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Design of a Two-Layer Intelligent Framework for Energy Management in Microgrids Utilizing Deep Learning-Based Prediction and MISOCP Optimization

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Abstract

With the rapid increase in energy consumption and the expansion of renewable energy usage, microgrids have emerged as an effective solution for enhancing the sustainability, flexibility, and efficiency of power systems. In this study, an adaptive two-layer Energy Management System (EMS) is designed and presented for microgrids. The first layer utilizes Mixed-Integer Linear Programming (MILP) with a rolling horizon strategy to focus on economic optimization over a medium-term horizon. The second layer employs nonlinear optimization using the Particle Swarm Optimization (PSO) algorithm to accurately manage short-term and real-time network conditions. Additionally, intelligent forecasting models based on deep learning, such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM), are used to improve the accuracy of load and meteorological parameter predictions. A precise model of the Battery Energy Storage System (BESS), considering converter efficiency, aging processes, and optimal charging strategies, is also proposed as part of the innovation. Simulation results demonstrate that the proposed two-layer structure exhibits high adaptability to uncertainties and can significantly improve performance, reduce costs, and enhance the sustainability of microgrids.

Keywords: *Microgrid Energy Management, Two-Layer Optimization, Deep Learning Prediction, Mixed-Integer Second-Order Cone Programming (MISOCP), Battery Energy Storage System (BESS)*

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1. Introduction

The accelerating pace of global energy demand, coupled with the widespread integration of renewable energy resources, has fundamentally reshaped the architecture and management requirements of modern power systems. Traditional centralized power generation models are increasingly being challenged by decentralized, flexible, and sustainable alternatives that can address both technical and environmental imperatives. Among these alternatives, microgrids have emerged as an essential component for ensuring energy security, efficiency, and resilience, particularly in the context of increasing penetration of distributed energy resources (DERs) and renewable energy technologies [1, 2]. Defined as localized networks of interconnected loads and distributed energy resources with the capability to operate both in grid-connected and islanded modes, microgrids represent a paradigm shift in the way energy is generated, managed, and consumed.

The global impetus toward decarbonization has further accelerated microgrid development. Increasingly, governments, industries, and institutions are adopting renewable-based microgrids as part of sustainability initiatives to reduce greenhouse gas emissions and enhance reliability [3, 4]. However, the integration of renewables introduces high levels of uncertainty and intermittency, creating new operational and technical challenges that necessitate intelligent, adaptive, and multi-layered energy management systems (EMS). Advanced EMS frameworks have been recognized as a cornerstone for overcoming these challenges, particularly in managing fluctuations in supply and demand, ensuring system stability, and optimizing costs [5, 6].

The development of EMS for microgrids has been shaped by the dual objectives of sustainability and economic viability. Early microgrid models emphasized basic demand–supply matching but were insufficient to address the complex uncertainties introduced by renewables [7]. Recent innovations have introduced hierarchical and multi-layer frameworks designed to balance long-term optimization with short-term corrective action. For example, the use of mixed-integer linear programming (MILP) and mixed-integer second-order cone programming (MISOCP) in EMS design enables robust scheduling under uncertainty while ensuring computational feasibility [8, 9]. Complementing these mathematical frameworks, metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO) have been incorporated for nonlinear, real-time decision-making [10].

Hierarchical EMS structures typically include three levels: primary control for local devices, secondary control for coordination, and tertiary control for interactions with external systems [6]. However, the integration of two-layer EMS frameworks has proven particularly effective. In such systems, the upper layer focuses on medium- to long-term economic scheduling, while the lower layer is tasked with managing short-term fluctuations and ensuring real-time operational stability [8, 11]. This architecture enables a balance between profitability and adaptability, mitigating the risks posed by unpredictable renewable generation and variable demand patterns.

The growing sophistication of EMS frameworks has been underpinned by rapid technological advancements in forecasting, optimization, and energy storage systems. Forecasting models based on artificial intelligence and deep learning have significantly improved prediction accuracy for load demand, solar irradiance, and meteorological parameters, which are critical for effective EMS operation [12, 13]. For example, artificial neural networks (ANN) and long short-term memory (LSTM) models have been widely adopted to enhance forecasting reliability and thereby improve scheduling outcomes [14]. These approaches offer a marked improvement over traditional statistical models by accounting for nonlinearities and time-dependent variables in energy data.

Energy storage systems, particularly battery energy storage systems (BESS), play a pivotal role in enhancing the flexibility of microgrids. Accurate modeling of BESS is essential for optimizing charge–discharge cycles, extending battery lifespan, and reducing costs associated with degradation [15]. Studies have emphasized that incorporating converter efficiency, calendar aging, and cycle aging into BESS models leads to more reliable outcomes in EMS optimization [16]. Furthermore, advanced EMS frameworks that integrate these models can more effectively balance renewable variability, improve operational stability, and enhance the financial performance of microgrids [9].

The objectives of EMS frameworks in microgrids are inherently multi-dimensional, encompassing technical, economic, and environmental aspects. From an economic perspective, EMS must reduce operational costs, maximize revenues from electricity trading, and optimize resource utilization [17]. Technical objectives involve maintaining voltage and frequency stability, minimizing line losses, and ensuring reliable operation under both grid-connected and islanded conditions [18]. Environmental objectives emphasize minimizing carbon emissions and supporting global sustainability goals [3, 4].

Increasingly, hybrid strategies that combine these objectives are gaining traction, as they enable more comprehensive optimization. For example, integrated EMS models can simultaneously account for fuel costs, greenhouse gas emissions, and technical performance indicators, thereby delivering solutions that align with broader policy and sustainability frameworks [19, 20]. Such combined strategies are particularly relevant for community microgrids and institutional setups, where social and environmental considerations are as important as financial performance.

Despite significant advancements, microgrid EMS design still faces considerable challenges. The intermittency of renewable resources remains a critical issue, as inaccurate forecasts can lead to imbalances in supply and demand, necessitating corrective measures in real time [21]. The high computational complexity of optimization models also limits their scalability, particularly for larger microgrids with diverse energy resources [22]. Furthermore, energy storage systems introduce additional challenges, including degradation costs, limited capacities, and high replacement costs [8, 9].

Another pressing issue concerns standardization and interoperability. Current EMS solutions often lack standardized frameworks for integration across different platforms and technologies, which hampers scalability and wider adoption [18]. This is particularly problematic in multimicrogrid environments where multiple systems must interact seamlessly to ensure stability and efficiency [6].

In addition to technical challenges, behavioral and managerial factors play an increasingly important role. Studies have shown that pro-environmental behaviors, energy-saving habits, and green human resource management policies significantly influence the effectiveness of EMS implementations, particularly in institutional and organizational contexts [3, 12]. Incorporating these human-centered factors into EMS frameworks represents an important frontier for future research.

Addressing these challenges requires the development of adaptive, intelligent, and multi-layered EMS frameworks that can balance short-term responsiveness with long-term optimization. The proposed two-layer EMS structure embodies this approach by integrating MILP-based optimization in the upper layer for medium-term economic scheduling and nonlinear optimization in the lower layer for real-time adaptability. Such systems are supported by advanced forecasting models, comprehensive BESS modeling, and metaheuristic optimization techniques to ensure resilience and cost-effectiveness [10, 16].

Adaptive two-layer EMS frameworks also align with broader trends in sustainable energy system management. For instance, studies in resource management and sustainability emphasize the importance of balancing profit with long-term environmental responsibility, a principle directly applicable to microgrid operations [4, 13]. Similarly, research in public energy management and sectoral intellectualization highlights the role of smart systems and digitalization in optimizing resource utilization and enhancing governance structures [23]. These perspectives underscore the necessity of embedding adaptive EMS frameworks within a broader context of sustainability, governance, and behavioral alignment.

This study contributes to the evolving body of literature by proposing and evaluating an adaptive two-layer EMS framework for microgrids. The novelty lies in the combination of MILP-based medium-term optimization with PSO-based nonlinear real-time management, supported by deep learning forecasting techniques and precise BESS modeling. By integrating technical, economic, and environmental considerations, the proposed framework seeks to enhance adaptability to uncertainties, reduce operational costs, and improve sustainability outcomes. In doing so, it addresses key gaps identified in the literature, including the need for adaptive solutions to renewable variability, the incorporation of realistic storage models, and the alignment of EMS with sustainability imperatives.

2. Methodology

This study aims to address these gaps by proposing an advanced, adaptive two-layer EMS. In this system, the first layer operates based on a mixed-integer linear programming (MILP) approach using a rolling horizon, focusing on profitability. The second layer manages short-term variations and real conditions of the microgrid (MG) through precise nonlinear optimization. Furthermore, the battery storage model in this system is developed by considering converter efficiency, aging processes, and stored energy, and is evaluated through accurate simulation of an experimental MG.

Two-Layer Structure of the Proposed System

The resilience and adaptability of the energy management system to changes caused by uncertain input parameter forecasts are achieved through an optimization framework based on a rolling horizon strategy with corrective action, which falls under the category of online optimization. In this framework, optimization is performed at each time step or whenever new forecasts are available, and the connection between layers is enabled through common variables, facilitating corrective action. (Figure 1) illustrates the principles of operation of this approach in three consecutive iterations, in which three key concepts are defined: Prediction Horizon (PH), Scheduling Horizon (SH), and Control Horizon (CH). In each iteration, the system's initial state (IS) is defined, and using forecasts for the PH period, optimization is performed for the SH period, after which the resulting decisions are applied in the CH period [22]s.

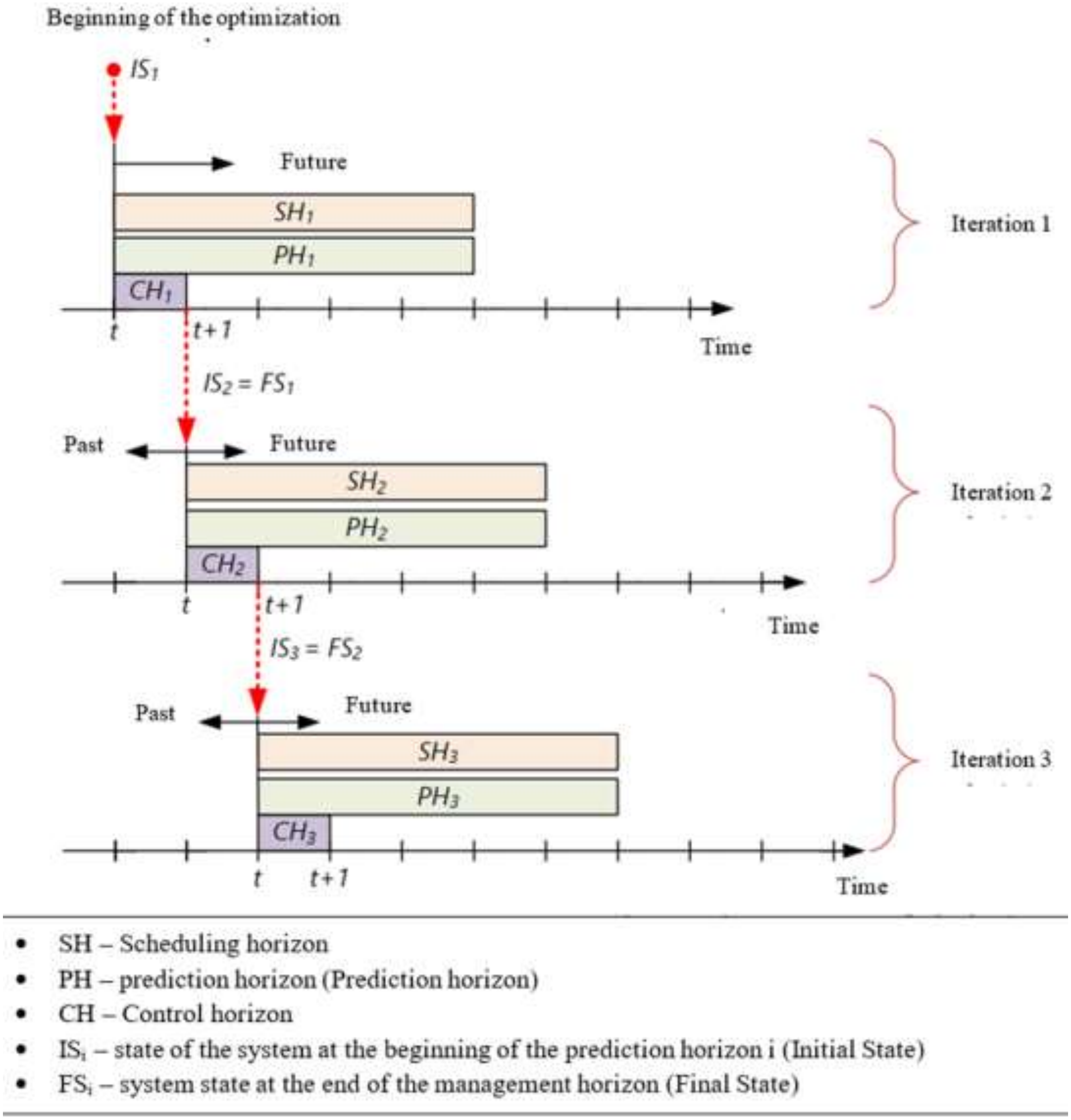

Figure 1. Moving horizon strategy with corrective action

In the rolling horizon optimization framework, the optimization decisions generated in each iteration are applied only to the current control horizon (CH), and by shifting the time step, the final state variables are transferred as inputs to the next iteration to define the system's new state along with the updated forecasts. This iterative process, through the transfer of state variables and continuous updates of forecasts, enables corrective action and adaptability to changes in uncertain parameters. Energy management is implemented in the form of a two-layer system, where the upper layer optimizes operations within the scheduling horizon (SH) based on medium-term forecasts, and its output is sent as a reference input to the lower layer. The lower layer then optimizes operations only within the shorter scheduling horizon (CH) using the updated short-term forecasts, and at the end, the state variables are returned to the upper layer for use in the next iteration.

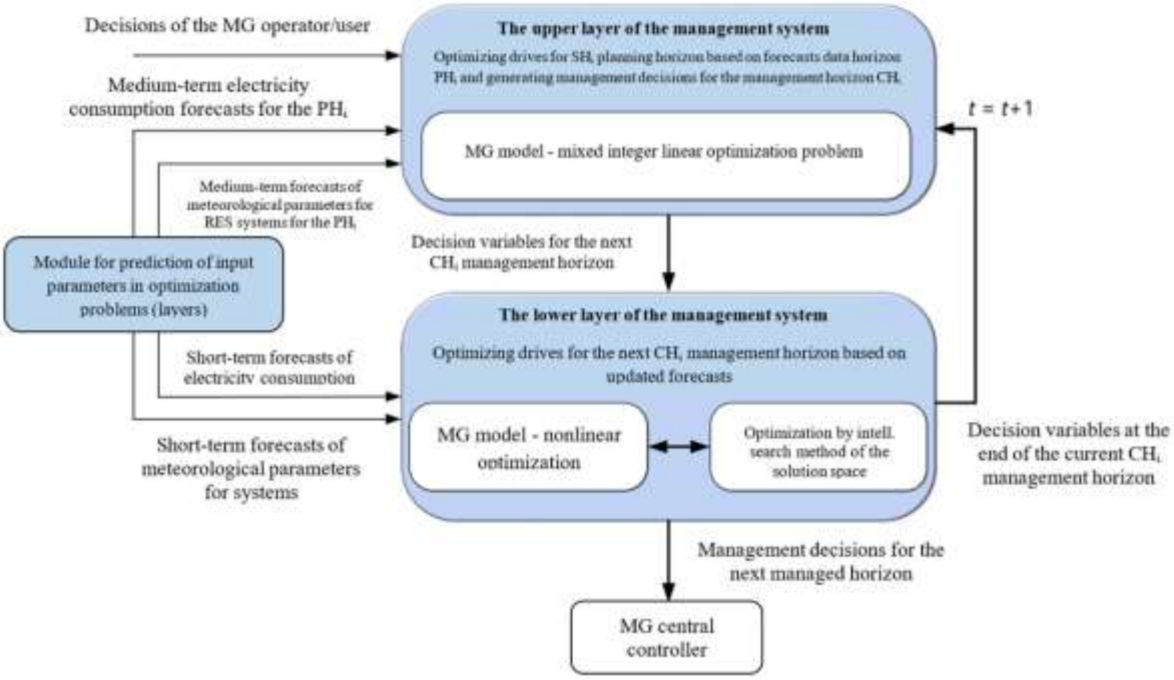

Figure 2. Block diagram of a two-layer adaptive microgrid EMS

In the lower layer of the microgrid energy management system (EMS), the optimization problem is solved nonlinearly in a simultaneous simulation environment, combining a metaheuristic optimization algorithm (specifically, Particle Swarm Optimization (PSO)) with power network analysis simulation tools. These methods allow for the solution of complex and nonlinear problems without the need for detailed knowledge of the objective function and constraints. The simulation tool, incorporating precise models of power system components and power flow equations, creates a non-approximated model of the microgrid, which leads to the nonlinearity of the optimization problem. Although metaheuristic methods are time-consuming, their use in the lower layer's short-term planning horizon reduces computational costs and aligns with the upper layer's control horizon (CH). In this simulation environment, the information exchange loop between the simulation tool and the optimization algorithm is continuous, requiring effective interfaces between these two components for proper operation.

Multilayer Optimization Strategy

In the upper layer of the energy management system, the optimization problem is solved using mathematical programming methods, which numerically minimize or maximize the objective function while considering the system's constraints. The objective function depends on variables that are defined within a permissible range, forming a set of possible solutions. These constraints include performance constraints and variable boundaries. The optimization problem's variables are divided into several categories: decision variables (inputs), state variables (indicating the system's status and linking inputs to outputs), output variables (optimization results), and operational variables (representing valid environmental conditions for the solution). The general structure of the optimization problem is expressed in the form of equation (1), where xxx represents the variable vector, ff(x) is the objective function, and c(x) is the constraint vector, with sets E and III representing the corresponding indices.

$$minimize\ f(x)$$

$$\text{with restrictions: } \begin{cases} c_i\ (x) = 0.\ i \in E \\ c_i\ (x) >= 0.\ i \in I \end{cases} .x \in R^n \qquad (1)$$

x: The set of variables that can be adjusted in the optimization process.

f(x): The objective function that needs to be minimized or maximized.

c(x): The set of constraints that limit the possible solutions to feasible ones.

E and I: Sets that indicate which constraints are equalities and which are inequalities.

Mathematical Modeling and Algorithms (MISOCP)

In the upper layer of the microgrid energy management system, the optimization problem is modeled as a Mixed-Integer Second-Order Cone Programming (MISOCP) problem with binary variables. This model features an objective function and linear constraints, and due to the binary nature of some variables (e.g., equipment being on/off), it allows logical decision-making for controllable elements of the microgrid. To solve such problems, the Branch and Bound algorithm is used, which divides the main problem into simpler subproblems and applies branching, bounding, and evaluation steps in search of the optimal solution. The MILP model in this study is implemented using an open-source algebraic modeling language based on Python and is connected to a numerical solver through an internal interface. This modeling language allows the optimization problem to be defined in a manner similar to the original mathematical form, facilitating the readability and development of the model.

$$minimize\ c^T x$$

$$\text{with restrictions:} \begin{cases} Ax = b \\ x \geq 0 \\ x_i \in Z\,.\,\forall i \in I \end{cases} ; \qquad (2)$$

x: Decision variable vector, including continuous and integer (binary) variables representing controllable elements of the microgrid.

c: Coefficient vector for the objective function, representing costs or weights associated with decision variables.

A: Constraint matrix, representing the linear relationships between variables in the system.

b: Right-hand side vector, representing constants in the equality constraints.

$x_i \in Z$ in $\forall i \in I$ ∈I: Integer constraints on specific variables indexed by set I, representing binary or integer decision variables.

$x \geq 0$: Non-negativity constraints on variables.

If integer variables can take only binary values (0 or 1), it is necessary to add to expression (2) an additional restriction shown below:

$$0 \leq x_i \leq 1 \qquad (3)$$

Modeling of Microgrid System Components

Battery Energy Storage System Model

The Battery Energy Storage System (BESS) is a key component in microgrids, enabling bidirectional energy flow. In the charging state, it acts as a consumer, and in the discharging state, it functions as a source. The BESS consists of a rechargeable battery and a bidirectional power electronic converter, which is responsible for controlling the energy flow between the DC and AC sides. The block diagram of this system is shown in Figure 3.

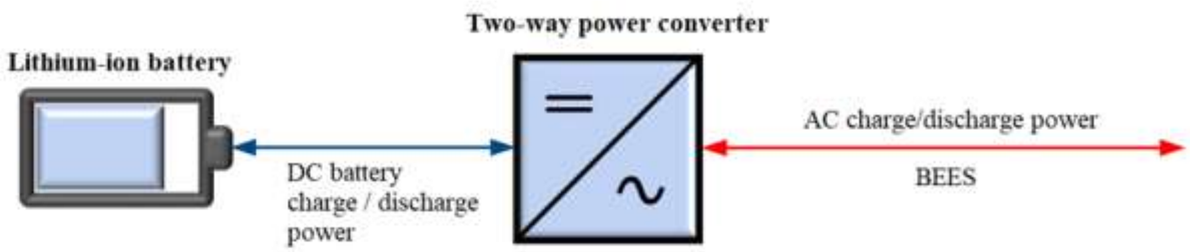

Figure 3. Block diagram of the BESS model

Bidirectional Power Converter and its Efficiency Model

The power electronic converter in the BESS is capable of transferring energy in both directions, from DC to AC and vice versa. The maximum power that can be exchanged on the AC side is controlled by the rated power of the converter and the binary status variable of the system. The following equations define the charging and discharging power limits:

$$P_{t,bess}^{ch\ ac} \leq P_{bess}^{nom} . s_{t,bess}^{BESS} \qquad \forall t \in T, \forall bess \in BESS \qquad (4)$$

$$P_{t,bess}^{disch\ ac} \leq P_{bess}^{nom} . (1 - s_{t,bess}^{BESS\ status}) \qquad \forall t \in T, \forall bess \in BESS \qquad (5)$$

In which:

$P_{t,bess}^{ch\ ac}$: charging power of the bess on the AC side in time step t,

$P_{t,bess}^{disch\ ac}$: discharge power of the bess on the AC side in time step t,

P_{bess}^{nom}: AC power of the bidirectional power electronics converter of the bess

$s_{t,bess}^{BESS\ status}$: binary variable of state of bess in the time step t , defines operation mode (charging or dischargin

If models with efficiencies less than 100% are used, the model can be simplified without the use of binary variables.

The efficiency of the converter is a non-linear and unstable function of its instantaneous load. As shown in Figure 4, efficiency decreases at low loads and typically reaches its maximum value at around 15% of the rated power. Since the efficiency function is non-linear, piecewise linear approximation is used to incorporate it into linear optimization models. The equation for this approximation is given in Equation 6, and its graph is shown in Figure 5 [24].

$$L(f(x)) = \sum_{k=1}^{m} f(a_k).t_k$$
$$x = \sum_{k=1}^{m} (a_k).t_k \ ; \ t_0 \leq y_0, \quad t_k \leq y_{k-1} + y_k; \quad with: \ k = 1,2,000, m-1, t_m \leq y_m - 1 \tag{6}$$
$$\sum_{k=0}^{m-1} y_k = 1 \ ; \ \sum_{k=0}^{m} t_k = 1 \quad where: \quad y_k \in \{0,1\}, t_k \geq 0, k = 0,1,\ldots,m-1$$

Where:

f(x) : a nonlinear function of the variable x that is linearized,

a_k : breaking point k,

y_k : binary variable of breaking point k.

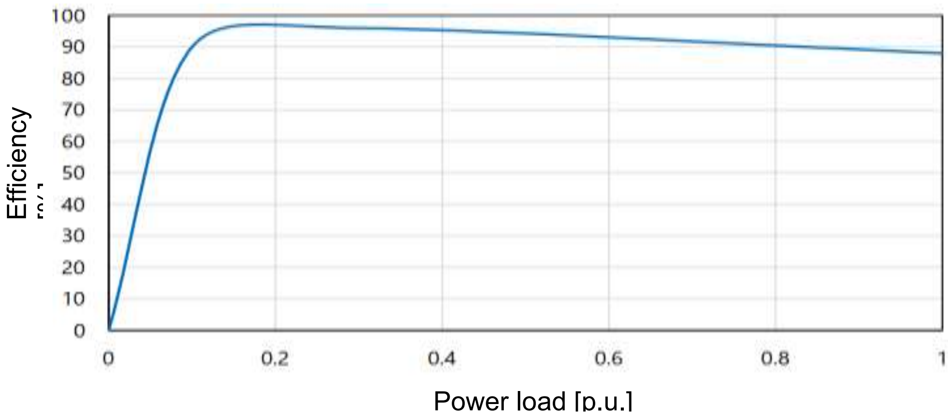

Figure 4. Efficiency of the bidirectional power electronics converter depending on the load

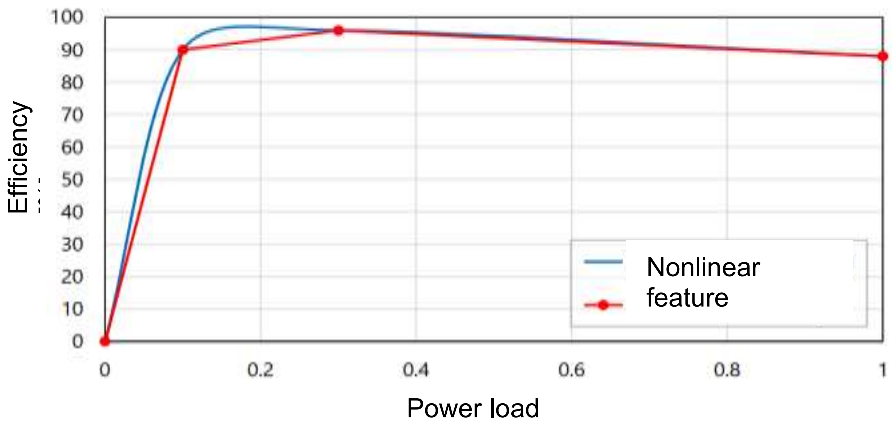

Figure 5. Linear approximation of 2way power converter efficiency depending on load by several sections

Using this linearized efficiency, the actual power at the battery side and the AC side is calculated as follows:

$$P_{t,bess}^{ch\ batt} = P_{t,bess}^{ch\ ac}.\eta_{bess}^{PCU}\left(P_{t,bess}^{ch\ ac}\right) \quad \forall t \in T, \forall bess \in BESS \tag{7}$$

$$P_{t,bess}^{disch\ ac} = P_{t,bess}^{disch\ batt}.\eta_{bess}^{PCU}\left(P_{t,bess}^{disch\ batt}\right) \quad \forall t \in T, \forall bess \in BESS \tag{8}$$

In which:

$P_{t,bess}^{ch\ batt}$: Battery charging power bess on the DC side in time step t,

$P_{t,bess}^{disch\ ac}$: Battery discharge power bess on the DC side in time step t,

η_{bess}^{PCU}: Energy conversion efficiency of the two-way power converter of the bess [24].

In this model, instead of using the state of charge (SOC) expressed in ampere-hours, the concept of state of energy (SOE) in watt-hours (Wh) is used. The energy model describes the battery's charge/discharge behavior, considering efficiency and power limitations as follows:

○

$$\begin{gathered}
SOE_t = \sum_{j=1}^{J-1} SOE_{t,j} \\
SOE_{t,j} \leq R_{j+1} - R_j \\
\Delta SOE_t = F_1 + \sum_{j=1}^{J-1} \frac{F_{j+1} - F_j}{R_{j+1} - R_j}.SOE_{t-1,j} \\
P_t^{ch\ batt} \leq \frac{\Delta SOE_t}{\Delta t.\eta^E}
\end{gathered} \tag{9}$$

Where:

SOE_t: state of charge of the battery in time step t

J : the number of segments of the linearized characteristic,

$SOE_{t,j}$: state of charge of segment j in time step t,

ΔSOE: energy that the battery can absorb during the charging process

R : breaking point on the SOE axis

F : turning point on the ΔSOE axis

η^E: energy efficiency of the battery

In this model, the minimum and maximum SOE constraints are considered to prevent battery degradation. Additionally, the initial SOE value at each time horizon is extracted from the results obtained in the previous step and is used in the form of Model Predictive Control (MPC).

PV System and Generator

The PV system model includes the PV field and the converter, and its output is a function of solar radiation and cell temperature [22]. The DC output power of the PV field, according to IEC 6124-2 standard and equation (10), is expressed as follows:

$$P_{t.pv}^{DC} = P_{pv}^{array\ STC}.\frac{G_t}{G^{STC}}.\left(1 - \frac{\gamma_{pv}}{100}.\left(\vartheta_{t.pv}^{mod} - \vartheta^{STC}\right)\right) \quad \forall t \in T, \forall pv \in PV \tag{10}$$

$$\vartheta_{t.pv}^{mod} = \vartheta_t^{amb} + \frac{NOCT_{pv} - 20}{800}.G_t \quad \forall t \in T, \forall pv \in PV \tag{11}$$

$P_{t.pv}^{DC}$ output DC power of the PV field of the PV system pv in the time step t,

$P_{pv}^{array\ STC}$ power of the PV field under standard test conditions,

G_t power of solar radiation in time step t,

G^{STC} solar radiation power under standard test conditions, which is 1 kW/m^2,

γ_{pv} temperature coefficient of power of the PV modules

$\vartheta_{t.pv}^{mod}$ the temperature of the cells of the PV system pv in the time step t,

ϑ^{STC} the temperature of the cell under standard test conditions is 25 ˚C

ϑ_t^{amb} ambient temperature in time step t,

$NOCT_{pv}$ nominal working temperature of the cell of the PV system pv

The output AC power is also modeled as follows, taking into account the converter efficiency:

$$P_{t.pv}^{AC} = P_{t.pv}^{DC}.\eta_{pv}^{inv}\left(P_{t,pv}^{DC}\right) \quad \forall t \in T, \forall pv \tag{12}$$

$$P_{t.pv}^{AC} \leq P_{pv}^{inv\ nom} \quad \forall t \in T, \forall pv \tag{13}$$

In which:

$P_{t.pv}^{AC}$ output alternating current (AC) power of the PV system pv in time step t,

η_{pv}^{inv} the efficiency of the inverter of the photovoltaic system pv,

$P_{pv}^{inv\ nom}$ nominal alternating power of the inverter of the PV system pv

The nonlinear efficiency of the converter is modeled using a piecewise linearization technique similar to the BESS section.

The controllable generators play a crucial role in ensuring reliability in the isolated operation of a microgrid and are modeled according to conventional Unit Commitment (UC) and Economic Dispatch (ED) models. The output power of each generator is constrained within permissible limits [20]:

$$P_{dg}^{DC\ min}.u_{t,dg}^{DG\ state} \leq P_{t,dg}^{DG} \leq P_{dg}^{DC\ max}.u_{t,dg}^{DG\ state} \quad \forall t \in T, \forall dg \in DG \tag{14}$$

In which:

$P_{dg}^{DC\ min}$ minimum output power of the controllable generator dg,

$P_{dg}^{DC\ max}$ maximum output power of the controllable generator dg

$P_{t,dg}^{DG}$ the output power of the controllable generator dg in the time step t,

$u_{t,dg}^{DG\ state}$ Binary variable of engagement of controllable generator dg in time step t.

The constraints on the rate of change of generation, both upward and downward, are also applied as follows [23]:

$$P_{t,dg}^{DG} - P_{t-1,dg}^{DG} \leq P_{dg}^{DG\ RU} \quad \forall t \in T, \forall dg \in DG \tag{15}$$

$$P_{t-1,dg}^{DG} - P_{t,dg}^{DG} \leq P_{dg}^{DG\ RD} \quad \forall t \in T, \forall dg \in DG \tag{16}$$

In which:

$P_{dg}^{DG\ RU}$:maximum change in output power during upward regulation,

$P_{dg}^{DG\ RD}$:maximum change in output power during down regulation.

The model also includes constraints on the minimum on/off time of the generator, which are modeled using binary variables $s_{t,dg}^{DG\ start}$ $s_{t,dg}^{DG\ stop}$ p [25]:

$$\sum_{t}^{t+T_{dg}^{DG\ on}-1} u_{t,dg}^{DG\ state} \geq T_{dg}^{DG\ on}.s_{t,dg}^{DG\ start} \quad \forall t \in T, \forall dg \in DG \tag{17}$$

$$\sum_{t}^{t+T_{dg}^{DG\ off}-1} (1 - u_{t,dg}^{DG\ state}) \geq T_{dg}^{DG\ off}.s_{t,dg}^{DG\ stop} \quad \forall t \in T, \forall dg \in DG \tag{18}$$

$$u_{t,dg}^{DG\ state} - u_{t-1,dg}^{DG\ state} = s_{t,dg}^{DG\ start} - s_{t,dg}^{DG\ stop} \quad \forall t \in T, \forall dg \in DG \tag{19}$$

$$s_{t,dg}^{DG\ start} + s_{t,dg}^{DG\ stop} \leq 1 \quad \forall t \in T, \forall dg \in DG \tag{20}$$

In which:

$s_{t,dg}^{DG\ start}$ the binary variable of starting the controllable generator dg in the time step t,

$s_{t,dg}^{DG\ stop}$ the binary stop variable of the controllable generator dg at time step t

$T_{dg}^{DG\ on}$ the minimum production time of the controllable generator t expressed in the number of time steps of the optimization problem,

$T_{dg}^{DG\ off}$ minimum production stop time of the controllable generator t expressed in the number of time steps of the optimization problem.

The total operating cost includes fuel cost and startup cost [17]:

$$c_{t,dg}^{DG\ cost} = c_{t,dg}^{DG\ startup} + c_{t,dg}^{DG\ fuel} \quad \forall t \in T, \forall dg \in DG \tag{21}$$

In which:

$c_{t,dg}^{DG\ cost}$: the total cost of operation of the generator dg in the time step t,

$c_{t,dg}^{DG\ startup}$: the cost of starting the controllable generator dg in the time step t,

$c_{t,dg}^{DG\ fuel}$:fuel cost of controllable generator dg in time step t.

The fuel cost is modeled with a quadratic function and is linearized in a piecewise form to be included in the MILP model [25, 26].

$$c^{DG\ fuel}(P) = a.P^2 + b.P$$

$$c^{DG\ fuel}(P) = \sum_{k=1}^{K} c_k.\lambda_k \quad (22)$$

$$P = \sum_{k=1}^{K} \Delta_k.\lambda_k$$

$$\sum_{k=1}^{K} \lambda_k = u^{DG\ state} \ (\lambda_k \geq 0, \quad k = 1, \ldots, K) \quad (23)$$

In which:

$c^{DG\ fuel}$the fuel cost of the controllable generator,

$a.b$ coefficients of the quadratic fuel cost function,

c_k breaking point k on the c^{DG} fuel axis

λ_k segment k output power of the controllable generator,

Δ_k turning point k on the P axis

3. Findings and Results

In this study, Artificial Neural Networks (ANN) with Long Short-Term Memory (LSTM) are used for short-term and medium-term prediction of input parameters in the EMS system. These networks are implemented in Python, and their characteristics in relation to the type of EMS layer and relevant temporal features are presented in Table 1.

Table 1. Characteristics of ANNs with LSTM used to predict input parameters in optimization problems of EMS layers

Layer	Prediction horizon	Time step	Size
Higher layer	24 hour	10 min	Power consumption of (unmanageable) electrical energy of
Lower layer	10 min	1 min	Power consumption of (unmanageable) electrical energy of MG
	10 min	1 min	The power of solar radiation
	10 min	1 min	Ambient temperature

Training Features: • The data used includes electrical and meteorological measurements, extracted from an online database covering the period from March 6, 2020, to May 8, 2022. • The data related to electricity consumption is shown in Figure 6, and the meteorological parameters (solar radiation, temperature, humidity, wind, air pressure) are shown in Figure 7.

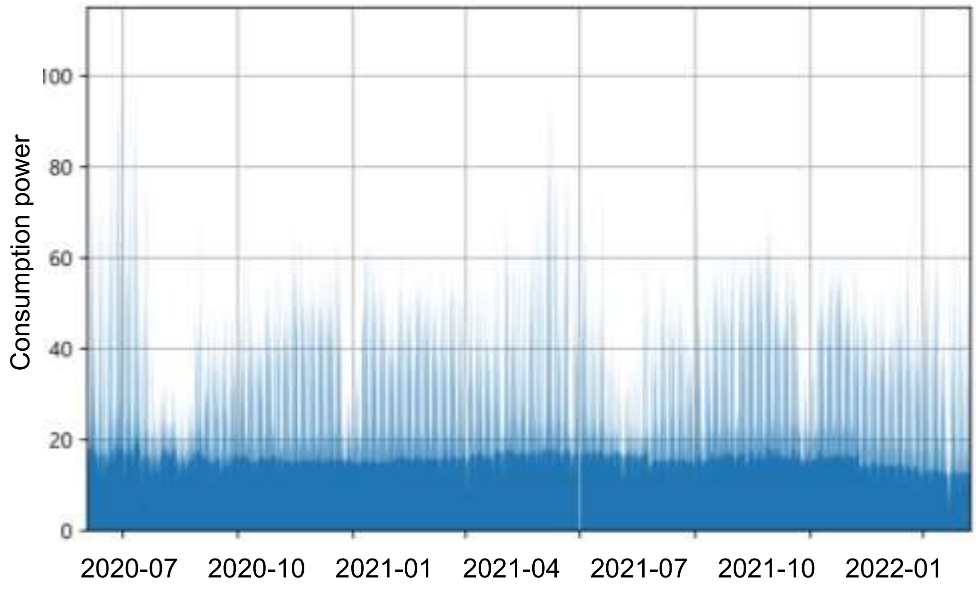

Figure 6. Measured uncontrollable consumption power profile of the test MG

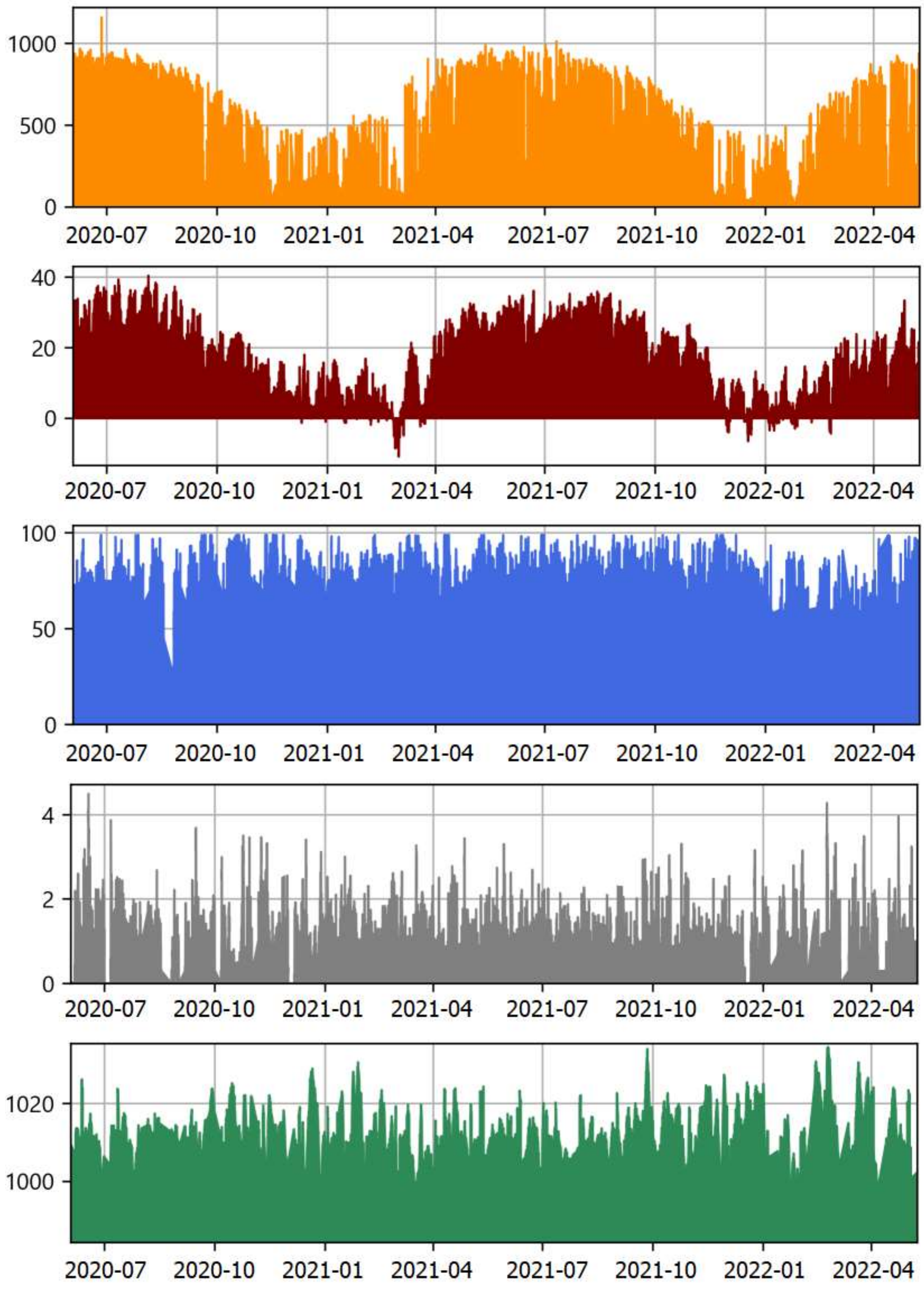

Figure 7. Input meteorological parameters to the ANN

• The data is specified with different forecasting horizons (10-minute and 24-hour) and time intervals (1 minute and 10 minutes) in Table 1.

Additional Input Data: To improve the prediction accuracy, the following non-physical variables were also used as inputs to the network: • Current time of day, day of the year, week number, day of the week (numerical values)

• Binary indicators for holidays and weekends These features are detailed in the text and standardized using numerical values.

Data Preparation: • All inputs are normalized to the range [0, 1] according to equation 24 to reduce the impact of unit differences.

$$y_i = \frac{x_i - x^{min}}{x^{max} - x^{min}} \tag{24}$$

• The output of the networks is the forecast profile from time t to t+n, which is generated based on past data from t-m to t-1. The values of m and n vary depending on the EMS layer (as shown in Table 1).

• The overall structure of the neural network and its input and output vectors are shown in Figure 8.

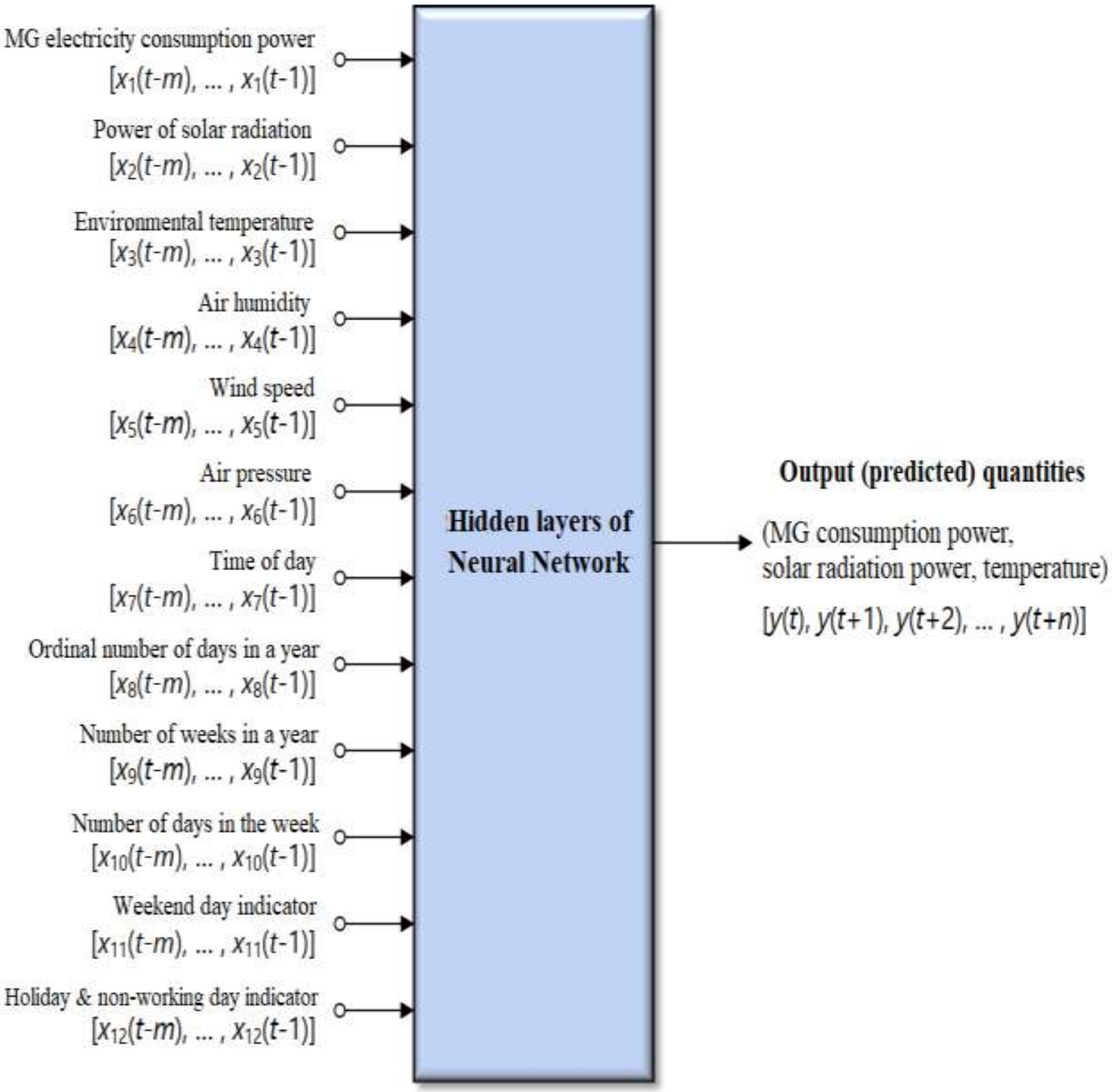

Figure 8. Schematic representation of ANN with long short-term memory used to predict input parameters in optimization problems of EMS layers for the reference cases: Simulation and Performance Evaluation of the System; Short-term Planning Results Analysis

Table 2. Comparison of the results of the planning for the four sub-components of the EMS objective function analysis

Index / Subcase	Subcase 1	Subcase 2	Subcase 3 (Reference)	Subcase 4
Objective Function Value [USD]	-25.168	-5.116	-33.418	-51.346
Net Operational Revenue/Cost [USD]	-25.168	-6.418	22.987	-13.507
Additional/Virtual Costs [USD]	0	1.302	-10.431	-37.839
Electricity Purchase Cost [USD]	31.404	14.87	31.472	19.237
Revenue from Selling Electricity to the Grid [USD]	6.235	8.454	8.484	7.153
BESS Cyclic Aging Cost [USD]	0	0	1.096	14.049
BESS Calendar Aging Cost [USD]	0	0	20.37	18.808
Value of Stored Energy in BESS [USD]	0	1.302	11.035	5.568
Static Load Shedding Cost [USD]	0	0	0	10.552

The analysis of the four subcases reveals that the performance of the Battery Energy Storage System (BESS) has the greatest impact on optimizing the short-term scheduling of the microgrid. In the second case, eliminating the battery degradation costs leads to increased utilization of the BESS and a reduction in operational costs, resulting in the best objective function value (least loss). In contrast, in the third case (reference), where degradation costs are included in the objective function, the battery is used less, and the objective function value worsens. The fourth case, which also includes islanding conditions, incurs the highest cost due to power supply limitations and the activation of demand response mechanisms. Additionally, the difference between the first and second cases highlights the importance of including the stored energy value in the objective function, particularly to avoid unnecessary charging and prevent additional costs at the end of the planning horizon.

Impact of the Optimization Framework on the Short-Term Scheduling of the Experimental MG Operations

In this section, the impact of the two-layer EMS optimization framework on the short-term scheduling of the experimental microgrid operations is analyzed. The EMS specifically consists of two interconnected layers, each with distinct characteristics and managed separately using predicted input parameters. These parameters include solar irradiance, ambient temperature, and microgrid power consumption, which are obtained through artificial neural network predictions and the GFS (Global Forecast System) service.

The simulation results show that the largest error in forecasting and its impact on scheduling, particularly in solar irradiance prediction, is evident, as the photovoltaic system is highly dependent on this parameter. This error leads to either a shortage or surplus of electricity in the microgrid, requiring further adjustments in the short-term scheduling of operations. On the other hand, predictions related to ambient temperature and microgrid power consumption are generally more accurate and have a lesser impact on the short-term scheduling adjustments.

For a more precise evaluation of the impact of the optimization framework, three different subcases have been analyzed: the reference case (subcase 3.1), which includes a two-layer EMS with a rolling horizon strategy (online optimization) and input forecasting for both layers; subcase 3.2, which uses only the upper layer of the EMS; and subcase 3.3, which uses only the upper layer without the rolling horizon strategy for offline optimization.

The results indicate that using the dual-layer optimization framework (reference case 3.1) provides the best level of adaptability to changes in input forecasts and results in the most optimized outcomes in the electrical energy exchange profiles and BESS (Battery Energy Storage System) performance. In comparison, in subcase 3.2, where only the upper layer is used, input forecasts for the lower layer are unavailable, causing greater deviations in energy exchange profiles and battery charge status. Finally, subcase 3.3, which lacks any online optimization strategy, leads to the worst outcome in terms of adapting to forecast changes, with more significant deviations in the profiles, especially compared to the reference case.

Overall, the use of the adaptive optimization framework with separate EMS layers has a significant impact on optimizing the short-term scheduling of the experimental microgrid operations. By using a rolling horizon strategy and updated forecasts, fluctuations due to incorrect predictions can be minimized, reducing the negative impacts on microgrid scheduling.

Sensitivity Analysis of the Objective Function to Parameter Changes

The sensitivity analysis of the objective function in the optimization of microgrid EMS shows that the installed capacity of the photovoltaic (PV) system and battery (BESS) costs have the greatest impact on the financial performance of the microgrid. Increasing the PV capacity leads to a reduction in costs and an increase in revenue, while changes in battery replacement costs and battery lifespan significantly affect operational costs. Additionally, the cost of electricity consumption has a greater impact on the objective function compared to the value of electricity delivered to the supplier. Other settings, such as the rated power of the power converter and the involved load, have a lesser effect. Therefore, optimizing these parameters can help reduce costs and increase the microgrid's profit.

4. Discussion and Conclusion

The findings of this study highlight the significant advantages of adopting an adaptive two-layer energy management system (EMS) for microgrids, particularly in addressing the complexities introduced by renewable energy integration and system uncertainties. The results demonstrated that the proposed framework, which combines medium-term mixed-integer linear programming (MILP) optimization with short-term nonlinear optimization guided by metaheuristic algorithms, not only improved system adaptability but also enhanced financial performance, reduced operational costs, and optimized the utilization of the battery energy storage system (BESS). Importantly, the inclusion of degradation costs and converter efficiencies in the BESS model provided realistic insights into its long-term sustainability and operational trade-offs. These outcomes reinforce the importance of considering both economic and technical objectives in EMS design, moving beyond simplistic models toward adaptive, multilayered strategies.

One of the central results of this study was the demonstration that two-layer optimization significantly improved system resilience to forecasting errors, particularly with respect to solar irradiance prediction. The adaptive structure allowed real-time adjustments in scheduling to mitigate the negative effects of inaccuracies in renewable energy forecasts, which are well-documented challenges in the literature [5, 21]. By updating forecasts and shifting decision variables dynamically, the system reduced the extent of deviations in load balance and energy trading, thereby maintaining both stability and profitability. These results align with earlier studies emphasizing the importance of rolling horizon optimization and online correction mechanisms [10, 22]. Together, this body of work underscores the need for predictive and adaptive frameworks that can operate effectively under uncertainty, positioning two-layer EMS designs as a benchmark for future microgrid operations.

The role of BESS was particularly evident in the performance outcomes of the system. The results showed that when battery degradation costs were excluded, utilization increased, leading to lower short-term costs, but at the expense of long-term sustainability. Conversely, when degradation was factored in, operational costs increased, but the system maintained a more sustainable utilization pattern. This trade-off is consistent with findings from prior research that emphasized the need for accurate modeling of storage degradation and converter efficiency to balance economic performance with system reliability [15, 16]. By integrating these factors into the optimization problem, this study contributed to bridging the gap between theoretical models and real-world microgrid applications, where battery replacement and maintenance costs constitute a major portion of lifecycle expenditures.

Another key finding was the sensitivity of the objective function to photovoltaic (PV) system capacity and battery costs. Increasing PV penetration reduced costs and improved revenue, whereas higher battery replacement costs significantly undermined economic viability. These outcomes resonate with previous studies demonstrating that renewable integration, when combined with effective storage management, can lower operational costs and enhance sustainability [7, 19]. However, without adequate management of storage degradation, the financial advantages of renewables may be offset. Thus, the results highlight the critical importance of simultaneously optimizing generation and storage components, an approach already recommended in earlier models of hybrid PV–wind–battery microgrids [11].

The proposed EMS also proved effective in balancing multi-objective goals. By integrating economic, technical, and environmental constraints, the system achieved cost savings while ensuring reliable operation and reducing greenhouse gas emissions. These results reflect broader trends in microgrid research, where hybrid optimization frameworks are increasingly adopted to simultaneously account for environmental and financial objectives [3, 4]. In particular, the ability of microgrids to provide ancillary services such as voltage support and load management further enhances their contribution to grid stability, as highlighted in prior studies [20]. By demonstrating that two-layer EMS structures can efficiently incorporate these multiple goals, this research strengthens the case for adopting multi-objective optimization as a standard in microgrid design.

The integration of artificial intelligence for forecasting also played a crucial role in the system's performance. The study employed deep learning techniques, including artificial neural networks (ANN) and long short-term memory (LSTM), which provided accurate predictions of load demand and meteorological parameters. These forecasts proved vital for minimizing scheduling errors and reducing reliance on costly corrective actions. Previous studies have confirmed the superiority of such models in capturing nonlinear patterns in energy data compared to traditional forecasting methods [12, 14]. Furthermore, the incorporation of behavioral and sustainability-oriented factors in energy management, such as pro-environmental behaviors and green management strategies, aligns with broader research that emphasizes the human and institutional dimensions of energy optimization [13, 23]. Thus, the combination of advanced predictive analytics and adaptive optimization represents a holistic approach that integrates both technological and social factors in energy management.

A noteworthy implication of the findings is the alignment of the two-layer EMS framework with global energy sustainability initiatives. By ensuring cost efficiency, system resilience, and emissions reduction, this model contributes to the pursuit of the United Nations Sustainable Development Goals (SDGs) and broader decarbonization agendas. Similar conclusions have been drawn in prior work emphasizing that advanced EMS structures can serve as enablers of sustainable development by reducing dependency on fossil fuels and enhancing the resilience of local energy infrastructures [3, 5]. This makes adaptive EMS models particularly valuable for developing economies, where financial constraints and infrastructural vulnerabilities often hinder the effective adoption of renewable energy systems.

When compared with existing literature, this study's results reaffirm the value of hierarchical and two-layer EMS models, while also extending knowledge through more realistic modeling of storage degradation and converter efficiency. Prior work demonstrated that layered EMS approaches outperform centralized or single-layer structures in terms of adaptability and cost reduction [8, 9]. The present findings reinforce these conclusions and add empirical evidence from simulations that account for long-term battery sustainability, a feature often missing in earlier models. Similarly, while prior research highlighted the technical viability of two-layer systems, this study illustrates their practical alignment with environmental and financial objectives, positioning them as not only technically feasible but also economically and socially advantageous.

Finally, the outcomes of this study illustrate the importance of integrating EMS frameworks into broader energy governance and policy structures. As emphasized in research on public sector energy management, the intellectualization and digitalization of energy systems are central to achieving efficient and transparent operations [23]. By demonstrating that adaptive two-layer EMS frameworks can simultaneously manage uncertainty, optimize costs, and support sustainability goals, this study provides evidence for policymakers to support the wider adoption of such systems in community, institutional, and industrial contexts.

Despite the strengths of this study, several limitations must be acknowledged. First, the accuracy of the EMS is heavily dependent on forecasting models for renewable generation and demand. Although deep learning techniques improved prediction accuracy, errors in solar irradiance forecasts remained a significant challenge, as observed in the simulations. Second, the computational complexity of the proposed optimization models may limit scalability in larger systems with more diverse resources. Solving MILP and nonlinear optimization problems simultaneously requires considerable computational power, which could be a constraint in real-world applications. Third, while the BESS model incorporated degradation and efficiency factors, the analysis did not extend to a full lifecycle cost–benefit assessment, which could provide further insights into long-term sustainability. Lastly, the study was conducted under simulated conditions, and experimental validation in real-world microgrid environments remains necessary to confirm the practical applicability of the findings.

Future research should focus on enhancing the forecasting accuracy of renewable energy sources by incorporating real-time meteorological data and hybrid predictive models that combine deep learning with physical models of solar radiation and temperature. Additionally, research could explore ways to reduce the computational complexity of multi-layer EMS frameworks by employing decomposition algorithms or distributed optimization techniques, making them more scalable for larger networks. Investigating lifecycle cost analysis for storage systems, including recycling and second-life applications of batteries, could also provide more comprehensive insights into sustainability. Furthermore, expanding the scope of analysis to multimicrogrid environments and investigating interoperability challenges between multiple EMS frameworks would advance the development of large-scale, integrated energy systems. Finally, interdisciplinary research that combines technological, behavioral, and policy perspectives would be valuable for ensuring that EMS frameworks align not only with technical feasibility but also with institutional and societal priorities.

Practitioners designing and operating microgrids should prioritize the adoption of adaptive, two-layer EMS frameworks that balance medium-term scheduling with short-term corrective actions. Implementing detailed models of storage systems, including degradation and efficiency, is crucial for realistic planning and long-term financial sustainability. Utilities and energy managers should also invest in advanced forecasting tools, particularly those based on artificial intelligence, to minimize errors and improve scheduling performance. Policymakers and regulators can support the deployment of such systems by creating standards for interoperability, incentivizing renewable–storage integration, and encouraging the inclusion of environmental performance indicators in EMS objectives. In practice, adopting adaptive EMS frameworks can enable communities, institutions, and industries to achieve cost efficiency, energy security, and environmental responsibility simultaneously.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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