e.g. duration test benches.

The second plant proposed has less flexibility because the compression chiller cannot charge the storage, for obvious reasons. Therefore, one degree of freedom in the possible operation of the plant is missing, compared to the first solution. Nonetheless, the plant presents less components and in the cold loop it is easier to control the temperature level of the water provided to the cold users, whereas on the hot side, the issues described for the first solution cannot be avoided.

On the bases of these considerations, the plant adopted in Pontlab is the third one of those proposed. Indeed, in this case it is possible to guarantee that the thermal fluid (hot or cold) is provided to the users at the right temperature. If the storages charge is not sufficient to provide the correct temperature level then either the boiler or the compression chiller can be activated in order to establish the correct temperature in a relatively small time. This layout is also easier to be managed using conventional devices like commercial boilers and compression chillers, which are usually controlled by temperature set-points, thus in a semi-automated way.

3.1.5 The control system

The control system of the plant consists of a series of thermocouples and energy meters, which act as sensors, a control system (PLC+SCADA) that receives inputs from the sensors and evaluates the modifications to apply. In addition, it comprises inner and outer controllers of the devices installed (i.e. the bypass valves and the control systems based on temperature measurements of boiler and compression chiller). The control system can also operate on the CHP, reducing its set point, on the renewables, reducing the power they feed in the local grid, if necessary, and on the modulable/interruptible/deferrable loads. It is important to notice that the control system, conversely from the optimization system that considers time-steps of fifteen minutes, operates based on the inputs received by the sensors in the plant in real time, hence it can change its operation several times during a single time-step of optimization. This should always be kept in mind during both plant operation and its optimization. Whereas the first has a quick response time and it is featured by several aspects typical of the components of these energy plants (e.g. hysteresis in the operation of chiller and storage) and transient conditions, the latter can only consider mean values during the time-frame analyzed. This is why it is to be preferred to address the optimization and the real time operation of the system with different procedures, as will be discussed in the next section related to the control algorithms.

Depending on the temperature levels of the storages and the fluid returning from the users, the bypass can be either opened or closed. The bypasses are an important feature of the thermal layout and are operated as follows: if the temperature of the fluid at the outlet of the hot storage (cold storage) is lower (higher) than the temperature of intervention of the boiler (absorption chiller) then the bypass opens and excludes the storage from the users' loop. This solution does not prevent completely the mixing of fluid at different temperature at the inlet port of the storage. Nonetheless it has two great advantages:

- The loss of perfect stratification, given also the mass of the storages compared to the inlet and outlet mass flow rates, involves only the bottom (upper) part of the storage itself;
- The control temperature for bypass operation at the storage outlet ensures that the user is fed with at least the required level of temperature at all times. When it can be done by the storage the bypass is closed, conversely, the boiler (compression chiller) intervenes and the bypass excludes the storage.

The control logic operates as described hereafter.

- Summer period, storage used (Figure 16): The heat recovered from the CHP is deviated to the absorption chiller by switching the three-way valves SW1 and SW2. The absorption chiller charges the storage and the bypass is kept closed by three-way valves SBP1 and SBP2. Therefore, the cold fluid is delivered to the compression chiller and, if its temperature is low enough, sent to the users without intervention from the compression chiller, vice versa otherwise. Depending on the cooling load demanded by the users, the temperature at the users outlet can differ. The bypass is kept closed as long as the temperature at the storage outlet is lower than the temperature of intervention of the compression chiller.

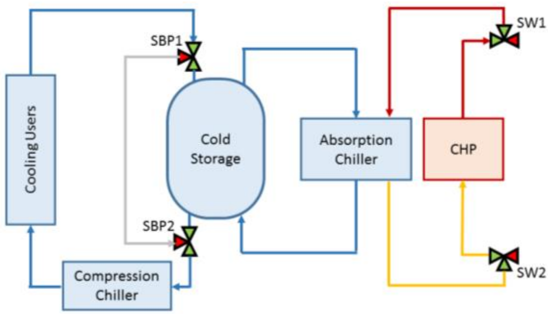


Figure 16 - Summer operation, bypass closed

- Summer period, storage by-passed (Figure 17): in this case the bypass valves SBP1 and SBP2 keep the bypass opened while the absorption chiller, if active, charges the storage. The users load is satisfied only by means of the electric chiller. This condition is maintained until the outlet temperature of the storage is higher than the compression chiller intervention.

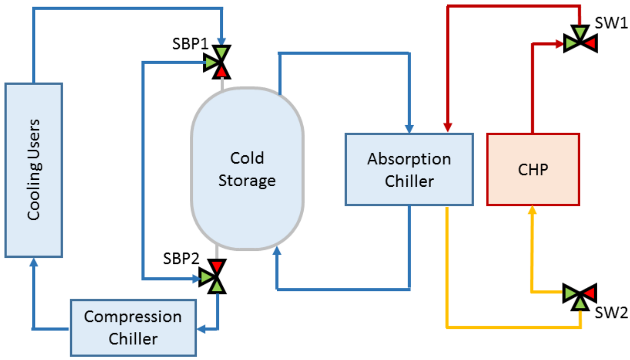


Figure 17 - Summer operation, bypass opened

- Winter period, storage used (Figure 18): During winter period the three-way valves SW1 and SW2 are set so to connect the CHP to the hot storage instead of the absorption chiller. The two three-way valves controlling the bypass (WBP1 and WBP2) in this case connect the upper port of the storage to the boiler and the heat users. As described for the summer period when the storage is used, as long as the temperature of the storage delivery port is higher than the boiler intervention temperature this does not activate, the bypass valves WBP1 and WBP2 keep the bypass closed and only the loads are supplied through the storage.

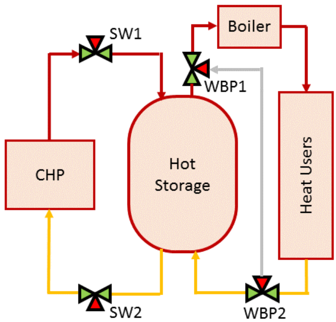


Figure 18 - Winter operation, bypass closed

- Winter period, storage by-passed (Figure 19): In this case, the valves WBP1 and WBP2 keep the bypass open, being the temperature of the fluid at storage outlet, lower than the intervention temperature of the boiler. When the bypass is opened, the boiler is in charge of providing the heat required by the users while the CHP can recharge the storage.

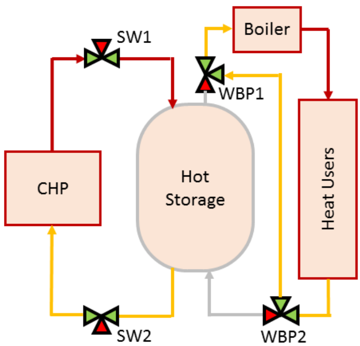


Figure 19 - Winter operation, bypass opened

The SCADA system is a fundamental component of the SU, indeed, it can be considered the brain of the system. All the data acquisition, management of operation and communications are handled by the

SCADA. Its first role is the acquisition of the inputs for the next day such as load profiles, weather forecasts and energy prices, in order to perform the optimization of the operation for the day ahead. This is done by means of an ad hoc algorithm, developed within this research project, which runs directly in the SCADA and will be described in the next chapter. For the "present" day, on the basis of the optimization algorithm outputs, the SCADA defines the set points of power output for the co-generator, the possible curtailment of renewables and of low-priority loads. The algorithm provides these set points as constant values for a period of 15 minutes, therefore the SCADA needs also to ensure that within this time-frame the actual loads (that may vary during the 15 minutes) are always satisfied. The electric loads are managed thanks to a real-time algorithm, which ensures also the compliance with the power exchange profile with the grid. Conversely, the thermal loads are managed as described before depending on the temperatures measured along the piping of the system. In order to minimize the difference between real-time and foreseen operation, every 15 minutes, the SCADA performs an update of the optimization of the energy system operation, which is referred to as *advanced dispatching*. The different algorithms that run on the SCADA and their variations will be described in the next chapter. The SCADA system has two more fundamental roles: the storage of all the data acquired during the day into a database that can be accessed also in remote and serves as Human Machine Interface, both locally and from remote. A detailed description of the SCADA system is provided by [110].

3.1.6 Data acquisition from the plant for later analysis

One of the advantages of this research compared to what is found in the literature regarding SG, is the possibility to work on an actual system, whose operation is monitored every day. The monitoring and reporting capabilities provided by the SCADA system installed in Pontlab, ultimately allow the researchers to test the controlling algorithms not on expected values for a given user, but on real data acquired from the system. Therefore, it is possible to test the upgraded versions of the algorithms offline, while reducing the mismatch between the expected and the actual performance of the plant as much as possible. Considering the importance of the data acquired for the tests carried out on the control algorithms, a list of the data measured and the structure of the daily reports is provided hereafter.

Every 15 minutes the average value of the following parameters is stored in the daily report:

- Active power:
    - Total, CHP, PV, WT, L1 loads, L4 loads, Chiller, Simulated Load, Oven, Total loads, Total Gen, Pontlab overall;
- Electric power required by loads, in detail:
    - Bench DS3; CH1200, Compressor, DCT600, Fan-coil, Heater, Lights, SU250
- Heat power (produced and requested):
    - CHP, boiler, L1 loads;
- Cooling power (produced and requested):
    - L1 loads, Absorption chiller, Compression chiller;
- CHP set point from SCADA
- GME electric price
- Operation mode (Summer/Winter)
- CHP gas consumption
- Temperature measurements:
    - CHP Outlet, CHP Inlet, Absorption chiller Outlet, Absorption chiller Inlet, Hot Manifold, Cold Manifold, Hot Storage, Cold Storage, Boiler Outlet, Boiler Inlet, Cooling Tower Outlet, Cooling Tower Inlet;
- Water flow-rates:

    - Cold bypass flow, hot bypass flow, CHP water flow, Absorption chiller water flow;
- Weather station:
    - External temperature, Wind speed, Wind direction, External humidity, Solar radiation, Rain Intensity;
- Weather forecasts:
    - Solar radiation, Wind Speed, External temperature.

During offline tests, the input files of the algorithms, will be based on these measurements. The daily report contains additional information, which is calculated from the data acquired. As an example, there are calculated the costs for the operation of the system during the day analyzed if the system were operated:

- In a conventional way, i.e. electric energy from the grid, boiler and electric chiller dedicated to the heating and cooling load;
- With just a CHP operated in TLF or ELF modes;
- With the CHP and the absorption chiller, once again operated in TFL or ELF modes.

These simple calculations provide a useful comparison between a standard operation mode and the one proposed by the day-ahead optimization algorithm and actually performed during the day in examination.

3.2 Present operation scenario

The Smart User described in this chapter is indeed a valuable test bench for Smart Grid technologies and approaches on a real system. Nonetheless, it is required to operate efficiently and economically in the present conditions, i.e. the present tariff and incentive scheme as well as the unconstrained renewables interface with the grid. It is a fact that the Italian energy system is already in a stressful condition in terms of economy of operation of standard centralized power plants because of the increasing presence of renewables with dispatching priority. Nevertheless, it still does not include incentives or regulations to promote a different approach, which might allow a greater presence of RESs feeding electricity to the grid while limiting the detrimental effects caused by their natural intermittent behavior.

3.2.1 Tariffs, incentive schemes

The present tariff scheme adopted in Pontlab falls under the Real Time Pricing category introduced in the chapter dedicated to the state of the art. Each hour of the day, Pontlab pays the electricity at its price in the Italian electricity market (IPEX). The Unified National Price (PUN) varies greatly in a single day and during the year. Just to give a numerical example, the minimum price paid for energy in 2013 was 0 €/MWh whereas the maximum was 151.88 €/MWh. This dynamic pricing of electric energy offers great opportunities for the optimized operation of the SU, especially when this optimization involves daily management of the storages. The gas price conversely is stable during the day but it would be incorrect to think that the thermal management of the system is not influenced by the electric price. Indeed the production of electricity and thermal power is strictly connected when considering a CHP inside the energy system. Therefore, there can be effective strategies for CHP operation that can maximize, for example, the economy of management of the system. The incentives considered for the Smart User as configured are mainly of three different kinds:

- Incentives from electric solar power production: 403 €/MWh for the energy produced, this incentive is granted from the Energy Account incentive scheme granted by the Italian government. Considering that the plant was already existing, the value of the incentive depends on the type of PV plant (on ground, on roof,

roof-integrated) and from the year of the beginning of operation of the plant itself.

- White Certificates (TEE) granted for the production of electric energy with high efficiency: granted by the Authority for Electric Energy and Gas (AEEG) for the primary energy savings (PES) obtained from projects that reduce the natural gas consumption. In the present case, the SU featuring a CHP, if operated correctly, can be enlisted for receiving the incentive.
- Natural Gas discount: a discount on the price paid for natural gas used for electric energy production is granted if the co-generation is carried out at high levels of efficiency and the PES value is greater than 0.

Theoretically, the use of a wind turbine could enlist the plant for Green Certificates remuneration; nevertheless, the energy produced by the WT installed in Pontlab is negligible and therefore this incentive is always disregarded.

3.2.2 Constraints to be met

The operation of the SU must ensure compliance with several constraints. The most obvious, yet important, is the balance between demand and generation. Regarding heating and cooling, Pontlab is independent and by means of CHP/Absorption chiller and Boiler/Compression chiller it can satisfy its loads completely. For electricity, due to the high needs, Pontlab cannot rely only on its own generators, therefore the balance between loads and supply is met taking into account the electricity grid and exchanging power with it. Nonetheless, the portion of Pontlab onto which the SU operates presents a smaller amount of electric load, therefore the power balance with the grid does not always imply that the grid is powering the plant. When considering the actual system operation, the way it is controlled by the PLC+SCADA system needs to be considered, especially the fact that the plant is operated with fixed flow rates and controlled by temperature measurements. This is a fundamental aspect to consider when designing a control algorithm for an energy plant. Not all the assumptions that one can think of might be reasonable for the plant itself, even if, theoretically, they are effective and efficient ways to manage the system. For example, the black-box approach, where all the components are described by energy and mass balances is very common in the literature. Nevertheless, if the real system is controlled by temperature, some solutions may be feasible, whereas others may not, depending on the plant layout and operating conditions. Moreover, a desirable constraint to system management is the cyclic operation of the storages, i.e. at the end of the day, the energy stored is the same they had at the beginning of the day. Indeed, when considering a daily optimization, this is highly recommendable in order to avoid a day “taking an advantage” at the expense of the following one; nonetheless, this is not mandatory.

3.3 Future operation scenario

The literature presents several examples of scenarios, many different energy policies, incentive schemes, tariffs and regulations. In our case, the definition of a possible future scenario was done in collaboration with Enel S.p.A., one of the most important energy producers in Italy and partner of the project. It is important to notice that the future operation scenario is considered only when evaluating the performance of the optimization algorithms in offline mode, although in the future, ad hoc tests on the real system might be performed. Defining a completely new set of prices, tariffs and incentive schemes would have been out of the purpose of the study. Therefore, when evaluating the future scenario, only one, yet very important constraint was added: a fixed grid exchange profile.

3.3.1 Fixed Grid Exchange Profile

The fixed energy exchange profile with the grid is based on Enel's suggestion regarding a possible future regulation starting from 2016. According to this regulation, the energy fed in to the grid by generation plants should be known and granted in advance of one day. At the moment there are no limits in terms of maximum shift from average value or total energy taken or fed from/to the grid during one day. The only constraint is that during each hour of the day, the energy exchange profile should be kept constant and communicated during the day before its occurrence, see Figure 20. It is likely that in the future there will be incentives and penalties in case of compliance or not compliance to the grid exchange profile communicated. Moreover, a band of compliance might be as well implemented in the place of a single value. Nonetheless, the values of these incentives and penalties are hard to assess at the moment. Therefore, in the future operation scenario considered in this study, no incentive is granted for compliance with the profile defined the day before, whereas there is a penalty in case of non-compliance. The penalty is set at 0.4 €/kWh, this value is high enough in order for the optimizer to ensure that it is respected most of the time: indeed, its weight on the economy of operation is relevant.

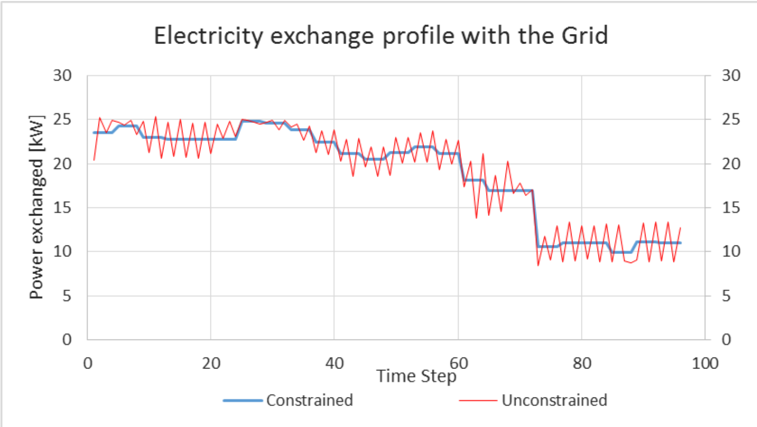


Figure 20 - Comparison between unconstrained and constrained electric energy exchange profile with the Grid

4 THE MANAGEMENT OF THE PLANT

The previous chapter dealt with the hardware components of the plant and introduced the control system. The focus of the present research is to define the optimal controlling strategies for the real plant. This chapter deals with this topic providing a detailed description of the algorithms running inside the SCADA system and controlling the system. The algorithm currently implemented in Pontlab presents some drawbacks which have been faced during the study and for which an effective solution was found. Nonetheless, the upgraded algorithm has been studied and tested only offline until now, whereas its implementation in the actual plant is planned for the near future.

4.1 Algorithm structure

As was mentioned in earlier chapters, the controlling system must operate in three different moments. The first optimization of the operation of the system is performed during the day before of the planned operation and it is performed by the "Day Ahead Algorithm" (DAA). The second optimization occurs during the present day, and it is done in order to update the solution to the new values of the input variables that are provided by the energy market, the weather forecasts and the desired activities for the day. The algorithm in charge for this optimization is called "Advanced Dispatching Algorithm" (ADA) and it runs once every 15 minutes. The final, yet very important, part of the controlling algorithm is the "Real-Time Algorithm" (RTA); its role is to ensure that the loads are satisfied regardless of their average value within the 15 minutes time frame that was considered by both DAA and ADA. A diagram representing the sequence of algorithms operating on the SU is presented in Figure 21. Before venturing in a precise analysis of each procedure created to control and optimize the management of the energy system a brief description of the intents and roles of each algorithm is presented hereafter.

4.1.1 The Day Ahead Algorithm

The Day Ahead Algorithm is the basis of the whole optimization system, it operates on time-steps of 15 minutes each. Its scope is to receive the inputs required for the assessment of the optimized operation for the next day and to deliver a solution, possibly the global optimum, for the optimization problem. The inputs are provided both manually, like the activities planned for the next day (i.e. loads to satisfy) and automatically, like weather forecasts and energy prices for the next day. Some other inputs do not vary from day to day because they are related to the hardware installed, not the way it is operated. Once all the inputs are defined, the algorithm performs an optimization. The algorithm output is a file containing all the set points for the controllable devices for each period of 15 minutes considered. Along with these set points, the output file includes the expected value of several other variables, as well as the foreseen costs and emissions of each time step. The time scales of choice are very important. If the data of a single day is considered for the optimization of the plant then, at maximum, a period of one day is optimized. Thus, the operation cannot be planned for a whole week in advance; it would not make sense because the time-frame considered in each run of DAA is still one day. This decision also limits the size of the storage, which can have at maximum a daily cycle of operation and therefore, the amount of energy they exchange with the system typical for one day of operation. The second relevant time scale is the duration of each time-step: 15 minutes is a smaller window than those of most of the algorithms that are found in the literature. However, as will be clear when considering the loads profile measured in the plant, a bigger time step would have both lost great part of the details of the operations and increased more than necessary the corrections applied by the RTA. On the other hand, a smaller time step, considering the cycle of operations of the devices installed, especially the climatic chambers that feature the highest frequency of load variation, would have implied longer computation times at a cost of little benefits.

It is worth to notice that the DAA provides a suggestion for the optimized operation of the SU, which is strictly dependent on the inputs provided. Neither a stochastic analysis of the probability of occurrence of those inputs, nor a scenario analysis, were set for two reasons. First, because the optimization considers a short period, one day, and it is run the day before the one considered in the algorithm. Thus, the inputs provided are expected to be sufficiently accurate, where "sufficiently" means that the solution proposed is not supposed to be ineffective for the next day in any case. The second reason is the presence of the ADA and the RTA. These ensure that the solution is updated when more reliable inputs are known and that the solution is respected within the 15 minutes of operation considered.

4.1.2 The Advanced Dispatching Algorithm

The Advanced Dispatching Algorithm fulfills the important duty of updating the solution suggested by the DAA according to the latest information available. Indeed, between the moment when the DAA and the ADA are launched, there might be a variation of the planning of the activity (uncertainty of loads profile), of weather conditions and forecasts (uncertainty related to RESs productivity and expected thermal or cooling loads) as well as a change in the energy prices or costs. As was mentioned above, the variations, although enough to justify the presence of the ADA are not expected to disrupt completely the suggested operation performed by the DAA because the period considered for the optimization is relatively small. The ADA works in a similar way to the DAA, indeed it takes the same kind of inputs, performs a similar optimization (i.e. using the same techniques) and provides similar outputs. Nonetheless, due to the way it is employed, it imposes a strict limit in terms of computational time required to achieve an optimal solution. Considering it must upgrade the simulation once every time-step, the maximum computation time allowed for it to run is shorter than 15 minutes. Theoretically, only the ADA must comply with this limited time for the run, but, being extremely similar to the DAA in terms of inputs, outputs and procedure, it imposes the same constraint also on DAA.

4.1.3 The Real Time Algorithm

The Real Time Algorithm conversely to the DAA and ADA does not perform any optimization, but acts in a twofold way: it always serves as a link between the ADA and the real system and, in the future scenario, it ensures that the promised power exchange profile with the grid is respected at all times. Moreover, differently from the DAA and the ADA, it manages only the electrical part of the SU. The thermal plant is managed in real-time by the SCADA thanks to the information provided by the temperature sensors and energy meters in the plant. In addition, due to the inertia of the thermal plant itself, a proper real-time operation, i.e. with almost instantaneous intervention, is not required. The RTA takes as inputs the energy requested by the electrical loads and the planned set point of the CHP. In order to maintain the power exchange communicated to the DSO the day before, it exploits an electric storage. The size of the storage depends on the length of the time step, the variability of CHP set point allowed and most importantly by the difference between the expected operation provided by the DAA and the ADA and the actual values of loads and RESs productivity in real-time. Thus, once again, the importance of the ADA is clear: performing an update of the solution provided by the DAA it allows both a minimization of the energy capacity of the storage employed by RTA and of the minimum time for CHP set point upgrade. This last aspect is especially important because a continuous variation of the CHP power output means that the engine operates in transient conditions for the whole time, with lower efficiency and reliability.

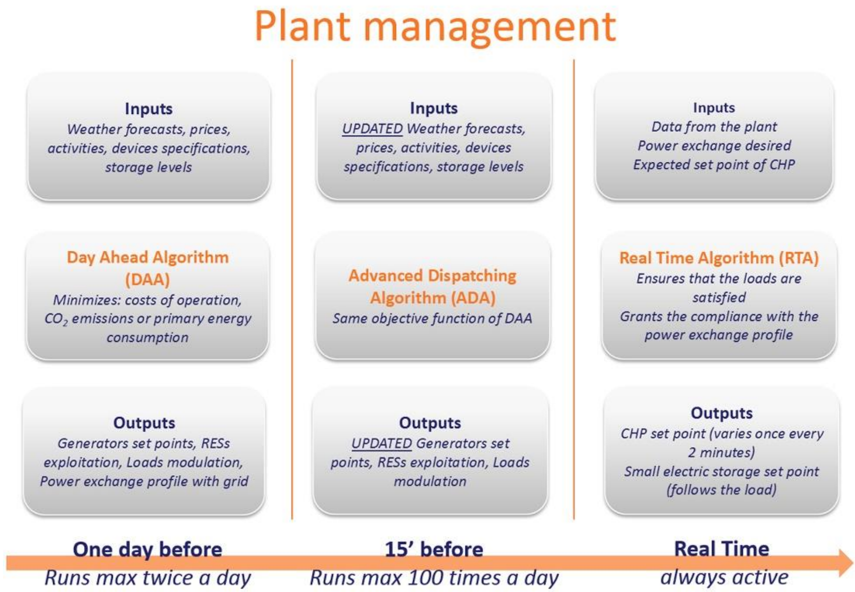


Figure 21 - Algorithms sequence diagram

4.2 The daily optimization of the plant during the day before

This section is dedicated to a detailed analysis of the algorithm designed to achieve the goals described in the state of the art for the Smart Grid and its components. There are several versions of the DAA that are considered and tested in the present Thesis. The first one that will be discussed here is the one called "Single Step" (SS from now on). This version of the algorithm was the first one developed and it is the only one that could be tested both offline and online so far. For the way it is designed, it cannot optimize the operation of the SU for the day as a whole, but only considering one time-step at a time. Hence, the algorithm has been modified in order to ensure that the solution proposed could be closer to the global optimum solution for the day. The modification on the DAA demonstrated also the importance and greater flexibility proposed by some plant layouts compared to others. Because of the time required between the test of the new versions of the algorithm, written in MatLab© code, and their implementation on the SCADA, which must be done with a fast computing executable written in C++, these updated versions have been tested offline. The offline tests, as it will be clear from the chapter dedicated to the results, showed the potential of the updated approach, nevertheless, dedicated tests on the SU will be performed in the near future.

The core of the optimization algorithm is a Genetic Algorithm. The choice to use a meta-heuristic algorithm comes from what it was highlighted in the chapter dedicated to the state-of-the-art. They can deal with non-linear constraints or objective functions. Thus, there is no need to linearize the problem, which ultimately leads to errors or unfeasibility of the proposed solution, not to mention the risk of losing the relation with the actual system, in terms of both equations and their readability from an engineering point of view.

4.2.1 The Genetic Algorithm

The optimization software is based on an Evolutionary Algorithm, in particular on a Genetic Algorithm (GA). Among the different meta-heuristic algorithms, it was chosen because of its renown capability to solve complex optimization problems in a short amount of time and for its simple mathematical form that permitted a good tuning of its working parameters and control of the algorithm features.

The development of this kind of algorithms started from Alan Turing's proposal of a "learning machine" based on the principles of evolution in 1950, whereas the simulations on computer of evolutionary processes started in 1954 with the works of Nils Aall Barricelli. This kind of simulations continued with other authors employing artificial evolution methods in their research by Alex Fraser, Burnell and Crosby. The basis of modern genetic algorithms was set by a series of papers published by Hans-Joachim Bremermann in the 1960s, but the approach became popular through the work of John Holland only in the early Seventies.

GAs are based on Darwin's Evolutionary Theory, which considers that in a population of individuals, the reproduction tends, in the long term, to give birth to individuals with improved characteristics compared to those of their parents and ancestors. Indeed, the better the individual fit into their environment, the greater are the chances they will survive to it and reproduce. The evolutionary process is influenced by three aspects:

- Chance of reproduction: based on their adaptation to the environment, some individuals are more likely to reproduce than others, both because they might survive longer, or because they might be more appealing to their partners thanks to their characteristics;
- Mixing of features by means of mating: two individuals with different genotypes will have offspring whose genotype will be a mix of those of their parents;
- Introduction of new genotypes: occasionally, a gene may undergo a mutation, changing a particular feature of the individual. The mutation introduces new features inside the population, therefore the process has a great potential but can be also highly disruptive.

GAs try to resemble these natural processes at a computational level. In particular, each individual represents a possible solution to the problem, randomly chosen within the search space of all the possible solutions. The chromosomes of the single person represent the variables of the problem. The algorithm falls under the category of population based meta-heuristic algorithm. In fact it requires a set of individuals onto which it operates in order to refine the solution. The set of individual is called population; the first generation of the population is usually randomly generated. Each variable, representing a chromosome of an individual is assigned a random value within the constraints set. Chromosomes are often represented by binary numbers, expression of the value of the variable they embody. Continuing the evolutionary metaphor, the genes are represented by the single bits of the binary number. There are examples of GAs adopting real values instead of binary ones to describe a chromosome, although they are not common because the binary representation is definitely easier to handle. The population is usually kept constant in number in most of the variation of GAs; still, there are implementations of GAs with a dynamic population where the total number of individuals changes during the evolutionary process. The "global characteristics" of each of the individuals are evaluated on the basis of a fitness function, which in the theory of evolution represents the adaptability of the individual to its environment. In the computational case, the fitness function represents the objective function.

Once that all the individuals are assigned with a fitness value, the worsts of them are rejected because less interesting for their partners and less likely to survive in their environment. The best ones, in a fixed percentage, take their place; this process is called *selection* and gives a higher chance of reproduction to worthy individuals. At the end of the replacement of the individuals, the reproduction process called *crossover* starts, which resembles the mating of two individuals and the generation of their offspring. The analogous chromosomes of the mating individuals, representing the same variable, are crossed: a part of a single chromosome is substituted with the same one of the same chromosome of the other parent, in order to change its value. Depending on the kind of crossover (single point, double point, random masking) the values of the variable in the children are going to be more or less similar to the values in the parents. At the end of the crossing, the population has changed in quality but not quantity because the offspring are in the same number of the original parents and substitute them.

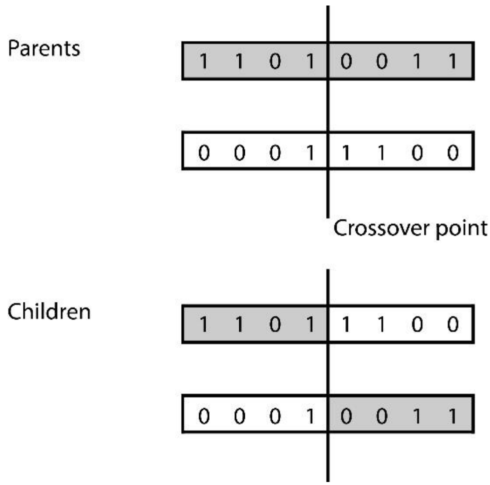


Figure 22 - Single point crossover process representation

The next operation performed on the population is the *mutation*, which acts on a minimal number of the total genes of the population, but in a randomized way. Mutation introduces new genotypes, which were not present in the original population. After the crossover and mutation phase the fitness of each individual in the population is evaluated again. To summarize, one iteration of the GA is represented by:

1. The *evaluation* of each individual (i.e. possible solution to the problem) by means of the fitness function (i.e. the value that the objective function assumes);
2. The *substitution* of a fixed percentage of the population (the worst individuals) with the best ones, in order to carry out an evolution of the population itself;

3. The *reproduction*, consisting in the crossing between the chromosomes of adjacent individuals, in order to create a new generation of population;
4. The *mutation* of some genes introduces new structures in the population, increasing the chance to find a peculiar new feature that enhances the fitness of the population to its environment.

The cycle is repeated several times, with the stopping criterion that can be of two types: when the difference between the value of the best individual of the population at the *n-th* step and the corresponding for the *n+1-th* step is under an established tolerance, or upon reaching a prescribed number of cycles.

When talking about the solution provided by meta-heuristic algorithms, the quality of the solution cannot be based on the proximity to the global solution of the problem, because most of the times, it is unknown and the algorithm itself does not provide any means to determine how far the solution found is from the ideal one. Therefore, from now on with "quality of the solution" will be meant its value compared to the solution provided by a different algorithm, which is assumed as reference, or, in the few cases when it can be calculated analytically, the global solution of the problem. Part of the quality of the solution in a meta-heuristic algorithm is also its steadiness, i.e. the variance between the solutions found when running the algorithm several times on the same inputs. A good algorithm is stable and therefore a good solution must be reliable.

From the analysis of the literature it was clear that hardly one implementation of a meta-heuristic algorithm is exactly the same of another, even among algorithms of the same kind (like among GAs). This work is no exception and further details about the peculiar GA adopted are provided in the following section.

4.2.1.1 Algorithm description

The core script for the DAA is written in C++ language. This allows a single run of the GA to be fast (500 times more than MatLab©) as is required by the limit on the computational time due to the adoption of a similar version of the same script in the ADA. The algorithm takes four sets of inputs of different kinds and these are organized in .csv files that are read by the algorithm upon launch:

- Vectorial inputs: containing values of input parameters that can change for each time-step considered. These inputs must be supplied once a day to the DAA because they are strictly related to the activities carried out inside Pontlab, the information about energy prices coming from the energy market and the weather forecasts. Thus they are likely to change every day and must be supplied to the DAA before each day considered;
- Scalar inputs: this file must be supplied each day to the DAA as well but it contains variables that do not change for the entire day, e.g. the operation mode of the plant (summer or winter) and the levels of charge at the beginning of the day for each storage;
- Technical inputs: a file that allows the algorithm to know the specifications of the plant onto which it operates. E.g. the file contains information about the rated power of several components, the coefficients used to correlate the thermal power output of the CHP to its electric power, the maximum power that the storages can exchange with the system, their capacity, the costs of O&M of the devices installed and any other parameter that the DAA needs to know in advance in order to simulate the system;
- Algorithm inputs: this last file includes the settings of the GA, i.e. the size of the population, the resolution (in bit) of each variable, the number of variables, crossover and mutation

percentages, the number of selected individuals for the selection process, the values of stopping criteria as well as several options that can be activated or de-activated. Some of these options include: the presence of an initial not-randomized seed in the population and the choice of the objective function.

The variables on which the algorithm operates are the set points of the generators or loads that can be controlled by the SCADA, which are:

- The CHP electric power output: to which corresponds either a heating power output or a cooling power output, depending on the mode selected (summer or winter operation). The maximum value is the rated power of the CHP, whereas the minimum value is the minimum power output that the manufacturer suggests for the engine;
- The actual exploitation of RESs (PV and WT): in this case the maximum value depends on the availability of the renewable source, whereas the minimum value is zero, i.e. the curtailment of power produced by the PV or WT is total;
- The modulation of the low priority loads: for each kind of energy request (electric, thermal or cooling), there can be a modulable fraction. The maximum value of each of the three variables depends on the kind of activities expected for the next day and therefore on the devices used.

Thus, for each time-step there are six variables, each variable is represented in the GA by an 8-bit binary number, that can assume 256 different values, from 0 to 255. The total number of possible combinations is around 10^{14} different solutions for each time step.

The simplified series of steps composing the main function of the algorithm currently implemented on the SCADA reads as follows:

1. All the variables required are initialized;

2. Depending on the number or rows in the vectorial input files, the total number of time-steps to analyze is defined;
3. All the input files are read and the values contained are assigned to the respective variables;
4. For a number of times equal to the total number of time-steps:
    a. The initial population is created, in a random manner or including some individuals that for example are representative of TLF or ELF operation modes;
    b. While the variance of the fitness among the population is higher than the value of tolerance or the iteration number is lower than the limit value (both set in Algorithm inputs file):
        i. The iteration number is increased by 1;
        ii. The fitness of each individual in the population is calculated;
        iii. The selection process takes place;
        iv. If the related option is activated: the probability of mating of the best performing individuals is increased by temporarily increasing their occurrence in the population;
        v. The crossover process is executed;
        vi. The mutation process is performed;
        vii. A visual output is sent to console, it contains: number of the time-step, current iteration, fitness variance, minimum fitness value, maximum fitness value; storage temperature;
    c. The computational time for a single run of the GA is evaluated;
    d. The output variables of the last member of the population evaluated (at convergence) are saved as a row of the output matrix;

5. The output matrix is copied on the output file containing all the values of the output variables for each time-step which is created as .csv file.

It is worth mentioning the peculiarities of the GA adopted in this case, especially regarding its key functions: selection, crossover and mutation. These functions are the core of the GA and the way they are "personalized" can have a great impact on the performance of the algorithm. The selection process is performed copying the best individual onto the desired number of worst individuals, called *selection number*, therefore at the end of the process there will be "selection number" plus one identical individuals in the population. A possible variation could be to copy the best individuals on the same number of worst individuals. In this case, each valuable member of the population would have double chances to mate. Both possibilities were tested, during the design of the algorithm, but the first option was chosen for its greater stability and faster convergence to solution. The crossover, as explained in the previous section, mates two random individuals of the population and generates two new individuals. In the algorithm designed, to allow the GA to explore better the solution surface, the fitness of the children is neither evaluated nor compared to their parents in order to decide whether the parents or the children should survive to the next generation. The newer individuals always replace the old ones, ensuring that the features contained in the genome of the population are crossed in a higher number of ways. Therefore, there will be more chances for one individual to reach a different, and possibly better, solution both at the beginning, when the population is spread on the solution space, and later during the optimization when it is approaching a minimum. Finally, the mutation process acts selecting random genes in the whole population, instead of a single gene in a random individual. Again, this is done in order to boost the exploration skills of the GA, allowing it to potentially modify more genes of a single individual or more individuals in a milder way. The number of selected individuals for the selection process is not the only important parameter for a tuning of the algorithm, other parameters that have a great influence on GA's performance are the crossover and mutation rate, as well as the population size and the number of iterations allowed.

4.2.1.2 The simulation of the SU plant: the fitness function

Inside the algorithm, assigning a fitness value to each individual in the population is performed by the *fitness function*. This function is where the plant behavior is evaluated in order to assess the costs, the emissions and the primary energy savings associated with the management of the energy system. This function therefore serves also as a link between the physics of the system and the optimization problem. Whereas most of the other functions (crossover, mutation, selection) can be implemented in different optimization processes, once they are defined, the fitness function must be adapted to the specific plant onto which the algorithm operates. It is to be noticed that the fitness function, although including the equations describing the energy system, is not capable of simulating the actual behavior of the plant itself within the time-frame considered. This would not even be possible, because the inputs are provided as average values within the period analyzed. Therefore, time-dependent and transient phenomena that act in the scale of seconds or even a couple of minutes, cannot be taken into account. An example is represented by thermal inertia phenomena of storages, piping and devices: every single one of them is assumed to be able to provide the required power when needed. This is a reasonable assumption which does not add errors to the analysis because the inaccuracy is inherently included in the way the loads and all the variables are described, i.e. steady for 15 minutes, which is not necessarily true on the actual plant. Indeed, the closer the simulation is to the real behavior of the system the lower will be the errors in the fitness evaluation performed. Nevertheless, the purpose of the model included in the fitness function is to ensure that the proposed plant operation takes into account the physical constraints of the real system, therefore reducing the chance to suggest unfeasible solutions. There is no intent to be extremely accurate though, nor any need for it, considering the optimization process is always updated to the present working conditions by the Advanced Dispatching Algorithm on the actual plant. Moreover, the Real Time Algorithm, along with the controller of the auxiliary units, will manage the system in a safe and appropriate way, regardless of the suggested operations provided by the optimization algorithms. Every effort has been made in order to allow the employment of the defined algorithm to the highest number of cases possible. Nonetheless, some configurations of the energy plant feature different constraints from the others and therefore require a dedicated set of equations in order to be described and simulated. Hereafter, the fitness function implemented in the GA running on the SCADA system of the SU is described. This version of the algorithm performs the optimization of one time-step (i.e. 15 minutes) at a time, with the suggested operation resulting from the sequence of optimized time-steps. As will be highlighted in the next sections, this version presents limitations that do not allow it to achieve a proper daily optimization of the plant. The fitness function described hereafter takes into account one individual at a time, then, another function ensures that all the individuals are evaluated.

The analysis of the system starts from the assessment of the values of the algorithm variables contained in the individual: the power produced by PV, WT, the modulation of electric, heating, cooling loads and the electric power produced by the CHP. Depending on the season, the thermal power recuperated from the CHP or the cooling power produced by the absorption chiller is calculated as follows:

$$P_{th,CHP} = a + bP_{e,CHP} + cP_{e,CHP}^2 + dP_{e,CHP}^3 \qquad \text{Eq. 5}$$

$$P_{c,absorber} = COP_{abs}(a + bP_{e,CHP} + cP_{e,CHP}^2 + dP_{e,CHP}^3) \qquad \text{Eq. 6}$$

Where *a, b, c, d* are numerical coefficients obtained by the regression of the experimental curve between electric power and thermal power produced by the CHP. These coefficients are provided in the technical inputs file. These equations are the first example of non-linear behavior of the system. The CHP is considered turned on only if the electric power production is assigned to it during the random generation, the crossover or mutation processes in the GA is greater than its minimum value, as defined in the technical input file. If the time-step considered is the first one, the temperatures for the storages $T_{c,strg,previous}$ and $T_{th,strg,previous}$ are set to their initial value, defined in the scalar input files. Otherwise, the values are obtained from an auxiliary matrix created during the analysis of the previous time-step. Then, depending on the season, the model of the plant takes two slightly different directions, coherently to the use of one side or the other of the plant (see, Figure 16, Figure 18). Considering the thermal layout described in the previous chapter, during summer operation mode the heating load is satisfied by the boiler, whereas the CHP works along with the absorption chiller to supply refrigeration and electricity to Pontlab. Conversely, during winter operation mode, the cooling load is assumed to be satisfied by the compression chiller only, whereas the heating and electricity needs are satisfied by the CHP. For brevity sake, only the summer case is examined. The winter case is symmetrical apart from the fact that the storage is considered fully charged when the temperature inside it is the maximum one and empty when the temperature reaches the minimum value allowed, the opposite of the cold temperature storage.

For the summer operation, the following power balance is evaluated:

$$\Delta P_{c,attempt} = P_{c,absorber} + P_{c,modulation} - P_{c,load} \qquad \text{Eq. 7}$$

Equation 7 calculates the cooling power that is in excess or deficit considering the set point of generators and the load. Note that the modulation of the loads can be listed among the generators. The energy stored inside the cold storage is determined as well:

$$c_{strg,level,previous} = \frac{m_{c,strg} c_{p,H_2O} (T_{c,max} - T_{c,strg,previous})}{3600} \quad \text{Eq. 8}$$

Where the factor 3600 is required to transform the energy calculated from kJ to kWh.

Successively, a series of if-then clauses defines the behavior of the system when charge and power constraints for the storages have to be met. These represent another non-linearity of the problem because, depending on a given condition, the plant does not behave in the same way. The first evaluation is performed on $\Delta P_{c,attempt}$, if it is lower than zero, i.e. there is more request from the loads than the generators are supplying, then the power that the storage must supply is equal to the deficit of power found.

$$P_{c,strg,attempt} = \Delta P_{c,attempt} \quad \text{Eq. 9}$$

The power that the storage should supply can or cannot be in compliance with the maximum power output of the storage. The storage power of charge/discharge is a function of the mass flow provided by the recirculation pump in the users' loop, the user maximum power request, and the level of charge of the storage, which depends on the start value imposed and the evolution of the charge level during the day. First, the power assigned to the storage is compared to the maximum that can be provided. If the power assigned to the storage complies with its maximum value, then the energy level at the end of the time-step is estimated as:

$$c_{strg,level,attempt} = c_{strg,level,previous} - P_{cstrg,attempt} \Delta t \quad \text{Eq. 10}$$

If the level of charge is higher than the minimum level allowed then the attempt values of the storage charge level and power assigned to the storage are finalized. Moreover, because the storage could provide all the power mismatching in the power balance between loads and generators, there is no reason to activate the compression chiller nor to dissipate cooling energy in excess. In addition, the temperature inside the storage is calculated according to equation 11:

$$T_{c,strg} = T_{c,max} - \frac{3600 c_{strg,level}}{m_{c,strg} c_{p,H_2O}} \qquad \text{Eq. 11}$$

If the attempt value of the energy level, considering the attempt value of the power supplied by the storage, were too low compared to the minimum level allowed, then the final level of charge is imposed at the minimum value allowed and the attempt value of the power of the storage is finalized as:

$$P_{c,strg} = \frac{(c_{strg,level,previous} - c_{strg,level,min})}{\Delta t} \qquad \text{Eq. 12}$$

Then the temperature inside the storage is calculated. This temperature, in the case of the cold storage is at its maximum value. In addition the following are calculated: the power that must be dissipated (none) and the power that the auxiliary unit, i.e. the compression chiller, must supply, which is simply:

$$P_{c,chiller} = P_{c,strg,attempt} - P_{c,strg} \qquad \text{Eq. 13}$$

Instead, in the case where the power requested to the storage by the power balance described in equation 7 is higher than the maximum value allowed, then the power that it will provide is set to its maximum value and the level of charge is verified again following equations from 9 to 12.

A similar procedure is followed for the case when the power balance is in favor of generation side. In this case the storage will need to be charged, if possible, by the same amount that the power of the generators is in excess compared to the loads. If the power charging the storage is less than the maximum value allowed then the energy contained in the storage at the end of the time-step is evaluated and finally the values of power and charge of the storage are finalized. Conversely, the power is limited to the maximum value and again the final level of charge is evaluated and modified if not in compliance with the maximum value set.

There is also a third case, unlikely but to be considered, when the power balance between generators and loads is respected from the beginning, i.e. the attempt value for the storage power is zero. In this case the storage is not required, as well as the auxiliary compression chiller or the heat dissipater. When all the three power balance cases are analyzed, the power required by the thermal loads, which the boiler must provide, is calculated.

As mentioned above, a similar procedure is followed for the case of winter operation. The only difference being that the generator is not the absorption chiller but the CHP itself, the auxiliary unit is the boiler and the storage is a hot one. Therefore, the storage is at full charge when its temperature is at the maximum level, conversely it is empty when its temperature reaches the minimum value. In the case of summer operations, the power that the boiler must supply for thermal loads is calculated at the end of the procedure just described.

A power balance is evaluated also for electric loads, in this case though there is no proper storage but the electricity grid, therefore:

$$P_{e,grid} = P_{e,load} + P_{e,chiller} - P_{e,CHP} - P_{e,PV} - P_{e,wind} - P_{e,L2} \qquad \text{Eq. 14}$$

The thermal power that the CHP requires to produce its electric power output is calculated by means of a cubic correlation of the electric power output, the coefficients were provided by the manufacturer:

$$P_{in,CHP} = a_1 + b_1 P_{e,CHP} + c_1 P_{e,CHP}^2 + d_1 P_{e,CHP}^3 \qquad \text{Eq. 15}$$

The total efficiency of the CHP is calculated considering both the electric power and thermal power, actually exploited for either the heating or cooling supply.

$$\eta_{e,CHP} = \frac{P_{e,CHP}}{P_{in,CHP}} \qquad \text{Eq. 16}$$

$$\eta_{th,CHP} = \frac{\left(P_{th,CHP} - P_{th,waste}\right) + \frac{\left(P_{c,absorber} - P_{c,waste}\right)}{COP_{abs}}}{P_{in,CHP}} \qquad \text{Eq. 17}$$

$$\eta_{tot,CHP} = \eta_{e,CHP} + \eta_{th,CHP} \qquad \text{Eq. 18}$$

With the resulting PES being therefore:

$$PES = 1 - \left(\frac{1}{\left(\frac{\eta_{th,CHP}}{\eta_{th,boiler}} + \frac{\eta_{e,CHP}}{\eta_{e,grid}}\right)}\right) \qquad \text{Eq. 19}$$

Then, all the costs and emissions related to the defined operation of the system are calculated. The operating and maintenance costs for the CHP are calculated in the case that it is turned on in the present time-step, conversely a penalty for its unemployment is derived. In addition, during summer operation, for the absorption chiller a similar cost for O&M or non-exploitation is defined. The same costs are evaluated for each generator in the system: PV, WT, boiler and compression chiller. All O&M costs are defined in terms of €/h. The possible discount on the natural gas cost and eligibility for TEE certificates is evaluated based on the efficiency level and PES value reached compared to the values defined by the legislator for the achievement of High Efficiency Co-Generation (CAR, from the Italian "Cogenerazione ad Alto Rendimento") certification of the plant. In case the evaluation is positive, a discount of 30% is allowed on the cost of natural gas used for electricity production, which means that for the boiler the price paid remains the same. From the input thermal power required by the CHP and the boiler, and the Lower Heating Value of natural gas, it is possible to calculate the total expenses for the fuel supply. For the case of Pontlab, the TEE certificates are omitted because the connection of the SU with the grid is virtual and therefore all of the electricity produced is always absorbed by the facility; nonetheless, the algorithm allows to consider them when defining the total cost of the daily operation of the system. Another incentive calculated is the one related to PV electricity production granted within the frame of Energy Account incentive scheme. Depending on the sign of $P_{e,grid}$ the costs or profits derived from the electricity exchange with the grid are calculated. The modulation costs are calculated based on the power modulated and the cost associated with each activity not performed or limited due to the modulation, which is expressed in €/kW. Similarly, a possible penalty for noncompliance with the proposed grid power exchange profile can be determined when a profile, or a rule to define it based on the optimal one obtained when the algorithm is run without penalty on the grid profile, are provided. Finally, based on the power set points of each generator (grid included) the total primary energy supply and emissions produced by the operation of the SU in the present time-step are calculated.

One out of three possible fitness values, i.e. objective functions, can be selected, to be minimized by the GA: cost function, primary energy consumption and emissions produced.

$$C_{tot} = C_{CHP,fuel} + C_{CHP,ne} + C_{CHP,O\&M} - C_{CHP,TEE} - C_{PV,EA} + C_{PV,O\&M} + C_{WT,O\&M} + C_{boiler,fuel} + C_{boiler,O\&M} + C_{chiller,O\&M} + C_{abs,ne} + C_{abs,O\&M} + C_{e,fromgrid} - C_{e,togrid} + C_{profile,grid,penalty} + C_{e,L2} + C_{th,L2} + C_{c,L2} \quad \text{Eq. 20}$$

$$E_{pr,tot} = E_{prCHP} + E_{pr,boiler} + E_{pr,grid} \quad \text{Eq. 21}$$

$$CO_{2,tot} = CO_{2,CHP} + CO_{2,boiler} + CO_{2,grid} \quad \text{Eq. 22}$$

Because the GA takes into account one time-step at a time, the selected objective function is minimized in each time-step and then the values are summed to define the total value for the day. As will be discussed in the following sections, this is one of the most important limitations of the approach followed for the design of the first version of the algorithm running on the SCADA system in Pontlab.

4.2.1.3 Tuning of the algorithm

The importance of the tuning of the parameters involved in the optimization process performed by the GA is well known in the literature. An early example of the improvement that can be achieved by an appropriate tweaking of their values is provided by Grefenstette J. J. (1986) [111]. Ideally, the most of the meta-heuristic algorithms, the GA would need to accomplish two different tasks in order to reach the global optimum of the problem:

- Explore the solution space;
- Once the best solution is approached, converge into it.

Nonetheless, GAs and other meta-heuristic algorithms are known to be unable to find the exact global optimum of the problem, nor to know how far the global optimum from the solution onto which they converge is.

This does not even depend only on the algorithm itself but also on the shape of the solution space. Just to provide a visual example, let us imagine that the algorithm should find the highest peak on a map, see Figure 23 and Figure 24

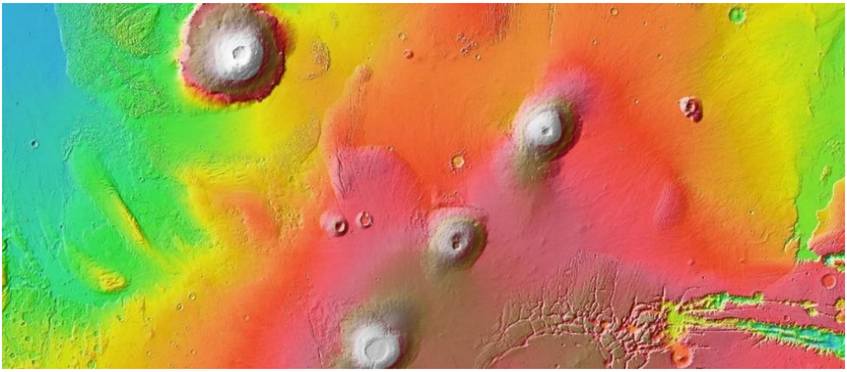


Figure 23 - Four clear peaks on Mars' surface

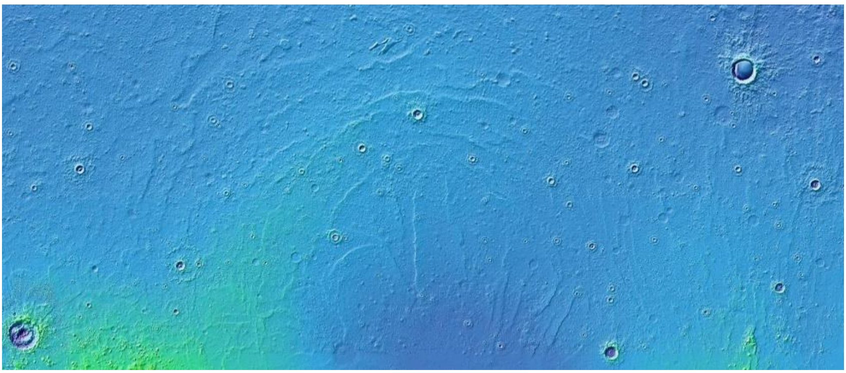


Figure 24 - A portion of Mars' surface with numerous small peaks and large plains

If the map is mostly plain apart from a few big mountains with only a single peak, clearly defined and with one definitely higher than the others, the algorithm is likely to find the global optimum, or at least get close enough to it. On the other hand, if the map is a very rough surface with no clear peaks apart from very narrow and isolated few, the algorithm is unlikely to find the highest one. Moreover, depending on how narrow the peaks are compared to the solution space, it might as well be unable to find a peak at all. Not only, ideally, the solution found should be the global optimum but also it would be preferable to reach it in the shortest possible time. It is clear that finding the global optimum, thus exploring the whole search space, and small computational times are discording goals. Hence, the choice of the parameters is to be done trying to achieve the best compromise between the two aspects.

Depending on the tailoring of the key procedures adopted by the GA, i.e. selection, crossover and mutation process, and the value of the tuning parameters, the exploration capabilities and convergence on a good solution of the algorithm can be modified. For example, a constantly high mutation rate boosts exploration skills of the GA but it is risky because it makes it hard for the algorithm to converge due to the disruption of any cluster of good solutions found after some iterations. On the other hand, a variable mutation rate at different times, such as a higher one during the initial phase when the solutions are dispersed on the search space, and a lower one in the later phases when a possibly good solution is about to be found can improve both the exploration and the convergence. It is up to the programmer and the engineer to define, based on the peculiarities of the case study, which modifications to apply in order to achieve an optimal result. Similarly, in some works presented in the literature, the population may vary depending on the number of iterations or the fitness VS iteration curves, as well as the crossover rate and the number of individuals chosen for the selection process. When considering only one time-step at a time in the optimization process, repeating the optimization for each time-step until all of them have been examined, the size of the problem is not an issue. Hence, there is no need to adopt such expedients in order to achieve a solution which is stable and good enough compared to those obtained with a standard ELF or TLF operation of the CHP.

The tuning of the SS algorithm was performed by means of a Design Of Experiment (DOE) technique, which is a common approach to the design of an experimental campaign that allows the systematical analysis of the influences of the tuning parameters on the solution and their influence on one another. The number of experiments required by DOE depends on the number of parameters and the number of levels, which is the number of possible values that each parameter can assume. For a general case, the number of experiments is defined by the following equation:

$$n = l^p \qquad \text{Eq. 23}$$

Where, *n*, is the number of experiments that must be performed, *l*, is the number of levels and *p* is the number of parameters. Being an exponential function of parameters, the number of experiments increases at high rates when many parameters are selected. It is always a good practice to keep the number of parameters as low as possible, selecting only those that are expected to be heavily influencing the solution.

The algorithm version tested is the Single Step one, written and compiled in C++ for faster execution speed. For the tuning of the parameters, the SS algorithm was tested on a single day representing a sample of a realistic operation of the SU; the input values are not reported here for sake of brevity. The parameters for the tuning process were selected based on their well-known influence on the algorithm performance according to the literature studies:

- Population size: the higher the number of individuals in the population, the better will be the exploration capabilities of the algorithm. On the other hand, each iteration is going to be longer computationally wise because of the higher number of processes to perform;

- Crossover rate: an increase of the rate enhances the exploration skills of the algorithm at the cost of higher computational times due to the increased number of mating processes to perform at each iteration;
- Mutation rate: a bigger rate introduces a greater number of new genes in the population but the algorithm becomes unstable because good solution clusters are often disrupted by the mutation process if the rate is too high;
- Maximum number of iterations: allowing more iterations to take place means giving more opportunities for the algorithm to explore by means of mutation and refine the solution with crossover; on the other hand, computational time increases linearly for the worst case (when convergence does not reach the imposed tolerance).

The optimization process can still be interrupted by reaching the tolerance value for the fitness variance. Nevertheless, this value was set low compared to what was done in the offline tests, in order to ensure that the desired number of iterations could be reached unless the solution found was extremely well defined. Two are the measures of optimality of the parameters selected: fitness value achieved and time of execution. Thus, the quality of the solutions obtained is evaluated by a multi-objective function. For both the time of execution and the fitness, two values, expected to be the maximum and minimum that can be achieved are set. It is not important that these values are exactly the minimum and maximum registered during the experiments, what matters is that the highest value is higher than the highest value scored in the experiments and vice versa for the lowest. Therefore, t_{max} and t_{min} were set equal to 100 s and 0.5 s respectively, whereas, $€_{max}$ and $€_{min}$ were set to 35 € and 30 €. The values of computation time and fitness value need to be non-dimensional to be comparable. Indeed what is evaluated is the difference between the maximum value and the one of the current experiment, divided by the difference between the maximum and minimum value set for the variable:

$$t_{adim} = \frac{t_{max} - t_{exp}}{t - t_{min}} \qquad \text{Eq. 24}$$

$$€_{adim} = \frac{€_{max} - €_{exp}}{€_{max} - €_{min}} \qquad \text{Eq. 25}$$

With these, the simplest objective function that can be written is formed by the sum of the two. In our case, considering that the variability on the time of execution was greater compared to the one of the fitness value, a weighted sum was defined, with a 0.7 coefficient set for the t_{adim} and 0.3 for $€_{adim}$. The output function can assume a maximum value of 1 and a minimum of 0.

$$Y = 0.7 * t_{adim} + 0.3 * €_{adim} \qquad \text{Eq. 26}$$

The values for each level of each parameter are set as follows in Table 7.

Table 7 - Parameters and Levels employed in the DOE

Population	*Crossover Rate*	*Mutation rate*	*Iterations*
128	20%	0.5%	500
512	60%	1%	1500

The set of parameters for each experiment are listed in Table 8. In order to reduce the effects due to the natural variability of the algorithm results, each run is repeated five times and the results considered are the average of the values in each run.

Table 8 - Experiments list of the DOE

Experiment	*Population*	*Crossover Rate*	*Mutation rate*	*Iterations*
1	128	20%	0.5%	500
2	512	60%	1%	1500
3	128	20%	1%	500
4	128	20%	0.5%	1500
5	128	60%	0.5%	500
6	512	20%	0.5%	500
7	512	20%	1%	500
8	512	20%	0.5%	1500
9	512	60%	0.5%	500
10	512	60%	0.5%	1500
11	512	60%	1%	500
12	512	20%	1%	1500
13	128	60%	1%	1500
14	128	60%	0.5%	1500
15	128	20%	1%	1500
16	128	60%	1%	500

Another parameter, which is relevant during the optimization process, is the number of individuals selected for the selection process. The first tests performed suggested that this value should have been kept as a fixed percentage of the population, therefore it assumes different values for the experiments featuring a population of 128 or 512 individuals. The value to assign as the percentage of selected individuals was defined out of the DOE for two reasons. The first is to reduce the number of parameters of the DOE and therefore the number or experiments (adding one would have meant to double the experiments). The second is that the number of individuals selected is assumed not to interfere with the values of the other tuning parameters, thus it could be set beforehand for all the experiments. The test to assess its ideal value was performed on the same test case used for the DOE, with the tuning parameters being those of experiment number 14, see Table 9. The diagram in Figure 25 shows the fitness value obtained as a function of the number of selected individuals that varies in the range of 1% to 50% of the population.

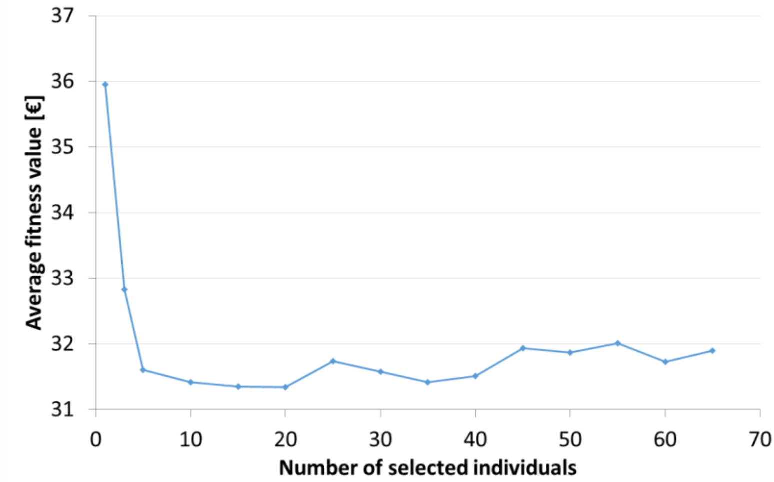


Figure 25 - Influence of selection process on the fitness value

It can be observed how the best values are scored for a number of individuals of about 15% of the total population. Thus, this is the value assumed for all the experiments performed in the DOE. The results obtained are reported in Table 9, where the best experiments, #10 and #14 are highlighted in bold. Considering experiments #6 and #7 or #13 and #14 it is evident how influential is the mutation rate on the computational time. When the other parameters have the same value, an increase in mutation rate is followed by an increment of computation time. On the other hand, the effect on the fitness is much less relevant, therefore the exploration is sufficient with a value of 0.5%. A factor of four in population size turns into an almost doubled computation time (see #1 and #6 or #10 and #14) which is also followed by minor improvements in the value of the fitness function. A higher crossover rate usually leads to better fitness values without a relevant increase in computation time, because the time required to run the crossover process is relatively low in a single run, with the heaviest process being the evaluation of the fitness of all the individuals in the population. The effect of the number of iterations on the output function depends also on the values assumed by the other parameters, i.e. it interferes with the other parameters. The greatest interferences are found between: population size and number of iterations; population size and mutation rate; mutation rate and number of iterations.

Table 9 - DOE results

Experiment	*Time [s]*	*Fitness [€]*	*Y*
1	0.8258	31.7870	0.8905
2	95.9622	31.3986	0.2445
3	11.9746	31.9830	0.8003
4	0.8332	31.6116	0.9010
5	0.7942	31.7070	0.8955
6	1.6266	31.2142	0.9192
7	28.7856	31.5746	0.7065
8	1.6106	31.2174	0.9191
9	1.6164	31.2596	0.9166
10	**1.7782**	**30.9022**	**0.9369**
11	31.8892	31.4286	0.6935
12	87.7942	31.6204	0.2886
13	37.8958	31.9864	0.6177
14	**0.8014**	**31.2008**	**0.9258**
15	35.5564	32.0104	0.6327
16	12.7640	31.7768	0.8071

From Table 9 it can be seen that the best performing sets are #10 and #14. The first is the best in terms of fitness value achieved, the latter is the second best in terms of computation time. Nonetheless, considering that the difference in terms of time is 100% between the two experiments, whereas the difference in fitness is just 1%, the set of parameters of choice for all the runs of the GA onwards is the one of the 14th experiment. Furthermore, the set of parameters of choice allowed a very stable solution in several runs of the algorithm, which is very important if it is desirable to perform a single run of the GA on each time-step in order to avoid repetition and reduce the computational time.

4.2.1.4 Daily optimization VS Single Step optimization

The first approach used to optimize the daily operation of the SU was to analyze the whole day at once with the GA. Indeed, the variables of the optimization were, in the worst case, 100 times more than in the case of the analysis of a single step at a time. The total number of quarters of hour in an average day is 96 and this is the number of time-steps usually considered in the tests performed. Nonetheless, when the time is switched from legal to solar, the day lasts 25 hours, which means 100 quarter of hours; in the same way, when the time is switched from solar to legal, the day lasts 23 hours. At computational level, there are two problems when considering such an increase in problem dimension:

- The dimension of the solution space increases exponentially with the number of variables, from 256^6 to 256^{600};
- The number of parameters concurring to the definition of the fitness function increases by a factor of 100.

The first issue has a dramatic impact on both the computational time and the quality of the solution. The size of the solution space, 256^{6*96} has a similar order of magnitude to 10^{1387}. The size of the problem is extremely wide, greater than most of the functions onto which GAs and other optimization algorithms are theoretically tested in the literature, see A. Ghosh et al. 2011 [112], T. Chen et al. 2012 [113], S.W. Leung et al, 2012 [114]. To give an idea of the number of possible solutions among which the GA has to find the global optimum let us indulge a second in an astronomic comparison. The mass of ordinary matter in the Universe is estimated in the order of 10^{53} kg, the mass of an atom of Hydrogen, the smallest and most common in the Cosmos, is $1.67372*10^{-27}$ kg. That means that if the whole mass of ordinary matter in the Universe were made of Hydrogen, the total number of atoms would be "just" 10^{81}. Problems of this size can be solved in reasonable times and with accuracy only by MILP techniques, which exploit the properties of linear problems to execute extremely fast procedures to find the minimum (or maximum) of the problem, which is unique for problems of this kind (see 2.2.1).

The second issue influences the roughness and shape of the solution space. Each parameter adds a minimal contribution to the objective function. If we imagine the solution space as a 2d surface, it is likely to be very rough, with narrow peaks with noise-like shape, as well as few depressions, wide compared to noise but still narrow compared to the total size of the problem, representing local minima, one of which is also the global one.

On the early tests performed on the GA to assess its capability to optimize more steps at a time, the results were not promising for the whole day version. Three different versions were compared:

- Whole day on 96 time-steps of fifteen minutes each;
- Whole day on 48 time-steps of half an hour each;
- Single-step analysis of the whole day, 96 time-steps in total.

The inputs onto which the three versions were tested are the same apart from the size of the time step in the second case. With half the steps, their duration must double to reach the same time of the day. Therefore, the values of the parameters of two consecutive time-steps were averaged in order to be assigned to the algorithm as inputs. The tests proved that the single-step analysis was the quickest with a computational time lower than 3 minutes on MatLab© and with an almost steady fitness value of 70€. The whole day algorithm with 48 time-steps took over 2 hours to perform 15000 iterations, achieving a fitness value of 125€. Even worse were the performance of the whole day algorithm including 96 time-steps: calculation times of over 12 hours to reach 20000 iterations and a fitness value around 240€ for the same exact day of the single step version. Considering that the whole day global optimum must be equal or better than the one of the single step, which represents a subcategory of the problem, it is clear that the approach adopted was completely ineffective. Indeed the time of execution can be greatly enhanced translating the code from MatLab© to C++. Nonetheless, the fitness values obtained by the whole day algorithm were not satisfactory in any way.

From this early analysis, it is clear that the optimization of the whole day at once cannot be done with the Genetic Algorithm alone. Nevertheless, its importance is relevant for the study. Indeed the potential to exploit some advantageous condition at a time depends on the conditions during a different time of the day, which is something that the SS algorithm cannot take into account. When considering, and optimizing, one time-step at a time, it is impossible to achieve a true optimization of the whole day. What can be achieved is an optimized operation of all the devices within the fifteen minutes period. The difference between the two optimizations is the same between "the sum of the optimums" or "the optimum of the sum", the latter being a better optimum compared to the first. Obviously, using a GA, there is no guarantee to reach the global optimum in either ways, for it is the meta-heuristic algorithm itself that is not able to guarantee convergence on the global optimum. Nonetheless, a proper daily optimization should consistently score better results than the single step one in every situation, in order to be considered effective. This is the goal pursued with the design of the optimization algorithm: achieve the daily optimization of the plant while keeping it light at a computational level.

How to achieve that goal has been an exciting part of this research. Although there might be quicker algorithms compared to GAs, as well as better performing ones in terms of quality of the optimized solution, considering the difference between the results obtained by the SS algorithm and the whole day one, it is hard to imagine a single algorithm that can close the gap by using its "brute force". A more clever approach would be to determine which components of the plant are responsible for the difference between a daily and a single step optimization. Once these components have been identified, it is fundamental to define a possible strategy to "detach" their optimization from the one of those that could be optimized in the single step without reducing the quality of the solution. The next section deals with this topic and provides insight on the shortcomings of a SS algorithm when applied to a generic plant and in particular to the one in Pontlab.

4.2.1.5 Components requiring an extended view over the day in order to be optimized

At an energy level, all the components of a plant fall under one or both of two different categories: generators and loads. Considering Pontlab SU plant, among generators we can list: the CHP, the auxiliary boiler, the absorption chiller, the compression chiller, the PV and the WT as well as the electricity grid and the thermal storages. Among the loads, on the other hand, each device that absorbs energy, from the actual loads to the power grid and again the thermal storages. Those components that can be inserted in both categories can all be considered as energy storages. Before assessing which of these components have a fundamental role in differentiating the solution representing the sum of the optimums and the one, which is the optimum of the sum, let us assume that a plant without any storage device is obliged to work in standalone mode. In this case, at any given time, the sum of the energy provided by the generators must be equal to the sum of all the energy required by the loads. The optimization that can be performed on plant operation is therefore limited to the choice of which generator supplies more energy or, if there are several, which loads to modulate at any time. There is no room for a daily strategy because there is no way to store energy, the system is constrained to produce and absorb the same quantity of energy. Thus, this is an example of a case where the whole day optimization and the single step one would achieve the same exact result.

If we allow some of the loads to start at a variable time instead of a fixed one then the chance to decide when to increase the load (activating one of those that can be shifted) leads to the need for considering the whole day. Indeed, otherwise it is impossible to assess the best moment to activate the loads that can be shifted. In Pontlab at the moment these loads are not managed yet, and the activities to carry out are defined beforehand. Nonetheless, an algorithm for an ideal Smart User should include these kind of loads in the optimization. The addressing of this aspect is expected for the future, as will be described in the chapter dedicated to conclusions and future developments.

The other elements, which for their behavior, introduce the need for a daily sight on the problem are the energy storages. In the case of the present plant installed in Pontlab, there are three storages, two proper that are the hot and cold thermal storages, one virtual, which is the electricity grid. The electricity grid is considered a virtual storage for two reasons:

- The costs associated to its usage vary over time, which is not true in general for a normal storage. Indeed storing energy into the grid has a negative cost (usually) which is the sale price of the electric energy to the grid, and this may vary during the day. In the same way, withdrawing energy from the grid has a different cost depending on the time when the energy is purchased.
- The grid, theoretically has no limit of charge, or at least, the limit is too high to be taken into account when considering a single power plant, no matter how big, connected to it.

Moreover, the idea of relying on the grid as electricity storage is in contrast with the goals and philosophy of the Smart Grid. That is why, although it practically acts as a storage, in this study it will not be considered as such, at least when dealing with the problem of daily optimization.

Each storage allows at any time to increase the generators' power output creating an additional load, due to the request of charge of a storage, or, conversely it can also decrease it, when it discharges and therefore acts as a generator itself. From what has been said, it becomes evident that in order to achieve the daily optimization of the plant, the storages' operation during the day must be optimized.

4.2.2 The storages' management

In the previous paragraphs the importance of daily optimization was introduced as well as the components that are most influencing the difference between an optimized management of the system considering one time-step at a time or the whole day at once. Apart from loads that can be shifted or interrupted during the day, a key role in the need for a daily optimization is played by storages of any kind of energy. It was also demonstrated, by referring to tests carried out on the GA, how difficult it is to reach a refined and daily optimized solution for the operations of the SU. As was shown in the chapter dedicated to the state-of-the-art, many authors dedicated their researches on the topic of storage optimization. Some of them linearized the simulation of the physical model and therefore were able to implement very fast and reliable linear solvers; some others designed and composed different algorithms for the scope. This section presents one of the possible solutions to the problem of storage optimization for energy systems whose description involves several non-linear aspects. This can be considered one of the greatest achievements of the present research.

4.2.2.1 Goal of the optimization

As previously stated, when talking about the performance of evolutionary algorithms, the quality of their solution can be evaluated only by comparing it with those found by other algorithms in terms of value of the objective function, stability of the solution and the computational time required to find it. For most of the optimization problems requiring an evolutionary algorithm are too hard to solve analytically and thus it is difficult or impossible to find the global solution to compare with those suggested by the other algorithms. Therefore, the goal of the optimization performed is to find a solution with the following characteristics:

- Value of the objective function: equal or better of the one provided by the single step algorithm when both are tested in several conditions, either fictional or realistic;
- Stability of the solution: several runs of the algorithm should provide similar or equivalent results, this also suggests that the solution found is likely to be the global optimum of the problem;
- Feasibility: the solution should be feasible for the energy system considered;
- Coherence: the solution proposed should prove to be "intelligent", demonstrating an ability to take advantage of peculiar costs/loads condition during the day.

The ideal solution should have all of the above characteristics. The second and the third one are general requirements, which should be met regardless of the optimal use of the storages. On the other hand, the first and the fourth imply the optimal usage of the storages.

4.2.2.2 Approaches adopted

The approach envisioned is to optimize the storage operation without optimizing at the same time all the other variables; this would allow a great reduction of the size of the search space. To understand whether this approach can be adopted, let us consider a generic energy system including different storages, during each time-step, several of its components are either producing or consuming energy. The actions of producing and consuming energy are not representative of the system during the period considered but rather the actions it performs to go from a state to another. Once the layout of the energy system considered is fixed, the state of the system is defined by only a few variables, i.e. the charge level of its storages, the current time step and the possible configuration of the energy system (e.g. if a given valve is opened or closed). This concept is not different from the fact that Temperature is a variable of state for a system, whereas the heat the system receives or releases from/to the environment is not. Moreover, all the information required to take decisions in terms of charge/discharge cycles of the storages are known in advance and available in the same input files that the GA adopts. Therefore, it should be possible to define an optimized strategy for the storage, resulting in a power curve of the storage usage during the day, separating it from the optimization performed by the SS algorithm. This means to find an optimized sequence of states for the whole day, whereas, the way the system passes from one state to the other is optimized separately.

Because storages can operate as both loads and generators, in terms of energy balances in the time-step, the following assumption is reasonable: the storage discharge can be represented by an increase of generation or decrease of the load, vice versa, charging the storage is energetically equivalent to increasing the load or decreasing the generation. Because the definition of the set points for the generators is up to the GA, the choice is to modify the load profiles according to the storage usage. By "energetically equivalent" is meant that whereas in terms of average power produced or consumed the assumption is physically sound, it might not be in terms of plant control, i.e. the suggested operation may differ from the one actually feasible on the plant, depending on its layout and control system. This is always to be taken into account when dealing with optimization algorithm applied to actual systems, in this case, a small power plant, as will be stressed in the following sections.

4.2.2.3 Limits of the early approaches

In this section are briefly described two of the early logics imagined to define the ideal storage power and charge profiles to be supplied to the SS algorithm. In addition, their shortcomings are highlighted with the intent of providing to the reader useful information to avoid following proved-wrong paths.

Some of the early attempts to define an optimized strategy for the storage operation include:

- Definition of rules for storage charge/discharge based on possible control logics (e.g. common sense);
- Definition of rules for storage charge/discharge automated via fuzzy-logic.

Indeed, it is logical to think that a good employment of the storage is to produce more than necessary and stock energy when it is cheap to produce, conversely, to discharge the storage when producing energy is expensive. Therefore, based on the average value assumed during the day by selected inputs and evaluating the same inputs in a given time-step can provide a hint regarding an optimized operation of the storage. This was the idea behind the first early attempts. The parameters that were considered as most influential in the definition of power profiles for the storages were: the electric and thermal loads considered (heating during winter and cooling during summer), the electricity costs and the natural gas costs. In order to take into account also the specifications of the equipment installed in the plant, two more parameters were relevant: the maximum electric and thermal power output of the CHP. Based on these inputs a set of rules was designed using, in the first case, logic and common sense, in the second attempt, a fuzzy-logic controller. In the first case, the set of rules was defined as if the storage were operated manually and therefore thinking about the optimized solution for each specific situation. The set of rules already presented the first issue of this approach. The rules were specified as Charge, Discharge, Charge more, Discharge more or none of the above. Therefore, an important role in the definition of the final profile was played by chaos and the way the generic rule; e.g., “Charge” was translated in a random value of power within a specified range. The higher the randomness allowed by the set of rules, the worse the results achieved. In every test, the set of rules performed worse than the SS algorithm that was assumed as baseline. This leads to the second issue, which is the definition of the rules themselves: in order to reduce the randomness, new inputs for the evaluation of the present conditions must be introduced, the number of cases to define grows exponentially being equal to the number of possible combination of inputs. Moreover, as the definition of the cases increases it becomes very hard to define a reasonable rule that is always true in the case considered. As the process of cases definition became more and more intricate and complex it was clear that the procedure proposed was not feasible.

A way to reduce the randomness of the solution without the need to specify a high number of cases (i.e. rules), “by heart”, was to apply an automated procedure that could lead from a set of inputs to the ideal output using a small set of rules. A fuzzy-logic controller would have been an ideal tool for the purpose. One of the fundamental hypothesis underlying fuzzy-logic controllers is that the rules set should be always valid within the range of inputs for which they are specified. If this hypothesis fails then it is impossible to define a unique output given a set of inputs, because the rules are no longer certain and unique themselves. Once the possible combinations of the inputs were defined, from an analysis carried out that in some cases, it emerged that the rule could not be distinctive because, depending on the exact value of each input and the relationships between them it was possible to have different ideal behaviors. It could be debated whether the ambiguity could have been removed with a different set of inputs or increasing the number of inputs and consequently the number of cases to analyze and thus rules to define. The first option looked improbable, considering that the set of inputs selected was certainly very influential on the solution. The second option, conversely, could have potentially increased by several times the number of cases to define, without granting, at the same time, the absence of any ambiguity.

For the reasons illustrated in the present section, the early approaches were discarded in favor of a different concept. The basic idea was still the assumption that the information regarding the storage usage could be optimized separately and transmitted indirectly, in the form of a modified load, to the SS algorithm, but it relied on a completely different method for optimization to define the ideal storage operation for the whole day.

4.2.3 The shortest-path algorithm and its capabilities

In the previous section it was discussed how the states of the system were defined in terms of storage charges and time-step considered, suggesting that the optimization of the daily operation of the SU could be achieved by finding the best sequence of states during the day. There are algorithms that perform very well when they seek the best possible sequence of states that leads from a starting state to an arrival one. As a family, these algorithms are referred to as *shortest-path algorithm*s. They are renowned for their reliability, speed and accuracy. Because of this, they are used in every-day devices such as navigation systems when the user is looking for directions (preferably the shortest or fastest route) from a place to another. These algorithms work on structures, defined *graph,* which are an abstraction of the system and represent the possible connections between different system states. In the case of the ideal route finding, each state represents a location and each connection a possible route from one location to another. Continuing with the example of the navigation system, the states of the system are not influenced by the weight of the car, the speed at which it is travelling, whether there is wind or rain; the only variable defining the state of the car is its position. These variables may influence the costs associated to the transformation from one state to another, which in the graph are represented by the connections between states. Therefore, it can be noticed how the description of the system, and thus its optimization, can be divided in two parts

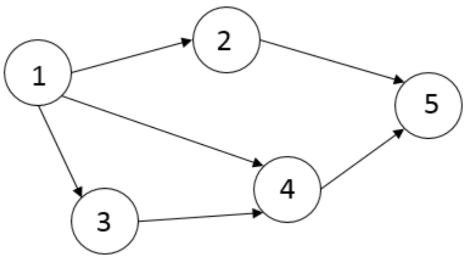
- The description of the physics of the system, which can be performed with the desired degree of detail and is adopted to define how the system can evolve from one state to another;
- The definition of all the possible states that the system can assume.

Once the states of the system are defined and the transformation from one another can be simulated by means of an ad hoc model, which in our case is the SS algorithm, the shortest-path algorithm can be adopted to optimize the sequence of states. Recently, other researchers, such as Facci et al. (2014) [115], have employed similar approaches for the description of energy systems. There are several algorithms dedicated to the search of the shortest path within a graph, e.g. Dijkstra, Bellman-Ford, A*, Floyd-Marshall, Johnson. Each one requires the graph to have specific properties in order to be used. A brief introduction on graph theory is provided hereafter with no intent to be complete. It should be meant as a quick reminder or introduction to the topic for the interested reader.

4.2.3.1 Brief introduction to Graph Theory

A graph is a set of elements, defined *nodes* or *vertexes* of the graph, which can be connected one another by means of lines called *edges*. A graph G is defined as a couple $(V(G), E(G))$, where, $V(G)$ is a finite, non-empty set of nodes and $E(G)$ is a finite, non-empty set of edges, and is defined as the set of edges of G such that the elements of E are couples of elements of V. There can be two families of graphs: oriented and non-oriented graphs. An oriented graph contains oriented edges, meaning one-way edges from the first node of the couple to the second, i.e. it is possible to go from node i to node j but not the opposite. In a non-oriented graph, on the other hand, it is always possible to go both from node i to j and from j to i. A path in a graph is a sequence of nodes, reached one after the other. A great part of graph theory is related to the study of the paths and the way to optimize these paths in graphs with different features. There are several ways to represent the edges of a graph, a convenient way for programming is what is called the *adjacency matrix*: if a graph G is composed of the set of nodes $\{v_1, \dots, v_n\}$, the adjacency matrix of G is a $n \times n$ matrix $A = (a_{ij})$ where, each element a_{ij} can be defined as follows:

$$a_{ij} = \begin{cases} 1 \; if \; edge \; (i,j) \in E, \\ 0 \; otherwise \end{cases} \qquad \text{Eq. 27}$$



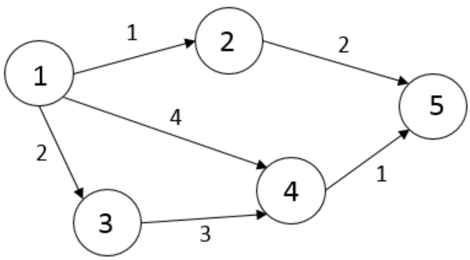
	1	2	3	4	5
1	0	1	1	1	0
2	0	0	0	0	1
3	0	0	0	1	0
4	0	0	0	0	1
5	0	0	0	0	0

Figure 26 - Oriented graph and its adjacency matrix

Figure 26 presents an example of oriented graph and its adjacency matrix, where each row represents the starting node of a given edge and each column the arrival node, e.g. element a_{12} has value “1”, which means that there is an edge in the graph starting from node 1 and arriving in node 2. On the other hand, a different element, such as a_{42} has value “0”, meaning that there is no edge in the graph connecting node 2 to node 4. Being an oriented graph, whereas it is possible to reach node 2 from node 1, the opposite is not allowed (to do so there should be one more edge aiming from node 2 to node 1), therefore a_{12} is equal to one, whereas a_{21} is equal to zero. If the graph in Figure 26 were non-oriented the following would be always true:

$$a_{ij} = a_{ji} \qquad \text{Eq. 28}$$

Thus, the adjacency matrix would be symmetrical. The adjacency matrix can also provide information on the "costs" associated to each edge. With *cost* or *weight*, it can be meant a proper monetary value, such as the expenses to travel from a city representing node A to another representing node B, just like any measurable value that is associated to the transformation of a physical system that leads it from state A to state B. For example, citing again the problem of navigation systems, the distance to travel from a location to another. In the case when the matrix with the information on the connections between nodes, presents the costs of the existing connections, the matrix is called *weighted adjacency matrix*, an example is showed in Figure 27



	1	2	3	4	5
1	0	1	2	4	0
2	0	0	0	0	2
3	0	0	0	3	0
4	0	0	0	0	1
5	0	0	0	0	0

Figure 27 - Weighted graph and weighted adjacency matrix

In graphs theory, with the terms "shortest-path" is meant the solution of the problem seeking the less expensive route between to nodes, i.e. the sequence of edges linking two desired nodes whose sum of the costs is the lowest possible in the graph. Let $G = (V, E)$ be an oriented graph with a cost function $w: E \rightarrow \mathbb{R}$, which associates to each edge a value from the Real numbers set. Given a path, $p = \langle v_0, v_1, \dots, v_k \rangle$, the cost of the path is the sum of the weights of each edge that constitute the path itself:

$$w(p) = \sum_{i=1}^{k} w(v_{i-1}, v_i) \qquad \text{Eq. 29}$$

The weight of the shortest path from u to v is thus defined as:

$$\delta(u,v) = \begin{cases} \min\{w(p) : u \overset{p}{\leadsto} v\}, & \mathit{if\ a\ path\ between\ u\ and\ v\ exists} \\ \infty, & \mathit{otherwise} \end{cases}$$

The shortest path between node u and node v is therefore each path p with a weight $w(p) = \delta(u,v)$.

In the present case, because the starting state, i.e. the state of charge of the thermal and electrical storage, is known in advance, the shortest-path problem is of the "single source" kind. For this type of problem, one of the best performing algorithms is the one developed by Edsger Dijkstra, which takes his surname.

4.2.3.2 Dijkstra algorithm description

Dijkstra algorithm can efficiently find the shortest path between a starting node and *all other nodes* in an oriented and weighted graph featuring only positive costs. The search is performed updating the values of the costs from the starting node to every other node at each passage, so that when a lower weight path is found, the total cost to reach a given node is updated. The cost associated with reaching a given node is finalized, i.e. it is the lowest possible, when its cost is the minimum of all the nodes already reached. Let us formalize the concepts that underlie this algorithm:

Lemma 1: Given an oriented and weighted graph $G = (V, E)$ with weights $w: E \to \mathbb{R}$ let $p = \langle v_1, v_2, \dots, v_k \rangle$ be a shortest path between vertex v_1 and vertex v_k and, for each i and j such that $1 \leq i \leq j \leq k$ let

$p_{ij} = \langle v_i, v_{i+1}, \dots, v_j \rangle$ be the sub-path of p from vertex v_i to v_j. Then p_{ij} is the shortest path between vertexes v_i and v_j.

Demonstration: Decomposing the path p as $p = \langle p_{1i} + p_{ij} + p_{jk} \rangle$ then $w(p) = \langle w(p_{1i}) + w(p_{ij}) + w(p_{jk}) \rangle$. Let us suppose that a path p_{ij}' with weight $w(p_{ij}') \leq w(p_{ij})$ might exist. Then, $p' = \langle p_{1i} + p_{ij}' + p_{jk} \rangle$ would be a path between v_0 and v_k shorter than p, but this is in contradiction with the hypothesis made, therefore impossible. □

Corollary 1: Let $G = (V, E)$ be an oriented and weighted graph with weights $w: E \to \mathbb{R}$. Let us assume that the shortest path p from a source s to a destination vertex v might be divided in $s \overset{p'}{\leadsto} u \to v$ for some vertex u and path p'. Then the weight of the shortest path between s and v is $\delta(s, u) + w(u, v)$.

Demonstration: Known *Lemma 1*, the sub-path $p'$is a shortest path between the source s and the vertex u, therefore:

$$\delta(s, v) = w(p) = w(p') + w(u, v) = \delta(s, u) + w(u, v) \qquad \text{Eq. 30}$$

Considering a graph $G = (V, E)$ and s the source or initial node with $s \in V$, the representation of the shortest paths is carried out associating to each vertex $v \in V$ a predecessor vertex $\pi(v)$. Let us define then $G_\pi = (V_\pi, E_\pi)$ as the sub-graph predecessor of G with:

$$V_\pi = \{v \in V : \pi[v] \neq NIL\} \cup \{S\}$$

$$E_\pi = \{(\pi[v], v) \in E : v \in V_\pi - \{S\}\}$$

A sub-graph predecessor of G_π is a *tree* of the shortest paths for G if:

- V_π is constituted by all the vertexes of G that can be reached from vertex s;
- G_π forms a tree with root in s;

- The simple path from s to v in G_π coincides with the shortest path between s and v in G.

The representation of the tree can be done using an array π with the same dimension of the number of nodes, such that $\pi[u]$ includes the node from which, in the path, u is reached. For each vertex v the algorithm keeps the following attributes:

- $d[v]$ which represents an estimate of $\delta(s, v)$;
- $\pi[v]$ which represents the predecessor of v in the path with weight $d[v]$ from s to v

The Dijkstra algorithm utilizes a technique defined as *relaxation* of the edges. This allows it to update the values of $d[v]$ and $\pi[v]$ during the search for the shortest path: when an edge (u, v) is relaxed, it is verified whether it is possible to find a path from s to v with a cost minor then $d[v]$ when using the edge (u, v). At each step, the algorithm considers a set S including the vertexes whose weights when walking on the shortest path, have already been finalized, i.e. S includes the vertexes $v \in S$ such that $d[v] = \delta(s, v)$. The adjacent vertexes to those in S for what is called a *boundary* between the vertex whose shortest path from the source is known, and all the other vertexes. Inside the array d, at each step of the Dijkstra algorithm, the weight of the best path for each node which was found until that step is saved. Among the nodes forming the boundary of the set S, the algorithm seeks the vertex $u \in V - S$ featuring the minimum weight from s and when it is found, it is added to the set S and relaxes, i.e. updates, all the edges connected to the node u. If the total costs to reach the nodes reached during the relaxation is lower than the previous value they were assigned, then the value is updated and the predecessor of those nodes is u, otherwise they remain un-modified both in terms of cost and predecessor. To understand better the procedure, a pseudo-code of the algorithm is provided hereafter:

1. The first node s is included in the set S;

2. All the vertexes adjacent to s are relaxed, i.e. the cost to reach them from s is updated;
3. Among the vertexes adjacent to s, the one with the shortest path is:
    a. Added to set S;
    b. The weight of the path from s to it is finalized;
    c. Its predecessor is set to s;
4. All the vertexes adjacent to the node just included in S are relaxed;
5. Continues repeating step 3 and 4 until all the nodes have been evaluated and included in S or the desired node is included in S.

Figure 28 shows a visualization of the algorithm steps during a full run. The source is the node with cost 0 in the diagram on the top left, the costs of the shortest path from that node to any other node of the graph are encircled inside the node. The weight of each edge is on the arrow from one node to another. The nodes in black are those that are included in the set S, the grey one is the one that is being included in S at the considered step. The red edges are those followed to reach the predecessors of each node in their shortest path from the source. As can be seen, in the second step (diagram on the top right), the nodes adjacent to the source are relaxed with values 10 and 5 which are the costs of the paths to reach them from the source. The node selected is the one whose path-weight is 5 being the minimum among those relaxed. Therefore, 5 is finalized and the node is added to the set S. The weight of each path reaching a node adjacent to the one just added to S is relaxed, and among them, the one with the minimum weight is selected. It can be noticed that the node that at the second step had cost equal to 10 receives an update of its cost, which is now equal to 8. All the other nodes that can be reached from the node of cost 5 are evaluated and the one with the minimum path, which is the one with cost 7 is added to S. The algorithm proceeds until all the nodes are finalized, as it can be seen in the bottom right diagram.

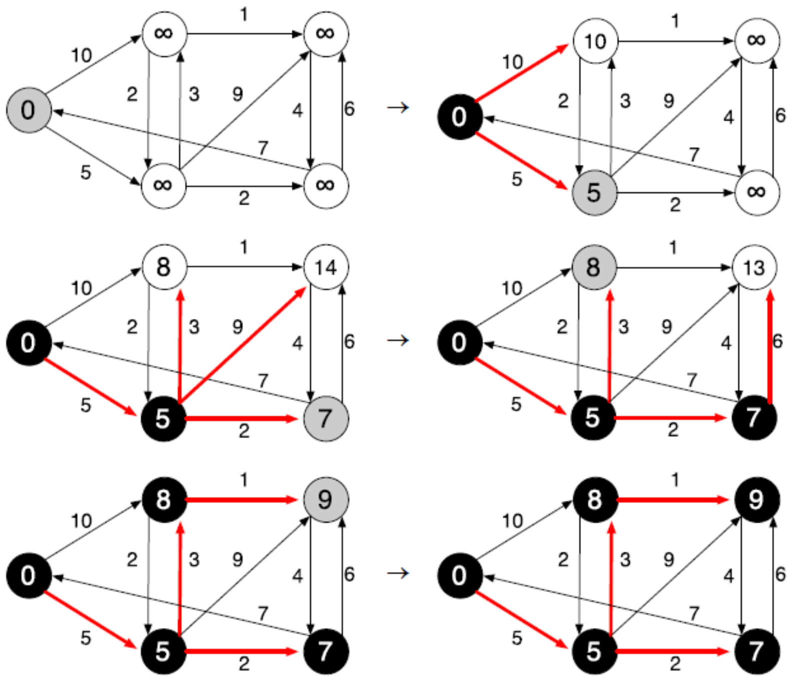


Figure 28 - Visualization of Dijkstra algorithm procedure

One of the most important characteristics of this algorithm, when applied to physical systems, is that the computational time it requires is $O(V^2)$ which means that adding states of the system to evaluate, i.e., variables does not exponentially increase the complexity of the problem, which grows "just" in a quadratic way. In the next section, the application of Dijkstra algorithm to the problem of daily optimization of the storages is described in detail.

4.2.3.3 Application of Dijkstra algorithm to the Smart User

Before detailing the algorithm designed, it is useful to describe the way the storages are modelled and how the graph for the analysis of the daily operations is created. The total number of storages that can be active at any given time is two: the cold and the electric one during summer or the hot and electric one during winter. If the thermal storage is divided in t levels of charge and the electric storage in e levels, considering the number of time-steps of a single day, n, the maximum number of system states is:

$$V = t \cdot e \cdot n \qquad \text{Eq. 31}$$

Therefore, the graph to be created has V nodes. Going from one state (i.e. a combination of levels of charge of the thermal and the electric storage) to another, implies a given amount of power to be either supplied or absorbed by the storages. Thanks to the energetic equivalence between the energy absorbed or released by the storage and the energy produced by a generator or requested by a load, the information regarding the power usage of the storage can be passed to the SS algorithm by means of a modification of the corresponding load profile. The power of the storage must respect the maximum and minimum power constraints set for it. This check must be performed each time the original input is modified. On the other hand, once the maximum and minimum charge levels for the storages are defined at the beginning of the algorithm, there is no need to perform a check to verify whether the power considered to reach a node from another might charge or deplete the storage over the limits imposed. Indeed the constraint of charge level is always verified by the way the graph is defined, see Figure 29 for reference. The first node of each time step represents the maximum level of charge of both the storages (electric and thermal). On the other hand, the last node of each time-step represents the state where both the storages are at their minimum charge.

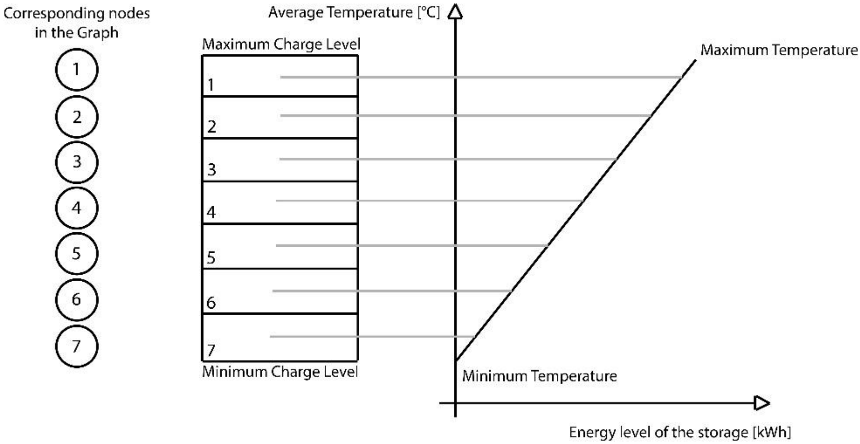


Figure 29 - Example of hot thermal storage representation with seven levels of charge

The number of possible combinations of sequences in the graph is still high, $(t \times e)^n$, but here is where the Dijkstra algorithm comes in aid, thanks to its computational complexity equal to V^2. Let us consider an example with 100 time-steps and 10 possible levels of charge for each storage, for a total number of combinations of 100^{100} = 10^{200}, the computational complexity is only in the order of 10^8! The downside of this approach, is that the SS algorithm needs to assess the costs to pass from a combination of levels of charge in a time-step to another combination in the next time-step. In order for the Dijkstra algorithm to work, each connection between a combination and another should be evaluated. The number of maximum runs of the SS algorithm, nonetheless, is not $n \cdot (t \cdot e)^2$, but, in the worst case:

$$m = (2t - 1) \cdot (2e - 1) \cdot n \qquad \text{Eq. 32}$$

The reason is that, in order to provide different results, the SS algorithm must receive different inputs, which means, in this case, different values of the power exchanged with the system by the thermal and electric storage. Actually, for similar decrement or increment of the charge level of the storages, the value of power exchanged with the storage itself is the same, and therefore all the edges in the graph that feature the same power exchanged with the storages will have identical costs. In Figure 30 an example of a graph is reported for five time-steps and three levels of charge for both the thermal and electric storage. It can be noticed that for each storage, divided for example in l levels, to go from one time-step to the successive one, the possible steps of power are $l-1$ positive ones, from the minimum level of charge up to the maximum, the same number of negative ones and one associated to null power. The total number is indeed $2 \cdot (l-1)+1=2l-1$. Which, considering t thermal levels and e electric levels leads to equation 32.

As will be illustrated in the following chapter, dedicated to the analysis of the results, the number of subdivisions of the levels of charge of the storages is very influential on the benefits that can be achieved with this algorithm compared to the SS one. Indeed the latter defines each variable with an 8 bit resolution, thus 256 different levels, whereas a reasonable number of subdivisions of the storage charge is in the order of 20 to 30, depending on the maximum power output and capacity of the storage itself. Indeed, when the storage is large, and its maximum power output is small, many of the possible connections between nodes will be impossible, and therefore the actual resolution of the analysis for the storage might be insufficient to achieve good results. Because of this, the future developments for the algorithm include different ways to create the graph for the problem, which will reduce the number of unfeasible edges in the adjacency matrix.

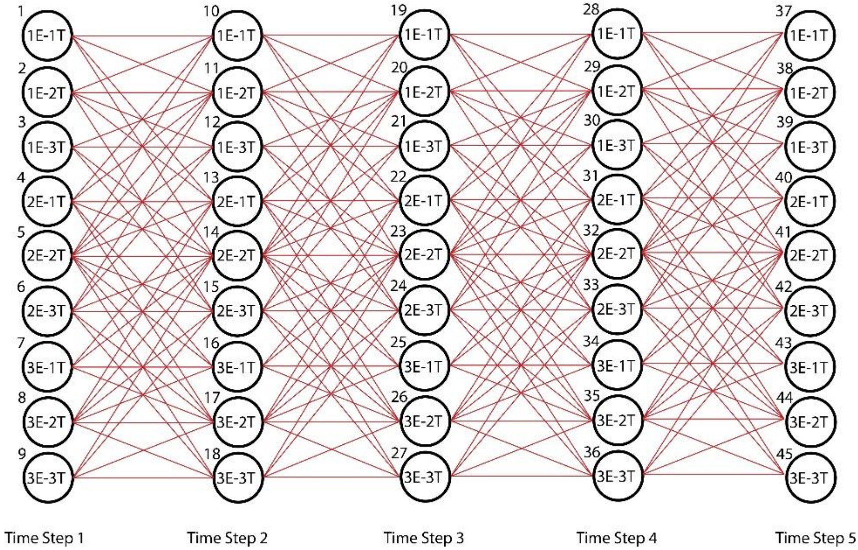


Figure 30 - Example of Graph with 5 time steps, 3 charge subdivisions for both Thermal and Electric storage. The storage is allowed to charge up or discharge down of only one level for time-step

The algorithm designed to optimize the storage operation consists of three different parts:

1. The computation of the modification to apply to each type of load involved in the analysis. At the end of this phase an appropriate input file for the SS algorithm is produced;
2. The execution of the SS algorithm, used to assess the costs of the transformation from one state to another;
3. The execution of Dijkstra algorithm to find the optimized sequence of states, i.e. storage charges, during the day.

Although it is meant to be translated in C++ language in order to be faster and lighter, the above algorithm was first developed in MatLab©.

Depending on the thermal layout of the Smart User plant, the operations of the system itself differ. This happens because some devices or layouts can add further constraints to plant operations. Although there is plenty of possibilities for the thermal layout of the SU plant, these options ultimately fall in two categories, mentioned in the previous chapter: all generators in parallel with the storage, or auxiliary generators in cascade to their respective storage and the user. The advantages and disadvantages of each scheme have already been discussed in the chapter dedicated to the design of the Smart User. Hereafter a description of the different algorithms used for the two general layouts illustrated in Figure 13 and Figure 15 is provided.

4.2.3.4 Generators in parallel with their storages

The first algorithm presented here was designed to work with the plant where all the generators can charge their respective storage, whereas the loads are satisfied directly only by the storages themselves. The layout considered is the one presented in Figure 13.

In order to build the graph required for the daily optimization performed by the Dijkstra algorithm, the storages charge are divided in a desired number of levels. Depending on the size (capacity) and the power of charge/discharge allowed by the storages, the number of ideal subdivisions may differ. For most of the tests carried out offline the choice was to subdivide the thermal or the electrical storages in 30 levels when they were optimized alone. On the other hand, when both were to be optimized at the same time, the number of subdivisions of choice was 8 for each storage due to computational limits. The higher the ratio between capacity and power that the storage can provide the higher is the number of subdivisions recommended. Indeed, if the number of subdivisions is too low, the power of charge/discharge required making one step up or one step down in terms of storage charge could be too high compared to the power specifications of the storage itself, see Figure 31.

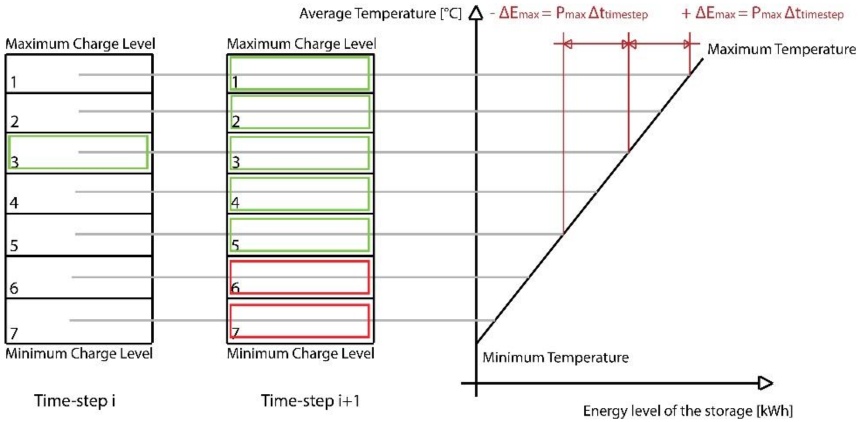


Figure 31 - Reachable storage charge levels when considering a maximum power exchange with the storage, nodes representation.

The algorithm begins receiving from the SCADA (online tests) or from the user (offline tests) the level of charge of the storages at the beginning of the day. Once these two values are known, it is possible to identify the starting node on the graph. Other inputs required are those illustrated for the GA. Indeed, the first part of the shortest-path algorithm needs to define the inputs for the SS algorithm (used in the version described in 4.2.1.1) whose output is required to define the costs of the edges in the graph. For each time-step considered, the original electric and thermal (or cooling) load is modified $(2e-1)(2t-1)$ times which corresponds to the total combinations of possible thermal and electric power of charge/discharge of the storages. Thus, the GA will receive a number of time-steps, which is no longer corresponding to the duration of a day but depends on the number of edges' costs to calculate. As previously stated, the number of combinations to analyze is well below the total number of edges of the graph, because only those featuring different power exchange with the storages actually matter and will have different values. From Figure 30 it can also be noticed that some edges are missing because the connection between nodes is unfeasible in terms of power. This reduces even further the total number of edges to calculate.

Nonetheless, to speed up the process, each case is evaluated only once. Therefore, the tuning of the algorithm is vital to ensure that the solution found in the first run is stable and reliable. When the generators are all capable of charging their storages, the constraints on storage power are limited to the maximum power of charge and discharge, both depending on technical limitations of the storage or the plant. Therefore, the constraints are set just referring to a possible maximum power for charge and discharge of the storages:

$$P_{max,discharge} < P_{strg} < P_{max,charge} \qquad \text{Eq. 33}$$

The cost of the edge corresponding to the P_{strg} imposed is evaluated only if it complies with the constraint, otherwise the corresponding time-step in the GA is skipped and a fictionally high value for the fitness function (i.e. edge costs) is provided as output. This imposes the GA to avoid running for cases that are not feasible in the actual plant, thus reducing the overall computational time. Once the cost of all the edges is known, it is possible to write the weighted adjacency matrix. This is done calculating, for each edge, the corresponding electric and thermal storage power, which is the key to writing the correct value of the fitness contained in the output of the GA inside the weighted adjacency matrix. In the case where some values of the fitness are negative, which can happen for the economic objective function when the production from renewables is greater than the loads to satisfy, these values must be transformed to positive in order for the Dijkstra algorithm to work. This is done simply by adding the absolute value of the most negative fitness, increased by 1 to avoid having zeros, to all the fitness values. The final results are not influenced by this modification for two reasons. First of all it is evenly applied to the whole matrix, therefore the preferred path will still be the same. Secondly, the final costs of the shortest-path followed are recovered directly from the original output file, where they are not modified.

When the weighted adjacency matrix is complete, Dijkstra algorithm runs finding the shortest-path between the starting node (i.e. the initial storages charge condition) to all the other nodes in the graph. Thus, when run, it is possible to find the best path to reach every possible charge levels combination during each time-step. This may turn particularly advantageous for the Advanced Dispatching algorithm, where the final condition of the storages might be preferred, during the day, different from the one initially thought.

4.2.3.5 Auxiliary units in cascade between storage and loads

In the case of thermal layouts similar to the Pontlab one, the previously defined procedure would lead to unfeasible solutions. Indeed, the previously described algorithm considers every thermal energy generator to be able to charge the thermal storage. Therefore, it might choose to charge it using the CHP or the auxiliary unit or a mix of both, depending on the optimization performed by the GA. This is no longer true for the more traditional or conservative plant layouts where the auxiliary units act as back-ups and thus, are installed between the storage and the load. Moreover, these units are controlled by temperature set-points, hence it is not possible to impose their power output in advance, even though it is possible to know which will be their average power output during a time-step, once their actual control system is reproduced. To do so, and yet employ the daily optimization algorithm developed, a greater number of constraints must be imposed on the algorithm. The challenge is to provide the correct inputs for plant operation in terms of average power, whereas the plant itself is controlled by temperature inputs, incurring the smallest error possible. Hereafter, an explanation of the assumptions and the hypothesis made in order to achieve this goal is proposed.

The first aspect to take into account is the way the bypasses operate on the plant. The bypasses are controlled by temperature inputs, in particular the bypass opens if the temperature of the fluid coming out of the storage is lower than the temperature of boiler activation (winter), or, higher than the temperature of chiller activation (summer). The storage is assumed as perfectly stratified; therefore, the temperature at the outlet is always the maximum inside the hot storage and the minimum in the cold one. This hypothesis is reasonable because although some mixing at the inlet of the storage might occur, seldom the fluid near the outlet would be influenced by the process, given the storage size and the mass flow entering or exiting the storage. If these assumptions hold, then the storage can actually be employed until the back-up boiler activates. At any lower temperature, even if the bypass were still closed, the CHP could not supply the load directly, and therefore it could be used to charge the storage and let the boiler follow the load. Another important assumption is made in the algorithm: the temperature coming out of the storage is proportional to its energy level. According to this, for the hot storage, whose total mass of fluid is 3000 kg, it means that to increase the temperature at the outlet of 1 °C 3.48 kWh are required, whereas on the actual storage the amount required could be less. Indeed, it depends on the temperature profile inside the storage itself, see Figure 32. The hypothesis made means also that the temperature profile inside the storage never changes. The actual system is controlled by temperature and thus it is required to know in advance the actual temperature at the storage outlet. On the contrary, the algorithm operates on average values during 15 minutes, therefore an energetic approach is to be preferred for the storage.

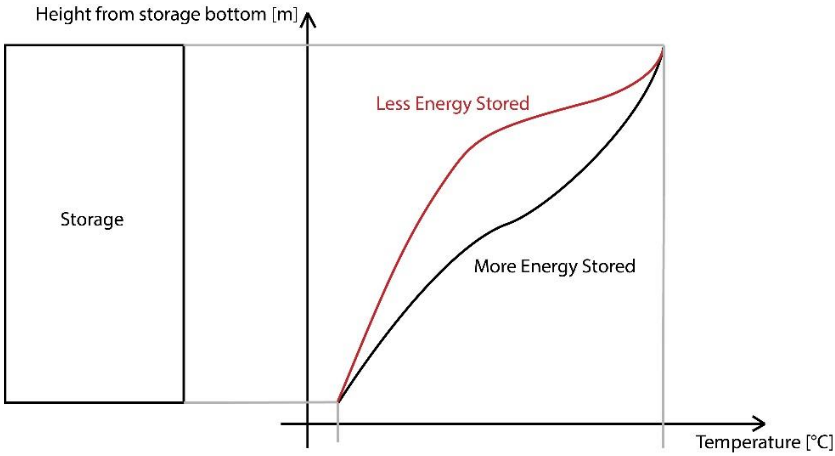


Figure 32 - Different thermal storage charge depending on the temperature profile within the stratified storage

The hypothesis introduced is a safe one though, indeed it may reduce the actual energetic capacity of the storage, considering it full when there might be still room to store more energy. All that said, the temperature corresponding to the maximum charge of the storage is the cut-off temperature for the CHP, 85 °C, for the hot storage, and the cut-off temperature of the absorption chiller, 4 °C, for the cold one. On the other hand, the minimum levels are those corresponding to the intervention temperature of the boiler and the compression chiller, respectively 60°C and 13°C. Let us consider the hot storage as example, the minimum temperature is the one of intervention of the boiler because until the boiler does not turn on, it means that the temperature at the storage outlet is at least 60 °C. If the boiler turns on, then the bypass is opened and therefore the storage is isolated from the plant. In this case, even if the CHP is turned off, the stratification of the storage is maintained and anyway the storage is kept isolated until the temperature at the outlet is higher than the one of intervention of the boiler. There is a limit temperature for which the behavior of the storage is harder to match when considering an energetic point of view on the one hand and the temperature profile in it on the other hand. This temperature is not unique. Actually, it depends on the temperature difference between the inlet and outlet of the user, which is a function of the power demand of the user and the mass flow rate in the piping. When the temperature inside the storage is lower than the temperature of intervention of the boiler summed to the temperature difference between user inlet and outlet, then the thermal fluid from the user enters the storage at a temperature lower than the temperature of boiler intervention at the previous time-step.

$$T_{limit} = T_{boiler,ON} + \Delta T_{load,previous\ time\ step} \qquad \text{Eq. 34}$$

If this happens, there can be cases where the CHP actually sends to the top of the storage fluid at a temperature lower than the one at the storage outlet. Similar reasoning can be done for the cold storage.

Depending whether the bypass is opened or closed the operation of the system changes, therefore there is a need to understand when the bypass will actually be opened, closed or both during one time-step, when assessing the cost of an edge in the shortest path algorithm. All the cases analyzed here consider the example of the hot storage. The bypass is surely closed when:

- Trivial case: the storage is charged over the limit temperature and at the end of the time-step the temperature in the storage is still higher than the limit one. In this case the water returns from the users at a temperature higher than the boiler intervention, therefore all the fluid in the storage is at a temperature higher than $T_{boiler,ON}$, the bypass is hence closed;
- Limit case: the temperature at storage outlet at the end of the time-step is lower than the limit temperature but still not the minimum of the storage. In this case, the temperature at the

bottom of the storage is lower than the temperature of intervention of the boiler. Nonetheless, the bypass is still closed because the average power balance does not need the boiler to intervene because the final charge of the storage is higher than the minimum value, therefore the storage cannot be depleted, which means the temperature at the outlet is still higher than the temperature of intervention of the boiler;

- Time-step successive to a limit case, still with a storage temperature greater than the minimum: in this case three possible situations can occur:
    - If the storage is charging it means that $P_{CHP} > P_{load}$ therefore for Pontlab, where the recirculation pump of the loads has a greater mass flow rate than the one of the CHP, $\Delta T_{CHP} > \Delta T_{load}$. The bypass will stay closed because at the bottom of the storage the fluid enters at a temperature higher than the one it had in the previous time step;
    - If the storage charge level remains constant then $P_{CHP} = P_{load}$ therefore, in Pontlab $\Delta T_{CHP} > \Delta T_{load}$ is still valid. Again, the storage receives water at a higher temperature then the one it had at the previous time step and thus the bypass is still closed;
    - If the storage is discharging, then $P_{CHP} < P_{load}$. In this case it is likely to happen that $\Delta T_{CHP} < \Delta T_{load}$ therefore the temperature at the bottom of the storage will be still lower than the boiler intervention temperature. Thus, the CHP might send to the top of the storage fluid at a temperature lower than the one of boiler intervention, inducing the bypass to open. Nonetheless, because the average power balance for the time-step is $P_{load} = P_{CHP} + P_{sto}$ and there is no need for a boiler intervention energetically wise (the

storage is not empty yet) then the bypass will eventually close. Indeed, the possible mixing occurring in the storage, which has an energy charge greater than the minimum level, will eventually increase again the temperature at the storage outlet and thus keeping the bypass closed.

Indeed in the last of the cases listed, or whenever $\Delta T_{CHP} < \Delta T_{load}$ is valid in similar conditions for a general plant, then there is an error in the evaluation of the bypass condition if it is considered as closed for the whole time-step. Nonetheless, given that from the energetic point of view the storage is not empty, thus its average temperature is greater than the one of bypass opening, there is no reason to believe that for most of the time the bypass will stay closed.

The bypass is definitely opened in one condition, if the power balance in equation 35 is verified.

$$P_{load} - P_{sto} > P_{CHP,max} \qquad \text{Eq. 35}$$

This is clearly explained considering that if the CHP thermal output is not capable to supply the load along with the storage then it means that the boiler must intervene to fill the gap, but the boiler can intervene only if the temperature at the storage outlet is lower than its intervention set point and thus the bypass is opened. This also means that when this happens, the storage must be depleted, it is not possible to reach a charge level higher than the minimum one when the condition in equation 35 is verified. If it were possible, it would mean that the boiler could not turn on and therefore the load would not be satisfied. When the storage is depleted and the bypass opens, it is possible to know the percentage of time of opening of the bypass compared to the total time of the time-step. Indeed, it will be proportional to the value of P_{boiler}

compared to P_{sto}, the greater the first compared to the second, the higher the amount of time of bypass opening.

The algorithm, both in the initial part where the input file for the GA is generated and within the GA fitness function itself, must be modified in order to take into account what has been just described. The modifications applied in the phase of input generation are described henceforth. In the case of generators in parallel to the storage, the input file of the GA included a total of $n(2e-1)(2t-1)$ rows, which represented all the possible cases of different connections between two nodes in the graph describing the energy system. In this case, on the contrary, the number is doubled in order to take into account that the behavior of the system changes depending whether the bypass is opened or closed. Therefore, for each possible combination of time-step, electric storage power and thermal storage power, two cases are considered: *option one* and *option two*. The *option one* case describes the behavior of the system when the arrival node of an edge, is the one corresponding to the minimum thermal charge level of the storage, *option two*, for every other case. When defining the input file, the power associated to the storage is an assigned variable, as the load. On the other hand, the CHP power output can be either free to be an optimization variable of the GA or must receive an imposed value, depending on the situation. This is done in order to avoid the GA suggesting unfeasible solutions. The possible cases list is:

- If $P_{load} + P_{sto} > P_{CHP,max}$, where P_{sto} is positive for charge and negative for discharge:
    - If the node of arrival in an edge is one corresponding to the minimum thermal charge level, then:
        - If the storage is charging, which is impossible because it is reaching its minimum value, then the GA will be skipped. Indeed, P_{sto} can be

either negative or zero when reaching the minimum level of charge;

- If the storage is maintaining its original charge or it is discharging, then the GA is allowed to run with P_{CHP} as an optimization variable. Indeed, because the storage is reaching its bottom level of charge, regardless of the power output of the CHP itself, the boiler will be used, therefore the CHP is still an independent variable;

  - If the node of arrival in an edge does not correspond to the minimum thermal charge level, then:
    - Regardless of the storage charging or discharging the plant is obliged to deplete the storage if $P_{load} + P_{sto} > P_{CHP,max}$ is verified, otherwise the boiler is not turned on and the load will not be satisfied. Therefore this case is impossible and the GA skips this case;

- If $P_{load} + P_{sto} < P_{CHP,max}$, which means that the CHP is capable of providing the power requested by the combination of load and storage, then:
  - If the node of arrival in an edge is one corresponding to the minimum thermal charge level, then:
    - If the storage is charging, the situation is unfeasible as in the previous case, because it is impossible to charge the storage and reach its minimum level of charge, the GA is skipped;
    - If the storage is discharging, again, because the charge level reached is the bottom one of the storage, then the CHP power output can be an optimization variable, the amount of power not

provided by the CHP will be supplied by the boiler;

- If the node of arrival in an edge does not correspond to the minimum thermal charge level, then:
  - Because in this case the boiler will not activate and the CHP is capable of satisfying both the load and the storage request, its power output is no longer an optimization variable, but must be imposed by the power balance $P_{CHP} = P_{load} + P_{sto}$. If the power output of the CHP were kept free, then its value could have been lower than the required one to fulfill the request of storage and load. Thus, the boiler should have covered the remaining power request, which is impossible on the plant because the boiler activates only when the inlet temperature of the fluid reaches the value of the lowest charge of the storage.

Once the input file is created and the GA produces its output thanks to the SS algorithm, the next step is to compile the weighted adjacency matrix in the correct way, which means, choosing the right value of fitness between *option one* and *option two*. In the algorithm, this is achieved considering for each couple of node (i.e. row and column of the adjacency matrix) the temperature of the storage corresponding to the node of arrival, and thus selecting the appropriate fitness value.

4.2.3.6 The modified fitness function

The SS algorithm employed to return the costs of the edges of the graph is a different version compared to the first one developed that was described earlier in this chapter. The main difference is found in the function that assess the average power output of the devices in the plant, their costs and emissions, and calculates the value of the fitness of each individual. Indeed, the power exchanged by the storage is no longer the result of the power balance between generators and loads, but it is imposed by the graph itself. Therefore, the fitness function has been modified in order to take into account the different way the system is controlled. Two slightly different versions are employed depending on the type of plant considered: generators in parallel or auxiliary unit in cascade. Let us introduce first the version for the plant with all the generators connected to their respective storage.

The fitness function is altered in the initial part, where in the original version the power supplied or absorbed by the storages was calculated. The cooling (or thermal) balance illustrated in equation 7 is still valid. The way the balance is verified is simpler though: if the power generated is in excess, it must be dissipated (there is no way to store it because the load has already imposed the power of the storage), if the power generated is lower than the load, then the auxiliary unit must activate. The information regarding the storage management is now provided by the MatLab© script implementing the Dijkstra algorithm, from which, knowing the nodes travelled, it is possible to define the evolution of storage power exchange during the day.

The same function must be further adapted to deal with plants similar to Pontlab. In particular, the GA receives as input three additional parameters: one that allows it to know which case it is examining, the imposed CHP thermal power output (or absorption chiller power output) if it is required by the case considered and the power absorbed or released by the storage. The possible cases to examine are three: if the input parameter called *Cpp_version* has value “1” then the CHP electric power output is one of the six optimization variables of the GA, if it has value “2” then the CHP receives the imposed value and it is no longer an optimization variable, if the value is “3” then the time-step is skipped, because unfeasible on the physical plant.

The algorithms designed offer a broad range of applications and can be implemented in plants featuring different thermal layouts. Both the versions have been tested off-line first. This has the advantages of a greater freedom in the definition of test cases to experiment and greater potential to stress the algorithm in order to evaluate its behavior even on unrealistic situations. Moreover, as it will be discussed in the next chapter, thanks to the daily data acquisition on Pontlab plant, it is possible to test off-line the actual working conditions that the algorithm would face once implemented on the physical plant.

4.3 The advanced dispatching algorithm

At the beginning of this chapter the role of the Advanced Dispatching Algorithm was briefly introduced as well as its importance, which has been also highlighted in several papers presented in the state-of-the-art chapter. Although it shows very little differences with the Day Ahead Algorithm, it is a fundamental component of the control system of the Smart User, especially when considering the future Smart Grid scenario where the DSO/TSO might constrain the electric power exchange of those plants feeding energy to the grid.

4.3.1 Goal of the Advanced Dispatching Algorithm

The main goal of the ADA is to update the optimization of the SU performed by the DAA, when a newer set of inputs or updated forecasts are presented. The presence of the ADA on the SU reduces the importance of possible scenario evaluations and stochastic analysis of weather and load data in order to achieve an accurate forecast during the day ahead. Indeed, the early optimization performed by the DAA can be updated “on the fly” according to the updates received. The inputs that might change from the time when the DAA and the ADA are launched include: the weather forecasts and therefore the productivity of RESs and the thermal loads, the desired activity to perform inside the SU, which might change the thermal or electric loads. Moreover, a sudden request for ancillary services from the DSO/TSO might be rewarded if answered by the plant. Therefore, it is very important that the suggested operation for the SU during the day before is updated often, in this case every fifteen minutes, to take into account any possible modification that occurs with the set of inputs during the day. The update of the suggested operation is even more important when considering the possible future Smart Grid scenario where the DSO/TSO might impose restrictions on the power exchange profile of the user with the grid. In this case, the analysis performed by the ADA becomes fundamental in order to reduce the stress on the Real Time Algorithm that is in charge of ensuring the compliance of the actual power exchange profile with the grid to the one proposed to the DSO during the day before. The requirement of an updated solution at the end of each time-step imposes a limitation on the computational time allowed for the run of the ADA algorithm; a complete run, from input assignment to output production and storage into the SCADA system, should take less than fifteen minutes.

4.3.2 Algorithm description

Because the ADA receives the same kind of inputs of the DAA and it returns the same outputs, the structure of the two algorithms is identical. Thus, once the version of the SS algorithm and the respective shortest-path one are defined according to the plant layout, then the same algorithm should be used as ADA in the present day. The main difference is that after each run, the number of time-steps considered is reduced, because the final time-step of the optimization is not 24 hours ahead of the beginning but the end of the present day, therefore each time it gets closer.

The limitation in the resolution of the shortest-path algorithm when used as ADA is the computational time, although this is a temporary issue, because new and better performing hardware is released every year. It is very important to limit the computational time required by it. In this sense, the fact that the algorithm presently written in MatLab(C) for offline test is meant to be translated in C++ for its application on the actual plant is a great advantage. By the time it will be implemented in a commercial controller, the algorithm designed is believed to be able to run well below the fifteen minutes mark. Indeed, at present, written in MatLab© code, it is already near the 30 minutes when considering both thermal and electric storages at the same time with eight subdivisions of the charge for each one of them. The reduction of the number of edges costs to evaluate achieved by an optimal definition of the graph and schematization of the energy system reduces the number of evaluations by a factor:

$$R = \frac{(2e-1)(2t-1)}{(et)^2} \qquad \text{Eq. 36}$$

In the same way, avoiding running the GA for unfeasible cases improves the computational time even more. The benefits are greater as the number of subdivisions of the electrical and thermal storages increases, which is desirable in order to improve the resolution of storage subdivision and ultimately achieve better results, as will be demonstrated in the next chapter.

4.4 The real time management of the plant

The Real Time Algorithm is a key component of the SU. Conversely from the DAA and the ADA, the RTA is not an optimization algorithm, its role is to ensure the correct operation of the plant once the suggested management has already been defined. A description of the operations performed by the RTA is provided in this section.

4.4.1 Goals of the Real Time Algorithm

The main goal of the RTA is to make sure that the electric plant is operated correctly within the 15 minutes window, which is the length of a time step in both the DAA and the ADA. Two are the main aspects that it needs to take into account:

- It must ensure that the actual load assigned to the CHP is satisfied in each moment;
- It must make sure that the power exchange profile with the grid promised the previous day is respected.

Both the optimization algorithms assume that each variable involved remains stable for the whole duration of the time step considered. It is easy to understand that this simplification must be adopted in the DAA and ADA in order to provide a valuable result in a reasonable time and because it is unlikely to know precisely the load profile one day in advance. Nonetheless, it is evident that this hypothesis finds no match in reality, where loads and renewables' availability change in a continuous manner over time. Hence, there is a need for a link between the operation proposed by the optimizers and the actual plant operation. The RTA achieves its goals modifying the original set point of the CHP defined by the DAA first and then rearranged by the ADA. In order to avoid the CHP to continuously follow the load, which would be detrimental for its performance and reliability, the RTA employs also an electrical storage, which operates in parallel with the CHP generator. The electrical storage size depends on the difference between the operation of the CHP defined by the ADA and the actual one requested during the time-step considered. The greater the differences between the actual and the forecasted operation and the time during which the CHP operates in steady conditions, the greater the electric storage size must be. If the generator set point seldom changes, then the actual load following must be performed at a greater extent by the electric storage, which therefore needs to feature a higher capacity. Indeed, the promised profile of energy exchange with the grid, which must be ensured the next day regardless of the differences in terms of loads and weather, depends on the forecasted operation. The ADA has a great influence on the RTA because with its updated optimization it can reduce the gap between the operation suggested by the DAA based on the forecasts of the day before and the real-time loads' condition and RES's generation. If only the DAA were used, the electrical storage required for load following would be definitely bigger than in the case where also the ADA is implemented to update the DAA solution. In detail, the algorithm operates as follows:

1. The required inputs are loaded, the inputs are:
    a. The real time electrical load of the user is acquired directly from the plant in the online tests. Conversely, during offline tests it is provided manually, and is based on the average load expected in the day before but modified by means of a noise function;
    b. The real time electric energy production of PV and WT, acquired from the plant or treated in the same way as the electrical load for the offline tests;
    c. The promised energy exchange with the grid profile, which is one of the outputs of both the DAA and ADA;
    d. The initial storage charge, which, in the online tests is acquired from the plant. During offline tests instead it has a default value of zero and it is allowed to assume both positive and negative values, for it gives a valuable help to designers to decide which is its correct size. In the offline tests it does not correspond to a real charge level (where negative values would have no meaning);

    e. The step length of the SCADA acquisition;
    f. The suggested CHP power output obtained by the DAA first and the ADA later;
    g. The time period that the algorithm can use to correct the power output of the CHP so that it can adapt to the new load and weather situation (called “time to pair”);
2. Those inputs provided as vectors with 96 elements are modified in order to match the size of the real-time data, which is acquired once every 5 seconds;
3. If the day tested is a fictional one then the real load applied to the CHP must be calculated starting from: the electrical load requested in real time by the user, the promised grid exchange profile and the power production of the renewables in real time;
4. The correction to be applied to the CHP operation in order to be in compliance with the promised grid exchange profile is calculated. The power output of the CHP conforms to the specifications of the actual generator installed at the SU facility, therefore the maximum power output is 25 kW and the minimum before turning off the CHP is 2.5 kW. The correction can be applied in two different ways:
    a. Both the CHP and the storage set-points are updated once every 5 seconds;
    b. Only the storage set-point is updated every 5 seconds, whereas the CHP one is updated once every given period of time (e.g. 5 minutes) allowing it to work better avoiding continuous transient conditions.

5. The correction is applied to the CHP power output of the ADA and it is based on the storage level at the previous time step: if the storage charges or discharges quickly the correction is strong, whereas it is moderate if the storage is slowly changing its level of charge. Another important set up parameter is the *time to pair*, the bigger this time period the bigger the storage size required. Indeed, if the time allowed for correction of the CHP set point is larger, the storage has to ensure that the gap between real-time loads and expected ones is covered for a longer time. Thus, it requires more capacity. Conversely, if the time to pair is small, then the CHP changes its set point more frequently, adapting itself to the load variation within the time-step; in this case the storage needs to provide less energy because the gap to fill will be smaller on average.

The algorithm was tested only offline on ad hoc test cases because of the need for an electric storage to be installed on the SU plant in Pontlab in order to perform an experimental campaign online. The offline tests will be verified online in the near future, upon electric storage installation on the plant. The results of the tests will be described in the next chapter.

5 TESTS PERFORMED

This chapter presents the results achieved by the algorithms described in the previous one. The tests were performed on two different kind of sets of inputs: benchmark inputs and actual days. The benchmark profiles were defined in order to highlight the behavior of the algorithm. These inputs present very distinctive load/costs combinations in a period of one day. Therefore, the results that the algorithm provides are very easy to read. Nonetheless, simple profiles as those designed for this purpose cannot provide useful information regarding the actual capabilities and performance of the algorithms on the actual SU. For this reason, the second set of inputs is composed of a collection of actual measurements carried out during the regular operation of the SU. Using the measured data for the off-line tests provides a greater degree of confidence regarding the correct behavior of the algorithms proposed on the actual plant. The optimization algorithms are not meant to perform an accurate simulation of the system but rather to take inputs averaged in the time-step and define a possible strategy for the optimized management of the SU. Therefore, they do not need a proper experimental validation. However, an online test is required in order to be fully confident of the solidity of the approach followed and the tools developed for the optimization of the operations in the SU. The possible mismatch between the expense of operation resulting from the optimizers and the actual costs of operation of the plant are caused by:

- Differences between the averaged inputs provided to the optimizers and the precise, real-time value of the same parameters during plant operation;
- Incorrect or over-simplified modeling of the system behavior in the optimizers;

In the first case, if the mismatch is caused by poor forecasts of the actual loads or weather conditions, then it can be corrected partly by the ADA algorithm, and partly by more accurate forecasts. On the other hand, if the difference is due to a great variability of the actual values in real-time, compared to their average value considered, then the error is systematic and can be evaluated only by online-tests. In the second case, the error can be fixed if it is caused by phenomena influencing the average value of a given input or output during the 15 minutes frame. Conversely, if the phenomenon acts repeatedly with a much smaller time-scale, then it cannot be avoided without increasing the time resolution of the optimization. Again, this can only be assessed with online-tests. In the early online tests of the SS algorithm, run without the ADA and RTA on the plant, the small mismatch observed was mostly due to the difference of operations performed by the user, compared to the one foreseen in the day before. Thus, the error can be fixed regardless of the algorithm implemented partly by the ADA and partly by the user itself. The error experienced is not due to the lack of resolution in the fifteen minutes time step. The thermal plant has its own inertia, therefore it is not affected by high-frequency load variations. On the other hand, the electric part of the plant is capable of following rapidly varying loads, but if their average value during the 15 minutes period is the same as the one considered by the optimizers, then the mismatch between the costs (or emissions or energy consumption) of operation is minimized. This happens because the interface of the system is the grid, and the costs associated to the exchange of power with it are constant for periods of one hour. Moreover, as was explained when discussing the RTA in the previous chapter, the CHP set point is not changed every 5 seconds as the SCADA receives the new measurements, but rather every 2-5 minutes; hence its operation (and associated costs) is actually an averaged one, although with a smaller period than the one considered by the optimizers.

In order to be reliable, the online tests require all of the three algorithms, DAA, ADA and RTA to be implemented on the SCADA system. Thus, they will be carried out as soon as all them are translated in C++ language and loaded on the SCADA. In this chapter, first the input sets employed in the tests will be presented. Then, the results obtained by the Single Step and the Shortest-Path Algorithm (DJ from now onwards) on both benchmark and typical days profiles are presented. In these first tests, the DJ algorithm is tested in the Smart User configuration, i.e. with all the generators capable of charging their respective storages. Then the focus is shifted on the different plant layouts and the advantage they offer when compared to the standard operation of CHP plants. Finally, the last part of the chapter is related to the offline tests performed on the Real Time Algorithm to assess the accomplishment of the goals set.

5.1 Tests on benchmark profiles

A real system is often featured by working conditions that can vary significantly during the day. The resulting optimized operation can be very complex and hard to read. Because of this, and the need to verify the coherence between the suggested operations proposed by the algorithms and the logic of control of the system, a set of simplified inputs representing different situations was designed. These are referred to as *benchmark profiles*. In all the benchmark profiles the power exchange profile with the grid is assigned as the VSO (i.e. zero net exchange with the grid at every time) and a penalty of 0.1 €/kW is applied for non-compliance to it. Although the VSO is an unlikely imposition, even in a future energy scenario, this is done in order to verify the algorithms' suggested operation in an easily readable and yet demanding condition.

5.1.1 Benchmark profiles intent and definition

In total, thirteen different profiles were designed in order to test the algorithms on non-real data. These profiles do not need to be realistic.

The important requirement is to be able to test different situations that the algorithm could deal with during operation on the actual plant, but proposed in a clear and easily readable way. All of the benchmark profiles are to be tested in summer operation mode, which means there is no thermal load request in any case. Because of the symmetry of behavior between the cold and hot storages, the algorithms provide analogous results if tested in winter operation mode. In the first three input sets, the storage optimization is considered as a plus, because the intent is to address the behavior of the algorithms when different loads and RESs' availability combinations are found. On the other hand, the sets of inputs named "Ad hoc #e" are specifically design to determine whether the correct management of the storage is obtained or not. For all this set of test cases, only the thermal storage is considered as part of the energy system, thus allowing a better readability of the results. Nonetheless, the approach is general and the lack of the electric storage is not restrictive.

The input profiles are:

- Constant Figure 34: as the name suggests, in this case all the inputs are constant throughout the whole day, even the sun radiation availability is kept constant also during the night. The electric power requested by the load is high enough to demand the whole power of the CHP at all times, even considering to employ both PV and WT at their maximum. The thermal load is zero (the input is to be tested with summer operation mode) whereas the cooling load is the one produced by the absorption chiller when the CHP is producing the electric power required to fulfill the electric load. The prices of electricity and natural gas are constant as well, see Figure 33. This is a very peculiar case; there is only one optimized solution, which is easy to be calculated because of the inputs. The CHP is expected to stay at maximum power the whole time as well as the RESs, no modulation occurring at any given time. The algorithms, when tested here, are expected to find this unique solution; the more they shift from it, and the worse they are performing. It is interesting to notice that because of the unique optimized solution, which rapidly worsens when an optimization variable changes its value from the optimized one even slightly, all the algorithms, because of their GA core take a lot of time to identify the best solution, if they reach it;

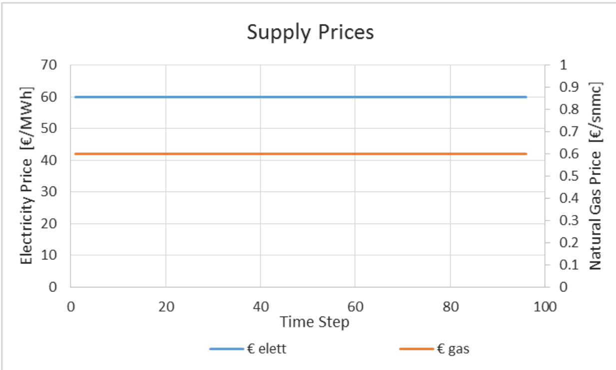


Figure 33 - Supply prices for electric energy and natural gas for cases: Constant, No RESs and With RESs

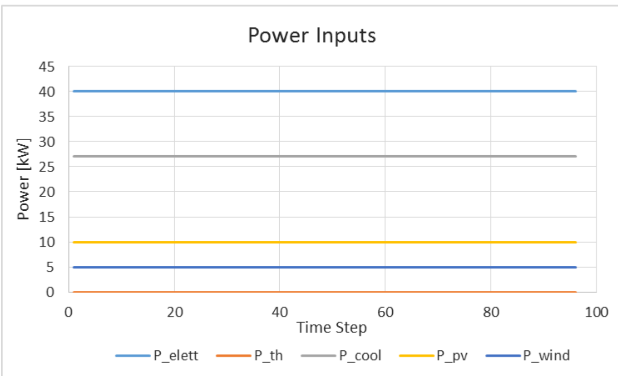


Figure 34 - Benchmark profile "Constant": loads and renewables availability

- No RESs (Figure 35): variable electric and cooling loads with no renewables' availability feature this set of inputs. The price for both electricity and natural gas is constant during the day. Every ten time steps the configuration of loads changes, therefore all of the possible situations are present. The combinations are composed considering that each load can be:
    - Zero;
    - Lower than the maximum power output of the respective generator;
    - Match the maximum power output of the respective generator;
    - Higher than the power output of the respective generator.

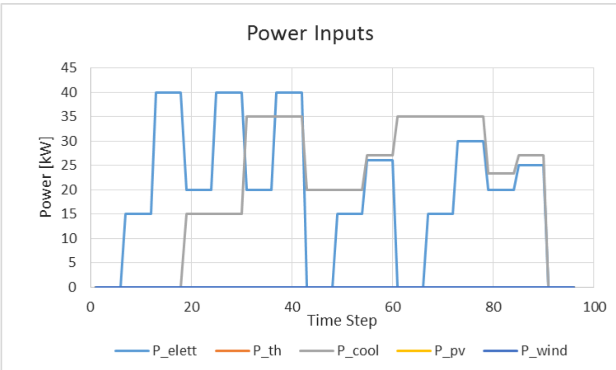


Figure 35 - Benchmark profile "No RESs": loads and renewables availability

- With RESs (Figure 36): This case has the same electric and cooling loads profile of the "No RESs" case but it adds the renewables' availability in the analysis; therefore, the number of possible situations tested during the day increases. Indeed, not only each load can be zero, lower, higher or matching the power output of its respective generator but also PV and WT availability can be: zero, lower or higher than the electric load. As in the “No RESs” case, prices are constant throughout the day;

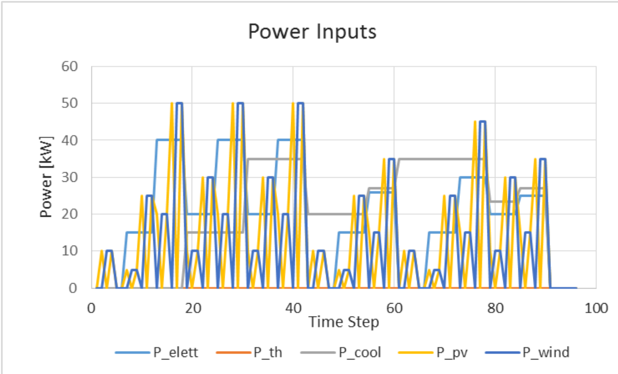


Figure 36 - Benchmark profile "With RESs": loads and renewables availability

- Ad hoc 1e (Figure 38): all “Ad hoc e” cases feature a variable electricity price during the day, which is always the same for all cases and constant natural gas price. The price profile (Figure 37) presents, besides the periods when the price is at its average value, four distinct periods:
    - A first one where the electricity price is one-sixth higher than the average value;
    - A second where the electricity price is two-thirds higher than the average value;
    - A third one where the electricity price is one-sixth lower than the average value;
    - A fourth one where the electricity price is one-third lower than the average value;

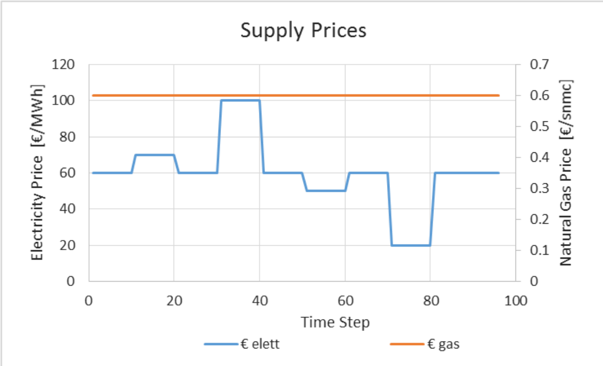


Figure 37 - Supply prices of electricity and natural gas for all "Ad hoc e" cases

When the load are on their average value, the cooling load is the one matching the productivity of the absorption chiller when the CHP is providing the exact electric power output required by the electric load. Each period lasts ten time-steps, i.e. two and a half hours, so that it is possible to completely charge or discharge the storage when a given situation occurs. If the algorithm exploits this chance correctly, the advantage is greater; on the other hand, if the algorithm suggests a wrong solution (e.g. decides to discharge the storage too soon) there is no room for making up in the following period. This specific ad hoc case presents constant loads during the whole day. Therefore, the different price is the only driver for an optimized solution of storage management, which can theoretically differ when considering the SS or the DJ Algorithm;

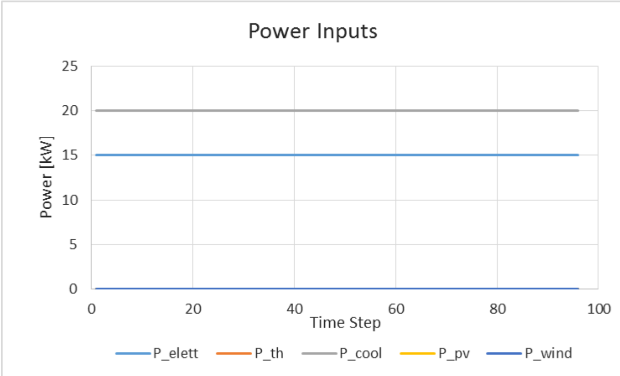


Figure 38 - Benchmark profile "Ad hoc 1e": load profiles

- Ad hoc 2e (Figure 39): In this case, the cooling load is constant, whereas the electric one presents two “spikes” the first one is an increment of two-thirds, the second a reduction of two-thirds, compared to the average value. Both the spikes occur when the price modifier is greater. Both the price and the load input drivers tend to charge the storage in the first half of the day and to discharge it in the second half. Indeed, when the electricity price is higher, it is desirable to use the CHP to fulfill the electric load. Thus, if the electric load increases when the prices are higher and the cooling load remains the same, then the storage is charged while the CHP electric power outputs increases to follow the electric load increment;

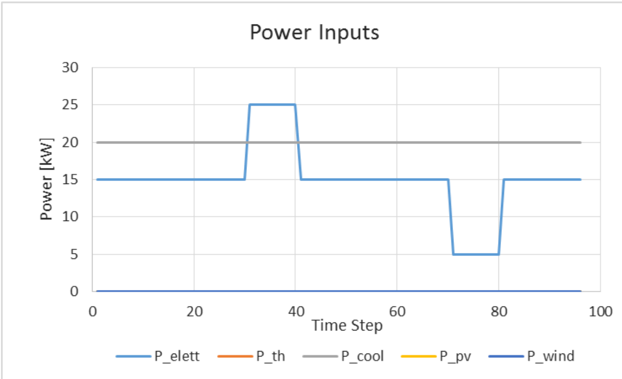


Figure 39 - Benchmark profile "Ad hoc 2e": load profiles

- Ad hoc 3e (Figure 40): Like in the previous case, only one of the loads changes during the day and presents two “spikes”. Conversely to the previous case though, the load changing here is the cooling one: the first change is a reduction of the load of one-third occurring when the electricity price increases by two-thirds, the second is an increase of one-third taking place when the electricity price is two-thirds lower than its average value. Like in the previous case, the storage should charge at first and then discharge. Both the “Ad hoc 2e” and “Ad hoc 3e” cases do not present significant “traps” for either the SS or Shortest-Path Algorithm. Indeed, the load driver occurs only when the greater price modifier is applied, therefore the suggested operation is straight-forward;

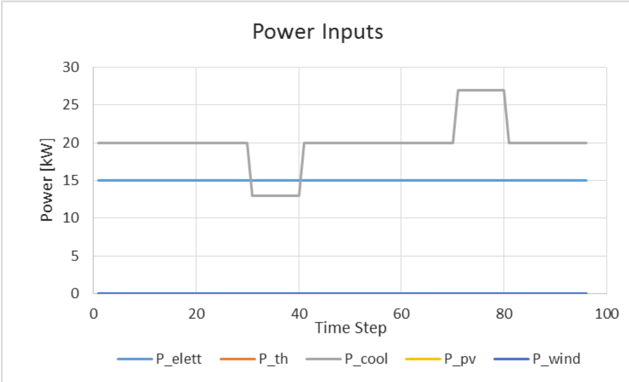


Figure 40 - Benchmark profile "Ad hoc 3e": load profiles

- Ad hoc 4e (Figure 41): This case is similar to the “Ad hoc 2e” but the electric load increases two times and then decreases two times compared to the average value. Both for the positive and negative spikes, one of the spikes coincides with the minor price modification, whereas the other occurs when the price change is greater. This is the first “trap” for the SS algorithm, indeed, because it does not take into account the inputs other than in the time-step it is analyzing, it could suggest the same kind of operation when the electric load increases or decreases. Nonetheless, considering the limited size of the storage, the optimal operation would be to charge when the load and price drivers are both maximum, therefore when the second and fourth load spike occurs;

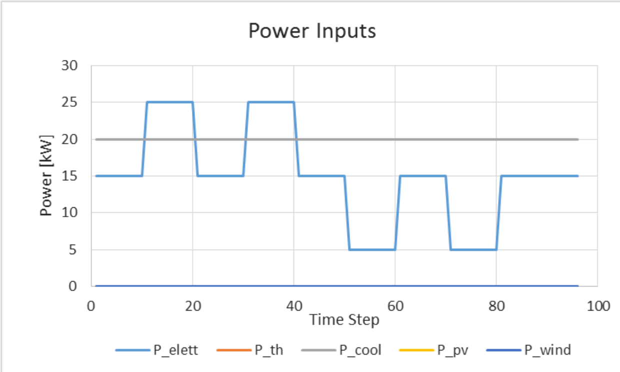


Figure 41 - Benchmark profile "Ad hoc 4e": load profiles

- Ad hoc 5e (Figure 42): Similar to “Ad hoc 4e”, but in this case it is the cooling load that varies whereas the electric one is constant. As in case “Ad hoc 3e”, when the price rises the cooling load decreases, inducing a charge of the storage;

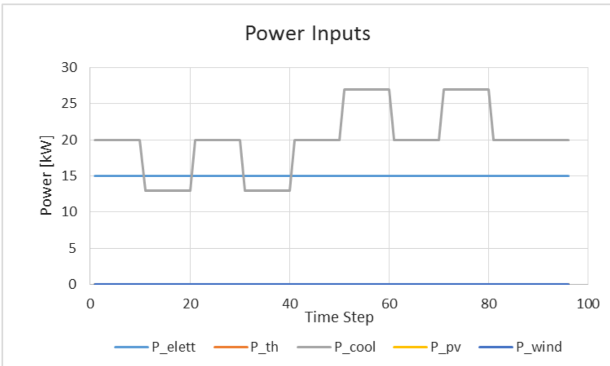


Figure 42 - Benchmark profile "Ad hoc 5e": load profiles

- Ad hoc 6e (Figure 43): Like in case “Ad hoc 4e”, the only load changing is the electric one, this time though the storage operation suggested by the electric load and the electricity price is no longer of the same kind. The minor price increment coincides with the minor increase of electric load, whereas the major increase corresponds to the major decrease in electric load. In the second half of the day the opposite happens. Thus, the first and last load modifications tend to charge the storage, conversely the second and the third;

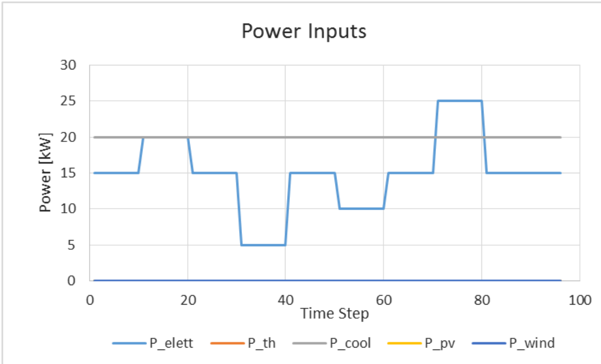


Figure 43 - Benchmark profile "Ad hoc 6e": load profiles

- Ad hoc 7e (Figure 44): Similar to “Ad hoc 6e” but the driver is the cooling load instead of the electric one;

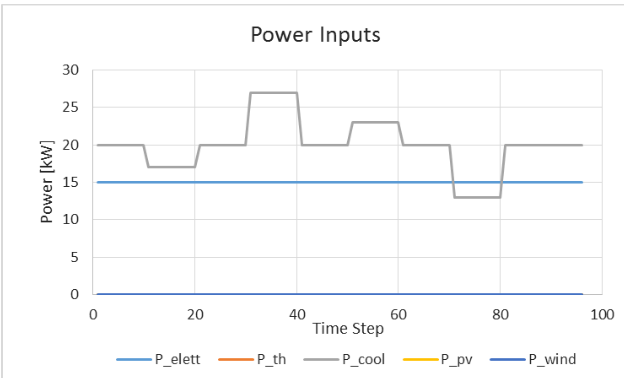


Figure 44 - Benchmark profile "Ad hoc 7e": load profiles

- Ad hoc 8e (Figure 45): Here both the electric and cooling load change during the day. The electric one changes when a minor price modification occurs. Conversely, the cooling load changes when a major price variation takes place. In this case the algorithm needs to decide which driver to follow for charging or discharging the storage, or at what extent adopt one or the other;

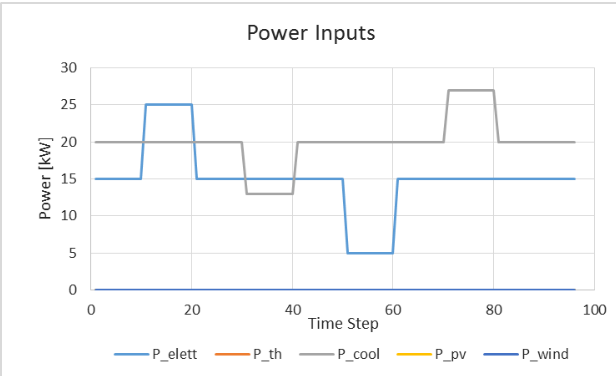


Figure 45 - Benchmark profile "Ad hoc 8e": load profiles

- Ad hoc 9e (Figure 46): Similar to “Ad hoc 8e”, in this case though, the electric load variations occur corresponding to a major price modification, conversely for the cooling load variations;

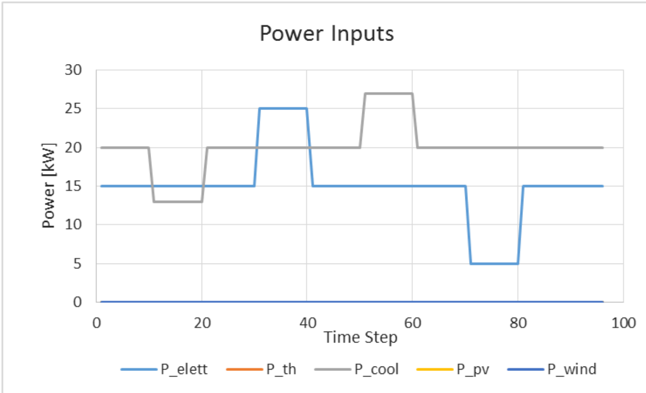


Figure 46 - Benchmark profile "Ad hoc 9e": load profiles

- Ad hoc 10e (Figure 47): In this case all the drivers (electric and cooling loads, electricity price) act at a different time of the day. Hence, the algorithms are required to find the best storage management among different possible combinations of loads and price.

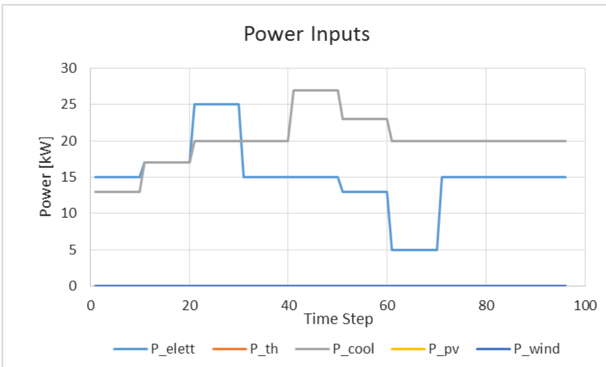


Figure 47 - Benchmark profile "Ad hoc 10e": load profiles

5.1.2 Algorithms performance comparison on benchmark profiles

For all the cases analyzed, the results presented here include: the CHP power output along with the power exchanged with the grid, the auxiliary unit power output (compression chiller when in summer operation mode, boiler otherwise), temperature of the thermal storage and charge of the electric storage when present, cost of each time step, modulated power, cumulative cost during the day. The first case analyzed is the constant inputs one, the results are shown in Figure 48.

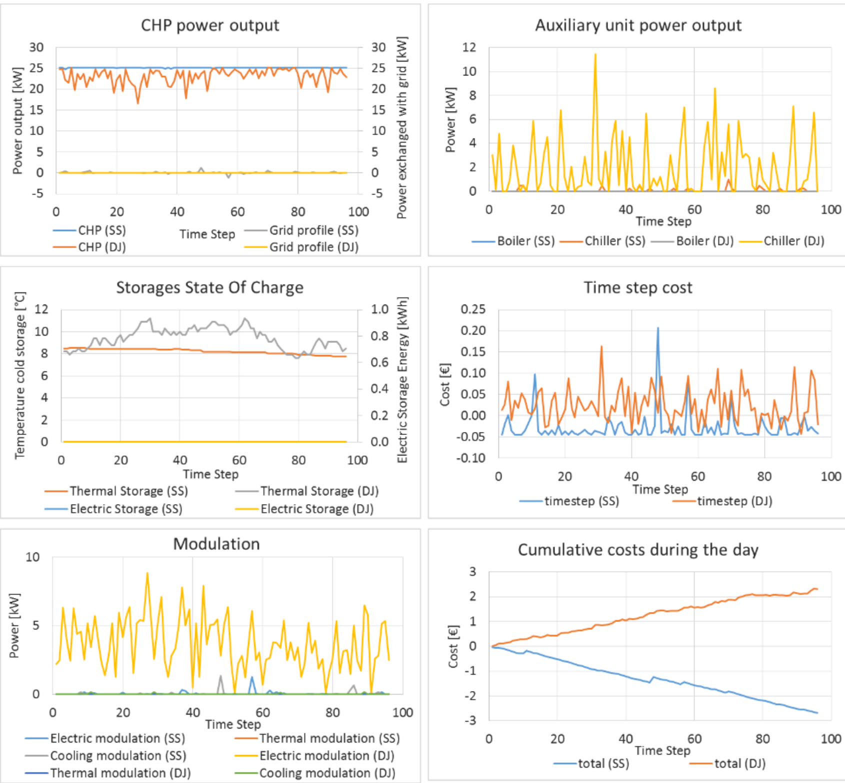


Figure 48 - Results of the comparison between DJ and SS on the "Constant" case

This is a unique case, where the SS performs better than the DJ in terms of overall costs. It can be seen that the CHP power output for the SS is more often at the maximum level compared to the DJ algorithm. Being the loads and generator balanced when used at their maximum, if the CHP is not exploited at its best by the algorithm, there is also a need of electric modulation, which leads to a cost increase, as happens for the DJ algorithm. The SS performs better than DJ because the constant case has a unique and narrow optimum solution, which is difficult to find for both meta-heuristic algorithms, but can be pursued more intensely by the SS thanks to its speed. Indeed, the SS algorithm took advantage of the fact that it needs to run only once the C++ program in order to provide a solution. Therefore it could be set to spend more time exploring the solution surface, something that it is not possible at the same extent for the DJ which has to run the C++ program several times. Moreover, in this case, there is no gain performing a daily optimization compared to the single-step one, because the ideal solutions are identical.

The second fictional day tested in the benchmark is the case of no renewables whose results are displayed in Figure 49.

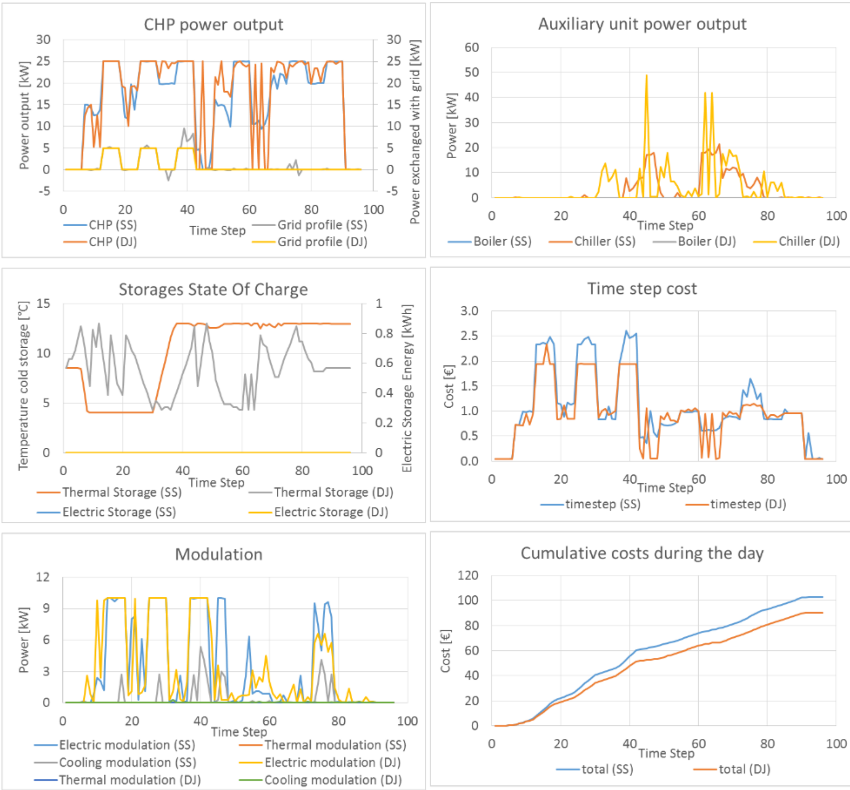


Figure 49 - Results of the comparison between DJ and SS on the "No RESs" case

In this case it can be noticed how the different load conditions occurring during the day, even with constant price of both natural gas and electricity, allow the DJ to perform better than the SS algorithm by means of a daily optimized storage usage. Indeed, the difference in terms of storage operation is relevant. The SS algorithm charges the storage completely during the first period when only some electric load is present, maintains the level up until the 30th time-step and then starts to discharge it as soon as the cooling load becomes higher than the maximum one the absorption chiller can provide. By doing so, it misses the chance to exploit the storage in any of the following time-steps because it is not capable of anticipating the loads conditions and prepare (i.e. charge) the storage in order to use it later. On the other hand, the DJ algorithm performs several charge/discharge cycles that by the end of the day allow it to achieve a result that is over 10% better.

Introducing renewables in the system adds variability to the daily operations and the storage usage proposed by the algorithms, see Figure 50.

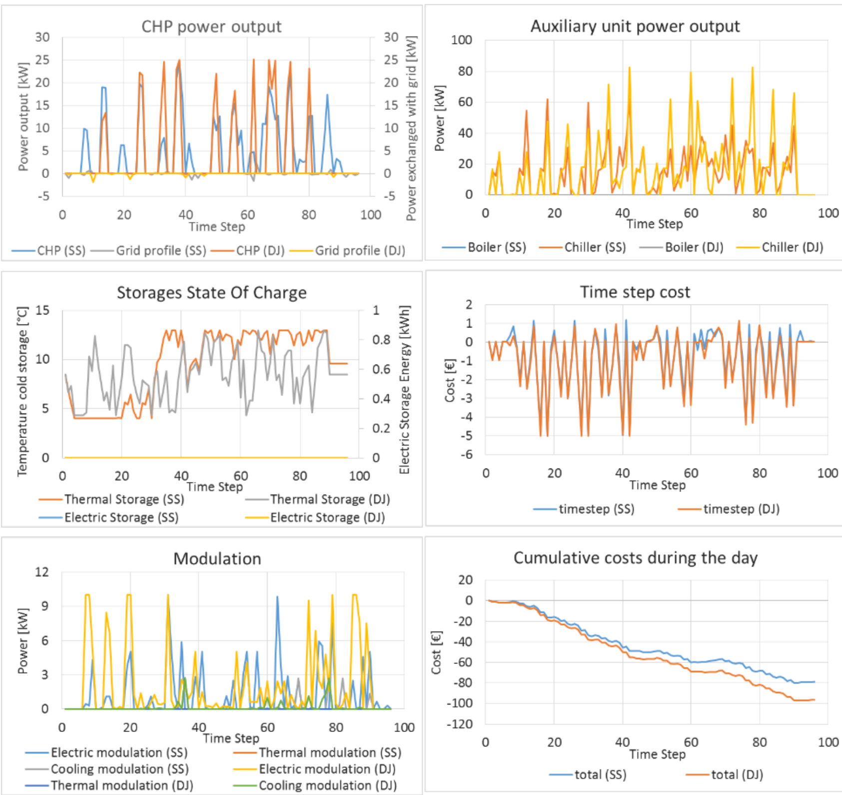


Figure 50 - Results of the comparison between DJ and SS on the "With RESs" case

In this case the DJ algorithm performs even better than in the previous case, achieving a result which is over 20% better than the SS algorithm in terms of daily costs of operation. Because of the high availability of renewables, the CHP is used seldom at full power, and, from the diagram of the auxiliary unit power output it can appreciated the fact that the DJ uses the auxiliary unit more than the SS algorithm. Sometimes the auxiliary unit is used to charge the storage, which cannot be done with every possible thermal plant layout, indeed it can be done when the auxiliary unit is installed in parallel on the storage with the CHP. For Pontlab layout, this is not possible and therefore the solution proposed by the DJ algorithm gives a precious hint regarding the design of a SU that is capable to take fully advantage of the optimization proposed. From the results just illustrated it can be inferred that the higher the variability of the inputs during the day, the greater is the margin for daily optimization compared to the single step one. Nevertheless, as was anticipated when describing the inputs set used to test the algorithms, it is hard to appreciate the way the optimization operates because of the numerous different conditions that occur during the day considered. The next series of results examined do not show such great variability of conditions, but they focus on typical situations that are simple enough to understand whether the solution proposed is reasonable from an engineering point of view and the behavior of the optimizer. The first is case “Ad hoc 1e”, whose results are presented hereafter in Figure 51. Considering the absence of modulated loads, in all Ad hoc tests, the diagram representing the modulation is omitted.

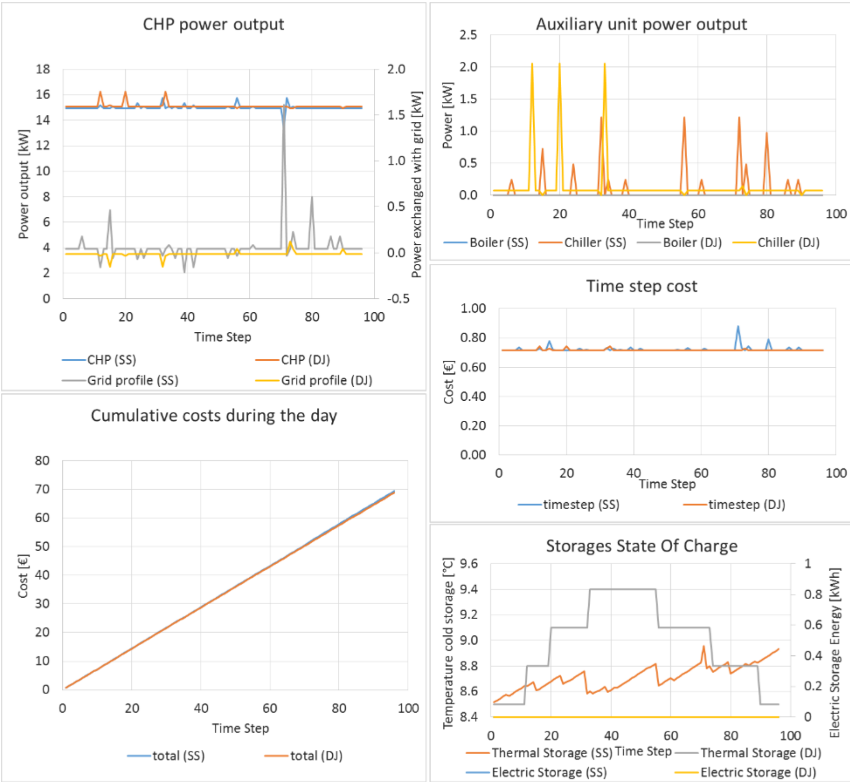


Figure 51 - Results of the comparison between DJ and SS on the "Ad hoc 1e" case

Being all the loads constant and balanced there is little or no chance to optimize the storage operation in order to take advantage of the variable costs. This happens because as the CHP set point is changed to charge or discharge the storage, the optimizer incurs penalties for lack of compliance with the zero-net power exchange with the grid. The operations suggested and the related economic performance of the system are therefore similar between the two algorithms. One thing that can be observed is that the DJ algorithm, as in the previous cases, allows the storage to return in the exact state of charge it had at the beginning of the day; whereas the SS algorithm cannot.

The situation is different for “Ad hoc 2e” input, see Figure 52.

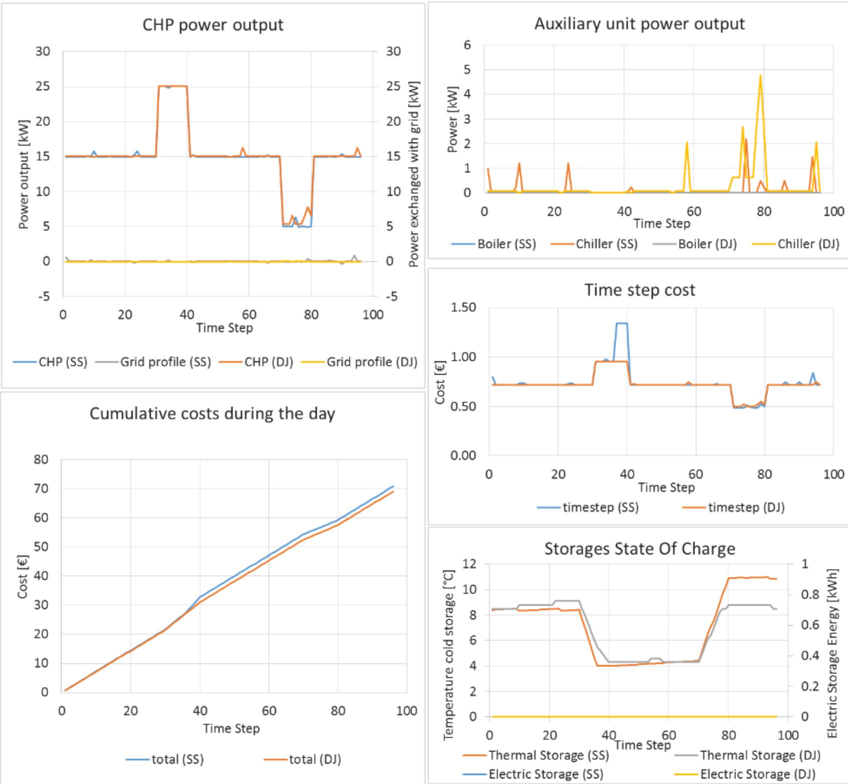


Figure 52 - Results of the comparison between DJ and SS on the "Ad hoc 2e" case

Two observations can be made, the first is that the DJ algorithm allows a little discharge of the system during the early part of the day, thus later it can charge more. This allows it to reduce the price it pays between the 35^{th} and 40^{th} time-step compared to the SS algorithm. The second observation is that in order not to incur penalties due to grid profile non-compliance, the DJ algorithm adopts the auxiliary unit. By its usage, it reduces the discharge of the storage and is able to return the storage at its original charge level by the end of the day. Nonetheless the load and price variation occur at the same time, therefore there is little margin to distinguish the DJ from the SS algorithm in terms of “smartness”. The third Ad hoc profile, “Ad hoc 3e”, where it is the cooling load that is changing instead of the electric one, is simlar and the results are not shown here for the sake of happens.

The operations suggested by the algorithms begin to differ significantly in the situation represented in Ad hoc 4e, see Figure 53. In this case there are four periods when the load shifts from its average value. These changes coincide with the electricity price changes. Still, the first price increment during the day is the smallest one, as well as the first reduction from the original value. Therefore, due to the limited storage capacity, the right way to operate the system would be to exploit at maximum the biggest price variations while being more conservative on the smallest ones. From the diagrams describing the system operation in this case it can be noticed how the DJ algorithm correctly takes advantage of the situation. Whereas the SS algorithm, which is unable to see over the boundaries of the time-step it is analyzing, fails to provide a clever solution. Thus, the economic performance shows an increased cost for the SS compared to the DJ algorithm by almost 10%.

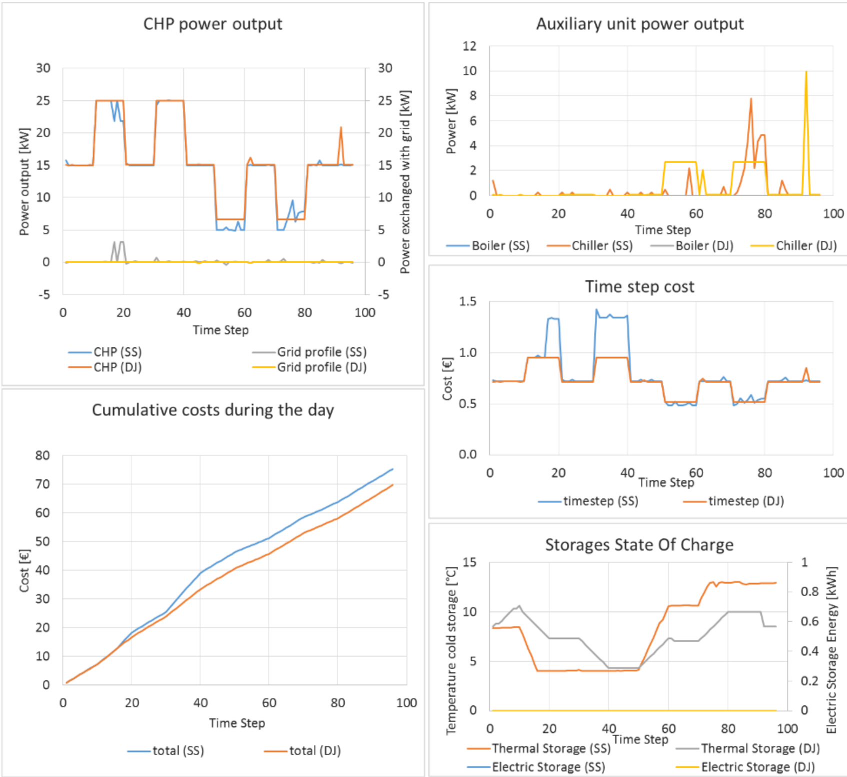


Figure 53 - Results of the comparison between DJ and SS on the "Ad hoc 4e" case

An interesting observation can be done for the following case, "Ad hoc 5e", which, although being similar in scope to Ad hoc 4e, features a peculiar behavior. The diagrams are reported in Figure 54. The unexpected suggestion of plant operation is found during the first charging period, where the storage suddenly discharges almost to its minimum level. During the single time step where this happens, there is a minor cost increase of the time step, as demonstrated by the diagram "Time step cost", but it can be also noticed that it allows the optimizer to charge more the storage during the high price period, therefore saving money. The interesting fact is that the optimizer is suggesting to dissipate part of the storage charge, in order to be able to charge the storage further later on. This is obviously an energetic non-sense, but economically wise it is reasonable as demonstrated by the better results achieved by the DJ algorithm compared to the SS algorithm that does not feature this kind of behavior. The usage of dissipaters to increase the economic revenues of the system, although making sense from the algorithm point of view, is not to be considered as a good design option. The algorithm can be instructed to avoid dissipating the heat contained in the storages, for example introducing a penalty for heat wasted.

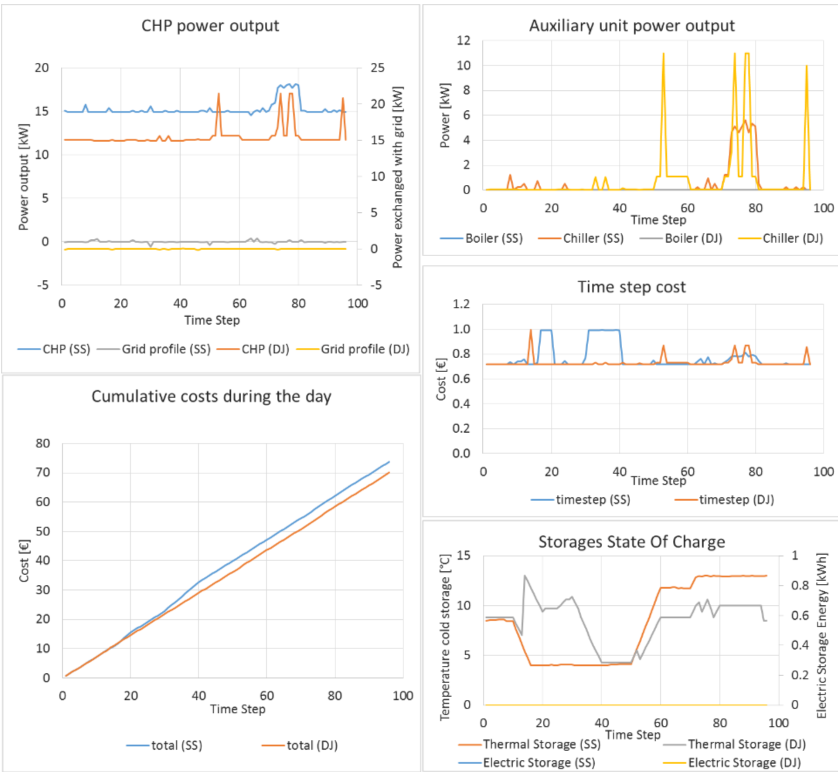


Figure 54- Results of the comparison between DJ and SS on the "Ad hoc 5e" case

The use of penalties influences the shape of the solution surface and can lead to poorer economical results; therefore, their use should be evaluated from case to case, system to system, depending on the number of times and with which intensity the heat should be dissipated according to the algorithm. If the number is minimal, then it is better to let the DAA introduce the heat waste and then allow the ADA to make up for the optimization once the storage charge is found to be higher than expected because the dissipation could not be done in the real system. Some thermal waste is also inherently connected with the way the DJ discretizes the storage charge. Once the power exchanged with the storage is assigned, either the generators could be obliged to produce more than necessary or part of the heat needs to be dissipated, due to the "roughness" of discretization in storage power level that cannot match the ideal value. This problem can be partially solved with an increase in the number of storage charge subdivisions, at a cost of higher computational times.

In cases Ad hoc 6e and Ad hoc 7e the cost difference between the solutions proposed by the DJ algorithm and the SS one is minimal, although the suggested operations of the storage vary slightly. For this reason they will not be presented here for the sake of brevity. On the other hand, some differences can be recognized in the operations proposed by DJ and SS on the "Ad hoc 8e" case, as illustrated in Figure 55.

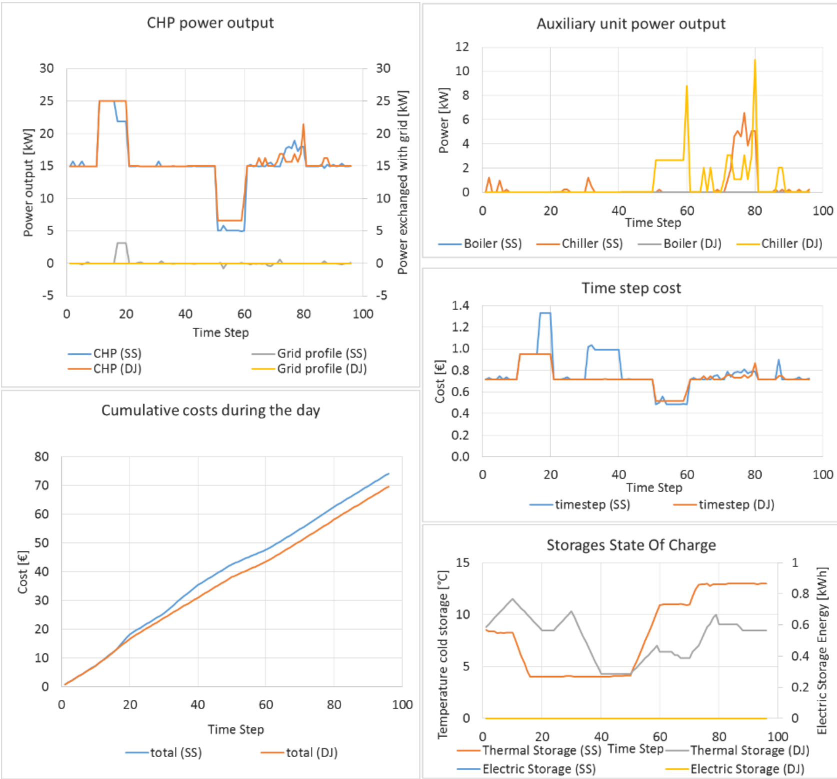


Figure 55 - Results of the comparison between DJ and SS on the "Ad hoc 8e" case

As in the previous cases analyzed, it can be noticed how the great part of the gain in economic terms is obtained during the second charging period. Indeed theoretically, a similar gain should happen during the second discharge period. However, because the storage is to be returned to its original charge level, there is no chance to fully discharge it for the DJ algorithm, whereas the SS one takes an advantage in these terms. If both the algorithms could leave the storage empty by the end of the day, the difference between the costs of each one would have been greater. Similar advantages are achieved in case “Ad hoc 9e”, even though with a different storage operation, in accordance with the fact that the load condition is different.

The last case of the series, “Ad hoc 10e”, features several different conditions and it is up to the algorithm to define an optimized strategy of storage management in order to maximize the benefits. From the diagrams presented in Figure 56, it can be observed that the Shortest-Path Algorithm performs better than the Single-Step once again. In this case, most of the difference is built during the period where the price is on its average value and the difference between the electric load and the cooling one reaches the maximum value. During the discharge phases, the gap is not increased even with different storage management. The SS algorithm continues to discharge between the 40th and 50th time-step until it exhausts the storage. The DJ algorithm on the other hand avoids to deplete the storage completely (loosing part of the possible gain). Then, it repeatedly charges and discharges the storage before keeping it stable at its final level.

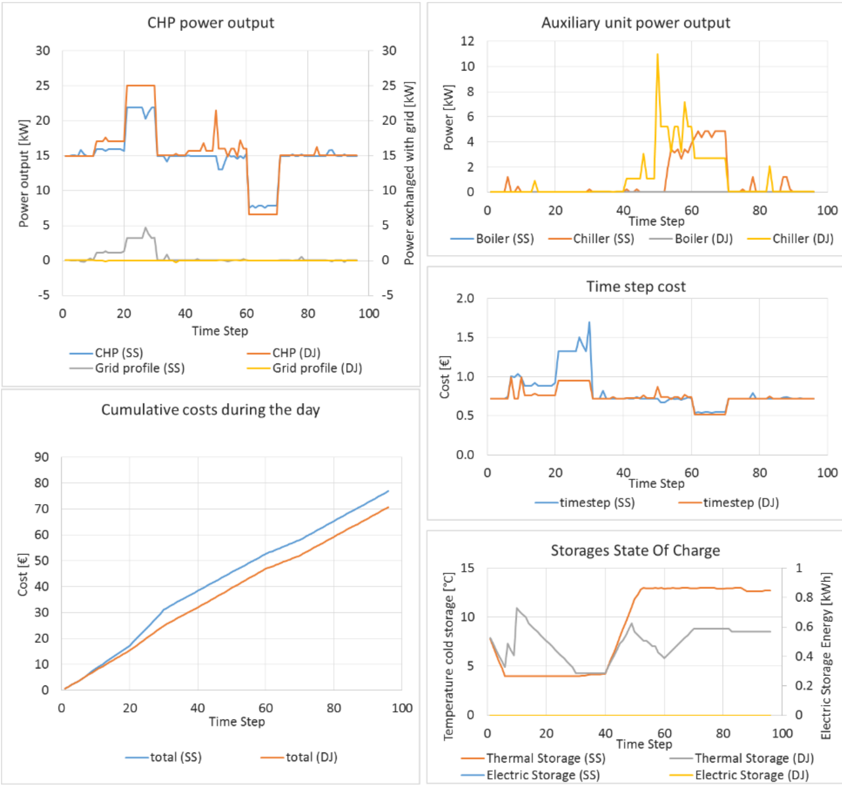


Figure 56 - Results of the comparison between DJ and SS on the "Ad hoc 10e" case

5.1.3 Discussion of the results

The tests illustrated were designed in order to understand the operations suggested by the algorithms, what kind of strategies they adopt to reach their optimized results and what is the actual use they propose for each generation device. Two observations can be made, the first is that apart from the constant case, where the SS algorithm is advantaged by the fact that it can invest much more time to find the same exact solution as the DJ algorithm, DJ performs equally or better in every situation. This complies with an improvement of quality of the solution. The second observation is that the operations suggested by the DJ algorithm as tested cannot be performed on every energy system, for they depend on the thermal layout that it implements. In particular, the adoption of the auxiliary unit to charge the storage when convenient is something that can be done only if the auxiliary unit is installed in parallel with the storage along with all the other generators.

5.2 Tests on actual days

The benchmark profiles, proved useful to judge the quality of the solutions proposed by the algorithms, especially when addressing the coherence of the solution with the physics of the energy system and whether its suggested operation are reasonable. Nevertheless, these profiles do not give an accurate indication of the possible savings allowed by the algorithm's implementation in a real system. To answer this question, a series of real profiles chosen from the data actually gathered by the SCADA on Pontlab plant, were defined. Two possible scenarios are evaluated. The first is the present scenario, where the DSO/TSO do not interfere with the operation of the user and thus it is possible to define an optimized scheduling of the operations of the plant without any constraint but the physical ones (e.g. the balancing of the power or the capacity of the storages). The second scenario considered is the future one, where instead the DSO/TSO requires the power exchange profile with the grid to comply with given rules. In this case, the rule defined in accordance with Enel S.p.A. is that the power exchanged with the grid must be equal to the average value assumed every hour by the unconstrained one proposed by the DAA the day before.

5.2.1 Days selected description

The days chosen as test ground for the algorithms show different combinations of loads and pricing conditions. The test days are nine in total. Four of them were selected for tests in summer-operation mode, whereas the other five in winter-operation mode. The operation mode for the test is the same adopted during the actual day when the data were acquired. In this way it is also possible to compare the results of the algorithms with the actual operation of the system.

The real days selected as test cases for summer operation mode are:

- July 28th, 2013 (Figure 57): A sunny day featuring a solar power availability at high levels, almost constant 10 kW_e electric load with +/- 50% differences between consecutive time-steps. The cooling load is nearly five times the electric load, with the first part of the day showing an average 40 kW_c request with shifts of +/- 25% from the average value. The price of the natural gas is constant and the electricity price varies once every hour with the minimum price paid in the early afternoon (42 €/MWh) and the highest at 21:00 (85 €/MWh);

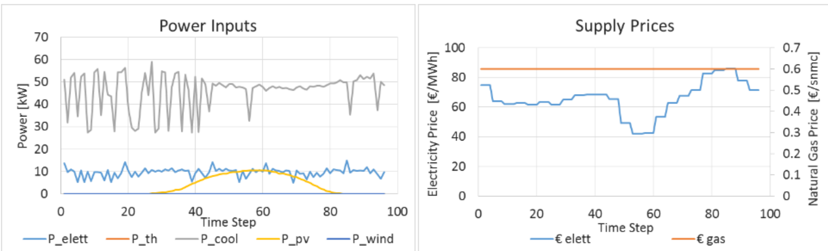


Figure 57 - Loads, renewable availability and supply prices for typical day "28-07-2013"

- September 9th, 2013 (Figure 58): Variable weather during the day, with the PV plants producing more than the electric loads require in some cases. The electric load is around 10 kW_e in the first half of the day, whereas in the second half its average value is less than 5 kW_e. The cooling load is high and, likely because of the operation of the climatic chambers, extremely variable from one time-step to the following (+/- 50%). The electricity prices vary less from one hour to the following one compared to the previous case. Nonetheless the difference between the minimum and the maximum price is higher, with the maximum being three times more than the minimum;

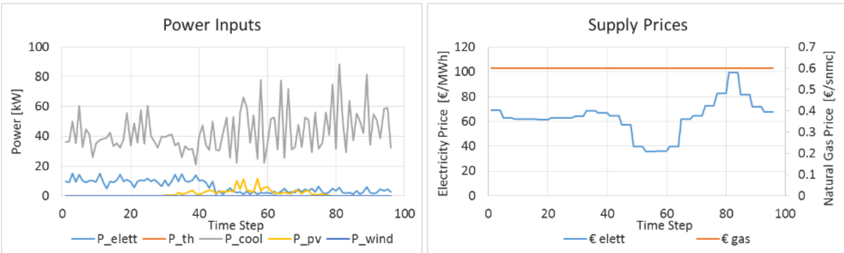


Figure 58 - Loads, renewable availability and supply prices for typical day "9-09-2013"

- September 18th, 2013 (Figure 59): Almost sunny day. The electric load is higher than in the previous cases, with a nearly constant value averaging around 20 kW_e. The cooling load is lower than in the previous cases but still featuring several lower and higher peaks, especially after the early morning. The price of electricity presents two valleys at 50 €/MWh (in the last part of the night and in the early afternoon) and two peaks, a minor one (80 €/MWh) in the late morning and a major one (90 €/MWh) during the evening;

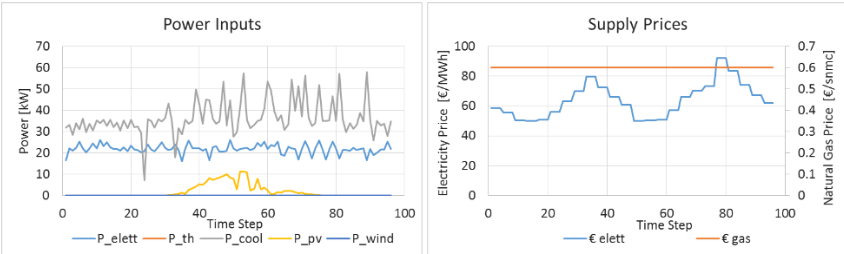


Figure 59 - Loads, renewable availability and supply prices for typical day "18-09-2013"

- September 29th, 2013 (Figure 60): Cloudy day and very low electric load (5 kW_e) with a cooling load more constant compared to the previous test-days averaging around 36 kW_c. The electricity price is steady for most of the day around 60 €/MWh (probably because of the cloudy day all over the country which reduced the PV productivity peaks) until the evening when again the price rises to 90 €/MWh.

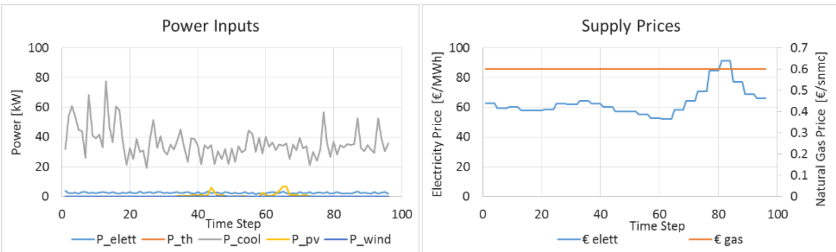


Figure 60 - Loads, renewable availability and supply prices for typical day "29-09-2013"

The real days selected as test cases for winter operation mode are:

- January 11th, 2014 (Figure 61): A sunny winter day where the PV productivity peak scores almost 8 kW_e. During winter operation it is easy to identify the load demand of the climatic chambers. This varies during the day once every half an hour with a very distinctive pattern. The average value of the cooling load is about 10 kW_c. The electric load is very small and present only until 15:00, then it turns to almost zero for the rest of the day. The thermal load on the other hand is consistent yet unsteady both during the day and from hour to hour. The highest peaks reach 40 kW_t whereas the lowest value is zero, registered at 15:45. The electricity price profile is different from the typical summer ones, with a more stable value featuring two "flat peaks" at 80 €/MWh (during the early morning and early evening) and two "flat valleys" at a little less than 60 €/MWh;

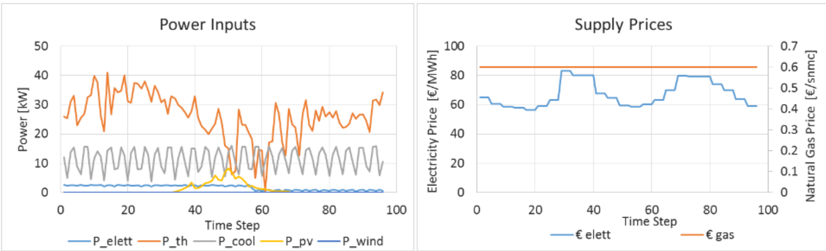


Figure 61 - Loads, renewable availability and supply prices for typical day "11-01-2014"

- January 13th, 2014 (Figure 62): A cloudy winter day with low PV power availability. The cooling load is still driven by the climatic chambers demands. This time the electricity load is at a steady value of 10 kW_e for the whole day except for a window of 4 hours in the afternoon, where the value is lower and near to the turn-off of the CHP. The thermal load presents a very unsteady profile featuring numerous high and low spikes varying +/- 100% from the average value of 19 kW_t. During an extended window of time compared to the one of the electric load, the thermal load decreases to an almost constant value of 10 kW_t. The electricity price shows its lowest value in the late night (32

€/MWh) and a high price period for the whole working day (from 8:00 to 20:00) with an average price of 70 €/MWh;

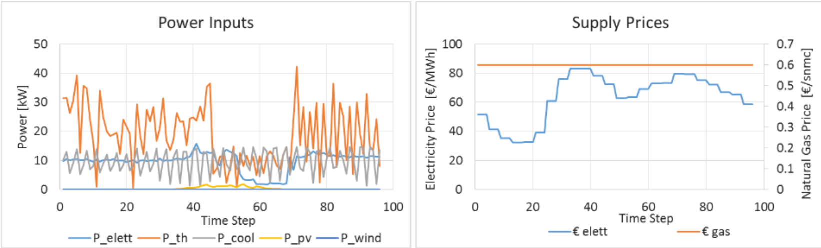


Figure 62 - Loads, renewable availability and supply prices for typical day "13-01-2014"

- March 17th, 2014 (Figure 63): This sunny spring day features a high PV productivity as well as a considerably lower thermal load request. The electric load is constant at 12 kW_e, whereas the cooling load changes once every 15 minutes to +/-70% of its average value of 10 kW_f. As usually happens on sunny days, the electricity price varies greatly during the day, with two distinct peaks: one in the early morning (70 €/MWh) and one in the evening at 90 €/MWh. The lowest value is registered during the night at 25 €/MWh;

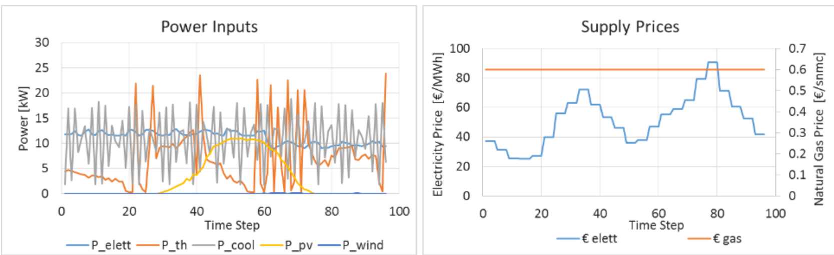


Figure 63 - Loads, renewable availability and supply prices for typical day "17-03-2014"

- March 22nd, 2014 (Figure 64): A day characterized by variable weather. The electric load presents two steady zones, one lasting until the evening at 7 kW_e whereas the second one is at 20 kW_e. The cooling load varies with high frequency due to the operation of the climatic chambers. The thermal load instead is very low and unsteady for the whole day. The electricity price is variable from the lowest value of 18 €/MWh to the highest value of 80 €/MWh; the variation from the minimum and maximum price is registered in less than 5 hours;

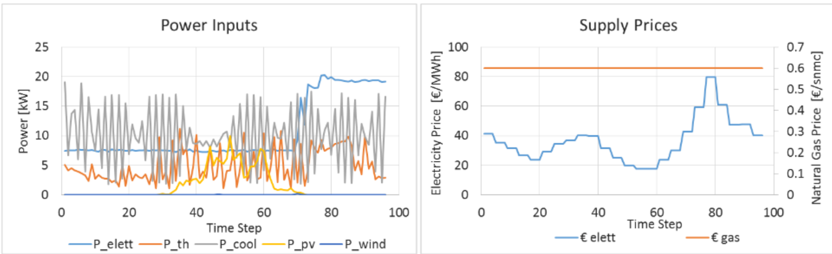


Figure 64 - Loads, renewable availability and supply prices for typical day "22-03-2014"

- March 23rd, 2014 (Figure 65): This day presents a variable PV production due to different weather conditions during the day, typical of spring. The electricity load registers nearly 20 kW_e until the evening when it drops to 7 kW_e. Both the cooling and thermal loads feature high frequency variations of +/- 70% around the average value. The electricity price presents a single high peak during the evening of 80 €/MWh, whereas the average value during the rest of the day is near to 25 €/MWh.

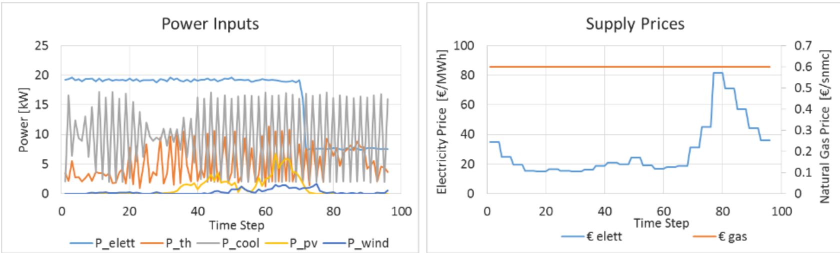


Figure 65 - Loads, renewable availability and supply prices for typical day "23-03-2014"

5.2.2 Comparison of algorithms performance on actual days (present scenario)

The tests performed allowed to understand the expected performance that the different algorithms would have on the actual system. Given the number of tests and the difficult readability of the behavior of the system from the data output, a detailed description of the results will be provided only for those presenting peculiarities or distinctive features. In addition, a summary table presenting the overall performance of both algorithms in every test performed will be presented and discussed at the end of the section.

The first case discussed is the “28-07-2013”, a summer day where the system was tested in summer-operation mode. Therefore, the cooling load is provided by means of the absorption chiller and, when required, the auxiliary unit. The storage managed by the Shortest-Path Algorithm is the cold one. From the diagrams in Figure 66 it can be observed that the CHP is exploited at maximum power in both cases. This is reasonable and happens in most of the summer days because the amount of cooling load to provide is always high, thus modulating the power output of the CHP would be detrimental. Nonetheless, the Shortest-Path Algorithm and the Single Step one provide two unique solutions for storage operations. Given that the cooling load is always high, the Single Step algorithm immediately uses the charge accumulated in the storage at the beginning of the day.

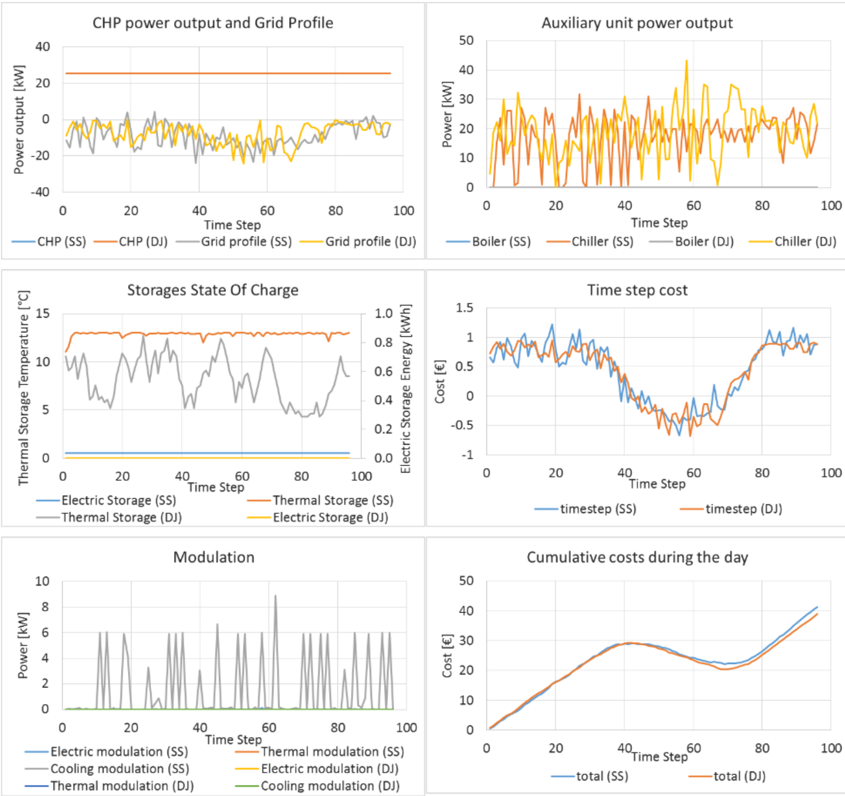


Figure 66- Results of the comparison between DJ and SS on the "28-07-2013 present scenario" case

It performs only a few, minor charges during the day, always followed by an immediate discharge. The downside of this behavior is that the system is often required to modulate part of the cooling load in order to avoid buying more electricity from the grid. On the other hand, the Shortest-Path Algorithm performs several charge-discharge cycles during the day, allowing the system to avoid modulating part of the cooling load. From the auxiliary unit power output diagram it can be noticed how the DJ algorithm, especially between time-steps 40 to 80, employs the auxiliary unit more often. Indeed, those are the time steps featuring a greater RESs' power production and, between time steps 50 to 60 also the lowest electricity price. These are favorable moments to charge the storage, selected by the DJ algorithm in such a way to avoid buying electricity from the grid at high costs and, on the other hand, avoid the modulation of the cooling load. This way of operating the storage results in an economic performance improvement of almost 6% for the DJ compared to the SS algorithm. The electricity exchange profile with the grid resulting from the two algorithms is slightly different and therefore, when the same day is tested in the future scenario, the two sets of inputs are indeed different.

The next case presented is a day operated in winter mode, "17-03-2014". This day is one of those featuring the greatest difference between the SS algorithm and the DJ one. The first thing that can be observed looking at the diagrams in Figure 67 is that usage of the CHP is much more limited compared to what happens during summer days. This is reasonable considering that the average heating load is several times smaller than the cooling load. To a different use of the CHP corresponds also a different grid exchange profile with the grid. It is interesting to notice how the peaks in CHP usage are located in correspondence with the peaks of electricity price, especially in the case of the DJ algorithm. The Shortest-Path Algorithm builds its advantage over the Single Step one in a series of single time steps between the 30th and the 90th, most of the times when the CHP is employed. The final difference between the two suggested operations is nearly 12% less expense for the DJ algorithm compared to the SS one.

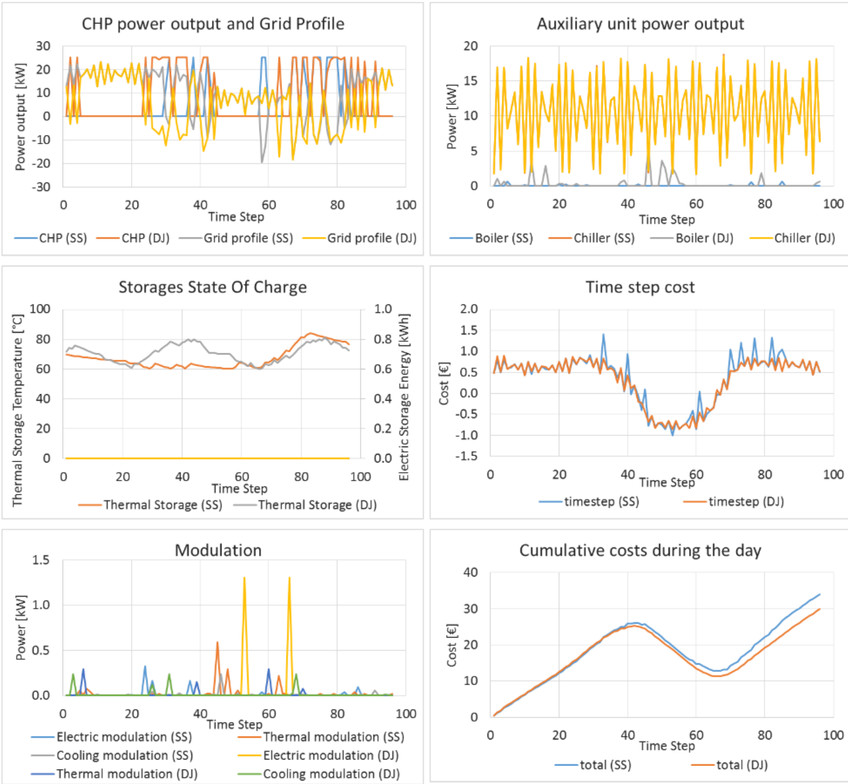


Figure 67 - Results of the comparison between DJ and SS on the "17-03-2014 present scenario" case

During most of the winter days analyzed an interesting behavior is observed: the waste of thermal energy. This heat dissipation is suggested during both charge and discharge of the storage. As was suggested in the previous chapter, this happens for two reasons:

- The resolution of power steps of the storage is poor, thus leading to the choice of a bigger discharge power than the one required at a cost of wasting part of it to achieve the energy balance of the thermal loads;

- It is adopted if the CHP is set to a higher point in order to satisfy the electric load while the thermal storage is full and thus cannot be charged more.

It is possible to exclude the heat dissipation from the proposed solution directly in the GA, applying a penalty to the amount of heat dissipated. However, as highlighted in the previous chapter, the result of this modification is detrimental for the system economic performance. A test to demonstrate this has been carried out and the results are illustrated in Figure 68. The penalty applied effectively eliminates the thermal energy dissipation, but from the diagrams in Figure 68 it can be inferred how it heavily interferes with the solution proposed. Indeed, the use of the CHP is greatly limited and also the management of the storage is very different from the original solution proposed. These differences ultimately lead to a worsening of the operation economy of 20% compared to the Single Step suggested operation. It is clear that this is not the right way to prevent the thermal energy from being wasted. A different solution, which is to be preferred but has a greater computational cost, is to increase the number of subdivisions of the thermal storage charge (i.e. increase the number of nodes in the graph).

Figure 68 - Results of the comparison between DJ and SS on the "17-03-2014 present scenario waste penalty" case

A test has been performed in order to observe the different behavior in terms of thermal waste when performing the same test with a greater number of thermal storage charge subdivisions. From Figure 69 it can be appreciated that increasing the number of subdivisions effectively decreases the amount of heat dissipated. Moreover, an increase in the resolution of storage charge leads to a further improvement of the economic performance. Nonetheless, the number of subdivisions required to impede completely this phenomenon is the one that allows the storage to have the same power resolution of the variables in the GA.

With the hardware adopted for the tests, this value is too high nowadays. Therefore, the thermal dissipation suggestion must be accepted. It is worth noticing that on the actual plant there are no means to actively dissipate heat from the storage, thus the suggested operation cannot be matched perfectly. This is where the ADA comes in aid, allowing the minimization of the error in storage charge prevision during the day thanks to its update of the initial inputs once every 15 minutes. With a greater number of subdivisions the gap between the SS and the DJ costs of operation increases as well, reaching over 16% with 80 subdivisions, up from almost 12% when adopting only 30.

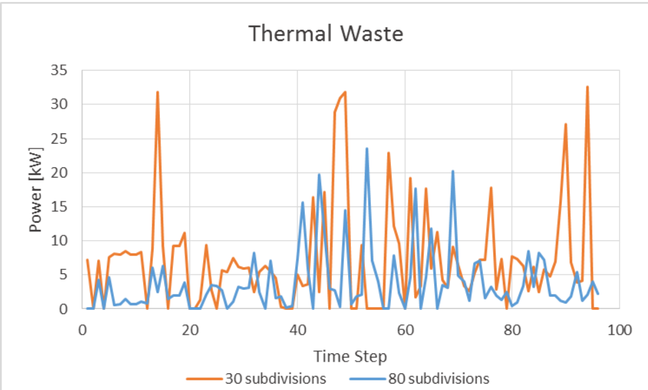


Figure 69 - Effect of the increment of thermal storage charge levels on the amount of heat wasted

5.2.3 Comparison of algorithms performance on actual days (future scenario)

In order to highlight the differences between the present and the future scenario, the tests described hereafter will be the same presented in the previous section. Hence, one summer case, “28-07-2013”, and one winter case, “17-03-2014”.

The first thing to notice in these two cases is the shape of the power exchange profile with the grid, which in the future scenario is imposed as input. These profiles are different for the SS and the DJ algorithms because the original profiles from which they are obtained are different. A downside of the way these profiles are derived is that the rule applied to generate them actually changes the input sets of the original problem. Thus, the original optimized solution suggested by an algorithm could be worsen greatly whereas one of a different one could be less influenced.

The operations suggested for the summer day are presented in Figure 70. The top-left diagram shows both the CHP power output and the grid profile exchange suggested by both algorithms. What featured a continuously changing profile now is almost steady for periods of one hour. When the curves illustrated in the top-left diagram present a spike in the grid power exchange profile, it means that the algorithm could not find a less-expensive solution to comply with the profile assigned, thus accepting a penalty for the shift from the resulting profile. The advantage granted in this case by the use of the Shortest-Path Algorithm compared with the Single Step is evident in the bottom-right diagram presenting the cumulative costs during the day. The gap between the two algorithms is now increased to over 31%. This results from the greater flexibility of operation allowed by the DJ algorithm compared to the SS one. It can be noticed how different is the storage management between the two solutions and also the greater use of the compression chiller performed by the DJ algorithm. This allows the definition of a solution featuring a better compliance with the profile assigned and a lesser need for load modulation to respect the promised profile, which leads to a reduction of costs of operation. The greater flexibility of management can be observed also in the center-right diagram, where the curve associated to the time-step costs of the solution proposed by the DJ algorithm is smoother than the one featured by the SS algorithm.

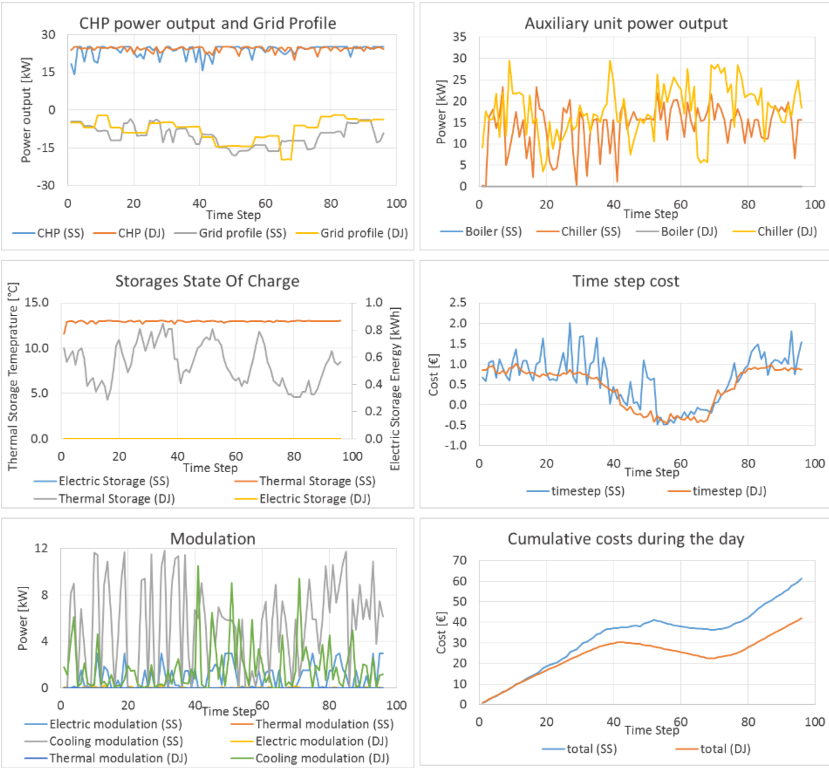


Figure 70 - Results of the comparison between DJ and SS on the "28-07-2013 future scenario" case

Similar considerations can be done from the analysis of the winter day, whose outputs are presented in Figure 71. In this case, the benefits due to the adoption of the Shortest-Path Algorithm increase up to 26% compared to the Single Step. In this test, given the segmented nature of the cooling load, it is inconvenient for either of the algorithms to respect the promised grid exchange profile. This is evident from the top-left diagram where the grey and yellow curves show numerous spikes during the whole day. However the DJ algorithm presents a minor number of non-compliances and this leads to the better result achieved by this solution. This is achieved by a dedicated management of the storage, which is used to back-up the CHP when it is not convenient to modulate its power output.

In the following section, a summary of the results obtained in the various test cases is presented, along with a discussion of the results themselves.

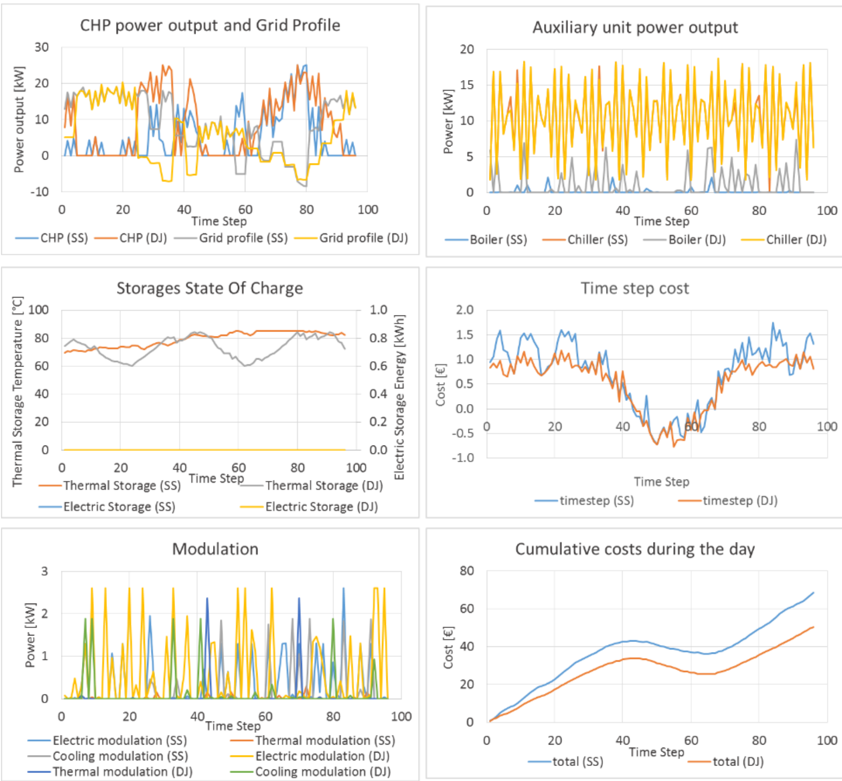


Figure 71 - Results of the comparison between DJ and SS on the "17-03-2014 future scenario" case

5.2.4 Discussion of the results

The analysis carried out shows the potential benefits that the introduction of an evolved algorithm for the plant management brings. The plant considered presents several energy generators, from RES to ICE, modulated loads and energy storages. Figure 72 illustrates the summary of the economic comparison between four different management strategies for the plant considered. All the economic performance are related to the costs of a conventional operation of the plant (i.e. buying electricity from the grid to supply the electric and cooling load, natural gas to supply the thermal loads). Two standard operation modes are added to the comparison, Thermal Load Following and Electric Load Following. On the other hand, the evolved strategies are those suggested by the Single Step and the Shortest-Path Algorithm. Considering that the standard operations (ELF and TLF) are not meant for the management of the plant in the future scenario, the comparison is done only considering a free power exchange profile with the grid. Indeed, it is evident how ELF and TLF would be ineffective to grant compliance with a profile promised in the day before operation. The comparison is further divided in: summer, winter and overall. From Figure 72 it can be noticed how the improvements allowed by the SS and DJ algorithms are just slightly better than those allowed by TLF and ELF during summer days. The reason is that a single CHP unit is under-dimensioned for the cooling loads during the summer season. Hence, the CHP is at maximum power most of the time. With the CHP power output maxed out at every time-step it is hard for the evolved strategies to take an advantage over the standard ones. The situation is different during winter days, where the thermal load is not persistent and its average value is lower than the maximum thermal capacity of the CHP. The diagram in Figure 72 clearly shows the ineffectiveness of standard operation of the CHP during winter period, where the improvement granted by the TLF is minimal and ELF strategy is detrimental. On the other hand, both the Single Step and Shortest-Path algorithms achieve a cost reduction, of 19% and 27% respectively, in respect of the conventional operation. The overall values consider the average benefit registered in the 9 test days considered. From this, the potential of the evolved strategies is evident, even in the present scenario.

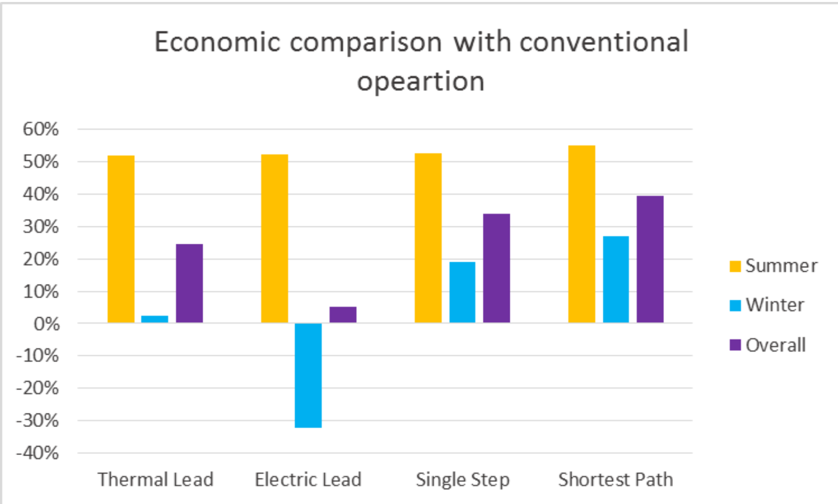


Figure 72 - Summary of economic performance of different operation strategies compared to the conventional supply in the present scenario

It is also interesting to analyze which evolved strategy performs best when the future scenario is considered. Figure 73 illustrates an economic performance comparison of DJ and SS algorithms in the future scenario, compared to the results obtained by the SS algorithm with the present scenario. As reference, also the performance of the Shortest-Path Algorithm in the present scenario are provided. The DJ algorithm achieves better results compared to those of the SS algorithm both in summer and winter period. On average the gap is 4% during summer and 11% during winter. When the rules of the possible future scenario are applied, the Single Step algorithm performance falls, reaching a cost increase of almost 35% overall, with one test case scoring over 100% cost increase. The expenses rise also for the Shortest-Path Algorithm, although this happens only in the winter period. The overall performance is worse by 14%.

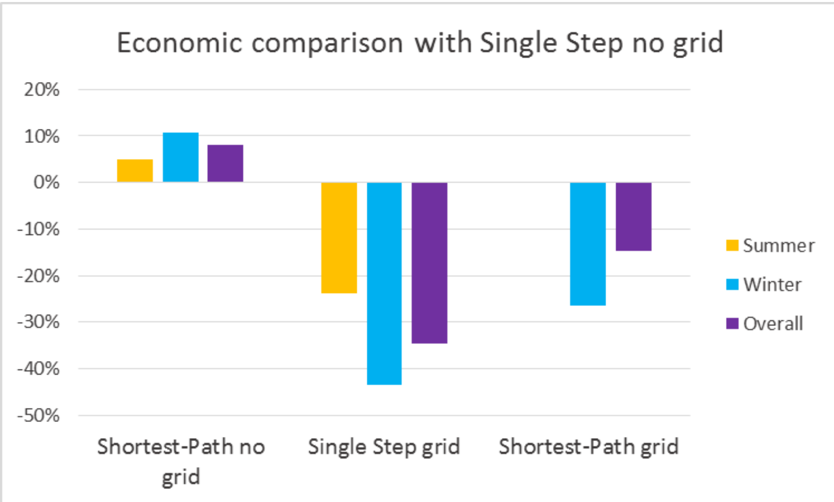


Figure 73 - Summary of economic performance between the Single Step and Shortest-Path optimization strategies in the future (Grid) scenario

From the analysis carried out it is evident that the evolved strategy proposed by the algorithm performing a proper daily optimization is preferable and more reliable. The algorithm proved to be versatile and capable of adapting the solutions proposed to the different test conditions.

5.3 Plant layout comparison

Once the Shortest-Path Algorithm demonstrated to be the best solution to adopt in the Smart User, another series of tests was performed; again, both in the present and future scenario. In the chapter dedicated to the description of the plant, it was pointed out how the thermal layout of the plant influences the choice of the algorithm and therefore the performance that can be obtained. In order to assess the influence of the plant itself on the performance achieved by the control strategy a comparative offline study was performed. Hereafter two thermal layouts are compared: the one defined as Smart User (Figure 13), where all the generators are connected in parallel to their respective storage, and the more traditional one featuring Pontlab (Figure 15), where the auxiliary units are in cascade between user and storage. In addition, for each of these two layouts, the influence of the storage on the performance was evaluated. In particular, the aim is to address which storage (electric or thermal) introduces the greater benefits in the test cases analyzed. Thus, for each case, first the solution without any storage is evaluated, then two equivalent tests, one featuring a thermal storage, one an electric storage are performed. The storages of choice in the tests are: the actual thermal storages installed in Pontlab for the thermal case; an electric storage that was evaluated appropriate for the Smart User plant by Yanmar Research Europe, in the electric case. Table 10 recaps the different storages features.

Table 10 – Storages' energetic figures

	Capacity [kWh]	*Max charge power [kW]*	*Max discharge power [kW]*	*Minimum state of charge allowed*	*Maximum state of charge allowed*
Thermal hot storage	87.2	38.6	76.8	60 °C	85 °C
Thermal cold storage	20.9	27.1	53.2	13 °C	4 °C
Electric storage	15	12	28	1.5 kWh	13.5 kWh

5.3.1 Pontlab thermal layout

Figure 74 presents the beneficial effects of the thermal and the electric storages implementation in a Pontlab-like plant. The comparison is performed against the results achieved on all the typical days test cases examined without employing any kind of energy storage. The first observation that can be made is that the convenience of one storage or the other depends on both the season and the scenario considered. The thermal storage, in the case of Pontlab thermal layout, can be operated in a limited manner because of the way the auxiliary units are controlled and the impossibility to directly manage the storage power output. Thus, given the low resolution of storage power exchange and the cooling load intensity, the cold storage does not introduce any real benefit in the plant. When a grid exchange profile with the grid is assigned, the influence of the cold thermal storage is even detrimental, although this result is closely dependent on the number of subdivisions imposed on the storage charge. If these were high enough, then it is likely that the negative effect of the storage would change into a null effect. On the other hand, the hot storage employed during the winter period has a clear positive effect when there is no profile defined by the DSO/TSO. This is due also to the heating load itself, which is lower than the CHP potential most of the time and therefore allows a better management of the storage operation. Regarding the electric storage, its importance is always greater during winter rather than summer. In the present scenario, the benefits are little during both summer and winter. However its importance is evident when a given grid profile must be respected, as the benefit of over 18% proves. The reason is clear as it provides a versatile tool to achieve a greater flexibility of operation to the plant. Considering both the summer and the winter period, it could be said that in the present scenario it is preferable to include a thermal storage, whereas in the future scenario it is definitely better to introduce an electric storage.

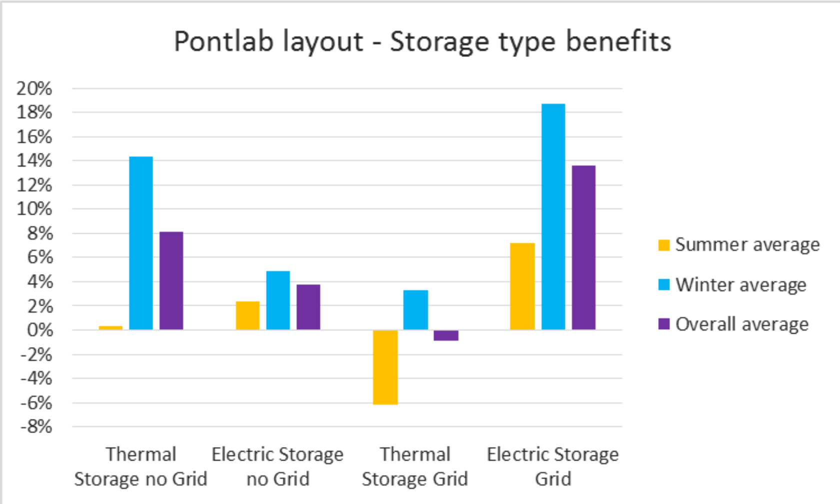


Figure 74 - Summary of economic performance for different storage solutions in both present (no Grid) and future (Grid) scenario with Pontlab thermal layout. Comparison against absence of storages.

5.3.2 Smart User layout

A similar series of tests was performed also considering the Smart User layout. The summary of the results is presented in Figure 75. The electric storage shows a trend similar to the Pontlab layout, although there is less difference between the performance of the plant without storages and the one featuring the electrical one. The likeness of the trend is explained considering that the only difference between the two plants is in the thermal layout. The minor difference, on the contrary, is due to two aspects. Firstly, the natural randomness of the optimization process, which is hardly to provide the exact same result in different evaluations of the same case. Secondly, to the fact that the DJ algorithm designed to operate on Pontlab plant can exclude the cyclic operation of the storages if required to reach the optimization goal. However, where the Smart User layout differs from the Pontlab one is the way the thermal storage is managed. The summary in Figure 75 highlights that, overall, the thermal storage implementation grants an average improvement of 9% both in the present and the future scenarios. In both cases the greater advantage is reached during the winter period, but the gap between winter and summer operation is reduced when considering an imposed power exchange profile with the grid. This is due to the electric energy consumption of the auxiliary unit, a compression chiller, during the summer period. Hence, the adoption of an actively manageable cold thermal storage can be used also to regulate the power exchange profile with the grid, activating or deactivating the compression chiller accordingly.

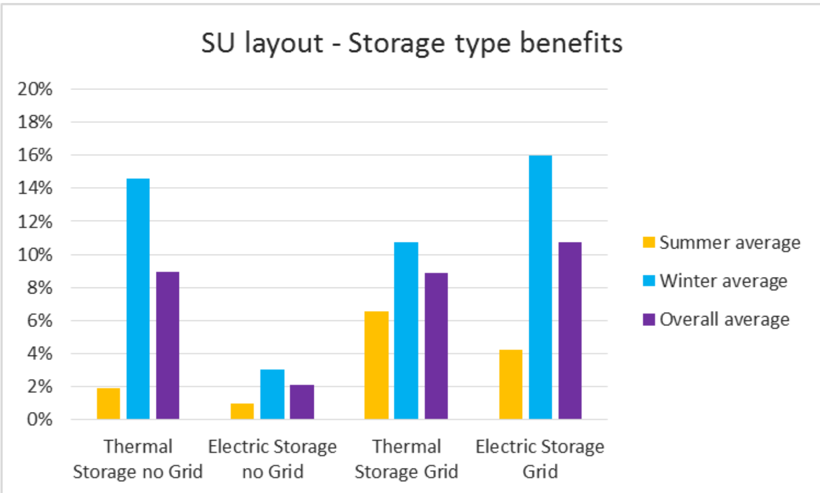


Figure 75 - Summary of economic performance for different storage solutions in both present (no Grid) and future (Grid) scenario with Smart User thermal layout. Comparison against absence of storages.

5.3.3 Plant comparison

An overall comparison among the conventional energy supply, CHP standard operation and the Shortest-Path algorithm applied both to

Pontlab and the Smart User layout is presented in Figure 76. The comparison is made considering only the operation in the present scenario, for the standard strategies will perform poorly in the future scenario.

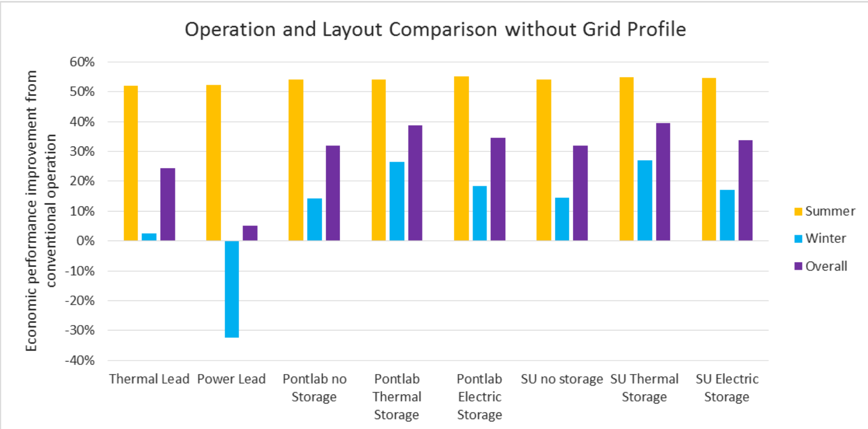


Figure 76 - Summary of economic performance for different operation strategies and storage solutions. Comparison against the conventional supply without any storage

As was also pointed out when discussing the difference between the performance obtained by the SS and the DJ algorithm, the margin of improvement in comparison to a TFL approach during summer is minimal. Again, this is due to the high cooling load and an under-sizing of the CHP in relation to the summer loads. On the other hand, during winter, the possible improvement is relevant, up to 25% compared to the best traditional strategy (TFL). In general, for both kinds of plant layouts, at present, it is better to employ a thermal storage rather than an electric one.

Further tests were performed in order to assess the potential of the exploitation of both thermal and electric storages at the same time. For both thermal layouts, but especially for the one with the auxiliary units in cascade, this is expected to provide a further improvement in the economy of daily operations of the plant. Nonetheless, the improvement is not necessarily the sum of the two contributions of the storages when considered alone. Again, the plant behavior is non-linear, thus the effects of the two storages cannot be added one to the other. The problem highlighted during the test is that because of the limited computational resources when using the DJ algorithm written in MatLab© code, the number of storages level of charge subdivisions is limited to 8 for each one. As was pointed out earlier, the resolution of storage level of charge is a key aspect for achieving a good quality of the optimized solution. With only eight levels at our disposal, the resolution is poor, and thus the plant operation suggested by the optimizer could not reach economic performance equal or better to those measured when considering only one storage. Indeed, 8 levels for each storage are insufficient and further tests will be carried out on the same algorithm translated into C++ code.

5.4 Real Time Algorithm tests and discussion

This section covers the resulting operation obtained by means of the Real Time Algorithm. Two main sets of inputs were used: the first set refers to the actual day, 23rd of October. In this case, both the data needed for the forecasting and the real time algorithm come from real time data measurements of a single day. The second set is referred to as "fictional day". This second set of inputs was created in order to test the real time algorithm on harsher conditions compared to those featuring the actual day.

The fictional day was created as follows:

- The real time data come from the 23rd of October 2013;
- The weather forecasts are those of the 9th September 2013;
- The load and costs are those from 18th September 2013;

- The penalty for not complying with the grid exchange profile was set to 0.1 euro/kW and the profile to be respected was the one provided as output by the single step forecasting algorithm, to which was applied the rule defined with Enel S.p.A.

Both the loads and the weather forecasts were chosen considering their similarities with those provided in real time for October 23rd. Thus, the real time data used could still be those of the 23rd of October. However, the weather forecasts and load planned result moderately wrong, which is an ideal condition for RTA test. If the difference between loads in the forecasts and the real day or between the weather forecasts and the real day were too high then the test would not have been appropriate for the real time algorithm, because it would have tested it on a very harsh and unlikely to happen situation.

In respect of the grid exchange profile chosen, many possible combinations of profiles and penalties were tested: the zero exchange profile (VSO) appeared not to be feasible for the actual plant with the given inputs, thus the need to find a profile that could be both: reasonable and not too specific. This led to the definition of the grid exchange profile based on what the forecasting algorithm suggested without any penalty assigned. The profile was then modified in order to shave the peaks and fill the valleys.

Actual day test

The actual day is featured by the weather and electrical load forecasts depicted in Figure 77, as well as the suggested CHP output profile for the day provided by the DAA.

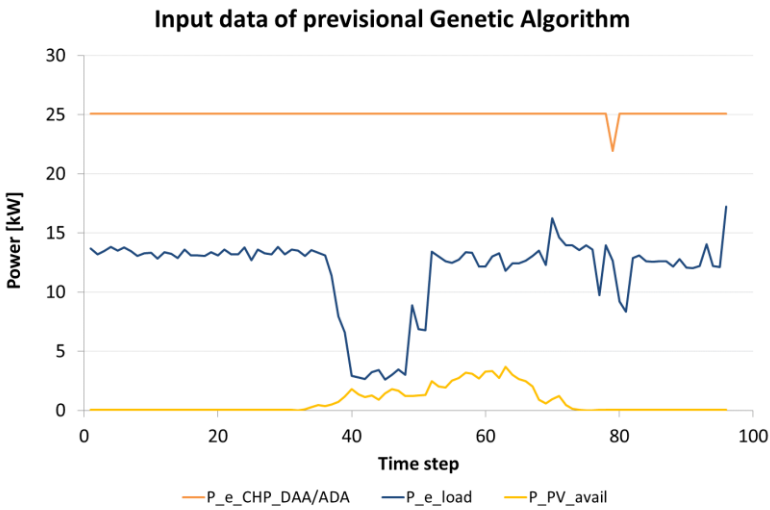


Figure 77 - Day ahead relevant input and outputs for the actual day

The real time data acquired by the SCADA for the same day are showed in Figure 78.

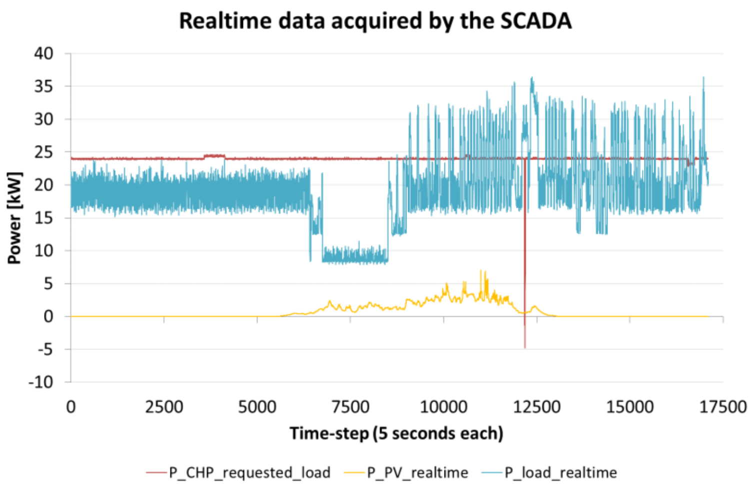


Figure 78 - Real time data acquired by the SCADA system in the actual day

Compared to the forecasts the differences are small, as should happen when the forecasts are accurate. The other main differences is the presence of numerous spikes in the real time load, which are not present in the day ahead input data because there the time step is 15 minutes. Thus, the input data are an average of the real ones.

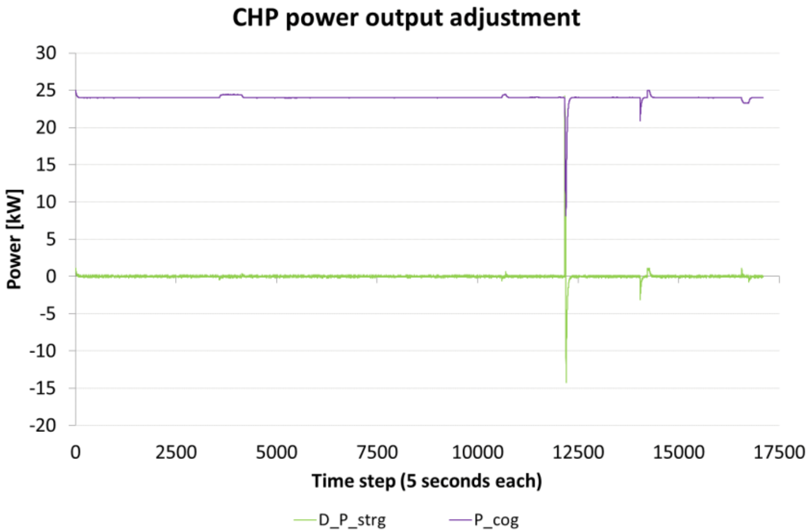


Figure 79 – Adjusted power output of the CHP and power output of the storage in the actual day

The real time algorithm provides the results shown in Figure 79 and Figure 80. The first diagram illustrates the CHP power output once adjusted to take into account the variability during the real time operation and the power output that the dedicated electric storage should provide. The algorithm also ensures that the maximum CHP power output is not overcome. The second diagram shows the required management of the electric storage. From the diagram, the recommended size and power output of the storage can be inferred.

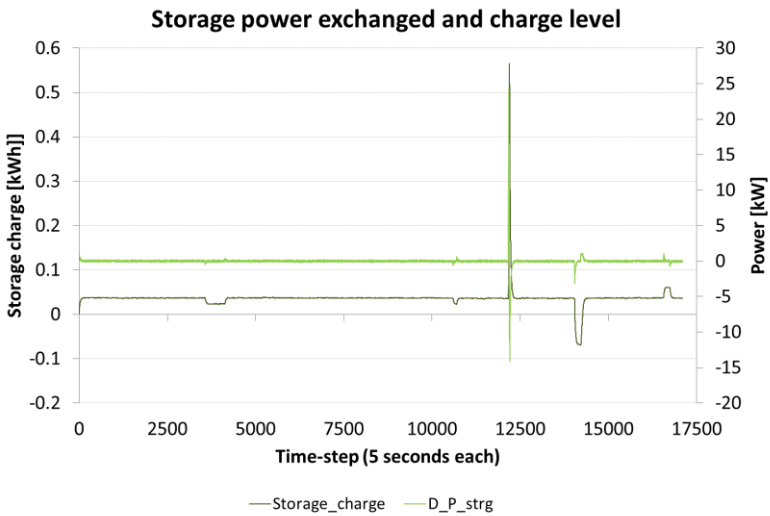


Figure 80 - Storage power exchanged and state of charge for the actual day

The maximum difference in terms of charge inside the electrical storage is around 0.6 kWh (+0.56 / -0.06 kWh), suggesting that the minimum needed size for the actual case tested is small. If it were not for the high power spike in the last third of the day the difference would have been less than 0.1 kWh. The power output required instead is compatible with the maximum power of the CHP.

As previously stated, the actual day tested is not very stressful for the system. Hence, alone, it is inadequate to test the RTA. For this reason the "fictional day" described in the following section was set up.

Fictional day tests

The input PV and electrical load forecasts used inside the forecasting algorithm are shown in Figure 81. It can be noticed that the CHP operation is no longer steady, there is some modulation. This happens because a grid profile to be respected was assigned to the forecasting algorithm along with a penalty in case of non-compliance. It can also be noticed that compared to the real time data, the PV productivity differs by some extent and that there is no expected load drop in the middle of the day. The promised grid profile can be seen in Figure 82. In this particular case the profile promised derives from the grid exchange profile that the SU would have done if there were no penalties applied for grid profile.

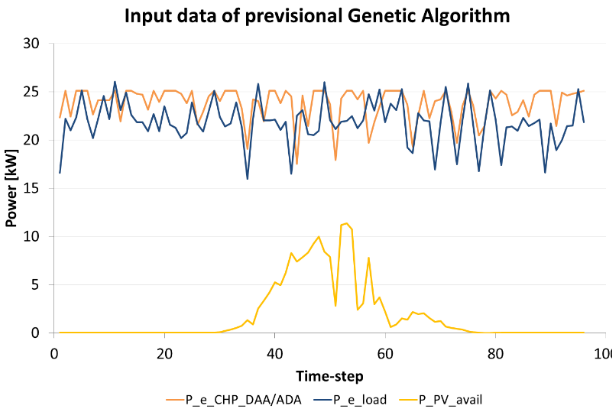


Figure 81 - Day ahead relevant input and outputs for the fictional day

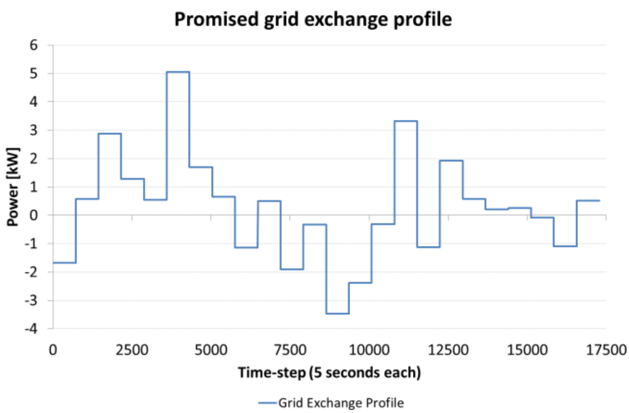


Figure 82 - Promised grid exchange profile for the fictional day

The real time load that the CHP must supply is calculated from the balance between the total user load, the grid profile to be respected and the renewables productivity. In the diagram in Figure 83 the real time requested load to the CHP, the total load and the PV productivity are depicted. All the hypotheses considered, for this particular kind of load profile the situation for the CHP is hard to handle. The load it should provide is as high as 36 kW, well over its capabilities. This will reflect on the real time operation, especially on the electrical storage size.

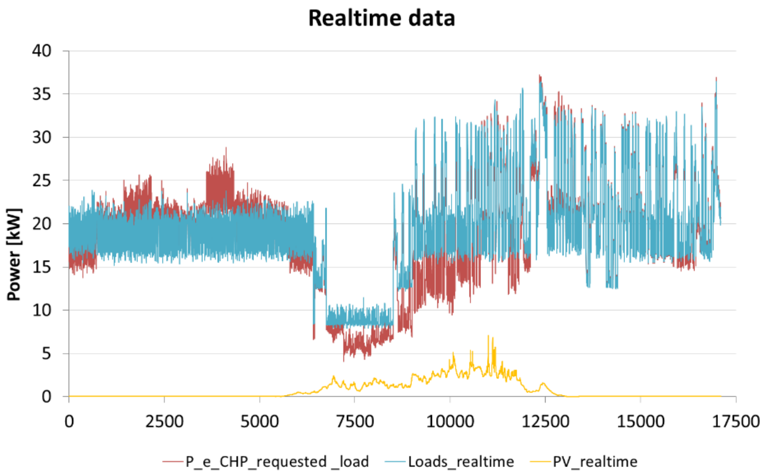


Figure 83 - Real time data for the fictional day

Given the presented inputs, the results provided by the real time algorithm are shown in Figure 84 and Figure 85.

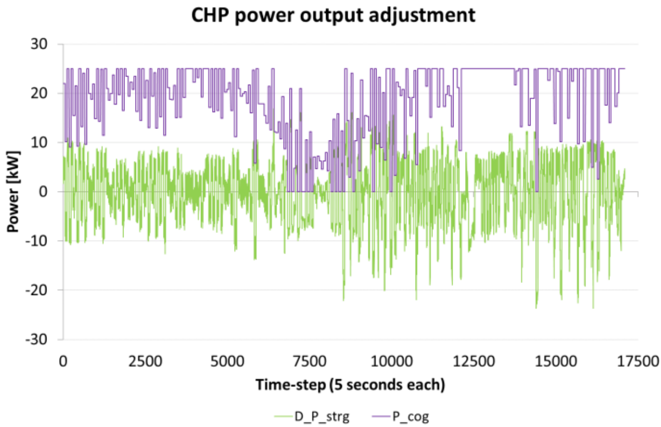


Figure 84 - Adjusted power output of the CHP and power output of the storage in the fictional day

The corrected power supplied by the CHP here is changed once every 5 minutes in order to prevent the CHP from operating in transient conditions at all times. In the latter part of the day, when the load requested to the CHP is high at all times the CHP is always on and at maximum power output.

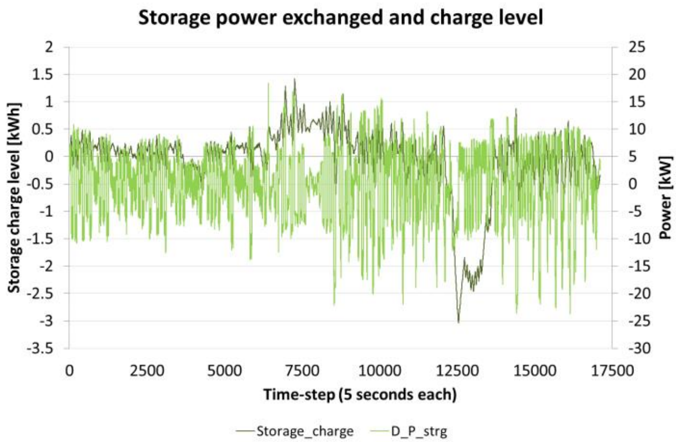


Figure 85 - Storage power exchanged and state of charge for the fictional day

The power requested from the CHP is often higher than its maximum potential because of the difference between the forecasted and the actual loads/renewables availability. The size of the storage required is around 4.5 kWh, less than the battery pack of a small electric car. On the other hand, the maximum power that the storage must supply is less influenced by a completely wrong forecast. Indeed, it is of the same order of magnitude of the CHP in most of the situations.

Fictional day modifications: limited load

The first modification applied to the fictional day was to reduce the electrical load to a value closer to the maximum CHP power output. The set of inputs for the forecasting algorithm is the same, in terms of loads, costs, renewables availability and grid profile imposed, therefore the expected CHP profile for the day is the same. The differences can be observed in the real time data, Figure 86, and in the algorithm results, see Figure 87 and Figure 88.

From Figure 88 it can be immediately noticed that having lowered the whole measured real time load, the almost zero electric load in the middle of the day leads to a completely different storage management. Nevertheless, the maximum size of the storage in this case is almost unchanged because it depends on the difference between the forecasted and actual load and renewables availability and the time the discrepancy lasts. Anyway, to assess the correct storage size for RTA, the best approach is to perform an extended campaign on the real time measured data for different days and situations. On the other hand, the offline tests performed are useful to test the correct behavior of the real time algorithm and perform sensibility analysis on the different parameters beforehand.

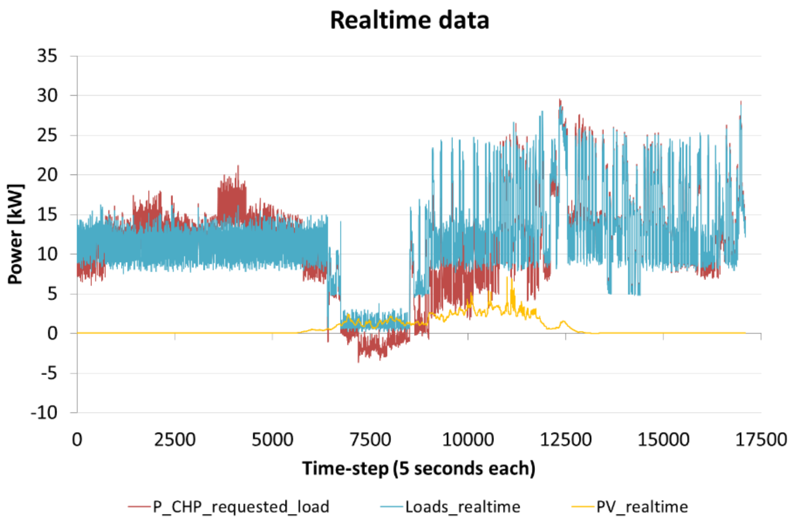


Figure 86 - Real time data for the fictional day with limited load (CHP set point changes every 5 minutes)

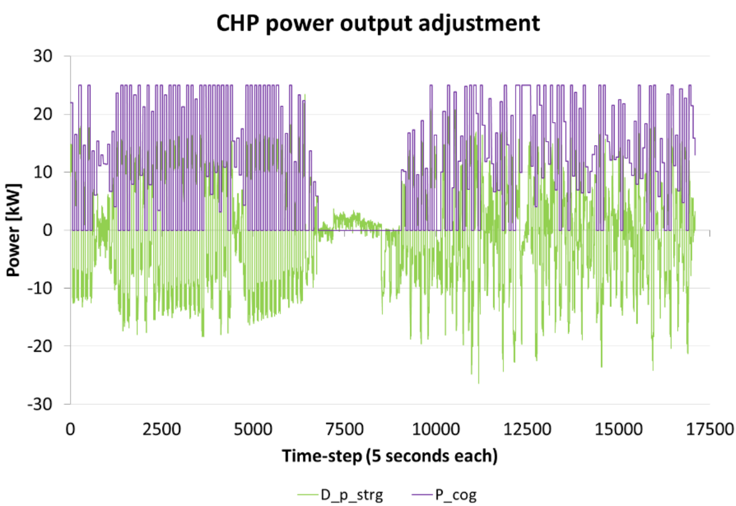


Figure 87 - Adjusted power output of the CHP and power output of the storage in the fictional day with limited load (CHP set point changes every 5 minutes)

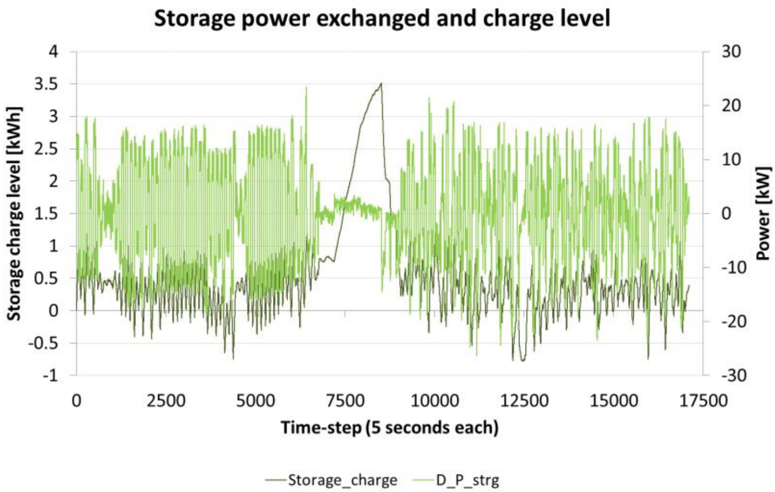


Figure 88 - Storage power exchanged and state of charge for the fictional day with limited load (CHP set point changes every 5 minutes)

Fictional day modifications: unsteady operation of the CHP

The previous test was repeated changing the way the correction had to be applied to the CHP, instead of deciding a set point every 5 minutes here it was set to every 5 seconds. As already said this is not an ideal way of operating the CHP because it makes the engine change load very frequently, therefore reducing its efficiency and stressing more the engine itself. The test aims at evaluating the difference in terms of storage size depending on the way the CHP is operated. If the difference results negligible then there is no reason to assign the set point of the CHP once every 5 seconds. The inputs adopted are the same as for the previous run and the related diagrams are not reported. From the diagrams in Figure 89 and Figure 90, representing the results of the real time algorithm tested in this condition, it can be noticed that the storage is about the same size of the previous case, around 4.5 kWh. Therefore, there is no need to work in unsteady conditions at all times. Indeed, it is better to assign to the storage the duty to follow the load and compensate the difference with what it was promised rather than to the CHP.

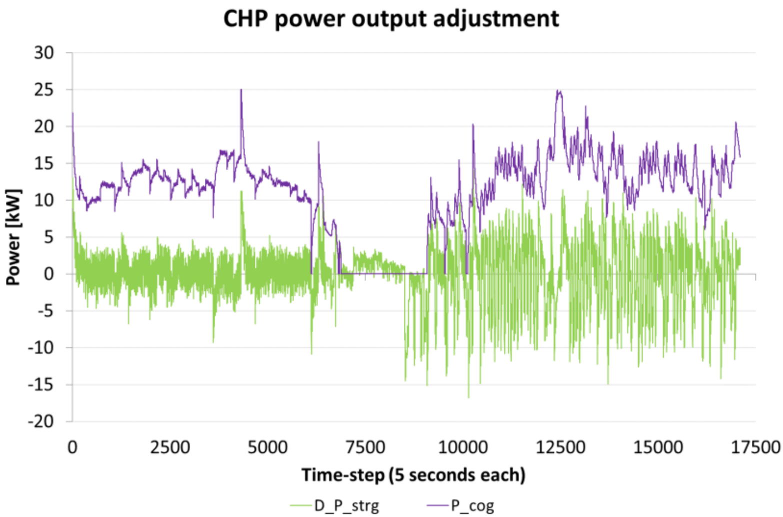


Figure 89 - Adjusted power output of the CHP and power output of the storage in the fictional day with limited load (CHP set point changes every 5 seconds)

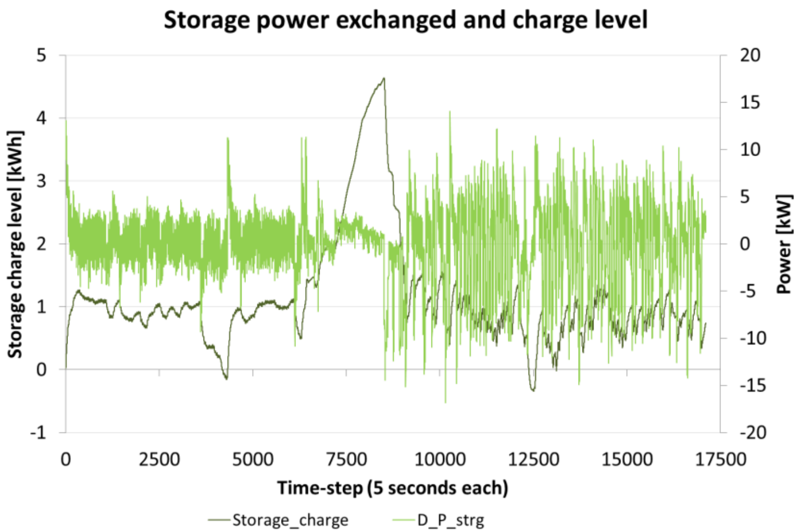


Figure 90 - Storage power exchanged and state of charge for the fictional day with limited load (CHP set point changes every 5 seconds)

Fictional day modifications: Time to pair comparison

The last test carried out was performed to assess the effect of the parameter “time to pair” which represents the number of time steps that occur before the correction is successfully applied on the forecasted CHP output so that it matches the actual request. All the inputs are the same as for the previous case but the value of the time to pair, was reduced to two minutes, down from five. The effect of this modification can be noticed considering Figure 91 and Figure 92.

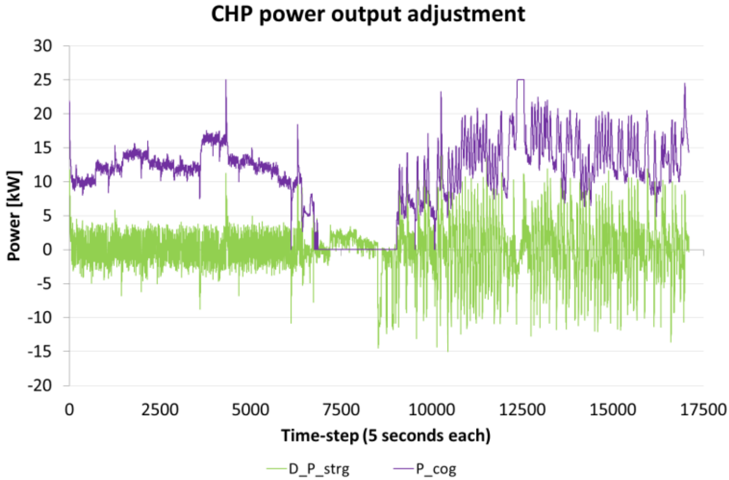


Figure 91 - Adjusted power output of the CHP and power output of the storage in the fictional day with limited load (CHP set point changes every 5 seconds and Time to pair set to 2 minutes).

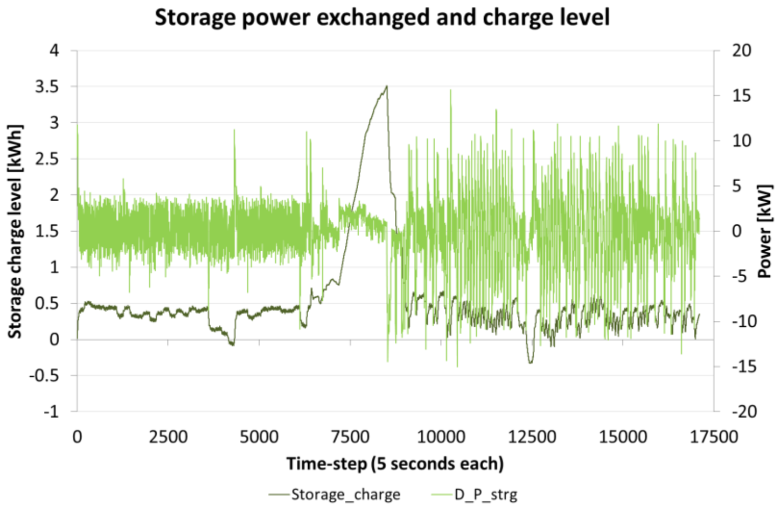


Figure 92 - Storage power exchanged and state of charge for the fictional day with limited load (CHP set point changes every 5 seconds and Time to pair set to 2 minutes).

The storage power exchanged and charge level diagram suggests that to a smaller time to pair corresponds a smaller storage (3.5 kWh) but has almost no effect on the power exchanged by the storage. Indeed, a lower time to pair means that the CHP will correct its power output faster, thus limiting the energy that the storage must provide in the meanwhile.

6 CONCLUSIONS

The increasing energy demand by industrialized and developing Countries is becoming a critical issue both in terms of how to supply the demand and effects on the World's climate. Renewable Energy Sources could serve as a powerful mean to inject more energy in the power system but those featuring the greatest potential in terms of power production are also affected by unpredictability. Because of their innate intermittency due to the possible rapid changes of weather conditions, solar and wind power are difficult to handle by the energy system, especially when their penetration in the grid reaches over the 30% of total rated power installed. A possible solution to allow a further increase in solar and wind power in the global energy mix is to ensure that their power output can be predicted and managed in the short-term. Thanks to their versatility and extended metering, monitoring and control system, Smart Grids show a great potential regarding the increase in economy of operation, environmental friendliness, security and reliability of the power system. Smart Grid are large-scale systems, typically regional or national, composed of smaller scale actors that share the same philosophy of construction, control, and purpose. The fundamental part of the Smart Grid is represented by intelligent users, which are capable of answering to different drivers so as to minimize the costs or environmental impact of their operation. Whereas the greatest asset of the traditional power system is its hardware, the most important tool of the Smart Grid is its control system and thus the strategies proposed for its operation. This Thesis project proposes to define an optimized strategy for the management of the end-user connected to the broader Smart Grid, its base component, the Smart User.

The control and optimization strategies are always connected with the physical plant, thus the first part of the project dealt with the definition of the Smart User design and its installation in an actual facility in order to carry out tests on actual data. This is rarely found in the literature, where most of the works rely on fictional data or are based on scenario evaluations from historic data. Nonetheless, the presence of an actual plant on which to base the tests, compared to the common practice, allows a deeper connection between the optimization strategy and the actual plant and thus enhances the fallback of the research on the final application.

The Smart User experimental plant is located in Pontlab facilities, sited in Pontedera (PI). Inside Pontlab facilities are carried out several tests of different kinds for industrial partners. This specific user was chosen among different candidates because of the chance to adopt both Demand Side Management strategy, thanks to its modulated loads, and generation curtailment strategies. Several different generators are installed in the facility, including: a PV field, a small wind turbine, two auxiliary thermal units (a boiler for heating and a compression chiller for cooling) and a co-generation unit coupled with an absorption chiller for the supply of cooling power during summer. Two thermal storages, one for the hot loop and another for the cold loop are installed and an electric storage can be virtually simulated. The tests carried out demonstrate the positive influence of storages on plant performance, thanks to the flexibility of operation that they allow. Regarding the electric plant layout, every generator and load is connected to a main switchboard, which is linked to the energy meter towards the grid and controlled by the SCADA system. On the other hand, two possible thermal plant layouts can be adopted for a Smart User. The most flexible one features all the generators installed in parallel to their respective storages. It allows the plant to achieve the best performance but it is also harder to control and operate with commercial equipment. The other possible layout is closer to the conventional thermal plants in tri-generation application; indeed, in this case the auxiliary units are in cascade between the storage and the load. Because the Smart User experimental plant is installed in an actual facility, for which all the technical and safety standards must be met, and because the Smart User was installed on a previously existing plant, the layout of choice for Pontlab was the latter. The SCADA system receives all the inputs from the temperature sensors and energy meters in the plant, as well as the price inputs from the electricity market and the weather forecasts. In addition, it receives from the user the activities planned for the following day. Thanks to the inputs provided, three algorithms run inside the SCADA: two dedicated to the optimization that provide as output the set points for the generators and the non-prioritized loads, one to the real-time balancing of loads and generators.

All of the algorithms were designed ad hoc for Smart User application during the Thesis project and introduce a new strategy for the management of energy systems in the literature. The two optimization algorithms act at different times, the Day Ahead Algorithm (DAA) during the day before operations, conversely to the Advanced Dispatching Algorithm (ADA) that runs every fifteen minutes during the day it optimizes. The DAA allows the user to prefigure its operations depending on the activities planned for the day ahead, the weather forecasts and cost conditions. In addition it communicates to the Distribution or Transmission Service Operator (DSO/TSO) the grid exchange profile it will grant during the following day, modified according to the rules set by the DSO/TSO. On the other hand, the ADA is required to refine the optimized solution depending on a possible modification of the actual weather conditions or forecasts, the planned activities or the possible request of ancillary services to the user. The role of the ADA is fundamental in order to avoid major errors in the plant management due to inaccurate forecasts and to help the Real Time Algorithm to ensure the compliance with the grid profile promised after the DAA has concluded its optimization. The Real Time Algorithm (RTA) does not perform any optimization. Instead, it corrects the expected electric power output of the co-generator once every few minutes, depending on the setup. To do so, it relies on a small electric storage that precisely follows the load and ensures that the promised grid exchange profile is respected at all times.

The optimization algorithms are designed aiming at reducing the contemporaneous number of variables to optimize at the same time while retaining a solution close to the global optimum of the problem, which is the daily optimization of the plant. For the purpose, there are two different optimization strategies working together. The optimization of the generator set points and loads curtailment during a 15 minutes period is performed by a Genetic Algorithm (GA), chosen for its computational speed and reliability when solving non-linear optimization problems. On the other hand, the daily optimization is performed by a Shortest-Path Algorithm. The difference between a daily optimization and the one allowed by the optimization of the generators and modulated loads set point every fifteen minutes resides in the presence of the energy storages. Indeed, a daily optimization makes sense if it is possible to increase/decrease the generation compared to the load (or vice-versa) or if it is possible to define when to activate some of the loads during the day. The first opportunity is provided by the energy storages, the second by some particular loads that are referred to as deferrable. In these cases, a daily optimization is capable to achieve better performance compared to one optimizing the operations of the various devices in a single time-step. In Pontlab, the greatest opportunity is offered by the presence of the thermal storages; therefore, to achieve a daily optimum, their management had to be optimized. Nevertheless, performing the optimization of the whole day at once greatly increases the dimension of the problem, up to a point where it is no longer possible to adopt the same strategy that is employed for the optimization of a single period of 15 minutes. Indeed, if the same GA is to be adopted, the search space would grow exponentially, from 10^{14} to 10^{1387}; optimization problems of this size can be tackled efficiently only by linear solvers. Nonetheless, the adoption of linear solvers on a non-linear system inevitably leads to errors that sometime can make the solution practically unfeasible. The use of separated optimization strategies for the generators and loads during a time-step and the storage management is allowed by the way the system is described. The Shortest-Path algorithm's application to the energy system is permitted by the representation of the storages charge combinations (one value for the electric, one for the thermal storage) as system states that can be reached by different paths, whose cost can be assessed by the genetic algorithm. Once all the generators set points and loads curtailments are optimized for each passage from one state of the system to another, the Shortest-Path algorithm seeks the less expensive path among the possible ones. The approach used, which finds no match in the literature, allowed the optimizer to run within the 15 minutes limit defined by the ADA during the offline tests carried out. Upon algorithm translation into C++ code, the computational time required for the optimization can be reduced further.

The first tests were meant to assess the different performances that can be achieved with either the Single-Step algorithm (i.e. the Genetic Algorithm alone) or the Shortest-Path Algorithm. Two series of test cases were employed. The first is a collection of fictional load and price profiles defined ad hoc in order to test the algorithms capabilities and different behavior suggested by the time-step optimization and the daily one. This series of inputs provides easily readable output, ideal for the purpose of evaluating the physical coherence of the solution proposed on a complex plant. The second series on the other hand is based on the actual data measured by the SCADA in Pontlab. This set of inputs allowed the understanding of the true potential of the approach in examination. The days of choice are different from one another and display a wide range of possible weather, price and load combinations. Four days were selected for the tests in summer-operation mode, whereas five different days were chosen for the winter-operation mode. The tests on actual days were performed considering two different scenarios: the first is the present scenario, where there is no restriction on the power exchange with the grid; the second, conversely, introduces a penalty for non-compliance with the profile promised during the day before. The rule set to constrain the power exchange profile with the grid was defined considering the suggestion of Enel S.p.A. This allowed introducing the rule that is most likely to be implemented in the near future on an actual plant.

Regarding the tests on the fictional days, the results show a clear advantage of the Shortest-Path Algorithm in most of the situations, with a few cases where it reaches the same result of the Single-Step and a single case where its performance is worse than that reached by the simpler algorithm. The peculiar case is the constant profile for the whole day, where no improvement is registered, a situation impossible to happen during the actual operation of the plant.

Regarding the tests on the actual days, because of the intensity of the cooling load during the summer period, which exceeds the potential of the absorption chiller during most of the time, the advantage of the proposed strategy is limited during summer, if compared to the traditional Electric Load Following (ELF) and Thermal Load Following (TLF). On the other hand, the advantage over the conventional operation or the TLF management of the CHP are of 19% and 26% for the Single-Step and Shortest-Path Algorithm respectively. None of the new strategies defined is compared in the future scenario against the traditional operation, indeed, the conventional ELF or TFL approaches are not adequate to respect an assigned profile with the grid, because they simply respond to a load condition, without considering any other variable in determining the set-point of the CHP. Thus, the comparison of the two algorithms in the future scenario is done in respect of the performance of the Single-Step in unconstrained grid exchange. The results evidence how the Shortest-Path Algorithm minimizes the overall decrement of performance at about 14%; whereas, when the penalty is applied to the Single-Step the performance decrement is of almost 35%.

Another comparative test is made, on the same actual days, between the two possible thermal layouts and, for each of them, among the choice of a thermal or an electric storage, both considering the present and the future scenario. The results show that for the Pontlab plant, where the operation of the thermal storage is less flexible compared to the ideal Smart User layout, there is an advantage in employing a thermal storage rather than an electric one in the present scenario. Conversely, when the grid profile becomes a constraint, the potential benefits of electric storage are greater than those allowed by the thermal storage during both winter and summer. Indeed, the overall improvement of the economy of operation when using a thermal storage is of 8% and -1% (i.e. it is detrimental) in the present and future scenario respectively. On the other hand, with the electric storage the benefit is lower in the present scenario, less than 4% but almost 14% in the future scenario. With the Smart User layout, being the management of the thermal storage more versatile, the gap between the two conditions (present and future scenario) is lower. The thermal storage achieves an overall benefit of 9% in both situations, whereas for the electric storage the improvement is 2% in the present scenario and 11% in the future scenario. Finally, a comparison is made between the conventional operation strategies and all the possible layouts and storage combinations in the present scenario. The improvements allowed by the ideal thermal layout are minimal compared to the more traditional plant in Pontlab in the present scenario. Thus, the improvements in respect of the conventional supply are almost the same for both layouts. It should be noticed though that the situation would change if the scenario considered were the future one, where the compliance with the promised power exchange profile with the grid requires the greatest versatility of operation possible.

The Real Time Algorithm was tested as well, on two different conditions that were considered sufficient to evaluate its performance offline the plant. One condition is an actual measurement performed on the plant, meaning that both the forecasts and the measured data during the day come from the same day of operation. In this case the RTA balanced the plant and respected the promised grid exchange profile employing a storage of low capacity (600Wh) and a power output close to the one of the CHP, 24 kW. The correction required in order to both balance the plant and ensure the power exchange profile with the grid was small because of the accuracy of weather and load forecasts. Hence, a more stressful test was prepared, creating a fictional day whose real-time data came from the same day of the actual-day test but the weather and load forecasts of the day before were artificially wrong. For reasonable errors (i.e. a possible shift between real-time load and weather conditions and forecasted value), the size of the storage required to accomplish the goals set for the RTA is higher than in the actual-day case. Indeed, the storage capacity rises to between 3.5 and 4.5 kWh, depending on the type of correction applied by means of the CHP and the storage. On the contrary, the power output remains in the range of the CHP maximum power output, or, in some of the cases tested, reduces to 15 kW.

All the algorithms tested performed as expected and achieved the objectives set for the project.

7 FUTURE DEVELOPMENTS

The activity carried out during the research project that this Thesis deals with is an ongoing process. The next steps will be the implementation of the optimization strategies tested offline onto the SCADA in the actual plant. This will allow the algorithms' performance to be evaluated when operating online. Further on, the optimization of the deferrable and interruptible loads will be tackled and added to the functionalities of the present optimizers. For now, it is unclear how their optimization will effect the computational time required to achieve an optimized solution. Thus, it is still to be assessed whether the optimization of these particular loads will be carried out only during the day-ahead or also in advanced dispatching on the actual plant. Another step ahead would be the implementation of an effective multi-objective optimization strategy, that would allow to consider all of the three possible objective functions (economic, environmental and energetic) at the same time. Finally, it is desirable to test the Smart User concepts and solutions developed in this work, onto different plants other than Pontlab, possibly featuring a diversification of generation solutions, storages and thermal layout configurations.

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