Application of Control Algorithms for Battery Scheduling in Grid-Connected Energy Prosumers

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2024 IEEE 22nd Mediterranean Electrotechnical Conference (MELECON) | 979-8-3503-8702-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/MELECON56669.2024.10608734

***Abstract*— This paper proposes an innovative approach in managing prosumer batteries using a rule-based control algorithm. The main information used in this work to develop actions on a Battery Energy Storage System (BESS) are the price of energy on the day-ahead electricity market, the prosumer consumption/production forecasts and the effect of charging/discharging operations on battery degradation. In order to evaluate the performance of the rule-based approach, a comparison with other optimization algorithms commonly used in the literature is proposed. Performance is evaluated in terms of economic gain and energy exchanged between prosumer and network. The rule-based algorithm proposed in this paper exploits a neural predictor to forecast load and production forecasts and processes the trend of the electricity market in order to find the best management of the BESS. The results obtained show the best performance of the proposed algorithm compared to the most common optimization methods and the possibility of easily extending this logic to control a large number of users. This is possible also thanks to the extremely low computational cost of the proposed approach, around twenty times faster than a Mixed-Integer Linear Programming (MILP) algorithm. This fact is very interesting regarding the diffusion of modern Renewable Energy Communities (RECs).**

Keywords—Renewable Energy Communities, Energy Management System, Battery Energy Storage System, Optimization Algorithms,

I. Introduction

Nowadays many national electricity systems are changing their configuration from a concentrated structure to a distributed structure, and this requires the introduction of new control techniques to efficiently manage energy flows.

Electrical systems based on a concentrated configuration are characterized by a few high-power generation plants and the energy moves to end users through transmission and distribution networks. The former are used to cover long distances and are commonly made up of High Voltage (HV) overhead lines. Only large industrial sites are directly connected to transmission lines while most users are served by distribution networks. The latter are characterized by Medium Voltage (MV) and Low Voltage (LV) levels and, near urban centers, are made up of underground cables in highly branched sections. Typically, users connected to distribution lines were passive systems that could only absorb energy but, today, new entities called prosumers are growing close to consumers. These new users are characterized by the presence of small production plants powered by Renewable Energy Sources (RES), typically photovoltaic and wind, capable of injecting energy into the grid. Prosumers are therefore active/passive users who absorb from the network when their self-production is not sufficient to cover consumption. On the other hand, when a surplus is available, this energy can be stored in batteries or fed into the grid. Medium-sized plants powered by RES and connected to MV lines are also growing which, together with prosumers, contribute in generating energy flows different from those typical of concentrated generation. This new scenario called Distributed Generation (DG) introduces new challenges from the point of view of the stability, reliability and efficiency of the entire electricity system [1].

As in many different industrial sectors, nowadays AI-based approaches play a fundamental role for classification, regression and optimization tasks [2],[3]. In particular, the introduction of new control techniques for the management of bidirectional energy flows [4]-[6], together with modern diagnostic methods [7], [8] and the diffusion of Battery Energy Storage Systems (BESS) [9]-[11] play a fundamental role in the development of Smart Grids (SGs). The latter are characterized by a high level of automation and collaboration between grid-connected systems to achieve the best organization of resources and loads. In fact, in the near future, the massive integration of RES will require real-time energy management between production plants, prosumers and consumers in order to guarantee voltage and frequency stability and avoid excessive energy losses. Therefore, the local balancing of energy flows will be fundamental, which will be achieved through the optimal management of individual BESSs, integrating community strategies between multiple users, distributing ancillary services to local medium-sized production plants and batteries.

As for the community strategies, one of the most modern solution introduced in Europe is the creation of Renewable Energy Communities (RECs). These new entities allow both public and private prosumers, consumers and production facilities to organize their production and loads, obtaining economic benefits from their balancing [12]-[14]. In the Italian legislative framework, a REC is defined as a virtual community, composed of different consumers and RES-based energy producers.

In this paper, a new approach is proposed for managing a grid-connected prosumer following a rule-based methodology. The idea behind this choice is to design a fast control algorithm, based on an if-tree structure, to be executed frequently and for a large number of users, while leaving sufficient time for acquiring new data from the metering devices, sending commands to the actuators, and running the load/production forecasting algorithms. The control logic developed on the prosumer BESS can be easily extended to manage the batteries on a Micro Grid (MG) and to coordinate the users involved in a REC. The main objective of the proposed approach is to control energy flows to and from the prosumer unit based on the electricity market situation and production and consumption forecasts.

The problem of energy flow management is addressed in the literature using many different techniques, most of which are based on optimization algorithms. For example Demand Response (DR) is considered a reliable solution to smooth the demand curve when the electricity system is under stress and, in [15], a new stochastic optimization is presented to model the day-ahead load profile of a residential energy hub. For a single prosumer, the minimization of energy cost can be achieved using different methods, such as Lyapunov optimization based algorithm [16] or Particle Swarm Optimization (PSO) [17]. The latter is also commonly used in the MG scenario [18] whose structure could be optimized with reference to the level of RES integration [19]. Balancing energy flows for a single user or for multiple entities connected to the same distribution network is based on the key role of batteries. In [20] a method is proposed that includes a single optimization objective function with multiple options, which enable simulation multiple business models in the same format. The first is relating to the injection of energy into the grid and its implications. In particular, there is an economic incentive to feed energy into the grid (energy account) while a penalty is applied for exceeding the injection limit (over injection). The second aspect is the benefit induced by the difference between the selling and purchasing prices. In other works the focus is on the integration of electric vehicle batteries [21], [22] and on maximizing the profitability of the grid-connected BESS in relation to their longevity [23]. Many of this paper uses machine learning and deep learning algorithms [24]. In fact, as in other industrial sectors, the introduction of artificial intelligence techniques represents the main development also for the management of energy flows.

The main contribution of this paper is to propose an Energy Management System (EMS) capable of maximizing the economic gain of a grid-connected prosumer characterized by a photovoltaic system and a dedicated battery, which allows the following advantages compared to other solutions:

- the rule-based approach guarantees greater processing speed than other optimization methods and can be easily adapted to many users while limiting the computational effort;
- the management method applied to the battery guarantees a comparable economic gain with respect to the experimented optimization techniques;
- as for the impact on the grid, the proposed EMS moves energy consumption and injection facilitating the peak shaving.

The approach proposed in this work could be used in the near future to find an advantageous coexistence between standard BESS management strategies and new possibilities linked to the participation of prosumers in RECs.

This paper is organized as follows: Section II presents the main characteristics of the proposed approach and summarizes the other optimization techniques used to obtain a comparison, Section III describes the simulations and use cases considered. The fourth section presents the main results obtained and, finally, the fifth section presents the conclusions.

II. Proposed Approach

As mentioned above, the main objective of this paper is to propose an EMS for a single prosumer capable of maximizing the efficient use of PV energy through optimal battery planning. The logical structure of the proposed system is based on a rule-based approach that exploits information from the day-ahead energy market, the current state of the prosumer's battery and PV load and production forecasts. Fig. 1 summarizes the overall structure of the proposed EMS.

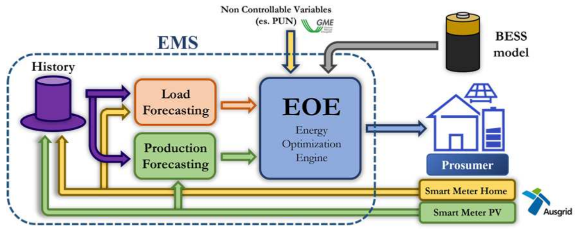


Fig. 1. General structure of the proposed Energy Management System.

In the proposed management strategy, the control actions are scheduled recursively every hour and this allows the progressive correction of forecast errors. In fact, the EMS generates the 72 subsequent interventions on the BESS every hour. These actions should be applied one for each hour but, if the prosumer condition at each step is different from the expected one, 72 new actions are generated. Implementing this control system requires three key characteristics:

- it is necessary to predict the energy flow between the network and the prosumer, i.e. the forecast of photovoltaic production and load;
- it is necessary to apply a control strategy based on market information that optimizes battery use;
- The optimization strategy should also include a battery degradation model to consider the battery replacement cost.

As regards the forecasting of load and production curves, in this work a Long-Short Term Memory (LSTM) neural network is used. These algorithms correctly balance the dependence of the final forecast on long-term and short-term historical events and are widely used to address the load forecasting problem. As for expected production, it is based on weather forecasts, therefore the main variations can be caused by temporary clouds.

In this section, the main characteristics of the rule-based approach are presented together with the optimization techniques used for comparison.

A. General Information

The first step to introduce the rule-based approach is to describe the energy price changes taken into account. In particular, the main price index used in this work is called PUN (Prezzo Unico Nazionale), which can be considered the primary result of the Italian day-ahead electricity market. Note that in this paper the Italian energy price is taken into consideration, but the management method can be applied to any electricity market allowing for robust performance. The PUN values are published every day by GME (Gestore Mercati Elettrici) and consist of 24 energy prices, one for each hour of the following day. They are average values of the 7 market areas in Italy and represent a reliable index for identifying the price of energy for sale and purchase.

Note that the PUN index indicates the price of energy without considering additional costs for the supply service and taxes. The latter are applied to the price of the energy purchased while they are not considered when the energy from the RES is fed into the grid. Based on the historical values of the PUN and the additional charges, which currently cover 40-50% of the entire user billing, it is possible to state that, in general, storing the excess energy of the photovoltaic system during the overproduction period and using it during night hours guarantee economic advantages. The main strategy on which the proposed method is based is to organize the sale and purchase based on forecasts and market information in order to maintain sufficient stored energy to cover the night period and maximize the profit on the surplus. For this reason, the direct consumption of the photovoltaic generator, which is called Self-Consumption (SC) and represents the best way to reduce the user's bill, can be managed by the system if forecasts and market information indicate more advantageous periods in which to use this energy. Regarding the production/consumption characteristics of the prosumer, these will be analyzed in detail during the presentation of the case study. However, it is clear that by comparing the expected production and consumption curves there will be periods of overproduction in which the surplus is stored or fed into the network and periods in which the prosumer must absorb from the network to satisfy its needs. To better understand the main aspects of the management strategy, it is necessary to highlight that the injection of energy into the grid during periods of overproduction identifies a "positive exchange", while absorption is defined as "negative exchange".

B. *Rule-Based Approach*

Based on the general information previously introduced, the main rules to maximize the cash flow can be summarized as follows.

- Program the battery discharge during the negative slots by distributing the available energy in the hours with the highest purchase cost.
- Schedule battery recharging to achieve a specific State Of Charge (SOC) target; this phase is scheduled during hours characterized by a low selling price.
- In each positive slot, set the minimum charge level of the storage system based on the forecast of energy demand in the following hours.
- Set the SOC target in the last positive slot of each day at least equal to half the battery capacity, this is to avoid instability in the expected load profile.

The main countermeasures implemented in the algorithm to mitigate the effects of imperfect forecasts can be summarized as follows.

- A correction is added to the SOC target level in the positive slots. This parameter corresponds to the average error made in predicting the aggregate energy of the previous negative slots.
- When the current slot is negative, the two hours with the highest energy purchase cost are identified on the PUN curve. If one of these is the current one, then the system is allowed to use all the energy necessary to cover consumption, skipping the programming made. In this way, it is possible to correctly manage situations in which the load is higher than expected.
- Similarly, if the current slot is positive and corresponds to one of the two with the lowest energy sales cost, the constraints on the SOC level are released allowing the complete storage of any unforeseen overproduction.
- In the case of a positive slot, it is necessary to intervene if the expected surplus does not occur. In this case the algorithm must intervene promptly by switching the battery to the discharge phase.
- Note that in the negative slots it is important to constantly check the energy available in the battery. If the stored quantity exceeds the expected demand for the remainder of the slot, the discharge limitation is relaxed to compensate for any unexpected energy demand.

C. *Optimization Algorithms*

As previously mentioned, the proposed rule-based approach is compared with other optimization techniques, such as for example Genetic Algorithms (GAs), Particle Swarm Optimization (PSO) and Mixed-Integer Linear Programming (MILP).

Genetic Algorithms represent a bio-inspired optimization technique that draws inspiration from the principles of natural selection and genetic processes to efficiently solve complex optimization problems. GAs iteratively generate and refine a population of potential solutions. The fundamental idea behind GAs involves coding potential solutions as individuals in a population, each characterized by a set of parameters or genes. The algorithm evaluates the suitability of these individuals based on their performance in solving the given problem. Solutions with higher fitness values are more likely to be selected for reproduction. Reproduction involves processes such as crossover and mutation, similar to genetic recombination and variation in biological organisms. The iterative application of selection, crossover and mutation promotes the evolution of the population towards increasingly suitable solutions over the course of subsequent generations. Through this iterative refinement, genetic algorithms efficiently explore the solution space, adapting and converging towards optimal or near-optimal solutions for the given problem. The optimization problem is formulated as a two-objective problem described in (1) and (2).

$$\underset{\boldsymbol{x}}{\text{minimize}}\ ff_i(\boldsymbol{x}), \quad i = 1, 2 \tag{1}$$

$$L_j < x_j < U_j \tag{2}$$

Note that $\boldsymbol{x}$ is the vector of the optimization variables, L_j and U_j are respectively the lower bound and the upper bound for the j-th variable.

The Particle Swarm Optimization algorithm is a stochastic optimization technique in which a population of potential solutions, called particles, move through the solution space, with the goal of finding the optimal configuration. Each particle adjusts its position and speed based on personal experiences and knowledge of the best spot found by the entire group. This particle update process is driven by finding the maxima or minima of a defined objective function. The update equations for a single particle are shown in (3) and (4), for velocity v and position x respectively, where ω is the inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers between 0 and 1, p_i is the personal best position of particle i and p_g is the global best position among all particles.

$$v_i(t+1) = \omega\, v_i(t) + c_1\, r_1\, (p_i - x_i) + c_2\, r_2\, (p_g - x_i) \quad (3)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (4)$$

The algorithm continues iteratively, updating speeds and positions until a termination criterion is met, such as reaching a specified number of iterations or reaching a satisfactory solution. The inertia weight balances the exploration and exploitation phases, controlling the impact of previous speeds on the current update. The acceleration coefficients determine the influence of personal and global best positions on the motion of the particle.

Mixed Integer Linear Programming is an optimization technique used to solve complex decision problems characterized by linear relationships and a mix of continuous and discrete decision variables. The main goal is to optimize a linear objective function subject to a set of linear constraints, where some variables are limited to integer values. This combination allows MILP to model real-world scenarios more accurately, as it addresses problems with both continuous and discrete decision aspects. In other words, MILP problems involve minimizing or maximizing an objective function, representing a cost or benefit, while respecting the constraints imposed by the system. From a general point of view, the optimization problem can be expressed as shown in (5) and (6), which are the objective and the linear constraints respectively.

$$minimize\ or\ maximize \quad c^T x \quad (5)$$

$$Ax \le b \quad (6)$$

Where c is the vector of coefficients in the objective function, x is the vector of decision variables, A is the matrix representing the coefficients of the linear constraints and b is the vector of constraint limits.

III. Use Case and Simulations

This section presents the main characteristics of the use case taken into consideration. The control algorithms previously described are applied on a single prosumer equipped with a 6 kWh battery.

A. Use Case: Single Grid-Connected Prosumer

The user considered for testing the performance of rule-based EMS and other optimization techniques is a grid-connected prosumer, extracted from an online database [26]. Its annual consumption is 3000 kWh, which is an average value for Italian users. Furthermore, this prosumer is characterized by a 3kWp photovoltaic generator, whose production is theoretically sufficient to cover global consumption. In fact, referring to the annual production capacity in Italy, a target of 1100 kWh/kWp can be assumed. Obviously, the effective Self-Consumption (SC) depends on the contemporary of consumption and PV production. Statistically, a mean value of percentual SC in Italy without domotic appliances is 30% and the remaining energy is injected to the grid. As mentioned previously, the energy injected into the network is remunerated at the market price and, in this paper, the value of the Italian PUN is assumed. It should be noted that the price of the energy that the prosumer absorbs from the grid when photovoltaic production is absent is higher due to the presence of taxes and system charges. In order to evaluate the performance of the control algorithms, one-year data is simulated using the PUN profile for the year 2022 as a price reference. As for the prosumer BESS, a 6 kWh LFP lithium battery is considered which can be managed by algorithms in order to organize daily self-consumption and maximize cash flow. In general, batteries are used to provide the surplus energy stored during the day at night but, in this case, further intelligent actions are introduced by control algorithms to choose the best energy management strategy.

B. Battery Degradation Model

In order to correctly evaluate the cost and effect of control actions on the BESS, it is necessary to introduce a battery degradation model and a battery efficiency model. Given $Q(t)$ as the charge level of the BESS at time t, $Q_{max}(t)$ the maximum charge level at time t and $Q_{max-nom}$ as the nominal capacity of the storage, the SOC can be defined by (7). As for the State Of Health (SOH) of the battery, equation (8) can be used.

$$SOC(t) = \frac{Q(t)}{Q_{max}(t)} \quad (7)$$

$$SOH(t) = \frac{Q_{max}(t)}{Q_{max-nom}} \quad (8)$$

To validate the proposed control technique, it is important to verify that the EMS does not cause excessive battery degradation. In this work, it is assumed that it is necessary to replace the battery when its capacity loss corresponds to 20% of the nominal capacity value. This degradation threshold is indicated as D_{max}. Therefore, whenever a specific sequence of actions is scheduled by the EMS, the corresponding cost is calculated via (9),

$$S_{cost} = \frac{D_{seq}}{D_{max}}\, BEES_{cost}\, 100 \quad (9)$$

where $BEES_{cost}$ is the total price of the battery and D_{seq} is its general degradation. The latter can be considered as the sum of two different effects, called cycle degradation D_{cycle} and aging degradation D_{age}. As described in [25], the cycle degradation directly depends on the battery use and, therefore, it can be expressed as a function of the temperature T, the Deep Of Penetration (DOP) and the charging/discharging rate C_{rate}. To evaluate the cycle degradation, this paper uses the method shown in [27]. Regarding degradation due to aging, the main parameters taken into consideration are ambient temperature, service time and SOC. In general, the relationship between time and battery aging is linear [28], high temperatures accelerate the degradation process [29] and the impact of SOC depends on the type of battery [30]. In this paper, a linear interpolation of the profiles given in [30] is used to model the aging degradation of lithium batteries commonly used in domestic applications with PV generators. As for the BESS efficiency, two terms are considered, for both charging and discharging phases. These parameters are not constant and mainly depend on the C_{rate} and SOC. In fact the C_{rate} depends on the instantaneous value of the current that is stored or absorbed by the battery, therefore it has a direct relationship with the losses due to thermal effect. In [31] both efficiency parameters are represented as curves as a function of C_{rate} and SOC. Assuming that the state of charge is managed to never fall below 10% of rated capacity, these curves can be linearized and easily used in the control algorithm.

IV. Results

In this section, the main results obtained by applying the proposed algorithm to the previously described prosumer are presented. The final cash flow evaluation is calculated on one-year data. Using the same data, a comparison is made between the different optimization techniques and the proposed EMS. The first result shown in Fig. 3 presents the behavior of the rule-based algorithm in the case of perfect production and load forecasts.

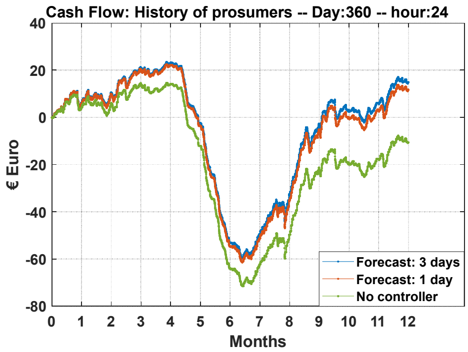


Fig. 2. Results obtained with perfect forecasts and without controller.

The annual cash flow obtained without implementing the regulator is also shown (green curve); in this situation the battery charges when a surplus is available and discharges when the PV production is not sufficient. The algorithm updates the battery actions every hour. The red and blue curves in Fig. 3 show that corrections made with perfect forecasts of the next 72 hours guarantee better results than knowing only 24 hours. The second result presented in Fig.4 shows that the presence of imperfect forecasts, if not correctly treated, leads to a drastic decrease in performance. Indeed, in this situation better cash flows can be obtained without applying the controller. However, by integrating the countermeasures described in section III.B it is possible to mitigate the effects of forecast errors. The controller allows satisfactory results to be obtained again (Fig.5). Finally, Fig. 6 shows the comparison between the rule-based controller and the other optimization techniques.

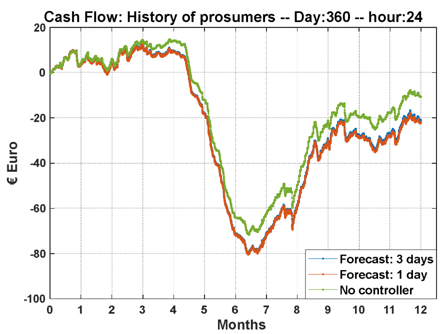


Fig. 3. Results obtained with imperfect forecasts and no contermeasures.

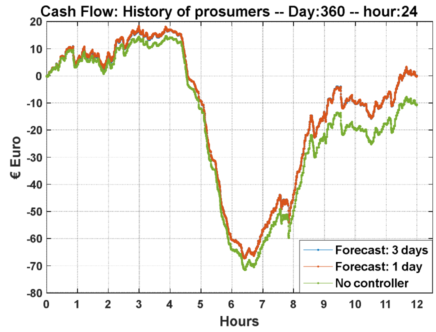
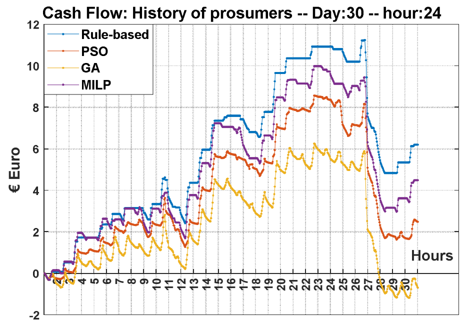
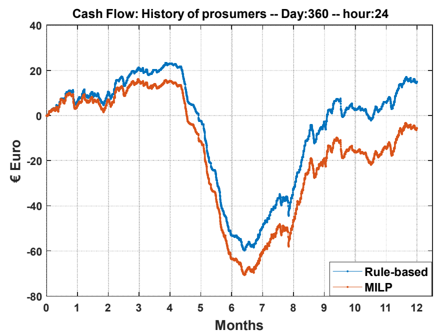


Fig. 4. Results obtained with imperfect predictions and application of countermeasures.



(a)



(b)

Fig. 5. Comparison between rule-based algorithm and optimization techniques: a) all methods evaluated in 30 days; b) best methods evaluated in 360 days.

V. Conclusions

In conclusion, it is possible to state that the rule-based algorithm proposed in this paper as EMS of a grid-connected prosumer allows good performance in terms of cash flow and energy exchange. The management strategy was presented, highlighting the corrections introduced to limit the effects of imperfect forecasts. Thanks to these interventions it is possible to improve the economic income deriving from the sale and self-consumption of energy. Finally, the results obtained with the EMS presented in this paper are comparable to those obtained through other optimization techniques, but the strategy processing time is significantly lower, making the rule-based approach more appealing. In particular, we estimated that the rule-based approach is about twenty times faster than the MILP algorithm. Thanks to this advantage, as possible future developments, it is planned to apply the algorithm to control multiple prosumers in the same REC.

Acknowledgment

This work was supported by the Italian Ministry for Research in the framework of the 2022 Program for Research

Projects of National Interest (PRIN) under Grant 2022K4CLL3.

REFERENCES

[1] B.G. Risi, F. Riganti-Fulginei, A. Laudani, M.C. Quercio, "Compensation Admittance Load Flow: A Computational Tool for the Sustainability of the Electrical Grid, " in Sustainability vol. 15, 2023, https://doi.org/10.3390/su151914427.

[2] T. Addabbo et al., "Smart gravimetric system based on Deep Learning for enhanced safety of accesses to public places," 2021 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Glasgow, United Kingdom, 2021, pp. 1-6, doi: 10.1109/I2MTC50364.2021.9460052.

[3] E. Landi et al., "A MobileNet Neural Network Model for Fault Diagnosis in Roller Bearings," 2023 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Kuala Lumpur, Malaysia, 2023, pp. 01-06, doi: 10.1109/I2MTC53148.2023.10176049.

[4] J. Zeng, X. Du and Z. Yang, "A Multiport Bidirectional DC–DC Converter for Hybrid Renewable Energy System Integration," in IEEE Transactions on Power Electronics, vol. 36, no. 11, pp. 12281-12291, Nov. 2021, doi: 10.1109/TPEL.2021.3082427.

[5] F. Corti, V. Bertolini, A. Reatti, E. Cardelli and M. Giallongo, "Comparison of Control Strategies for Dual Active Bridge Converter," 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON), Palermo, Italy, 2022, pp. 902-907, doi: 10.1109/MELECON53508.2022.9843012.

[6] M. Bindi et al., "Comparison Between PI and Neural Network Controller for Dual Active Bridge Converter," 2021 IEEE 15th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), Florence, Italy, 2021, pp. 1-6, doi: 10.1109/CPE-POWERENG50821.2021.9501168.

[7] M. Bindi, A. Luchetta, G. M. Lozito, C. F. M. Carobbi, F. Grasso and M. C. Piccirilli, "Frequency Characterization of Medium Voltage Cables for Fault Prevention Through Multi-Valued Neural Networks and Power Line Communication Technologies," in IEEE Transactions on Power Delivery, vol. 38, no. 5, pp. 3227-3237, Oct. 2023, doi: 10.1109/TPWRD.2023.3270128.

[8] M. Bindi et al., "Failure Prevention in DC–DC Converters: Theoretical Approach and Experimental Application on a Zeta Converter," in IEEE Transactions on Industrial Electronics, vol. 70, no. 1, pp. 930-939, Jan. 2023, doi: 10.1109/TIE.2022.3153827.

[9] M. Pasqui, A. Felice, M. Messagie, T. Coosemans, T. Tiozzo Bastianello, D. Baldi, P. Lubello, C. Carcasci, "A new smart batteries management for Renewable Energy Communities," in Sustainable Energy, Grids and Networks, vol. 34, 2023, https://doi.org/10.1016/j.segan.2023.101043.

[10] V. Lucaferri, M. Quercio, A. Laudani, F. Riganti Fulginei, "A Review on Battery Model-Based and Data-Driven Methods for Battery Management Systems," in Energies, vol. 16, 2023, https://doi.org/10.3390/en16237807.

[11] A. Canova, F. Campanelli, M. Quercio, "Flywheel Energy Storage System in Italian Regional Transport Railways: A Case Study," in Energies, vol. 15, 2022, https://doi.org/10.3390/en15031096.

[12] H. Sæle, A. Morch, A. Buonanno, M. Caliano, M. D. Somma and C. Papadimitriou, "Development of Energy Communities in Europe," 2022 18th International Conference on the European Energy Market (EEM), Ljubljana, Slovenia, 2022, pp. 1-5, doi: 10.1109/EEM54602.2022.9921054

[13] E. Belloni, F. Grasso, G. M. Lozito, D. Poli, F. Riganti Fulginei, G. Talluri, "Neural-assisted HVACs optimal scheduling for renewable energy communities," in Energy and Buildings, vol. 301, 2023, https://doi.org/10.1016/j.enbuild.2023.113658.

[14] M. Intravaia, L. Becchi, M. Bindi, L. Paolucci and F. Grasso, "Autoencoders for Hourly Load Profile Reconstruction in Renewable Energy Communities," IEEE EUROCON 2023 - 20th International Conference on Smart Technologies, Torino, Italy, 2023, pp. 280-285, doi: 10.1109/EUROCON56442.2023.10199058.

[15] M. Park, J. Lee and D. -J. Won, "Demand Response Strategy of Energy Prosumer Based on Robust Optimization Through Aggregator," in IEEE Access, vol. 8, pp. 202969-202979, 2020, doi: 10.1109/ACCESS.2020.3034870.

[16] R. F. Chidzonga and B. Nleya, "Energy Optimization for a Smart Home with Renewable Generation," 2019 IEEE PES/IAS PowerAfrica, Abuja, Nigeria, 2019, pp. 694-699, doi: 10.1109/PowerAfrica.2019.8928711.

[17] M. B. Arab, M. Rekik and L. Krichen, "Prosumer and Small-Scale Prosumer Energy management system," 2022 IEEE 21st international Ccnference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), Sousse, Tunisia, 2022, pp. 678-683, doi: 10.1109/STA56120.2022.10019097.

[18] U. Damisa and N. I. Nwulu, "Particle Swarm Optimization for Robust Power Management in DC Prosumer Microgrids with Battery," 2019 IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS), Kuala Lumpur, Malaysia, 2019, pp. 1-6, doi: 10.1109/ICETAS48360.2019.9117413.

[19] X. Ma, S. Liu, H. Liu and S. Zhao, "The Selection of Optimal Structure for Stand-Alone Micro-Grid Based on Modeling and Optimization of Distributed Generators," in IEEE Access, vol. 10, pp. 40642-40660, 2022, doi: 10.1109/ACCESS.2022.3164514.

[20] A. Yaniv, Y. Beck, "Optimal battery scheduling in solar-plus-storage grid-connected microgrid for profit and cost efficiency: A use case on an Israeli microgrid," in Journal of Energy Storage, vol. 77, 2024, doi: 10.1016/j.est.2023.109697.

[21] D. S. Nayak, S. Misra, "An operational scheduling framework for Electric Vehicle Battery Swapping Station under demand uncertainty," in Energy, vol. 290, 2024, https://doi.org/10.1016/j.energy.2023.130219.

[22] W. Li, Y. He, S. Hu, Z. He, C. Ratti, "Planning dynamic wireless charging infrastructure for battery electric bus systems with the joint optimization of charging scheduling," in Transportation Research Part C: Emerging Technologies, vol. 159, https://doi.org/10.1016/j.trc.2023.104469.

[23] M. Shabani, M. Shabani, F. Wallin, E. Dahlquist, J. Yan, "Smart and optimization-based operation scheduling strategies for maximizing battery profitability and longevity in grid-connected application," Energy Conversion and Management: X, vol. 21, 2024, https://doi.org/10.1016/j.ecmx.2023.100519.

[24] H. Kang, S. Jung, H. Kim, J. Jeoung, T. Hong, "Reinforcement learning-based optimal scheduling model of battery energy storage system at the building level," in Renewable and Sustainable Energy Reviews, vol. 190, 2024, https://doi.org/10.1016/j.rser.2023.114054.

[25] X.G. Yang, C.Y. Wang, "Understanding the trilemma of fast charging, energy density and cycle life of lithium-ion batteries," in Journal of Power Sources, vol. 402, 2018, https://doi.org/10.1016/j.jpowsour.2018.09.069.

[26] "Ausgrid," [Online]. Available: https://www.ausgrid.com.au/.

[27] M. J. E. Alam and T. K. Saha, "Cycle-life degradation assessment of Battery Energy Storage Systems caused by solar PV variability," 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 2016, pp. 1-5, doi: 10.1109/PESGM.2016.7741532.

[28] A. Krupp, R. Beckmann, T. Diekmann, E. Ferg, F. Schuldt, C. Agert, "Calendar aging model for lithium-ion batteries considering the influence of cell characterization," in Journal of Energy Storage, vol. 45, 2022, https://doi.org/10.1016/j.est.2021.103506.

[29] H. Ali, H. Beltran, N. J. Lindsey, M. Pecht, "Assessment of the calendar aging of lithium-ion batteries for a long-term—Space missions, " in Frontiers in Energy Research, vol. 11, 2023.

[30] P. Keil, S.F. Schuster, J. Wilhelm, J. Travi, A. Hauser, R.C. Karl, A. Jossen, "Calendar aging of lithium-ion batteries," in Journal of The Electrochemical Society, vol. 9, 2016.

[31] A. J. Gonzalez-Castellanos, D. Pozo and A. Bischi, "Non-Ideal Linear Operation Model for Li-Ion Batteries," in IEEE Transactions on Power Systems, vol. 35, no. 1, pp. 672-682, Jan. 2020, doi: 10.1109/TPWRS.2019.2930450.