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Development of an energy management system for the hybridization of high-power EV charging stations

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Abstract. The growth of the electric vehicle fleet must be supported by the deployment of efficient charging infrastructures; this in turn requires investments in localized energy production systems, often integrating storage systems and different power sources. The study analyses a charging station in central Italy, in which a hybrid engine-generator and photovoltaic panels have been installed to upgrade grid-connection. To optimize the performance of the system, a real-time online deterministic energy management system (EMS) has been developed and presented herein. The EMS is characterized by innovative cost-minimization and BESS state-of-charge management algorithms, while maximizing load coverage. The EMS is developed in CODESYS specifically for online PLC implementation and validated in Python. After ten years of simulation, the EMS reports a total energy provision cost of 0.629 M€, corresponding to a specific cost of provided energy of 30.47 c€/kWh, showing significant advantages with respect to more simplified control logics currently in use. Overall, the results prove the potential of hybrid technologies for high-power EV charging stations, highlighting that a dedicated online EMS with custom control algorithms could be key for the development of this technology.

1. Introduction

Electrification of road vehicles is considered as one of the key drivers towards a new paradigm of sustainable mobility, especially close to populated areas. However, to promote a real diffusion of electric vehicles (EV), significant improvements in the electric grid infrastructure are needed to increase its stability and power availability. Technical, economical, or environmental constraints often hampers such a development, especially in remote areas. To this end, multiple studies investigated lately the effect of on-site energy production (with both conventional generators and renewables) and storage systems in EV charging stations ([1], [2]). In these applications, which integrate multiple power sources and must deal with variable power demand, online real-time energy management systems (EMS) are needed to optimally manage the plant.

1.1 State-of-the-art

Multiple solutions have been proposed for the design of EMS depending both on the specific application and on the objective function (i.e., aiming to achieve either a single or multi-objective optimization). Moreover, the term “energy management systems” is widely applied to diverse scenarios. Building energy management systems (BEMS) are systems designed to monitor and control buildings energy needs, focusing on heating, ventilation, air conditioning, lighting, and power systems [3]. Differently, industrial energy management systems (IEMS) provide economic optimization through deferrable and non-deferrable load control, focusing on the variable cost of the energy source ([4], [5]). Lastly, another category of EMS consists of microgrid energy management systems (MEMS). Microgrids are low-voltage, small-scale electricity grids comprised of a wide variety of distributed energy resources (DER) operating in a controlled and coordinated manner to address the demand effectively. Microgrids can operate either in grid-connected (as part of the distribution grid) or islanded mode (disconnected from the primary grid and it is self-sufficient) [6]. MEMS focus on cost and emissions minimization by optimally controlling a complex power hub composed of multiple energy sources and storage systems [7].

In this branch of energy managements systems, the algorithms applied for key parameters optimization can be many [6]. The simplest approach involves the application of deterministic algorithms to analyze the different energy source cost and provide the optimal components scheduling. In [8], authors successfully developed a dedicated energy management algorithm for a hybrid supercapacitor-BESS storage in a connected microgrid, highlighting the numerical complication of such an approach. Similarly, authors in [9] evaluated the introduction of a dedicated EMS in a prosumer household, including day-ahead PV and load forecasting. However, purely deterministic EMS can only be applied to low- or medium-complexity problems, as the lack of proper optimization algorithms is critical for solutions with multiple local minima [10]. Indeed, for components' control management, both Mixed Integer Linear Programming (MILP) and metaheuristic algorithms have been widely used with success [6]. Superchi et al. [11] , proved the effectiveness of MILP optimization by managing the power scheduling of a renewable-based power station in a small island, reporting potential improvements in the exported energy as high as 87%. Habib et al. [12] similarly used improved MILP algorithms (I-MILP) to achieve multi-objective economic and environmental optimization for standalone rural microgrids including DERs and storage systems. Multi-objective optimization was also successfully implemented in [13], when applying evolutionary algorithms (EA) to optimally dispatch multiple storage and generator units in an islanded microgrid. A differential evolution algorithm was also used in [14] to optimally control various components of a high-complexity microgrid in both islanded and connected mode, using day-ahead optimizations. However, optimizers such as MILP or genetic algorithms require external libraries for solvers which can be easily implemented in computing codes but are problematic when they need to be embedded on a machine for real online control applications. Recently, machine-learning-based EMS have also seen some usage. While showing good adaptability and flexibility, data-driven EMS are however limited by the need of substantial amount of training data to solve the classification problem, obtained from other optimized solutions of energy management systems. Following this approach, authors in [15] were able to train and use a random forest regression model to achieve an economically optimal power dispatch, even outperforming their previous stochastic optimizer. Indeed, for microgrid optimization problems, machine-learning based approaches are mostly used for load and renewable source forecasting. In [16], authors were able to successfully build an accurate load and weather hybrid machine-learning prediction model allowing optimal day-ahead scheduling of a prosumer microgrid.

Focusing specifically on EV charging station optimization, a general lack of techno-economic analyses was observed. Bhatti et al. [17] were able to develop an EMS for an EV charging station in an islanded microgrid integrating PV installation, two diesel genset and lead-acid BESS. However, that case study lacked a techno-economical validation framework for long term economic simulation. Kouka et al. [18] similarly built a deterministic dedicated EMS for a connected charging station including BESS and PV installations. The goals of the work were self-consumption and customer satisfaction maximization.

Indeed, the literature regarding energy management systems application is often relegated to simulation software. In this work, an embedded EMS for real-time control of a high-power EV charging station was developed in CODESYS, a programming language strictly developed for PLC. CODESYS was also used in [19], where authors developed a two-level control system for a building with photovoltaic installation together with a BESS. The controller is able to target different objectives such as efficiency, cost efficiency, demand response, and grid optimization by strictly managing building loads and reactive power. In a much different setting, a CODESYS energy management system was developed by authors in [20]. This EMS is applied to a manufacturing robot on a conveyor belt, and the EMS goal is monitoring the robot by measuring energy consumption KPIs.

However, none of the studies published to date have specifically tailored the issue of real-time optimal energy management using PLC programming language in a real hybrid microgrid such as the one presented in this study. Instead, complex optimization techniques such as MILP or genetic algorithms have been widely investigated but cannot be embedded on machines. Moreover, an innovative BESS SoC semi-predictive control technique was developed to maximize PV self-consumption and minimize excess PV feed-in, known to be an inefficiency factor for intermittent renewable energies [21].

1.2 Rationale of the study and innovation

The rationale of this study moves from the rapidly increasing trend of power needed for EVs charging. This phenomenon is urging developers to introduce localized power production sources in charging stations, creating multiple islanded and connected microgrids. Such systems, often integrating renewable energy production and storage systems, require dedicated EMS for energy cost and load coverage optimization.

This work focuses on a techno-economic analysis of the EMS specifically developed for a high-power multi-fuel smart charging station. Most importantly, the EMS was conceived for real-time online use on the machine PLC, providing innovation in a field that currently makes use mostly of offline research approaches. Offline applications allow for testing more complex and accurate optimization algorithms on a pure research level, which, however, are often of scarce use for industry as barely implementable in real cases. To maximize PV self-consumption, an innovative semi-predictive BESS state of charge control algorithm was developed to further reduce operational costs.

2. Materials and Methods

2.1 Case study

The research project described herein aims at developing a real-time control-oriented online EMS and optimizing it for the energy hub realized in San Sepolcro (Italy) in the scope of the MUST project ("Multi-Fuel Smart Charging Station"), co-funded by the POR-FESR Toscana 2014-2020. The hub is equipped with multiple power consumption sources, including:

- Four standard AC EV charging points of nominal power 22 kW.
- A single splitable ultra-fast DC charging point of nominal power 180 kW.
- A natural gas compression station, with variable power ranging from 80 to 130 kW.
- A cooling station consuming around 40 kW.
- Auxiliary consumption around 8 kW.

Being the EV charging points of recent installation, the plant owners realized that more power was needed to satisfy the customer requests. As the medium voltage grid connection is not sufficient (150 kW) and cannot be expanded, the installation of a hybrid engine-generator together with around 17 kWp of photovoltaic panels was figured out. The energy hub was then upgraded with:

- A medium voltage grid connection providing up to 150 kW.
- A hybrid natural gas engine generator (216 kW Prime Rated Power, optimal efficiency at 170kW).
- A solar photovoltaic installation of 17.43 kWp.

The hybrid genset includes a Lithium Iron Phosphate Battery Energy Storage System (LFP BESS) of 150 kWh capacity, with 140 kW nominal discharge and 70 kW nominal charge power (Figure 1). The limited size of PV plant was due to the area constraints: differently, the engine-generator, BESS and inverter components were sized by the plant manufacturer to cover load demand when the natural gas compression station is active and a high-power EV is charging.

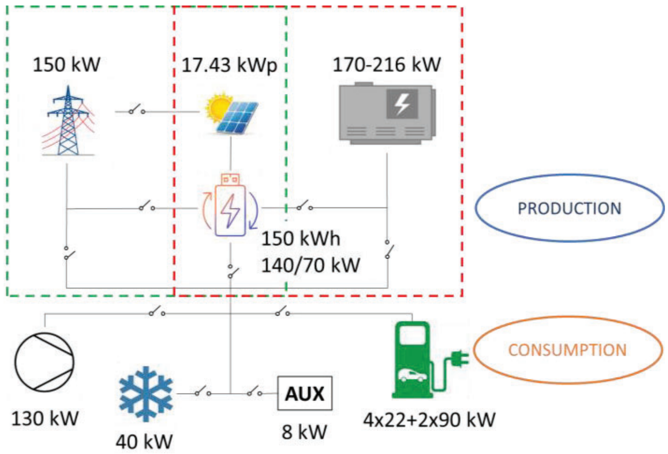

Figure 1. MUST plant scheme.

A key aspect of this project is that the genset cannot work in parallel with the grid due to certification reasons; the grid and the engine-generator must be then alternatively disconnected from the user when one or the other is in use. This forces the system to operate in two different "macro-states", highlighted in Figure 1:

1. Micro-Grid (red): including the generator, BESS and PV installation.
2. Grid-Connected (green): including the national grid connection, BESS and PV installation.

For both Micro-Grid and Grid-Connected modes, the components scheduling is analogue to a typical hybrid operation.

- Low power: when power requested is below a certain power threshold (P_{MIN}), only the BESS is used to provide power to the system. In Grid-Connected, low power mode is covered by the grid unless BESS state-of-charge (SoC) is 100%.
- High power: when power demand is above a certain power threshold (P_{BOOST}), both the BESS and the main power source (the genset or grid), are used in conjunction to provide the necessary power.
- Medium power: when power requested is between P_{MIN} and P_{BOOST}, the main power source covers the load requested and charges the battery at the same time, thus optimizing the generator efficiency.
- Forced charge: when the BESS SoC is below a certain threshold (SoC_{MIN}), a forced charge cycle is initiated by the main power source and does not until a SoC threshold is reached (SoC_{MAX}).

Multiple secondary control criteria are also implemented in the system but will not be disclosed for simplicity reasons. As one may notice, the two macro-states work analogously with different technical constraints depending on the power source. Therefore, the online EMS, developed for cost optimization, aims to evaluate which macro-state will be more economically convenient.

2.2 Methodology

The overarching goal of a higher economic convenience by the EMS translates into the need to minimize both the cost of energy provision and the occurrences where the plant cannot provide the requested power. The EMS will communicate to the main plant manager the optimal macro-state (either Micro-Grid or Grid-Connected), which will then evaluate whether to follow the EMS command or not depending on possible technical constraints, such as high load, low state-of-charge, or generator limit hours reached. Due to the hourly nature of the primary sources cost, the EMS runs and suggests the optimal macro-state with 1-hour frequency. As real-time online control is the main feature of the project, the developed EMS targets low complexity and computational cost.

This section will focus on the EMS development and structure, highlighting the innovative techniques introduced.

2.2.1 Economic optimization

This study focuses specifically on the development/optimization of the EMS, taking as an example an existing plant. For this reason, economic optimization only focuses on the minimization of energy cost, i.e., on the evaluation of the economically optimal macro-state to provide the user-requested power. In future scenarios, the same activity could be repeated also in the design phase of the plant itself, thus also evaluating the impact of the EMS on the profitability of the investment. Cost evaluation is here done by comparing the costs of the two main different energy sources: natural gas cost for Micro-Grid, and national (Italian) grid electricity cost for Grid-Connected. Moreover, in Micro-Grid scenario, the EMS will evaluate energy costs considering the generator always running at optimal efficiency working condition (170 kW), providing a constant value of the genset efficiency (25.1%, from manufacturer datasheet).

Furthermore, for Micro-Grid costs, an additional component is added to evaluate the operation and management costs incurred when operating the natural gas generator. The component life maintenance events and cost datasheet were provided by the engine-generator manufacturer (PRAMAC). In particular, the Micro-Grid total cost is reported in Equation (1):

$$COST_{MG} = (\eta_{GEN} * COST_{GAS} + COST_{O\&M}) \tag{1}$$

With:

- η_{GEN} being the optimal generator efficiency (25.1%).
- $COST_{GAS}$ being the gas cost (€/kWh).
- $COST_{O\&M}$ being the operating and maintenance cost (€/kWh), calculated as of Eq. (2):

$$COST_{O\&M} = \frac{COST_{INTERVALL}}{H_{INTERVALL} * OPT_{POWER}} \tag{2}$$

where:

- $COST_{INTERVALL}$ is the cost of the following O&M operation (€).
- $H_{INTERVALL}$ is the duration until substitution of the O&M operation (hours).
- OPT_{POWER} is the supposed optimal efficiency power provided by the generator (170 kW).

Then, the EMS will then evaluate optimal scenario (OptimalState) with Eq. (3):

$$OptimalState = \min\,(COST_{MG},\, COST_{GT}) \tag{3}$$

with $COST_{GT}$ being the cost of Grid-Connected state equal to electricity costs of the provider, supposed as a 3-tier standard electricity contract, typical of Italian appliances (Table 1). F1 usually corresponds to the most expensive tier, while F3 is the cheapest.

Table 1. Standard three-tiers contract hours.

MONDAY-FRIDAY	SATURDAY	SUNDAY

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F1	8:00-18:59	-	-
F2	7:00-7:59 | 19:00-22:59	7:00-22:59	-
F3	0:00-6:59 | 23:00-23:59	0:00-6:59 | 23:00-23:59	0:00-23:59

Electricity and gas costs are reported in Figure 2, highlighting the difference in costs between the three tiers for electricity price and the monthly variations.

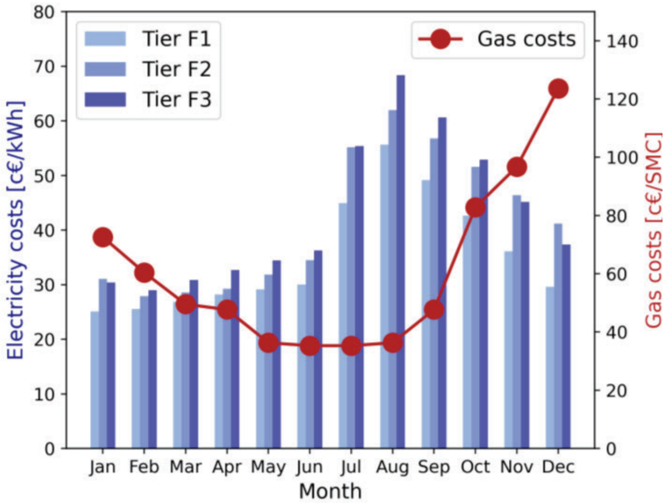

Figure 2. Variation of electricity and gas prices over time

As expected, tier F3 is usually the most expensive excluding some outlier months. Over the year, it can be observed how in summer the electricity prices observed a substantial spike while gas was at its lowest point. Indeed, cost variability further highlights how a dynamic energy management system such as the one developed in this work can provide significant operational savings independently from the application scenario.

2.2.2 Engine-generator usage manager

In this section, a semi-predictive control technique for the generator usage optimization is introduced. This algorithm is based on the constraint that the genset utilized in the plant has a limited set of hours until its end of life, corresponding to a total cap of 24000 hours, and a maximum of 2000 hours per year. These values are derived from a previous economic optimization done by the constructor to limit maintenance costs. Following this information, the EMS provides for each day a value of the generator working limit hours following Eq. (4):

$$H_{GG} = \frac{2000 - H_{WORKED}}{365 - D_{PASSED}} \tag{4}$$

where:

- H_{GG} is the generator limit hour for the day (hours/day).
- D_{PASSED} is the number of days passed since the start of the year (days).
- H_{WORKED} is the number of hours that the genset as worked since the start of the year (hours). This allows for dynamic and auto-adjusting daily thresholds, i.e., if the genset is not used during the first months of the year, more daily hours are allowed for future use, and vice versa.

The target of the algorithm, however, also involves the economic optimization. During the day, the gas price is constant, but the electricity varies following a the three-tier contract (Table 1), which is more expensive during the central hours of the day and cheaper in early morning or late night.

Following this logic, the generator working hour limit was set to be dynamic during the day, providing a buffer for exploitation when the electricity is most expensive. The semi-predictive generator management algorithm is mathematically described by the following set of linear equations (Eqs. (5), (6), (7)):

$$H_{GG\ LIMIT} = H_{GG} * \frac{hour}{24} \quad if\ hour \leq F1_{START} \tag{5}$$

$$H_{GG\ LIMIT} = H_{GG} * \frac{hour}{24} \quad if\ F1_{START} \leq hour \leq F1_{END} - H_{GG} \tag{6}$$

$$H_{GG\ LIMIT} = H_{GG} \quad if\ hour > F1_{END} - H_{GG} \tag{7}$$

where:

- $H_{GG\ LIMIT}$ is the hourly dynamic limit working hours of the generator (hours/day).
- hour is the current daily hour.
- $F1_{START}$ and $F1_{END}$ are the starting and ending hours of the most expensive electricity tier (hours).

This set of equations is used during operation from Monday to Friday (Figure 3A). On Saturday, a similar set of equations is applied, while on Sunday (Only F3, Figure 3B), a single linear/flat split is used (Figure 3C).

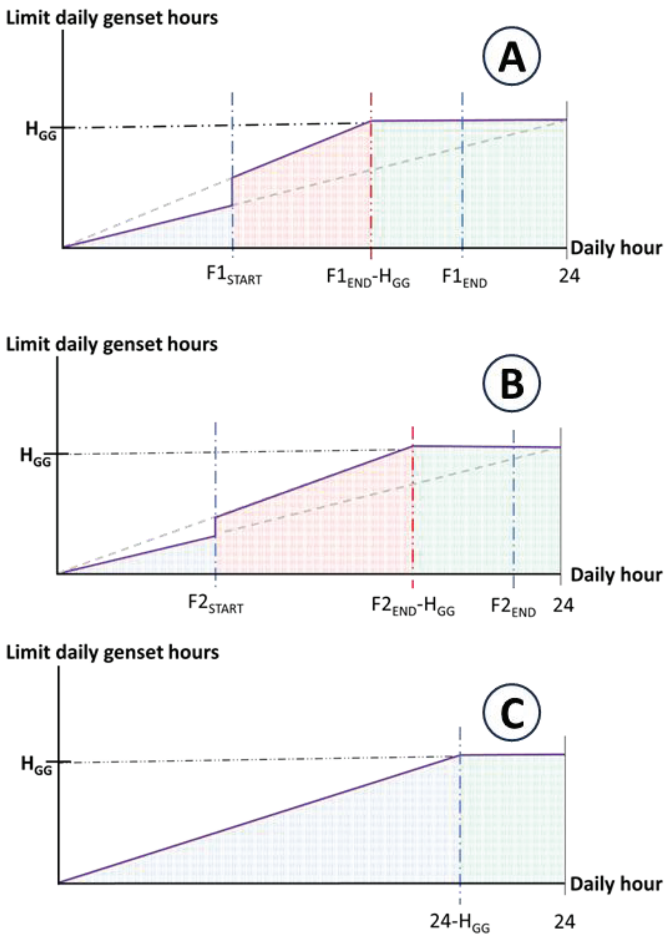

Figure 3. Generator working hour limitations, Monday-Friday (A), Saturday (B), Sunday (C).

2.2.3 Maximum state-of-charge limitation

The second innovative algorithm included in the EMS aims to reduce the amount of excess energy produced by the PV installation fed to the national grid. This happens when the power requested by the user is lower than the power produced by the PV panels and the battery state-of-charge is 100%. It is necessary to limit this quantity as feed-in energy is currently only partially retributed, and characterized by a decreasing trend in value as intermittent renewable energy sources increase [22]. In the considered scenario, excess energy retribution is valued as constant and equal to 9 c€/kWh, estimated based on constructor's data. While dependent on the hour and the season, this value is coherent with the average data of 2023 by Gestore dei Servizi Energetici (GSE) [23].

To limit the surplus of energy, the EMS provides a maximum threshold to the BESS SoC during forced charge cycles. A forced charging cycle occurs when the battery SoC goes below 30%: the primary energy source (either the genset in Micro-Grid or the grid connection in Grid-Connected) provides the maximum amount of power that the battery is capable of absorbing to the BESS until the maximum SoC is reached. By doing so, even if the maximum SoC is reached and low loads are requested during high irradiation hours, excess PV energy can be fed to the battery instead of being sold for low remuneration to the grid. Moreover, due to grid certification reasons mentioned in Section 2.1, energy can only be sold to the grid when operating in Grid-Connected mode (Figure 1). The criterion to provide the maximum SoC threshold is based on the future daily PV irradiation. In detail, the SoC setpoint is determined by the following formulas (Eqs. (8), (9)):

Zone A: $$SoC_{MAX} = 100\% - E_{PV\ FUTURE} * \frac{(hour - ss)}{(sr - ss)} \quad if\ ss < hour < sr \tag{8}$$

Zone B: $$SoC_{MAX} = 100\% - E_{PV\ FUTURE} * \frac{100}{BESS_{CAP}} \quad if\ sr \leq hour \leq ss \tag{9}$$

where:

- SoC_{MAX} is the imposed maximum state-of-charge threshold for forced charge cycles.
- *ss* is the sunset hour.9
- *sr* is the sunrise hour.
- $E_{PV\ AVG}$ is the daily average PV energy obtained from monthly irradiation (PVGIS database).
- $E_{PV\ FUTURE}$ is the daily expected energy from current hour to the next sunset, as fraction of $E_{PV\ AVG}$ dependant from the hour.
- $BESS_{CAP}$ is the BESS Capacity (150 kWh).

The SoC_{MAX} setpoint in Zone A is defined by a quadratic curve during the irradiation hours of the day, providing a minimum value at sunrise and a maximum of 100% at sunset. In Zone B, a linear interpolation is used instead to bring the setpoint value back from 100% to the minimum at sunrise. Moreover, a lower bound threshold is introduced for the maximum state-of-charge, equal to 70%. The setpoint avoids reaching excessively low values of the state-of-charge during higher irradiation months. This threshold was chosen as it ensured better economical results compared to other values during preliminary analyses. A graphical representation of this algorithm is reported in Figure 4 for two following days, with Zone A and Zone B highlighted as of Equations (8), (9).

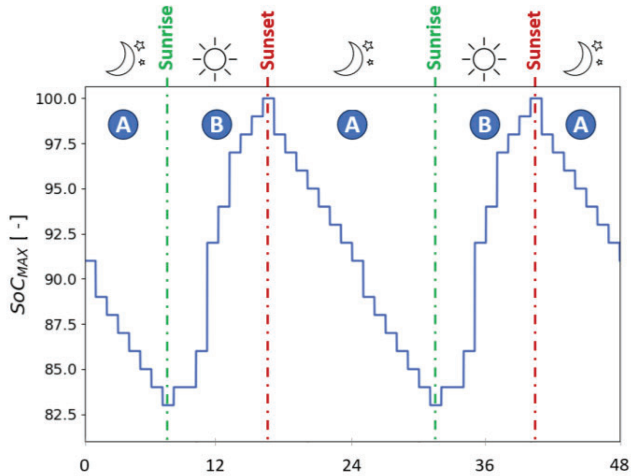

Figure 4. Example of maximum SoC management (two days of operation, January).

A schematic representation of the EMS working logic is presented in the flowchart in Figure 5, highlighting inputs and outputs of the system.

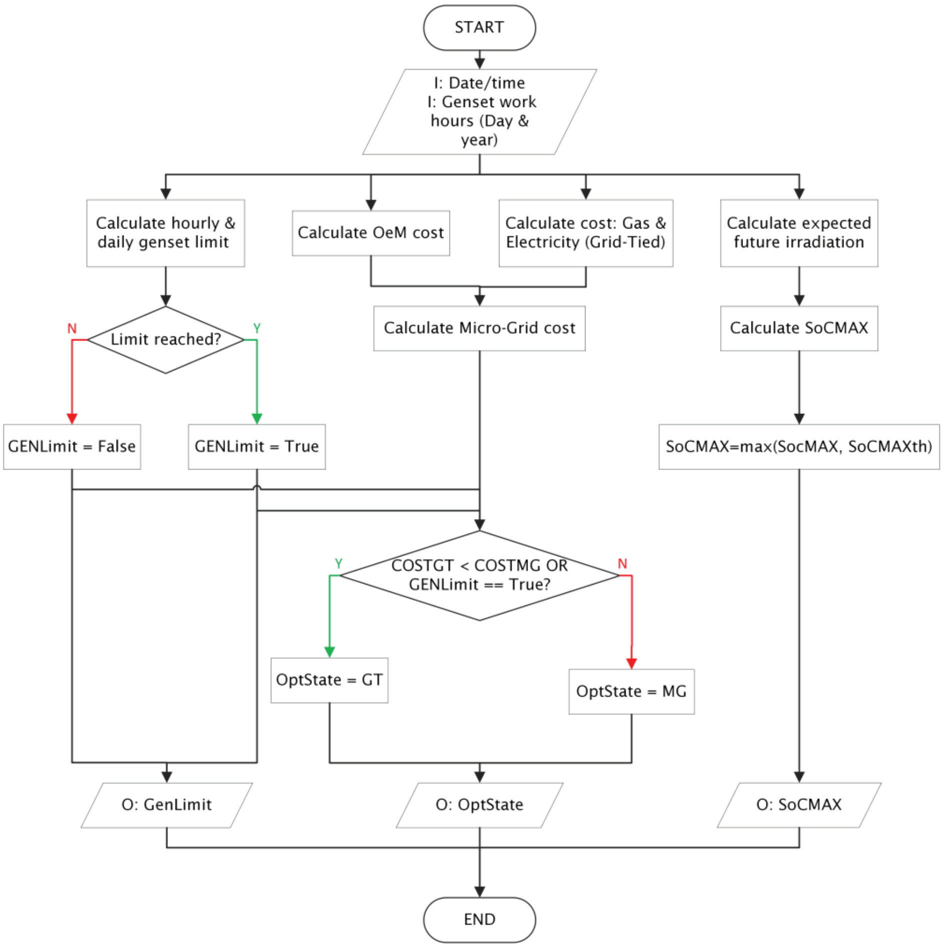

Figure 5. Simple schematic representation of the flowchart of the EMS.

2.3 Validation

To validate the developed EMS, a primary plant component manager was developed. The goal of the plant component manager is to handle the suggestion provided by the EMS on the optimal macro-state operation, and then decide whether to follow the suggestion or ignore it based on the current state or possible constraints, such as high loads, BESS forced charge cycle on-going, or low state-of-charge. Multiple finer control and monitoring criteria are implemented in the real embedded primary plant manager, as it can be observed in Figure 6. Some of them include load ramping techniques used to improve the system components, control or switches, and alarm management.

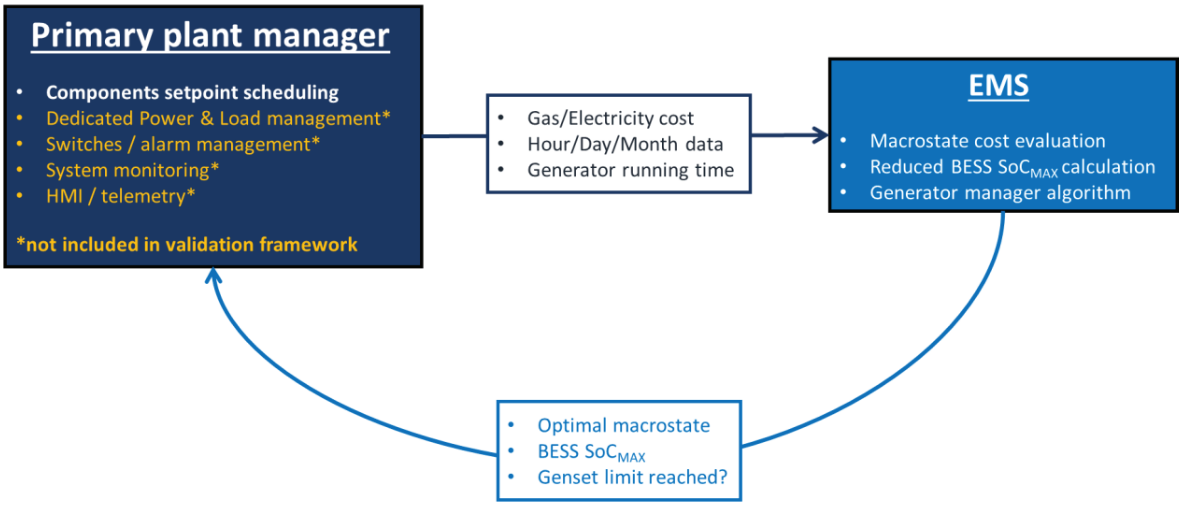

Figure 6. Graphical scheme of the software architecture embedded in the PLC, highlighting the roles of the Primary plant manager and the EMS.

The developed offline component manager can be considered, however, as a digital twin of the plant manager to reasonably validate the EMS. During Micro-Grid and Grid-Connected operation, the primary plant manager provides power output setpoints for each component (Grid, Genset, BESS) to optimally satisfy the user power request, enforcing the control logic briefly mentioned in Section 2.1.

2.3.1 Requested power

As the EV charging station is not active yet, the lack of requested user power historical data was problematic for the EMS validation. However, previous predictive analyses were run by the plant project managers to forecast the electric vehicle traffic in the station up to 2033. The data provided by the manufacturer is non-disclosable, but it is based on traffic estimation and EV percentage, starting from 2024 and predicted until 2033. This data was used to create a daily load profile. In detail, the EV charging loads are fixed for a set number of hours during the day, following expected traffic hours. Moreover, EV traffic is differentiated between ultra-fast charging (180kW) and standard charging (22kW) vehicles. This situation creates a daily pulsed load scenario (constant within the hour), which increases during the simulation time, as graphically represented in Figure 7. Being the starting simulation year 2024, a gradual increase is observed by following the daily load growth in 2027, 2030 and 2033 (final simulated year). A finer interpolation is used to simulate years in-between which are however not reported graphically for clarity.

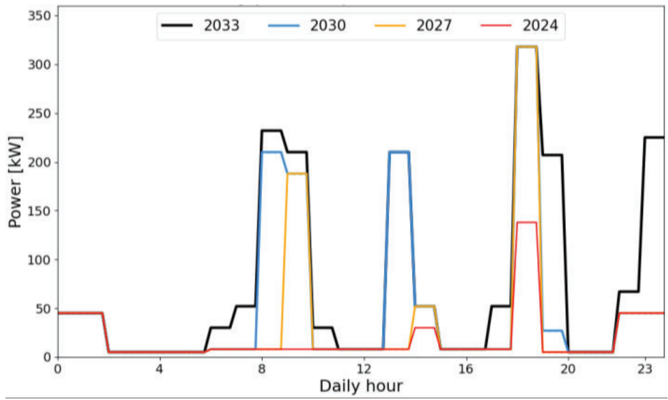

Figure 7. 2024 - 2033 expected daily load request (non-randomized).

Lastly, as the validation process is expected to follow a dynamic scenario, every hourly load accounted is corrected with a random multiplier, bound between 0.1 and 1.1. A new random multiplier is generated every 15 minutes. This allows the simulation to account for multiple different combinations of loads.

Together with EV traffic, baseline auxiliary loads, cooling loads, and compression station activation are included. Moreover, as traffic is usually reduced during the weekends [24], loads are corrected with a reduction factor (0.75 for Saturdays and 0.5 for Sundays) to realistically simulate this aspect.

This creates a final dynamic load demand with 15 minutes sensitivity over ten years accounting for multiple realistic factors, such as increase in EV traffic, reduced traffic on weekends and randomization factors.

2.3.2 Solar irradiation

The Energy Hub has installed in the system 17.43 kWp of photovoltaic panels. The PV installation is characterized by a 5° slope and +35° South inclination, with no shading. Similarly to load data, solar irradiation historical data was not available for the simulations. The PVGIS software (https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis_en) was used to provide average monthly energy production (Figure 8), together with daily irradiation distribution. This allowed the creation of an average daily PV production database.

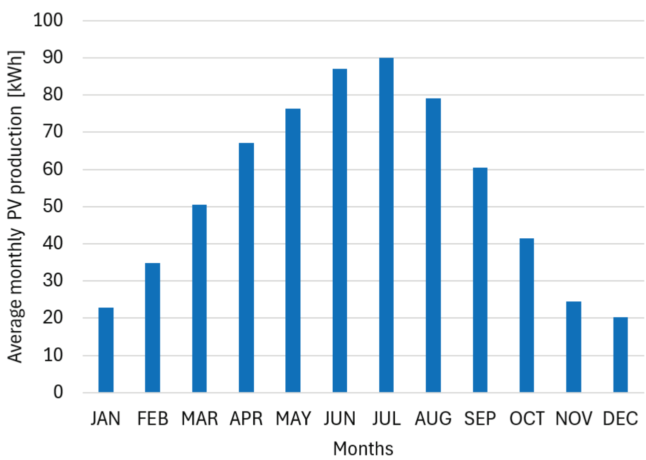

Figure 8. Average total monthly PV energy production from PVGIS.

The average daily PV production is modelled in the study to follow a triangular shape, having a subtended area equal to that of the real gaussian distribution of daily solar radiation. Monthly sunrise, sunset and irradiation peaks hour are imposed. For dynamic validation, the average PV hourly production is corrected with a random multiplier, with static upper bound of 1.45 (to maintain peak power) and dynamic lower bound between 0.25 and 0.85, increasing from January to July and decreasing from July to December. Similarly to the load request, a new random multiplier is generated every 15 minutes, to include the known intermittency of solar power.

2.3.3 Primary source costs

Lastly, after modelling the PV irradiation and load demand over the simulated 10 years, energy source (gas and electricity) costs were needed to evaluate the EMS optimization choices. To do so, the manufacturer (PRAMAC) provided monthly gas and electricity bills, which were used to build a year-round source cost database, with hourly and monthly cost fluctuations, as observed in Figure 2.

3. Results

As discussed, since the plant has been already installed and built, economic convenience is here evaluated through the cost of the energy provided to the user. This means that the developed EMS must be able to provide energy to the user at the lowest price for the Power Hub, and correctly communicate the most convenient macro-state to the primary plant manager. Other key parameters used for the effectiveness evaluation are the capacity to provide the requested power to the user and the excess PV feed-in energy to the national grid. In detail, the parameters considered in this study are:

- **Total Energy Cost** (C_{E_TOT}): the cumulative cost, in €, of the energy provided during the system operating life. This parameter does not account for CAPEX component costs, as the plant is already built and running. C_{E_TOT} therefore only accounts for primary energy source cost (natural gas or electricity) and O&M operations for the genset. This parameter will be the main deciding factor of the EMS effectiveness.
- **Specific Energy Cost** (C_{E_SP}): provides the specific cumulative cost, in c€/kWh, of the energy provided during the plant life. This parameter is given by the ratio of C_{E_SP} and the total energy provided.
- **Load Coverage** ($LOAD_{COV}$): the ratio between power provided to the user and power requested by the user. This value will be a key indicator of the EMS ability to handle different loads during its operation. Load coverage is prioritized by the primary plant manager even when the EMS suggests a different economically optimal condition, as customer satisfaction is crucial for the plant.
- **Excess Photovoltaic energy to grid** ($E_{SURPLUS}$): the excess energy, in kWh, produced by PV panels that cannot be used to charge the BESS and will be fed to the grid. One of the goals of this EMS is minimize feed-in energy, as it is a substantial source of inefficiency and stability issues for the grid [21]. This parameter will be analysed to evaluate the effectiveness of the SoC_{MAX} reduction algorithm explained in Section 2.2.3.
- **Normalized engine-generator average efficiency (**η_{GEN_AVG}): the average efficiency of the generator during the 10-years simulation normalized in respect to the maximum efficiency of the genset (25.1%). This parameter evaluates the validity of the engine-generator constant power assumption introduced in the EMS (as explained in Section 2.2.1).

To properly evaluate the effectiveness of the developed EMS, three different energy management cases are introduced for comparison purposes:

- **Grid-Only**: where the grid provides the amount of power requested by the user at any time, even for power above 150 kW. The cost of energy provided in this scenario corresponds to the electricity bill cost. Realistically, electricity cost should increase when increasing the power, but this was ignored as it would present a further point of convenience in favour of the EMS.

- **Gas-Only**: where a hypothetical generator provides the amount of power requested by the user at any time, even for power above 170 kW. In this scenario, the generator efficiency is capped at the efficiency of the generator at 100% Emergency Stand-by Power (240 kW). Costs in this scenario are composed of natural gas costs and O&M operating costs, including genset complete substitution after 24000 working hours.
- **Ideal**: In this scenario, the power requested is always provided using the least-cost energy source (natural gas or electricity). In the case of natural gas usage, O&M costs are evaluated in accordance with every other scenario. The difference between Ideal and EMS is that the Ideal scenario ignores technical limitations and secondary criteria when choosing the optimal macrosystem. Examples of technical limitations for the EMS include the impossibility of changing macro-state with low BESS SoC or the engine-generator limited working hours. Examples of secondary criteria include load coverage priority (using the engine-generator even when not convenient if the Grid-Connected mode cannot handle the power demand) or the impossibility of changing macro-state until a BESS forced charge cycle is finished. The ideal scenario also calculates the least-cost source with variable efficiency, bypassing the EMS assumption introduced in Section 2.2.1 of constant optimal genset efficiency allowing for real best-case evaluation. Therefore, the Ideal scenario sets out the optimal energy cost value obtainable through a simple gas-grid cost comparison analysis without any other technical limitations or criteria. The energy cost obtained in this scenario provides a reference value that our EMS needs to come close to prove its effectiveness.

All the three cases include the same PV production (analogous to the EMS scenario), but do not have a BESS included in the system. The power request of the three cases matches the power provided to the user in the EMS scenario. Realistically, with a proper optimization algorithm, the EMS energy cost is expected to be below Gas-Only and Grid-Only but above the Ideal scenario. To define the effectiveness of the algorithm, 10-year simulation analyses are performed with 1-minute timestep sensitivity in the CODESYS automation software [25], validated as well in a development version made with Python.

3.1 Techno-economic analysis

In Figure 9, the specific cumulative cost of provided energy (C_{E_SP}) is reported for the four different plant operation modes. For this analysis, the state-of-charge limiting algorithm is implemented with a minimum threshold of 70%, as this value resulted into cost minimization.

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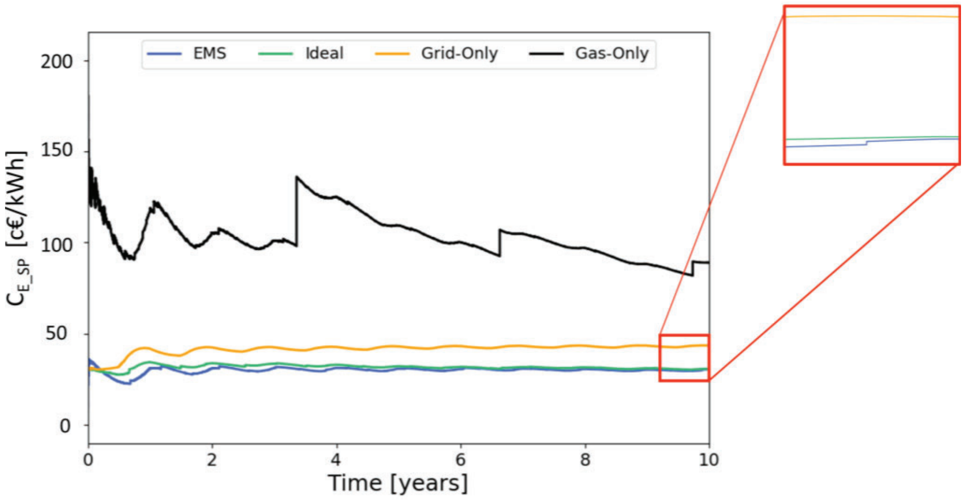

Figure 9. Specific cumulative running costs.

As it can be seen, EMS and Ideal specific cost present an almost equal value at the end of ten years of operation, with the EMS cost only marginally lower than the Ideal one. This is due to the introduction of the BESS, which allows the generator to run at higher loads (and therefore at higher efficiency) more often in the EMS mode. Increased convenience is then achieved when the gas cost is low, and the electricity cost is high. In the Ideal scenario (no BESS) even in a situation of gas-use convenience, low loads require a heavy partialization of the engine, hindering cost savings. This trend is more noticeable during the first years (Figure 10), where loads are lower, as shown previously in Figure 7. As time goes on and EV traffic (and therefore load) increases, the gap between the EMS and Ideal cases is reduced. Other scenarios (Gas-Only and Grid-Only) present substantial increases in cost, with Gas-Only being the least convenient due to obvious efficiency losses and costs related to more frequent maintenance.

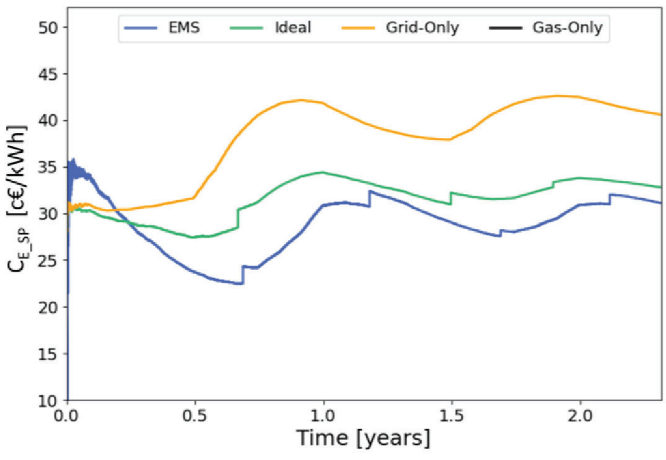

Figure 10. Partial zoom of Figure 9, highlighting the effectiveness of the EMS compared to Ideal.

Cumulative costs (C_{E_SP}) are also graphically reported in Figure 11, highlighting the operating total savings at the end of ten years of operation.

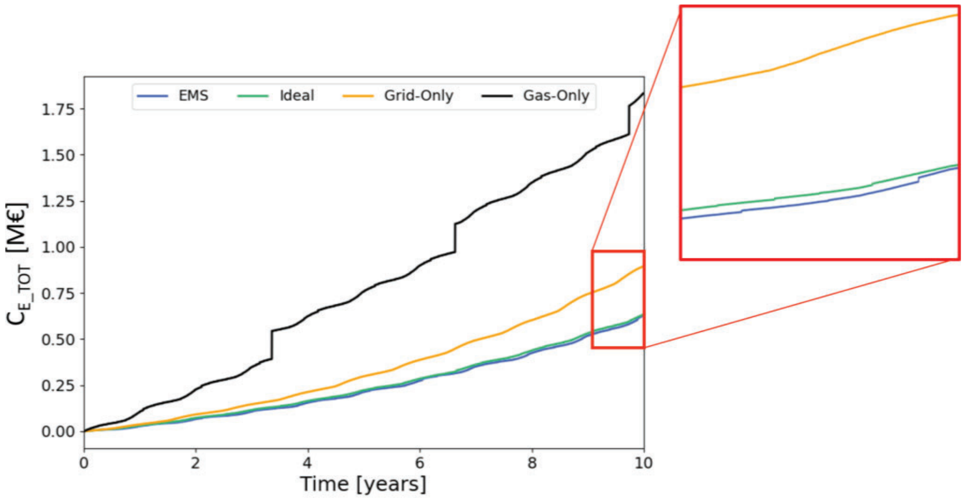

Figure 11. Total cumulative running costs.

Sharp vertical cost increases observed in Figure 9, Figure 10, and Figure 11 are due to the genset's maintenance costs when reaching a certain working hours threshold. In particular, the Gas-Only scenario presents three engine-generator substitutions, each scheduled after 24000 total working hours. Economic results at the end of the 10-years simulation are quantitatively reported in Table 2.

Table 2. Analysed scenarios cost comparison.

	C_{E_TOT} (M€)	C_{E_SP} (c€/kWh)	η_{GEN_AVG}
EMS	**0.629**	**30.47**	**86.9%**
Ideal	0.633	30.73	72.5%
Grid-Only	0.896	43.52	-
Gas-Only	1.83	88.73	25.2%

It can be observed how the EMS mode provides only marginal cost advantages (roughly 1%) when compared to the Ideal scenario, but substantially increased conveniency (over 40%) when compared to Grid-Only. Regarding the average genset efficiency, as expected the EMS scenario is characterized by the lowest partialization thanks to the integration of the LFP BESS. This demonstrates the effectiveness of the constant-efficiency assumption introduced in the EMS algorithm. Differently, Ideal and Gas-Only provide worse genset exploitation due to the lack of storage (Ideal) and forced engine-generator usage even for low loads (Gas-Only). Moreover, for the EMS scenario, information regarding energy provided and usage for the various power hub components is reported in Table 3.

Table 3. Plant components scheduling data.

	Provided energy (MWh)	Operative hours (hrs)
Generator	$1.88*10^3$	$1.51*10^4$
Grid	$2.13*10^2$	$6.76*10^3$
PV	$2.01*10^2$	$4.22*10^4$
BESS	$7.59*10^2$	$8.02*10^4$

Looking at the main power production components (the grid and the genset), it can be noticed how the latter provides significantly more energy (around eight times more), although it is used for only roughly double the time when compared to the grid. Indeed, the generator is mostly run at full power; even when the user request is lower than the nominal power, the genset runs at the optimal efficiency point to also charge the BESS. On the other hand, grid is used simply to cover the requested loads, while BESS charging only happens at low SoC values. Regarding BESS data in Table 3, the provided energy refers to the output energy from the storage system, while it should be remembered that this energy has been previously charged into the battery by one or more of the other three energy sources (Genset, grid, PV).

In Section 2.2.3, a BESS state-of-charge control algorithm was developed to reduce feed-in PV energy and maximize auto-consumption. The EMS values in Table 2 and Table 3 are relative to the introduction of the maximum state-of-charge limiter algorithm introduced in Section 2.2.3 (w/ SoC_{MAX}). However, reduced SoC thresholds are expected to impact negatively load coverage as less energy is stored in the batteries. Moreover, due to the marginal PV installation compared to average user request, negligible effects of the criteria are expected. Therefore, to study the algorithms effects on the system similar 10-year simulations were also run without any additional BESS SoC control (w/o SoC_{MAX}). In Table 4, the effects of the criteria introduction on energy cost, PV feed-in energy, and load coverage are reported.

Table 4. Effect of the integration of the SoC_{MAX} algorithm in the EMS.

	C_{E_TOT} (M€)	C_{E_SP} (c€/kWh)	$LOAD_{COV}$	$E_{SURPLUS}$ (kWh)	η_{GEN_AVG}
w/ SoC_{MAX}	**0.629**	**30.47**	92.3%	**2.7**	**86.9%**
w/o SoC_{MAX}	0.639	30.82	**92.4%**	$1.6*10^3$	84.5%

Results show that the limitation on the maximum value of the state-of-charge provides marginal economic benefit to the system in absolute terms, but relevant if we consider that an overall cost saving of 1.2% is obtained by the use optimization of a source which provides only about 6% of the total energy to the load. Without said limitation, the costs of the EMS would be higher than the Ideal cost (Table 2, Table 3). However, the system load coverage is marginally decreased, as the lowered maximum SoC requires more frequent forced charging cycles. As expected, the surplus of energy fed to the grid is reduced from around 1.6 MWh to only a few kilowatts, proving the technical effectiveness of the criterion. Even the average engine-generator efficiency is marginally improved: a reduced maximum SoC allows for more frequent hybrid operation and higher genset loads when not during a deep-charge cycle. In general, the state-of-charge control algorithm proves to be effective, but significantly better results are expected to be observed with the increase of the PV installation.

4. Conclusions

The study presents the development and optimization of an EMS for an energy hub including EV charging points, a compression station, and cooling loads. The EMS was developed in the CODESYS automation software for industrial online use in PLCs, but also validated here in a dynamic realistic 10-year simulation using a development version made with Python. The real time online EMS is conceived to suggest the optimal primary power source (engine-generator or national grid) with minimal computational cost.

Results highlight the effectiveness of the EMS algorithm, which allows the engine-generator to run at higher loads to charge the battery. This allows the system to be even more convenient than an ideal scenario, in which the minimal cost source is always used without technical constraints. Moreover, by integrating an additional algorithm in the EMS to limit the battery state-of-charge, energy provision total costs can be further reduced by roughly 1%. Indeed, with a reduced maximum state-of-charge, less surplus energy produced by the PV panels is fed to the grid (with reduced remuneration), and auto-consumption is improved. In this scenario, the reported total energy provision cost after ten years of operation would be 0.629 M€, with a specific energy cost of energy provided of 30.47 c€/kWh and 92.3% load coverage. For reference, the specific case study reported an average cost of electricity of 43.4 c€/kWh and 63.4 c€/SCM from provider's bill, highlighting the effectiveness of the algorithm introduced. This indeed shows significant advantages over other simulated operation scenarios, such as Ideal, Grid-Only and Gas-Only: in such cases, the total operative cost was reported to be of 0.633, 0.896 and 1.83 M€ respectively, with specific energy provision costs of 30.73, 43.52, 88.73 c€/kWh. The economic savings, improvements of PV self-consumption and increase in load coverage therefore strongly support the importance of the developed custom EMS for real-time hybrid microgrid applications such as the one analyzed in the observed case study.

Lastly, while significant advantages were observed when integrating the EMS into the simulated control system, experimental validation will be carried out once the EMS is fully operative on the actual charging station for confrontation on observed results, assessment of algorithm robustness and formulation of potential improvements. Future studies will involve the integration of forecast algorithms in the control logic, as this is expected to further increase the EMS effectiveness.

Nomenclature

BEMS	Building Energy Management Systems
BESS	Battery Energy Storage System
CAPEX	Capital Expenditures
DER	Distributed Energy Resource
EMS	Energy Management Systems
EV	Electric Vehicle
GSE	Gestore dei Servizi Energetici
IEMS	Industrial Energy Management Systems
LCoE	Levelized Cost of Energy
LFP	Lithium Ferro Phosphate
MEMS	Microgrid Energy Management Systems
MILP	Mixed Integer Linear Programming
O&M	Operations & Maintenance
PLC	Programmable Logic Controller
PV	Photovoltaic
SCM	Standard Cubic Meter
SoC	State of Charge

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