



Technical Sciences
Academy of Romania
www.jesi.astr.ro

Journal of Engineering Sciences and Innovation

Volume 11, Issue 3 / 2026, p. 443- 456

<http://doi.org/10.56958/jesi.2026.11.3.443>

**F. Electrical, Electronics Engineering,
Computer Sciences and Engineering**

Received 28 August 2025

Accepted 11 September 2026

Received in revised form 07 June 2026

Energy Management Algorithm in Smart Microgrids with Renewable Energies That Uses Battery Degradation Cost and Short-Term Consumption Prediction

TOMA PĂTĂRĂU*, DORIN PETREUȘ, ENIKO SZILAGYI

Technical University of Cluj-Napoca, Romania

Abstract. This paper develops a day-ahead energy management algorithm, based on mixed integer linear programming (MILP), dedicated to the efficient operation of island microgrids (without connection to the national grid). The proposed algorithm integrates two essential components: a short-term (24-hour) prediction method of the consumption curve of the loads connected to the microgrid, as well as a rigorous method of estimating the costs associated with battery degradation, resulting from charge/discharge cycles. The analyzed microgrid is composed of a geothermal generator, a biomass generator, a photovoltaic (PV) system, a battery energy storage system and an energy management system. The load forecasting method allows to anticipate consumption variations with increased accuracy, using historical data measured in the microgrid. This prediction is essential for making optimal decisions within the MILP algorithm, which aims to minimize the total operating costs of the microgrid, including those resulting from battery degradation. By correlating meteorological data and those obtained from the consumption prediction with a detailed model of battery behavior, a local resource scheduling strategy is obtained that maximizes battery life, ensures energy balance and contributes to system sustainability. The results obtained highlight the benefits of an integrated and adaptive approach to energy management in the context of island microgrids.

Keywords: renewable energy, smart microgrids, energy optimization algorithms, batteries.

1. Introduction

As global electricity demand continues to rise, nations are placing greater emphasis on integrating renewable energy sources into their power systems. Despite their environmental benefits, the intermittent nature of renewables can pose significant challenges to grid stability and power quality. To mitigate these issues, energy storage solutions - especially battery storage systems (BSSs) - are being increasingly

Correspondence address: toma.patarau@ael.utcluj.ro

explored as viable and effective technologies. Energy storage systems also allow better utilization of renewable energy resources. In remote areas and off-grid systems, islanded renewable energy microgrids offer a reliable and environmentally friendly solution for energy supply. However, operating and managing these microgrids is a complex task that requires the efficient, stable, robust, and resilient coordination of various renewable energy sources, storage systems, and loads [1], [2].

Energy management algorithms are used to perform this task. An energy management algorithm is defined as a control strategy designed to balance power generation and consumption while minimizing a cost function. The cost functions can minimize the energy costs, extend the lifetime of the storage system or perform other user defined functions [3] thus the energy management system plays an important role in increasing the reliability and efficiency of a microgrid. There are a wide variety of methods dealing with energy management in renewable energy microgrids.

Mixed-Integer Linear Programming is extensively used for energy management in renewable energy microgrids for cost reduction and grid resilience [4]. This method can fulfill the energy needs (independence from the grid) while obtaining cost savings for customers. Sukumar et al. [5] presented a mixed-mode energy management algorithm for controlling a microgrid with the goal of minimizing operating costs. They also proposed an optimal sizing method for the battery system. Linear programming and mixed-integer linear programming were employed to solve the energy management cost function. The study aimed to reduce the microgrid's daily operating expenses. The authors found that a battery with a higher state of charge (SOC) at the beginning of the day leads to lower operating costs.

Heyman et al. [6] applied two methods for optimal energy management control of the microgrid: a direct method and a Bellman's Dynamic Programming Principle (DPP) approach. The methods used obtained the global optimum in a very short time (less than a second). The solutions were close to the ones obtained with MILP formulation.

Rodrigo Palma-Behnke et al. [7] proposed an energy management method based on a rolling horizon (RH) approach for a renewable energy microgrid. The paper employed a forecasting-based mixed-integer linear programming (MILP) model to solve the problem at each step. The energy management system (EMS) provides real-time set points for each renewable energy generator and control signals for demand-side management. The authors also introduced a neural network for two-day-ahead consumption forecasting. The study showed economic benefits under various operating conditions. The rolling horizon has the advantage of dealing with updated data from the forecast algorithm.

Reference [8] presents an energy management system designed for a virtual power plant. The primary objective of the proposed system is to control power flow in a way that minimizes electricity costs and mitigates energy losses caused by the overproduction of renewable energy sources.

Lu and Francois [9] proposed an energy management system for a microgrid based on day-ahead power scheduling, incorporating power generation prediction and load

forecasting. The EMS delivers real-time power set points to microgrid units and coordinates droop controllers to support primary frequency regulation.

Teleke et al. [10] proposes a rule-based control strategy for a wind farm with photovoltaic arrays and battery storage. Based on solar and wind forecasting the renewable energy generators can be dispatched hourly. The rule-based controller charges and discharges the battery storage system based on state-of-charge and battery voltage.

Morais et al. [11] presented an optimal energy management system for a renewable energy park. The presented microgrid is composed of: photovoltaic panels, wind turbines, a fuel cell, loads and a battery management system. The dispatch strategy is based on the minimization of energy costs on optimal control of charging discharging cycles.

Korpas and Holen [12] developed an energy management system (EMS) for a hybrid power plant integrating wind energy and hydrogen storage. The system is designed to optimize expected profits from electricity trading in the day-ahead market, leveraging forecast data on power generation, demand, and market prices. However, the studies referenced rely primarily on basic forecasting inputs for electricity demand and renewable energy availability. Furthermore, the economic impact of the proposed control strategies is not thoroughly analyzed or quantified.

The present paper presents a day-ahead energy management algorithm designed for the efficient operation of islanded microgrids—systems that function independently from the national electricity grid. The algorithm is formulated using mixed-integer linear programming (MILP) to ensure optimal scheduling of energy resources while minimizing operational costs. It integrates two critical components: a short-term (24-hour) forecasting model that predicts the consumption patterns of loads connected to the microgrid, and a comprehensive cost estimation method that accounts for battery degradation due to charge and discharge cycles. By incorporating both predictive analytics and lifecycle cost considerations, the proposed approach enhances the reliability, sustainability, and economic performance of the islanded microgrid systems.

The structure of the paper is as follows: Section 1 reviews the state of the art; Section 2 describes the microgrid under study; Section 3 details the proposed algorithms; Section 4 presents and analyzes the results; and Section 5 concludes the paper with final remarks and future perspectives.

2. Renewable energy microgrid architecture

The analyzed microgrid, Fig 1, is composed of: a geothermal generator, a biomass generator, a photovoltaic (PV) system, battery energy storage system and an energy management system. The characteristics of the microgrid are summarized in Table 1. The cost optimization algorithms are executed on an external server, and only the final output - a scheduling plan presented in tabular form - is transmitted to the Energy Management Control System (EMC).

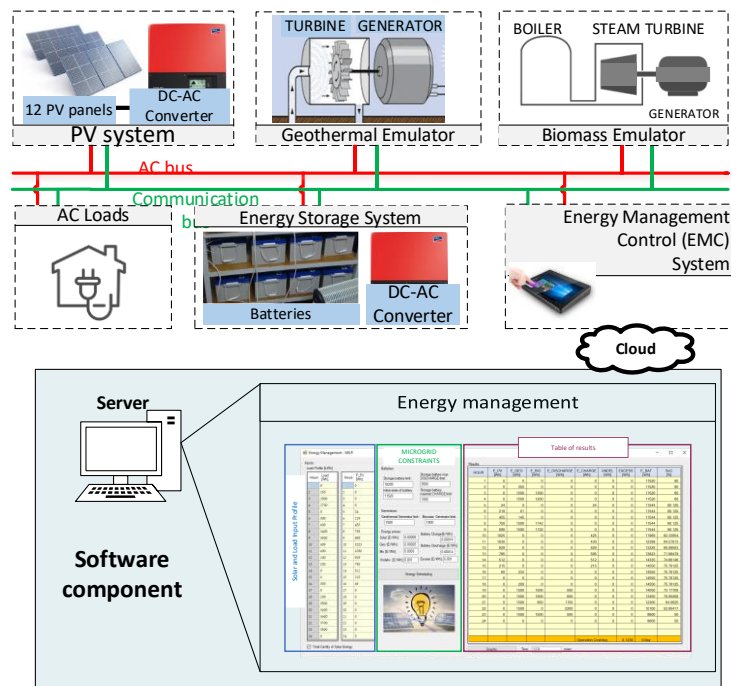


Fig. 1. Proposed microgrid.

MICROGRID CHARACTERISTICS

Units	Characteristics
Batteries WT-SG200-12	12V; 200Ah; 8 batteries; Capacity = 19200 Wh; Cost _B = ~380 € per piece
PV Panels ET-P660250WW/WB	Max Power = 250 W; PV Eff. = 15.6 %; Area = 992 mm x 1640 mm; Cost C _{PV} = 0.00005 €/Wh
Geothermal Emulator	E _{GEO MAX} = 1.5 kWh; Cost C _{GEO} = 0.00025 €/Wh;
Biomass Emulator	E _{BIO MAX} = 1.5 kWh; Cost C _{BIO} = 0.0004 €/Wh

3. Control architecture

The system features a three-level architecture control, Fig. 2. In addition to the Energy Management Control System (EMC), which operates at a higher level, the primary control layer is based on droop control mechanisms - specifically, active power versus frequency. This hierarchical setup ensures robust and reliable operation of the microgrid, maintaining stability even in the event of a failure in the upper-level control system. The secondary control level deals with energy management algorithms. It receives the power and the time interval each generator should stay ON, in a tabular form and sends the control signals to the generators. The tertiary control layer uses day-ahead load and weather prediction algorithms and battery degradation cost calculations. The data obtained after forecasting is used by the optimization algorithm to determine the operation setpoints to minimize energy costs. The novelty of the present paper states in the fact that it combines consumer behavior prediction, battery cost degradation and a cost optimization method based

on linear programming (MILP) in order to control the microgrid with minimum energy cost.

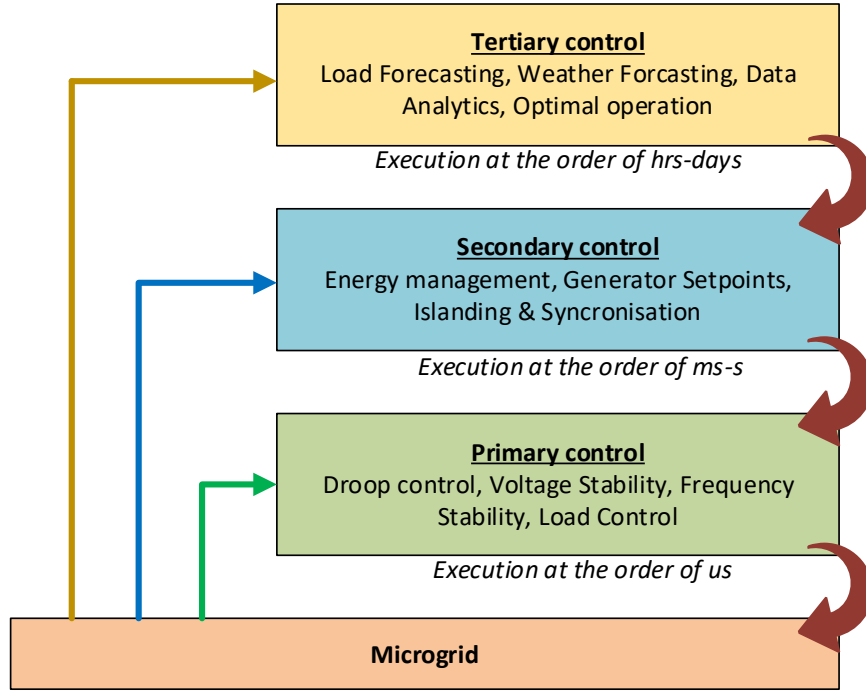


Fig. 2. Control architecture of the islanded microgrid.

3.1. Calculation of battery degradation costs

To ensure the microgrid operates reliably, the battery system plays an important role in balancing energy production and consumption through its charge and discharge cycles. The precise estimation of the associated service cost is influenced by multiple variables, including the number, timing, and repetition of these cycles, as well as the technical characteristics that depend on the system components. This calculation becomes even more complex when considering the microgrid's constraints, along with its specific financial obligations. Accordingly, the energy cost contribution of the Battery Storage System (BSS) should be thoroughly calculated and subsequently added in the energy management algorithm.

Various methods have been proposed in the literature to estimate battery degradation costs. One commonly used approach calculates the cost of degradation per kilowatt-hour (kWh) of energy, which depends on both the battery's capital cost and its total energy throughput (ET), as outlined in the following equation [13]-[15].

$$C_{BAT1} = Cost_B / ET \quad (1)$$

$$ET = C \times \eta_{rt} \times DoD \times LC. \quad (2)$$

In the above equation C_{BAT1} denotes the battery degradation cost coefficient; $Cost_B$ is the capital cost of the battery system; ET refers to the total energy throughput. C represents the nominal battery capacity, η_{rt} is the round-trip efficiency, DoD stands for the depth of discharge, and LC indicates the battery's life cycle. These parameters are typically available in the battery manufacturer's datasheets.

A second method determines the battery degradation cost based on state of charge (SoC) information from the batteries. This method is used in Homer Energy software [16]. This model links the hourly operational cost of the battery to a base cost factor, parameters related to the state of charge, and the battery's available capacity at each hour. It is calculated using Equation (3) [17]:

$$C_{BAT2}(t) = C_{BAT1} \times k_{SOCmin} \times (1 - SOC_{min}) \times P_{BSS}(t) \quad (3)$$

This method uses the cost coefficient determined in the previous method: C_{BAT1} . k_{SOCmin} is a scalar parameter that can be derived from the battery manufacturer's specifications. SOC_{min} indicates the minimum permissible state of charge, and P_{BSS} represents the available battery capacity.

In this study, the battery degradation cost is evaluated using the rainflow-counting algorithm (RCA). Unlike conventional methods, this approach accounts for the progressive reduction in battery lifespan caused by operational cycling, offering a fundamentally different perspective on degradation cost estimation.

In this method the DoD parameter is used to calculate the degradation cost of the battery since it is focusing on the optimal scheduling of the microgrid. The following equation describes accurately the number of complete charge/discharge cycle N_{Cycle} based on the DoD and on datasheet parameters. Coefficients a , b and c are used for curve-fitting and $C_E(SOC)$ defines the degradation cost of the battery.

$$N_{Cycle} = a \times DoD^{-b} \times e^{c \cdot (1 - DoD)} \quad (4)$$

$$C_E(SOC) = Cost_B / N_{Cycle} \quad (5)$$

However, to apply this equation accurately, two key assumptions must be carefully considered. First, it is assumed that charging and discharging at a specific Depth of Discharge contributes uniformly to cell degradation until the maximum cycle life at that DoD is reached. Second, the degradation effects of each charge-discharge cycle are considered independent of any previous cycles. Applying RCA method to equation (5) the proper degradation cost of the battery system is obtained, equation 6.

$$C_{BAT3}(t) = \begin{cases} C_E(SOC_t) - C_E(SOC_{t-1}), & \text{at discharge} \\ 0, & \text{at charge} \end{cases} \quad (6)$$

The algorithm begins by identifying local minima and maxima in the State of Charge (SoC) profile, ignoring intermediate fluctuations. It then evaluates the amplitude of half-cycles between each pair of local extrema. As the analysis progresses, it computes equivalent cycles. Mainly, the Rainflow Counting Algorithm quantifies the number of full or partial equivalent cycles based on a given SoC profile.

3.2. Load prediction

Load forecasting is a critical component in the effective and efficient energy management of intelligent microgrids. It provides essential insights to the intelligent management controller, enabling better energy conservation and operational decisions [18], [19]. This forecasting plays a pivotal role in short-term operational planning and supports long-term strategies for infrastructure development.

Forecasting can be categorized based on time horizons: short-term, medium-term, and long-term. Short-term forecasts are primarily used to optimize daily microgrid operations, while medium and long - term forecasts are used for participating in energy markets, setting electricity prices, and managing energy distribution at the larger power network level [20], [21]. Ultimately, the more accurate the load forecasting, the more efficiently the microgrid can operate, leading to significant reductions in operational costs.

There are a wide variety of methods used for load forecasting in literature: Kalman filter-based, Autoregressive Integrated Moving Average (ARIMA), artificial neural networks (ANN), Particle Swarm Optimization, Genetic Algorithm (GA), Firefly Algorithm (FFA), Grasshopper Optimization Algorithm, Empirical Mode Decomposition [22].

Based on a study from [22] Autoregressive Integrated Moving Average algorithm was used for load prediction in this paper. It was found that in the current renewable energy microgrid setup for in such cases where the load profile is relatively stable and exhibits minimal daily variation - ARIMA provides the most accurate load predictions. The algorithm implemented in MATLAB for load prediction using ARIMA is presented in the figure below.

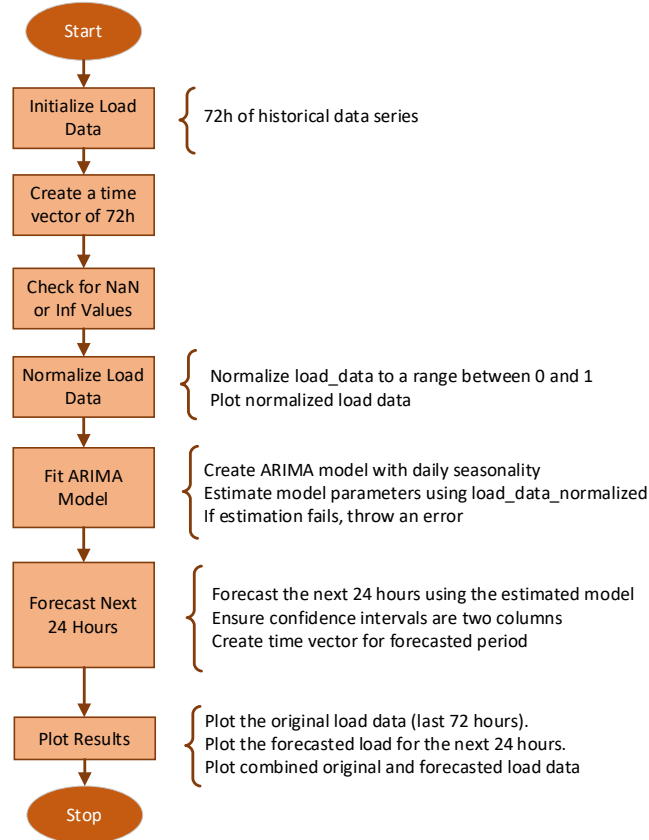


Fig. 3. Load forecasting algorithm using ARIMA.

3.3. Optimization problem

The optimization algorithm focuses on minimizing the operation costs of the microgrid. It aims to identify the most efficient microgrid operating strategy at minimal cost. It also focuses on optimizing battery system usage to prolong battery lifespan. The objective function used is described in eq. 7.

$$\min f_{cost} = \sum_{t=1}^{24} C_{PV} \cdot E_{PV}(t) + C_{GEO} \cdot E_{GEO}(t) + C_{BIO} \cdot E_{BIO}(t) + C_{PENALTY} \cdot (E_{EX}(t) + C_{UN}(t)) + f(Batteries) \quad (7)$$

In the equation above: C_{PV} is the cost of solar energy; E_{PV} is the amount of solar energy utilized, C_{GEO} is the cost of geothermal energy, E_{GEO} is the amount of geothermal energy used, C_{BIO} is the cost of biomass energy, E_{BIO} is the amount of biomass energy consumed $C_{PENALTY}$ is the penalty cost coefficient, E_{EX} and E_{UN} represent excess and undelivered energy, respectively $f(Batteries)$ is the battery cost calculation [1]. The constraints are represented in the table below.

CONSTRAINTS

Constraint	Equation
Power Balance	$\sum_{t=1}^{24} E_{PV}(t) + E_{GEO}(t) + E_{BIO}(t) + E_{DCH}(t) + E_{UN}(t) = Load(t) + E_{CH}(t) + E_{EX}(t)$
SoC	$E_{BSS}(t) = E_{BSS}(t-1) - E_{DCH}(t) + E_{CH}(t)$
	$SOC(t) = 100 \cdot E_{BSS}(t) / E_{BSS_RATED}$
	$50\% \cdot E_{BSS_RATED} \leq SOC(t) \leq 80\% \cdot E_{BSS_RATED}$
Limits	$0 \leq E_{PV}(t) \leq E_{PV_MAX} ; 0 \leq E_{GEO}(t) \leq E_{GEO_MAX} ; 0 \leq E_{BIO}(t) \leq E_{BIO_MAX} ; 0 \leq E_{CH}(t) \leq E_{CH_MAX} ; 0 \leq E_{DCH}(t) \leq E_{DCH_MAX}$

E_{CH} and E_{DCH} represent the energy charged to and discharged from the batteries, respectively. E_{BSS} denotes the current amount of energy stored in the battery system, while E_{BSS_RATED} indicates its maximum storage capacity. E_{PV_MAX} , E_{GEO_MAX} , and E_{BIO_MAX} define the upper limits for solar, geothermal, and biomass energy generation, respectively. E_{CH_MAX} and E_{DCH_MAX} specify the maximum allowable charging and discharging rates for the batteries.

4. Results

The table below summarizes the loads connected to the microgrid, which are dedicated to supporting all systems necessary for vegetable cultivation in a greenhouse.

LOADS CONNECTED TO THE MICROGRID

Load	Maximum power
Fans	600W
Special Lamps	2800W
Window opening system	600W
Electric drives	100W
Management system	100W
Ambient lighting	60W
Water pumps	600W
Total power consumption	5kW
Hourly maximum consumption	3.6kW

The load profile during 24h is presented in the figure below.

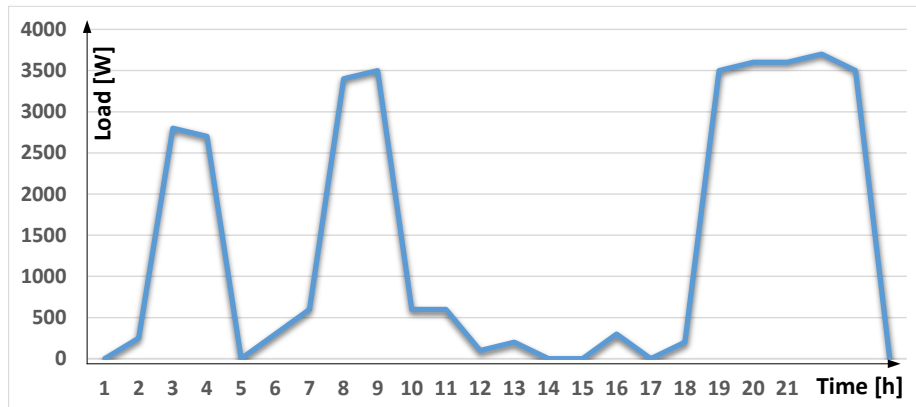


Fig. 4. Load profile during 24h.

Microgrid consumption, predicted using the ARIMA model with load variation, is shown in the figure below.

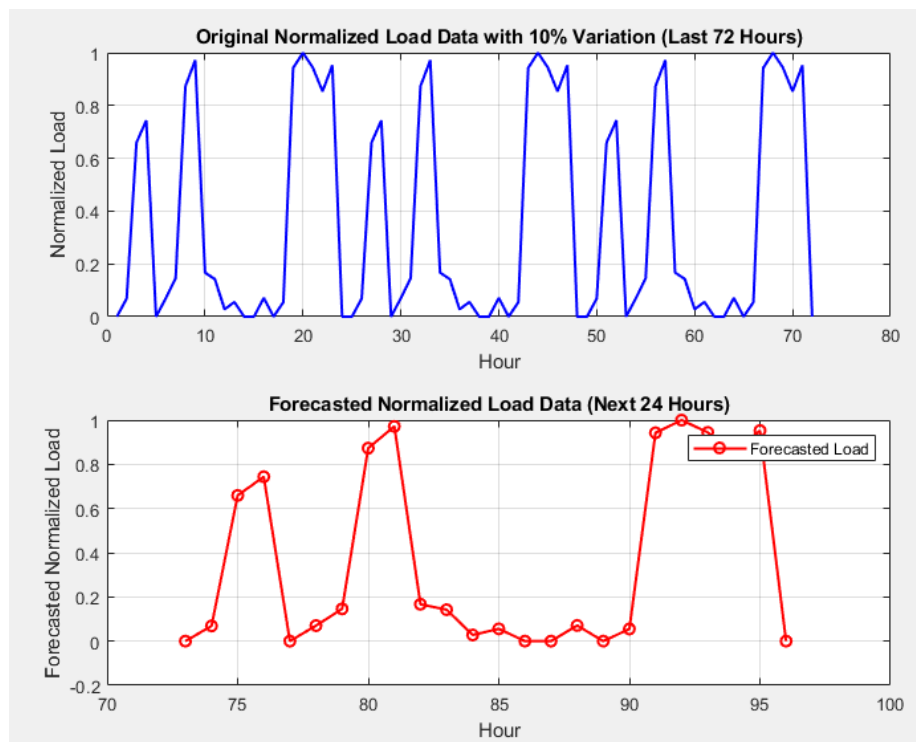


Fig. 5. The ARIMA-based prediction of microgrid consumption.

The algorithm uses 72 hours (3 days) of historical consumption data measured in the microgrid (blue graph, 0–72h, Fig. 5) to predict the next 24 hours (red graph, 72h–96h, Fig. 5). The amount of historical data is chosen as a compromise between prediction accuracy and computation time. The data in the graphs obtained with

ARIMA are normalized to the maximum load value of 4000W. It can be observed that the ARIMA algorithm predicts three consumption peaks.

The battery degradation cost is calculated using Rainflow counting algorithm and equation 6. The integration of the algorithm in the MILP optimization problem requires a predetermined SoC profile for a 24h time horizon. The calculated state of charge profile is represented in the figure below and illustrates that the SOC profile is characterized by two discharge cycles: SOC(7) $\rightarrow$ SOC(8) and SOC(17) $\rightarrow$ SOC(23). In the first case, the difference is only a few percent, whereas in the second case, the discharge exceeds 10%. The Rainflow algorithm aims to maintain the SOC value close to the desired or initial level, thereby promoting the efficient use of the battery system and minimizing excessive discharge as much as possible.

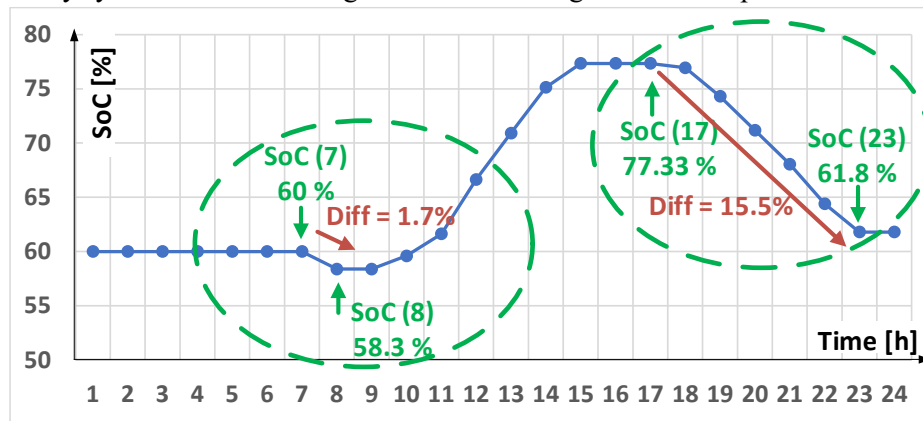


Fig. 6. SoC Profile.

Fig. 7 and Fig. 8 illustrate the utilization of the RCA algorithm in the case using Rainflow counting algorithm.

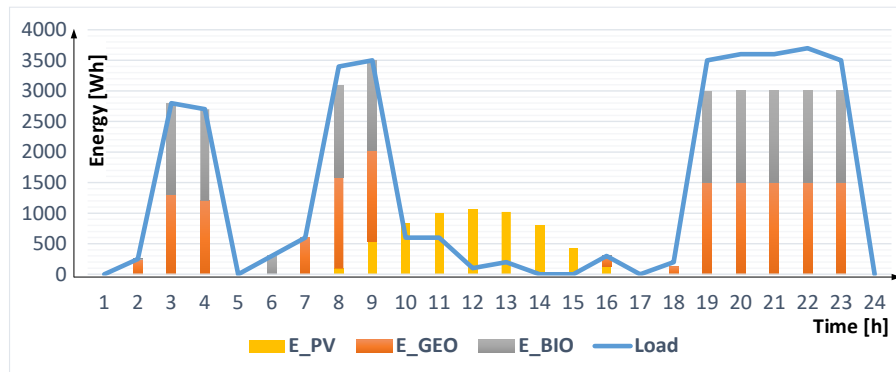


Fig. 7. Optimal scheduling plan for generators using the degradation cost calculation with rainflow-counting algorithm (RCA).

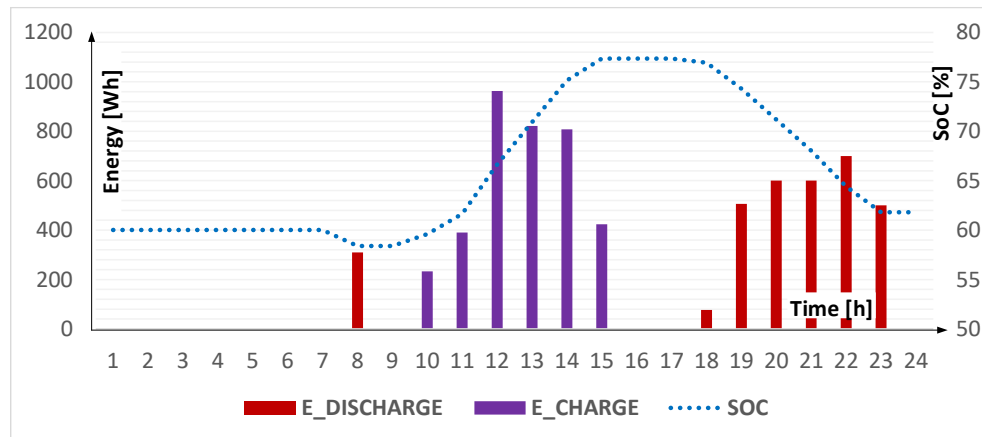


Fig. 8. Optimal scheduling plan for batteries with rainflow-counting algorithm (RCA).

Fig. 7 illustrates the generation of the required energy using geothermal, biomass, and solar sources. It is clearly observable that in the second half of the day, despite all generators operating at maximum capacity, the generated energy is insufficient to fully meet the consumption demand.

Figure 8 shows that although the morning consumption could be covered solely by the energy generators, the battery system is still utilized. This behavior can be attributed to the fact that the applied algorithms recognize the advantage of reducing the battery's state of charge in the morning to allow for the storage of solar energy during the afternoon hours. Furthermore, it is evident that in the evening hours, the battery system provides supplementary support to the microgrid, thereby preventing power outages and ensuring continuous electricity supply to consumers.

5. Conclusions

This study presents a day-ahead energy management algorithm based on mixed integer linear programming (MILP) tailored for the efficient operation of island microgrids disconnected from the national grid. By integrating a 24-hour load forecasting method and a detailed battery degradation cost model, the algorithm enables optimized scheduling of local energy resources - including geothermal, biomass, photovoltaic systems, and battery storage. The forecasting approach, grounded in historical consumption data, enhances prediction accuracy and supports cost-effective decision-making. Coupling this with meteorological data and a robust battery behavior model, the proposed strategy ensures energy balance, extends battery lifespan, and promotes the sustainability of microgrid operations. The findings highlight the effectiveness of a comprehensive and flexible energy management strategy for isolated microgrids and demonstrate the advantages of using a dynamic, integrated approach to managing energy in standalone systems.

References

- [1] Szilagyi E., Petreus D., Patarau T., *Optimal energy management for an islanded microgrid with battery degradation cost considerations*, 2024 IEEE 30th International Symposium for Design and Technology in Electronic Packaging (SIITME), Sibiu, Romania, 2024, p. 1-6.
- [2] Jose Maurilio Raya-Armenta, Najmeh Bazmohammadi, Juan Gabriel Avina-Cervantes, Doris Sáez, Juan C. Vasquez, Josep M. Guerrero, *Energy management system optimization in islanded microgrids: An overview and future trends*, Renewable and Sustainable Energy Reviews, **149**, 2021, 111327.
- [3] Jigar S. Sarda, Kwang Lee, Hirva Patel, Nishita Patel, Dhairya Patel, *Energy Management System of Microgrid using Optimization Approach*, IFAC-PapersOnLine, **55**, 9, 2022, p. 280-284.
- [4] Asueta D.C., Sard R.E., Álvarez P.T., *Optimising Microgrid Energy Management: A MILP Approach for Cost Reduction and Grid Resilience*, 2024 IEEE 22nd Mediterranean Electrotechnical Conference (MELECON), Porto, Portugal, 2024, p. 632-637.
- [5] Sukumar S., Mokhlis H., Mekhilef S., Naidu K., Karimi M., *Mix-mode energy management strategy and battery sizing for economic operation of grid-tied microgrid*, Energy, **118**, 2017, p.1322-1333.
- [6] Heymann B., Bonnans J.F., Martinon P., Silva F. J., Lanas F., Jiménez-Estévez G., *Continuous optimal control approaches to microgrid energy management*, **9**, 2015, p. 59–77.
- [7] Palma-Behnke R. et al., *A Microgrid Energy Management System Based on the Rolling Horizon Strategy*, IEEE Transactions on Smart Grid, **4**, 2, June 2013, p. 996-1006.
- [8] Lombardi P., Powalko M., Rudion K., *Optimal operation of a virtual power plant*, Proc. IEEE Power Energy Soc. Gen. Meet. (PES), 2009.
- [9] Lu D., B. Francois, *Strategic framework of an energy management of a microgrid with a photovoltaic-based active generator*, Proc. EPE Chapter “Electric Drives” Joint Symp. (ELECTROMOTION 2009), Lille, France, Jul. 1–3, 2009.
- [10] Teleke S., Baran M., Bhattacharya S., Huang A., *Rule-base control of battery energy storage for dispatching intermittent renewable sources*, IEEE Trans. Sustainable Energy, **1**, 3, 2010, p. 117–124.
- [11] Morais H., Kádár P., Faria P., Vale Z., Khodr H., *Optimal scheduling of a renewable micro-grid in an isolated load area using mixedinteger linear programming*, Renewable Energy, **35**, 1, 2010, p. 151–156.
- [12] Korpas M., Holen A., *Operation planning of hydrogen storage connected to wind power operating in a power market*, IEEE Trans. Energy Convers., **21**, 3, 2006, p. 742–749.
- [13] Lázár E., Pătărașu T., Etz R., 38th International Spring Seminar on Electronics Technology (ISSE), Eger, Hungary, 2015, p. 364-369.
- [14] Lázár E., Petreus D., Etz R., Pătărașu T., *Optimal scheduling of an islanded microgrid based on minimum cost*, 39th International Spring Seminar on Electronics Technology (ISSE), Pilsen, Czech Republic, 2016, p. 290-295.
- [15] Energy Modeling Software for Hybrid Renewable Energy System HOMER Energy, Boulder CO, USA, Accessed on Jan. 2024 [Online], Available: <http://www.homerenergy.com/download.html>
- [16] Energy Modeling Software for Hybrid Renewable Energy System HOMER Energy, Boulder CO, USA, Accessed on Jan. 2024 [Online], Available: <http://www.homerenergy.com/download.html>.
- [17] Battistelli C., Agalgaonkar Y.P., Pal B.C., *Probabilistic Dispatch of Remote Hybrid Microgrids Including Battery Storage and Load Management*, IEEE Transactions on Smart Grid, **8**, 3, 2017, p. 1305-1317.
- [18] Moradzadeh A., Mansour-Saatloo A., Mohammadi-Ivatloo B., Anvari-Moghaddam A., *Performance Evaluation of Two Machine Learning Techniques in Heating and Cooling Loads Forecasting of Residential Buildings*, Applied Sciences, **10**, 11, 2020, p. 3829.
- [19] Hernandez L. et al., *A survey on electric power demand forecasting: Future trends in smart grids, microgrids and smart buildings*, IEEE Communications Surveys and Tutorials, **16**, 3, 2014, p. 1460–1495.
- [20] Rodríguez F., Florez-Tapia A. M., Fontán L., Galarza A., *Very short-term wind power density forecasting through artificial neural networks for microgrid control*, Renew Energy, **145**, 1, 2020, p. 1517–1527.
- [21] Tayab U.B., Zia A., Yang F., Lu J., Kashif M., *Short-term load forecasting for microgrid energy management system using hybrid HHO-FNN model with best-basis stationary wavelet packet transform*, Energy, **203**, Jul. 2020, p. 117857.

[22] Patarau Toma, Petreus Dorin, Szilagyi Eniko, *A Comparative Study of Short-Term Load Forecasting Methods for Improved Energy Management in Microgrids with Battery Storage*, 48th International Spring Seminar on Electronics Technology, ISSE2025, May 2025, Budapest, Hungary. In press.