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Research article

Optimization of hybrid renewable-diesel power plants considering operational cost, battery degradation, and emissions

Aya Amer [a,*], Ahmed Massoud [b], Khaled Shaban [c]

[a] Electrical and Computer Engineering Department, Texas A&M University, College Station, Tx 77843, USA
[b] Electrical Engineering Department, Qatar University, Doha 2713, Qatar
[c] Computer Science and Engineering Department, Qatar University, Doha 2713, Qatar

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ABSTRACT

Renewable energy sources have immense potential for enhancing environmental sustainability; however, addressing their intermittency and irregularity is vital for optimizing economic benefits within microgrids. Integrating renewable energy systems with energy storage presents a promising solution. This study introduces an innovative energy management system designed for hybrid renewable power stations, incorporating battery energy storage systems and diesel generators. By accounting for battery degradation costs associated with charge depth and lifespan, the study transforms long-term battery expenses into real-time operational costs. The optimization problem is formulated as a mixed integer linear programming framework with the objectives of minimizing operating costs, battery degradation costs, and pollutant gas emissions. Through diverse case studies reflecting various market profiles. The proposed approach demonstrates reductions in overall system costs.

1. Introduction

Global interest in renewable energy sources (RESs) and energy storage systems (ESSs) has surged due to environmental concerns. Microgrids have evolved into sophisticated entities, integrating diverse distributed generators to supply anticipated loads to end users in a decentralized manner. Hybrid systems that combine RESs with conventional sources are gaining popularity for their improved supply reliability and resolution of RESs' intermittency and non-dispatchability issues. efficient energy management systems (EMSs) are crucial for optimizing these hybrid systems and maximizing their economic environmental benefits.

Several studies have explored power dispatch optimization in hybrid renewable power stations [1–4]. While heuristic methods like genetic algorithms and particle swarm optimization have shown promise [5–8], their applicability to complex systems with multiple variables can lead to suboptimal results and extended computation times. Alternative strategies like rule-based approaches have been proposed [9] to stabilize the output of RESs by dispatching battery storage on an hourly basis. Another alternative approach, proposed in Ref. [10], focuses on mitigating the fluctuations in solar photovoltaic (PV) output when connected to the grid. However, these methods necessitate the use of larger battery sizes to ensure effective hourly dispatch, which can pose challenges in maintaining power supply accuracy in instances where there are errors in the hourly forecast used for dispatch calculations. Furthermore, the rapid fluctuations in PV power being transferred to the battery system may lead to a reduced lifespan of the batteries.

In [11], a min-max approach has been presented for the dispatch of RESs, where the dispatched power is minimized during battery

* Corresponding author.
E-mail addresses: aya.amer@tamu.edu (A. Amer), ahmed.massoud@qu.edu.qa (A. Massoud), khaled.shaban@qu.edu.qa (K. Shaban).

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Nomenclature

Variables

λ_t^{SU}	DG start-up cost at time t (\$/kWh)
λ_t^{pur}	Electricity purchasing price at time t (\$/kWh)
λ_t^{sold}	Electricity selling price at time t (\$/kWh)
λ_t^{fuel}	Fuel cost at time t (\$/L)
P_t^{con}	Controllable load rated power (kW)
P_t^{PV}	PV output power at time t (kW)
$P_t^{PV/stc}$	PV output power at STC (kW)
T_c	PV Cell temperature (° C)
$E_t^{ESS/c}$	ESS charging energy at time t (kWh)
$E_t^{ESS/d}$	ESS discharging energy at time t (kWh)
P_t^{total}	Total power consumption at time t (kW)
P_t^{pur}	Purchased power from grid at time t (kW)
P_t^{sold}	Sold power back to the grid at time t (kW)
P_t^{DG}	DG output power at time t (kW)
$P_t^{ESS/dis}$	ESS discharging power at time t (kW)
$P_t^{ESS/ch}$	ESS charging power at time t (kW)
P_t^{ESS}	ESS power at time t (kW)
SoC_t^{ESS}	ESS state of charge at time t (kW)

Constants

G_{stc}	Solar irradiation at STC
G_{IN}	Incident solar irradiation (W/m^2)
T_r	PV reference temperature (° C)
$\eta^{ESS/c}$	ESS charging efficiency factor
$\eta^{ESS/d}$	ESS discharging efficiency factor
C_{bat}^{Cap}	ESS capital cost (\$)
$P^{DG/min}$	Minimum DG output power (kW)
$P^{DG/max}$	Maximum DG output power (kW)
$P_t^{ESS/max}$	Maximum ESS power (kW)
$P_t^{con/min}$	Controllable load minimum power (kW)
$P_t^{con/max}$	Controllable load maximum power (kW)
SoC^{min}	Minimum state of charge of ESS battery
SoC^{max}	Maximum state of charge of ESS battery
ξ_{gas}	Gas emissions factor (\$/kg)
l_t	Time-varying power limit (kW)
$P_t^{grid/max}$	Grid power limit (kW)
$FC_t^{DG/max}$	Maximum fuel consumption for the day (L)

charging and maximized during battery discharging. However, this method has drawbacks in terms of complexity and the need for larger battery capacities. In Ref. [12], a modified version of the min-max approach has been proposed to determine the optimal battery capacity for effective integration of a wind farm with the grid. A short-term power dispatch control algorithm was employed to smooth the transitions between consecutive intervals, and the battery's state of charge (SoC) was regulated to ensure safe operation. Nevertheless, the high number of charging-discharging cycles in this method may lead to economic concerns. Work in Ref. [13] introduced a short-term dispatch commitment technique for a wind power station using a dual battery scheme, which involves switching between batteries and an additional arrangement to minimize the impact of switching on the grid. Another dual-battery scheme, presented in Ref. [14], has utilized a statistical approach to dispatch power from the wind power station, determining the discharge rate based on the predicted time required for charging the other battery. This approach, however, requires a large battery size to store the generated wind power effectively.

Nevertheless, the studies mentioned above did not take into account demand-side management in the power dispatch problem. Additionally, the collaboration of other sources like shiftable load and DG in the power dispatch process can offer more appealing economic benefits while ensuring compliance with system constraints. In Refs. [15,16], an EMS was introduced for a microgrid that incorporates a PV source and an ESS. The EMS model formulation involved various constraints related to modeling the ESS units, which were approximated using piecewise linear models.

Unlike demand-side management and generation resources, the short-term dispatch of ESS significantly impacts its long-term lifespan. Frequent charging and discharging cycles can notably degrade the life of batteries. Increasing the capacity of the ESS can provide larger reserves for smooth operation and reduce the risk of load loss, but it comes at the cost of additional capital investment [17]. These dual requirements necessitate accurately linking the operational cost of the ESS to the long-term degradation process in real-time operations. In previous studies [18–20], the degradation cost of ESS was either disregarded or modeled in a crude and generalized manner. For instance, authors in Ref. [21] proposed an EMS that aimed to minimize operating costs and reduce pollutant gas emissions in a hybrid power station comprising PV panels, ESS, and DG. However, their study did not explicitly consider the degradation cost of the ESS, limiting the assessment of long-term economic viability.

In a similar context, a study in Ref. [22] developed an EMS for a hybrid power station that included ESS, PV, and DG. Their objective was to optimize power scheduling and storage operations to minimize operating costs. However, the study did not explicitly consider the impact of uncertainties in renewable energy generation forecasts, which is crucial for ensuring reliable and robust EMS performance. The EMS approach in Ref. [23] incorporated a degradation cost model for the ESS. However, the study did not explore the impact of pricing mechanisms and different model settings, leaving room for future research to investigate these aspects.

To establish a dispatchable wind power plant, a hybrid ESS framework comprising batteries and supercapacitors was suggested in Ref. [24]. This method utilized a statistical approach to design the hybrid storage system, aiming to maximize the utilization of harvested wind energy. However, the power capacities of the hybrid storage system, limited to economic feasibility, were unable to meet the required charge-discharge rates. In Ref. [25], a hybrid storage solution for solar power generation stations was introduced, employing a low-pass filter for power sharing between batteries and supercapacitors. Nonetheless, the chosen time constants for the filter may not have been optimal. Additionally, certain estimation methods employed in the dispatch calculations assumed no errors in the wind or solar forecasts. In Ref. [26], the authors present an optimal energy dispatch engine for PV-DG-ESS hybrid power plants, considering battery degradation and carbon emissions. The emphasis is on reducing carbon emissions, which is an important aspect for sustainable energy systems.

Although significant progress has been made in developing EMS for hybrid renewable power stations, several limitations persist in the literature. Firstly, the long-term degradation and maintenance costs of ESS are often overlooked, which hinders a comprehensive economic evaluation of hybrid systems. Secondly, backup options, such as diesel/gas generators, and demand-side management are not taken into account, and uncertainties in renewable energy generation forecasts are not adequately addressed in some studies, compromising the reliability and robustness of the proposed EMS. This work addresses these limitations by incorporating degradation cost models and uncertainty management techniques to enhance the effectiveness of EMS for hybrid power stations.

This paper presents an EMS for a hybrid energy plant, aiming to maximize the utilization of RESs, overall plant profitability, and reduction of system operational costs. The optimization problem is formulated as a mixed integer linear programming (MILP) framework with three objectives: 1) minimizing the total operating cost, 2) minimizing the battery degradation cost, and 3) minimizing pollutant gas emissions, while taking into account practical constraints of different energy sources.

Table 1 provides an overview of the advantages of the proposed EMS model over what has been presented in the literature. It highlights the unique contributions and improvements made in the proposed EMS model, such as the consideration of long-term degradation, incorporation of backup options and demand-side management, effective uncertainty management, optimization for multiple objectives, and the evaluation of overall system profitability. The contributions of this paper are summarized as follows.

- Introduction of a multi-objective optimal dispatch methodology for power sources, encompassing PV panels, a DG unit, and an ESS.
- Incorporation of demand response through controllable loads in the optimization problem.
- Development of a precise degradation cost model for batteries, maintaining ESS state-of-charge (SoC) limits to enhance lifespan.
- Validation of the proposed EMS across diverse electricity pricing mechanisms, showcasing ESS dispatch for multiple objectives and under various scenarios.

The remaining sections of this paper are structured as follows. Section II introduces the proposed system model. Section III elaborates on the objective function, energy source models and associated constraints, and optimization problem formulation. The performance evaluation is discussed in Section IV. Finally, Section V concludes the paper and outlines future research directions.

Table 1
Comparison of the proposed EMS model and EXISTING literature.

Feature	Multi-Objective			Demand Response Integration	Backup Options (DG)	Forecasting Accuracy	Maximize Overall System Profitability
	Operating cost	ESS long-term degradation cost	DG gas emissions cost				
[11]	Yes	×	×	×	×	×	×
[15,16]	Yes	Yes	×	Yes	×	×	×
[18–21]	Yes	×	Yes	Yes	×	×	×
[26]	Yes	×	Yes	×	Yes	×	Yes
[27]	Yes	×	×	×	×	Yes	×
Proposed EMS	Yes	Yes	Yes	Yes	Yes	Yes	Yes

2. System model

An important component in energy management is accurate modeling, which also aids the optimization algorithm in making accurate dispatch decisions. The proposed system's various energy sources are each separately modeled as shown in the following subsections.

A. Power Plant Model

The schematic diagram and related power flows of a typical power plant are depicted in Fig. 1. The power plant consists of various components, including the point of common coupling (PCC) to the grid, ESS, RES, DG, and aggregate auxiliary loads. Power utilities demand a consistent and stable power output from the generating station, particularly at the PCC. Deviating from the predetermined power commitment can result in substantial penalties for the power generation company. To mitigate the risk of incurring such penalties, it becomes imperative to incorporate an emergency power supply to address potential power supply failures caused by reduced generation from RESs. In such scenarios, a reliable hybrid power station should encompass renewable energy generation through sources like wind and/or PV, along with an ESS. Additionally, an emergency power supply, such as a diesel or gas-based generator, should be included to provide backup power during unforeseen emergencies. This comprehensive configuration ensures the dependability and resilience of the hybrid power station.

Depending on the system requirements, availability of renewable energy sources, and electricity market conditions, the power plant can operate in either a grid-connected mode or as an independent island micro-grid. Unless otherwise stated, the following discussion will concentrate on the grid-linked mode.

B. Load Demand Model

The essential loads should always have their energy needs satisfied. However, the EMS schedules the electricity for controllable demands, such as pumping systems. The total loads can be estimated using load demand forecasting. Based on the characteristics of the controllable load, the operator assumes that the load needs a certain amount of energy per day. In this paper, the deferrable load is assumed to have a power value range between the minimum and the rated power value of the deferrable load, and its daily energy consumption can be adjusted between the lower and upper bounds, as depicted in (1).

$$P_t^{min} < P_t^{con} < P_t^{max} \tag{1}$$

C. Photovoltaic Model

The deployment of RES in the power plant makes it more difficult for the EMS to monitor the current supply/demand balance. The power plant is modeled with a PV source. The incident irradiance G_{IN}, the current cell temperature T_c, and the maximum PV output power under standard test conditions (STCs), all influence the PV array's output power. This is shown in (2).

$$P_t^{PV} = P_{stc} \frac{G_{IN}}{G_{stc}} \left(1 + \propto (T_c - T_r) \right) \tag{2}$$

D. Energy Storage System Model

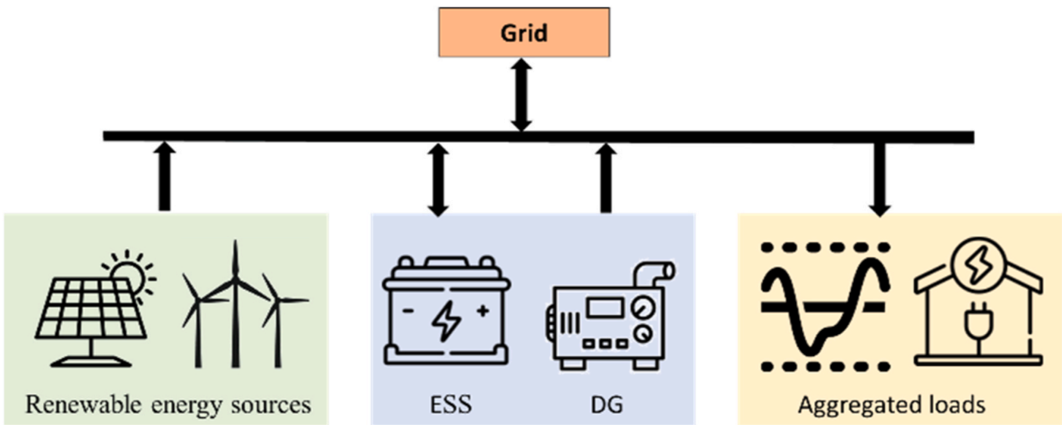

Fig. 1. Block diagram representation of the components of a hybrid power plant and related power flows.

The ESS's main tasks include preserving the instantaneous power balance and lowering the ongoing power plant operating costs. As a result, it is expected for the battery to function as the distributed generation unit for efficient dispatch. The battery state of charge (SoC) is taken into account to simulate the dynamic behavior of the ESS unit. The charging and discharging power should be divided since their efficiency is different in terms of power flow. The ESS's discrete-time model is expressed in (3).

$$SoC_t^{ESS} = SOC_{t-1}^{ESS} + E_t^{ESS/c}\eta^{ESS/c} - E_t^{ESS/d}/\eta^{ESS/d} \tag{3}$$

E. Diesel Generator Model

The DG has three operating power settings (off, low, and high), each of which has a specific fuel consumption and output power. When the generator is off, there is no fuel usage. Each generator can have a power level assigned to it by the EMS for each hour of the day. A nonlinear and nonconvex function can be used to model a DG's fuel consumption, FC_t^{DG}, as presented in (4).

$$FC_t^{DG} = m_i P_i + \delta_i C_i \tag{4}$$

where m_i is the slope and Ci is the Y-intercept of segment i. The slope m_i of the line segment i can be given (5).

$$m_i = \frac{C_{i+1} - C_i}{P_i^{max} - P_i^{min}} \tag{5}$$

F. Dynamic Pricing Model

The system operator typically determines the electricity prices in a constant or dynamic manner. Constant pricing models include fixed prices and time-of-use (ToU) prices. Fixed prices are regularly predetermined and do not respond to changes in the network. These pricing schemas have no impact on user patterns in microgrids as the cost of electricity does not alter with the amount of consumption. While ToU pricing issued by the operator encourages electricity consumption during off-peak hours due to significantly cheaper rates per kWh. Dynamic pricing, like real-time pricing (RTP), is responsive to locational marginal prices and frequently released hours in advance, enabling customers to plan and reduce operational costs. Microgrids and power plants can generate revenue by selling some of their extra generations to the utilities when bidirectional connectivity is permitted.

This paper adopts three pricing schemes, namely, ToU, one spike, and RTP pricing schemes. In the ToU pricing scheme, the price of electricity is represented by a two-level scheme with off-peak and on-peak values. In the RTP model, the system operator sets the price in response to market players' bids.

3. Problem formulation

This section formulates the optimization problem for EMS for hybrid power plants by specifying the multi-objective functions and all the relevant physical constraints for each power plant component.

A. Multi-Objective Function

The primary goals of the EMS suggested in this study are as follows: 1) to decrease the total operational expenses of the power plant, 2) to minimize the degradation cost of the ESS, and 3) to reduce the emissions of harmful gases from the DG. To combine these multiple objectives into a single objective function, each objective is multiplied by a predetermined weight. Hence, the overall objective function is formulated as the weighted sum of the cost functions associated with the grid load, ESS, DG, and pollutant gas emissions cost, as depicted in (6). The weight values vary according to each objective's relative importance.

$$C_{total} = \rho \bullet \left(C_t^{grid} + C_t^{ESS} + C_t^{DG}\right) + (1-\rho) \bullet C_t^{gas} \tag{6}$$

The first term presents the power grid cost C_t^{grid}, the ESS degradation cost C_t^{ESS}, and the DG operation cost C_t^{DG}. The second term presents the cost function for gas emissions.

1) Power Grid Cost Function

The grid electricity cost can be described as the difference between the purchased energy from the grid and the sold energy to the grid multiplied by the purchasing and selling electricity prices, as shown in (7).

$$C_t^{grid} = \lambda_t^{pur} \bullet P_t^{pur} \bullet \Delta t - \lambda_t^{sold} \bullet P_t^{sold} \bullet \Delta t \tag{7}$$

$$P_t^{total} = P_t^{pur} - P_t^{sold}$$

$$P_t^{sold} = P_t^{PV} + P_t^{DG} + P_t^{ESS/dis}$$

2) Energy Storage System Degradation Cost Function

The ESS cost model consists of two components: operation cost and degradation cost, as presented in (8).

$$C_t^{ESS} = C_t^{op} + C_t^{deg} \tag{8}$$

Equation (9) calculates the ESS operation cost.

$$C_t^{op} = \lambda_t^{pur} \bullet P_t^{ESS} \eta^{ESS/c} \bullet \Delta t - \lambda_t^{sold} \bullet P_t^{ESS} / \eta^{ESS/d} \bullet \Delta t \tag{9}$$

In accordance with the price of electricity, the operation cost function in (9) will impose the EMS to optimize the ESS's charging and discharging times.

The degradation of a battery's lifetime is influenced by the battery's cycle life and its energy output. The repeated charging and discharging, the rate of the charged and discharged power, and the timing of maintenance have a significant influence on the battery lifetime. Inadequate battery cycling may expedite the deterioration of the battery's lifetime. Moreover, other factors like a high or low SoC would significantly impair the performance of the battery. When the ESS is running contained by a specific range of the rated current, the impact of the charging power rate on its lifetime is minimal in contrast to other factors.

To this end, the actual full capacity of the battery and the depth of discharge (DOD) operates as the key indicators of battery longevity. In this paper, The DOD is referred to as the energy used during a single charging or discharging event in relation to the battery's full capacity. The capital cost of the ESS can be distributed over the number of life cycles (NLC) to demonstrate the per-cycle degradation cost of the ESS, as presented in (10).

$$C_t^{deg} = \frac{C_t^{Cap}}{NLC \bullet P_t^{ESS} \bullet DOD} \tag{10}$$

3) Diesel Generator Cost Function

The DG cost involves fuel consumption cost and start-up (SU) cost which is the cost to start a generator after it has been turned off. Hence, the total cost of the DG, C_t^{DG}, is described in (11)

$$C_t^{DG} = C_t^{fuel} + C_t^{SU} \tag{11}$$

The cost function for fuel consumption (FC) is determined by multiplying the price of diesel fuel per liter by the amount of fuel consumed, as presented in (12).

$$C_t^{fuel} = \lambda_t^{fuel} \bullet FC_t^{DG} \tag{12}$$

In the initial phase, fuel is consumed without generating any power. The cost during the start-up period is calculated by multiplying the cost per start-up, C_t^{SU}, by the total number of start-ups throughout the entire time horizon, as presented in (13).

$$C_t^{SU} = \lambda_t^{SU} \bullet \sum_{t=1}^{t+N} \delta_t \tag{13}$$

Where λ_t^{SP} is the start-up cost and δ_t is binary number represents the number of DG startup times.

4) Gas Emissions Cost Function

Carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O) are the three main polluting gases that are released as a result of the combustion of diesel fuel. 99.4% of all emissions are made up of CO2 emissions [21]. The overall polluting gas emission can be stated as a function of fuel consumption by understanding the emission factors linked to each gas emission per litter of diesel fuel combustion, as shown in (14). The cost function for gas emissions is multiplied by a factor measured in $/kg to unify the measurement of the entire objective function in $.

$$C^{gas} = \xi_{gas} \bullet (\mu_{CO2} + \mu_{CH4} + \mu_{N2O}) \bullet FC \tag{14}$$

B. System Constraints

In this section, we will explore the various practical and realistic limitations associated with each component of the system.

1) Power Balance Constraints

The total power consumption should adhere to the power balance restrictions defined in (15).

$$P_t^{total} = P_t^g + P_t^{PV} + P_t^{DG} + P_t^{ESS/dis}, \forall t \tag{15}$$

2) Power Limiting Constraints

The rate of power exchange at the point of common coupling affects grid stability, in particular for weak grids. In order to keep the rate of change of the grid power at the maximum permitted change, the grid operator may impose some restrictions. Moreover, the grid operator may impose restrictions on the purchased and sold power at time t, as shown in (16) and (17).

$$max_t\left(P_t^{pur} - P_t^{sold}\right) \leq \Delta P_t^{grid/max} \tag{16}$$

$$P_t^{pur} \leq l_{t\bullet} u_t \tag{17}$$

3) Energy Storage System Constraints

The ESS lifetime cycle depends on three main elements: the SoC, the NLC, and the charging and discharging power rate. These elements are modeled in the form of inequality constraints to ensure healthy battery operation, as presented in (18)-(23).

$$SOE_{n,t}^{ESS} = SOE_{t-1}^{ESS} - \eta^{ESS/c} \bullet E_{n,t}^{ESS}, E_{n,t}^{ESS} \leq 0 \tag{18}$$

$$SOE_{n,t}^{ESS} = SOE_{t-1}^{ESS} - 1/\eta^{ESS/d} \bullet E_{n,t}^{ESS}, E_{n,t}^{ESS} > 0 \tag{19}$$

$$SOE_t^{ESS} = SOE_t^{ESS/int}, if\ t = 1 \tag{20}$$

$$SoC^{min} \leq SOE_t^{ESS} \leq SoC^{max} \tag{21}$$

$$\left(P_{t+1}^{ESS} - P_t^{ESS}\right) \leq \Delta P_t^{ESS/max} \tag{22}$$

$$NLC \leq NLC_{max} \tag{23}$$

4) Diesel Generator Constraints

The output power at which the DG is functioning determines the efficiency of the DG. The manufacturer sets the DG's output power within its minimum and maximum boundaries to ensure proper mechanical performance and high operating efficiency. This is reflected by the inequality constraint on the DG output power in (24).

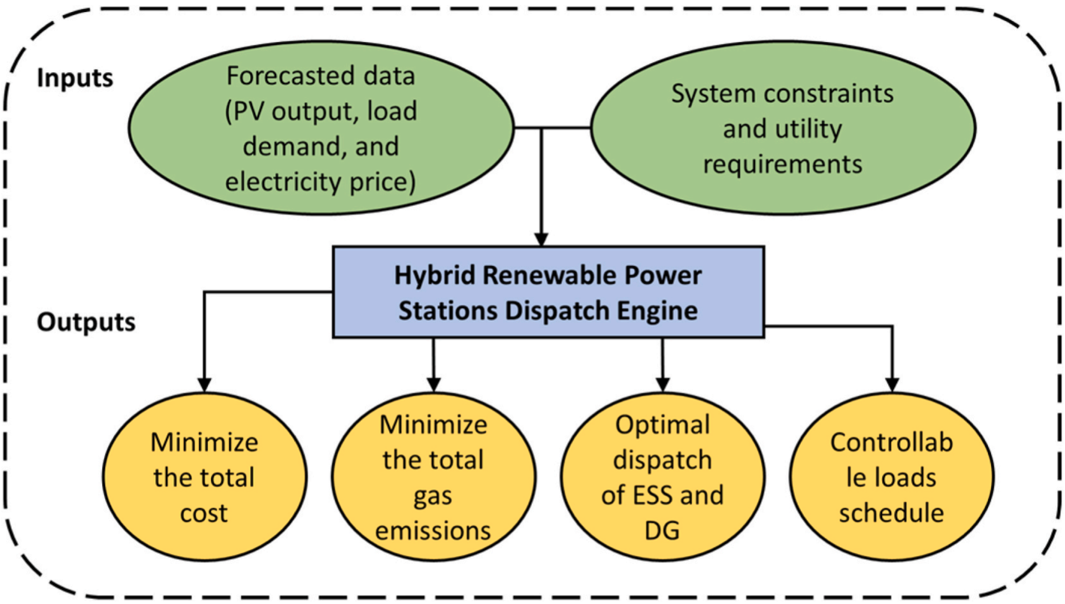

Fig. 2. The proposed EMS structure.

$$P^{DG/min} \leq P_t^{DG} \leq P^{DG/max} \tag{24}$$

Equation (25) presents the maximum fuel usage for the day. Due to the fact that you purchase your fuel a day in advance, you are only permitted to use the fuel that you have recently purchased.

$$FC_t^{DG} \leq FC_t^{DG/max} \tag{25}$$

C. Optimization Problem Formulation

As discussed, the EMS will maintain the output power of the hybrid power plant as per the scheduled commitment while maximizing the use of renewables and maximizing the total profit of the plant. The EMS model takes inputs such as the forecasted PV output, load demand, and electricity price to minimize the overall operational costs within a specified time period. The best possible solution technique will be identified considering the time required for calculation without compromising the accuracy of the solution. The objective is to determine the optimal values for all the variables that will optimize the objective function while satisfying model constraints. The optimization problem variables can be classified into two types: scalar and vector decision variables. The scalar decision variables consist of the best possible values for the DOD and the SOE_n^{ESS}. On the other hand, the vector decision variables include the optimum power scheduling for the DG P_t^{DG}, ESS charging power $P_t^{ESS/ch}$, ESS discharging power $P_t^{ESS/dis}$, controllable load power, and grid power. In summary, the EMS structure is outlined in Fig. 2.

The implementation of the EMS for Hybrid Renewable Power Stations is shown in Algorithm 1. The algorithm outlines the main steps and procedures involved in optimizing the power dispatch problem considering a specific pricing scheme (e.g., RTP, ToU,

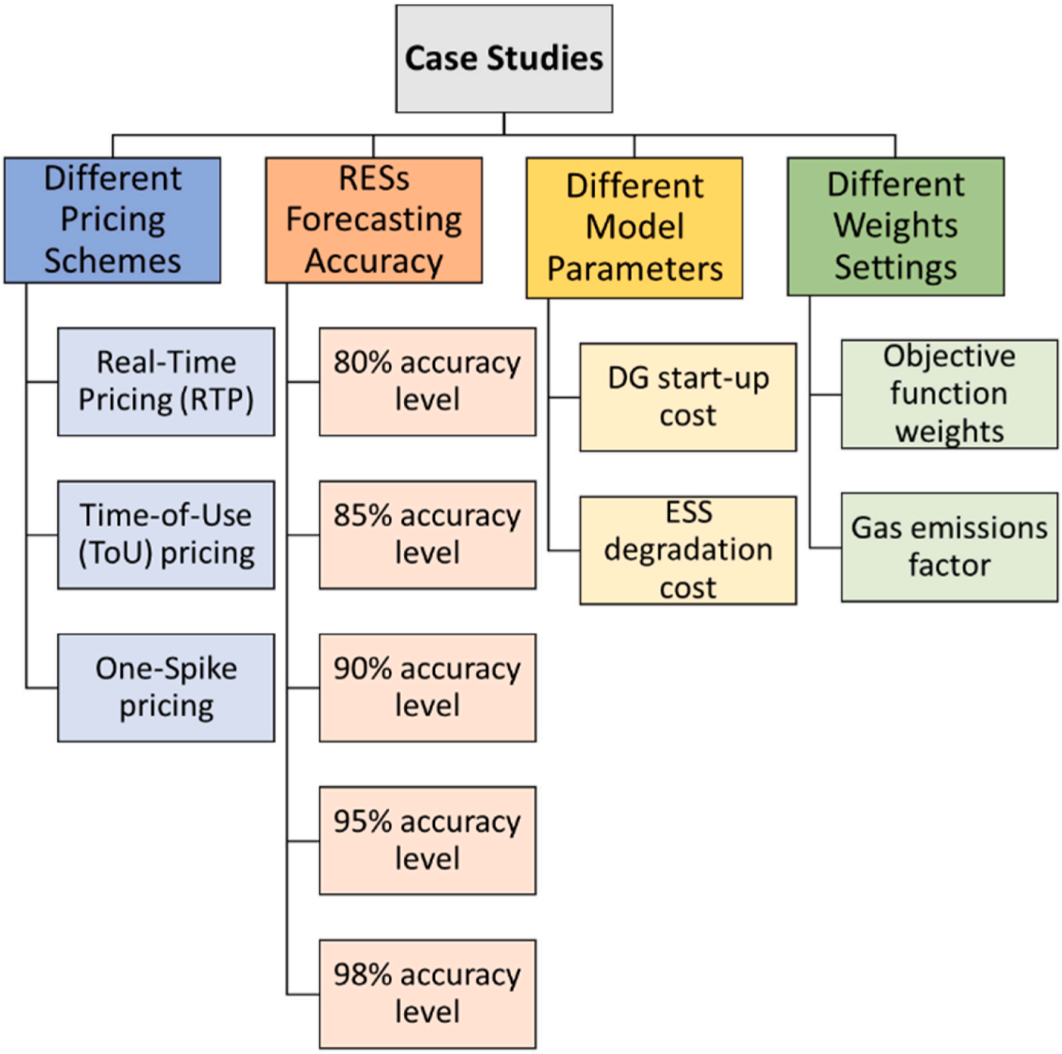

Fig. 3. The considered case studies in the simulation work.

OneSpike). The algorithm begins by initializing the system parameters and constraints, such as the maximum energy capacity and SoC limits of the ESS, the maximum power capacity and operating power levels of the DG, and the gas emissions factor for the DG.

Next, the algorithm generates renewable energy forecasts based on the specified accuracy level to estimate the energy generation from PV and other renewable sources. Subsequently, the EMS optimization is carried out using MILP for the chosen pricing scheme. The EMS aims to minimize the total operating cost by optimally scheduling the operation of the ESS, DG, and controllable loads.

After obtaining the optimized power schedule, the algorithm calculates the costs associated with each component, including the ESS, DG, and DG emissions costs, based on the power schedule. The ESS cost is calculated by considering the degradation cost and SoC levels within specified limits to ensure the ESS's optimal operation. The DG cost is determined by considering the startup cost and the operating cost during peak and off-peak hours, while the DG emissions cost is estimated based on the gas emissions factor.

4. Performance evaluation

A. Simulation Cases Setups

The simulation focusing on multi-objective optimization aims to evaluate the EMS's performance in achieving multiple objectives simultaneously. The EMS is expected to prioritize maximizing renewable energy integration to increase the penetration of renewable sources and reduce reliance on non-renewable sources. Additionally, it should optimize power scheduling to minimize pollutant gas emissions from backup power sources, contributing to a more environmentally friendly operation. By assessing the EMS's ability to balance these multiple objectives, this simulation case demonstrates its effectiveness in achieving a sustainable and economically viable operation for hybrid renewable power stations.

The proposed EMS is evaluated through distinct cases, encompassing a range of scenarios, as shown in Fig. 3, to assess its effectiveness.

1. Different Pricing Schemes: Three pricing models are considered: Real-Time Pricing (RTP), Time-of-Use (ToU) pricing, and One-Spike pricing. The RTP model utilizes real-time electricity pricing data obtained at 30-min intervals, allowing for dynamic adjustments in response to market conditions. ToU pricing divides the day into peak and off-peak hours, with different electricity prices set for each period. One-Spike pricing involves a single spike in electricity prices during a specific time interval. Under the ToU pricing model, peak hours (hours 4–9 and 15–20) have an electricity price of 1.5$/kWh, while off-peak hours (hours 0–4, 10–15, and 21–24) have a price of 0.55$/kWh. In the RTP, the 30-min interval data is adopted from Ref. [28]. In all pricing models, the electricity selling price is the same as the electricity purchasing price.
2. RESs Forecasting Accuracy: This case evaluates the performance of the EMS under different levels of RESs forecasting accuracy. Vary the accuracy of the predicted renewable energy generation from the PV and analyze the impact on the system's overall operation and cost.
3. Different Model Parameters: In this case, different model settings and parameters are varied to evaluate their impact on the proposed EMS. Parameters such as the start-up cost of the DG and the degradation cost of the ESS are adjusted to explore their influence on system operation and cost.
4. Different Weights Settings: The weights assigned to each objective function are varied. By systematically varying these parameters, the sensitivity of the EMS to different cost factors can be analyzed, providing insights into the optimal configuration and utilization of the hybrid renewable power station. This case allows for a comprehensive assessment of the EMS's flexibility and adaptability to different operational and cost conditions, providing valuable information for system optimization and decision-making.

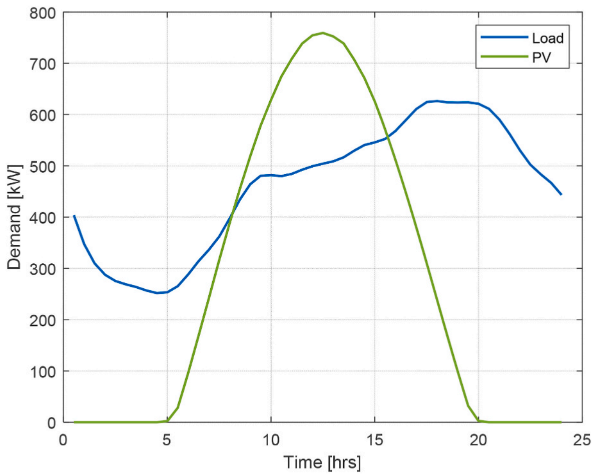

Fig. 4. Exact power of load and PV for 24 h.

B. Input Data

The available controllable loads power and PV power utilized for the simulations are depicted in Fig. 4, where the controllable load power is set at 0.6 MW and the PV's rated output power is 0.75 MW. Table 2 provides an overview of the system parameters employed in the simulations. The rated capacity of the ESS is 0.8 MWh with a rated charging and discharging power of 0.8 MW. The maximum rate of charging or discharging power is set to 0.3 MW. The DG operating power levels are [300, 500, 700, 1000] measured in kW, and [427, 806, 325, 765] are the fuel consumption for each power level measured in L. The scheduling horizon covers a duration of 24 h, with a time interval of 30 min. The objective of the EMS is to determine the optimal schedule for the ESS, DG operating power level, and controllable load power, while ensuring compliance with all operational constraints.

To solve the EMS optimization problem, an MILP formulation is adopted and solved using the MATLAB optimization toolbox. Since there are established solvers available with diverse algorithms capable of handling algebraic models and producing reliable results, a detailed comparison of their performances is beyond the scope of this paper. The simulation experiments are conducted on a computer equipped with an Intel Core i7 CPU @ 2.9-GHz processor and 16.00-GB RAM. The average computation time for each simulation is less than 1 s, indicating the efficiency of the proposed EMS.

The chosen system configuration and the computational setup provide a solid foundation for conducting the simulations and analyzing the results. The efficient computation time enables the evaluation of various scenarios and enhances the practical applicability of the proposed EMS.

C. Simulation Results and Discussion

1) Different Pricing Schemes

To study the effect of the electricity price shape on the power dispatch problem, three price schemes are utilized. Fig. 5 shows the results of the proposed EMS's optimum dispatch based on the RTP scheme. The scheduling power of the ESS, DG, and controllable loads are shown in Fig. 5(b). As anticipated, the battery charges during times of low price and discharges during times of high price. Similar to this, the DG is in operation at times of high prices to reduce the system's running costs while keeping the DG constraints. In order to reduce the system's running costs, the power scheduling of controllable loads in response to price signals or demand curtailment requests leads to reduced peak demand and potential cost savings. The ESS %SOC is presented in Fig. 5(a). It can be noticed that the %SoC is bounded between the lower bound SoC (20%) and the upper bound SoC (80%).

The ToU electricity price optimal power dispatch results are shown in Fig. 6. The battery is observed to be less responsive to electricity prices and to attempt fewer charging and discharging activities. It charges during off-peak hours and discharges at peak hours, while maintaining all the operations constraints. On, the other hand, the DG is operating for more time compared to the RTP case. It operates with a high-power level during the peak-price periods and switches to a lower power level during off-peak power prices. This is due to the high start-up cost of the DG. In addition, more energy is sold back to the utility grid at time 10–16 h due to excessive energy generated by the PV at that time.

Fig. 7 presents the optimal power dispatch results based on a one-spike pricing scheme. As can be seen, the battery is charged while the electricity price is low and discharged when the electricity price is comparatively high during the spike price hours. Similarly, the DG is operating around the high price periods with higher operating power during the spike price hours. Table 3 provides a summary of the cost comparison between the three price models.

2) Renewable Energy Forecasting Accuracy

This simulation case aims to assess the performance of the proposed EMS under varying levels of renewable energy forecasting accuracy. It is observed that the dispatch decisions are predominantly influenced during the daytime, when solar energy is abundant but intermittent, resulting in higher uncertainties regarding PV outputs. Table 4 provides a breakdown of the costs for each system component across five forecast accuracy level scenarios.

As the EMS seeks to minimize the ESS degradation cost and DG operation, it is reasonable to expect that changes in renewable

Table 2
System parameters.

Parameter	Value	Parameter	Value
P_{stc}	1000 kW	C_{bat}^{Cap}	2212 $
T_r	25 ° C	λ_t^{fuel}	1.5 $/L
$\propto$	0.005 W/° C	μ_{CO2}	2.557 kg/L
P_t^{PV}	0.75 MW	μ_{CH4}	0.0004 kg/L
P_t^{con}	0.6 MW	μ_{N2O}	0.000133 kg/L
P_t^{ESS}	0.8 MW	$SOE_n^{ESS/min}$	20%
$\eta^{ESS/c}$	95%	$SOE_n^{ESS/max}$	80 %
$\eta^{ESS/d}$	95%	λ_t^{SU}	10000 $
NLC_{max}	2000	$P_n^{DG/max}$	1000 kW
DOD	0.8	$P_n^{DG/min}$	300 kW

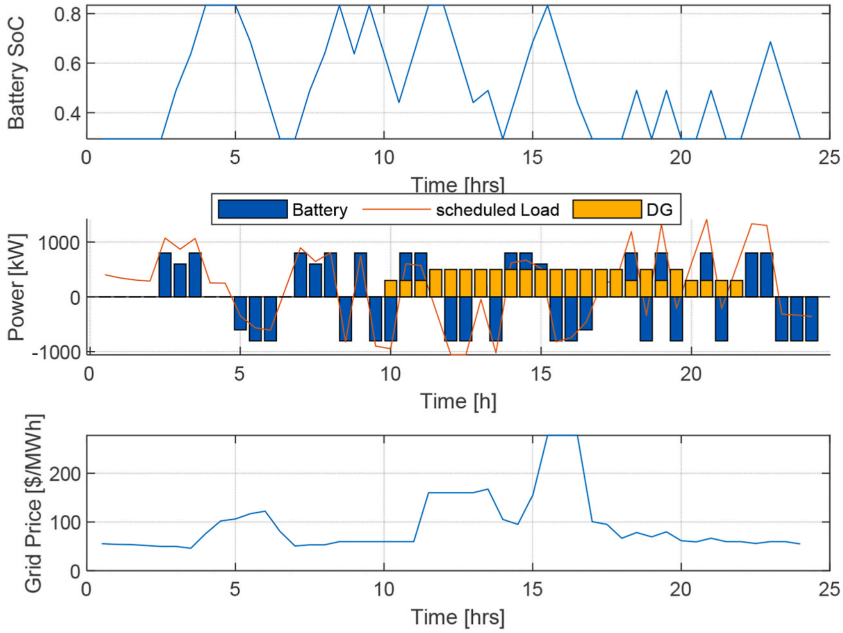

Fig. 5. The EMS optimal dispatch with RTP scheme.

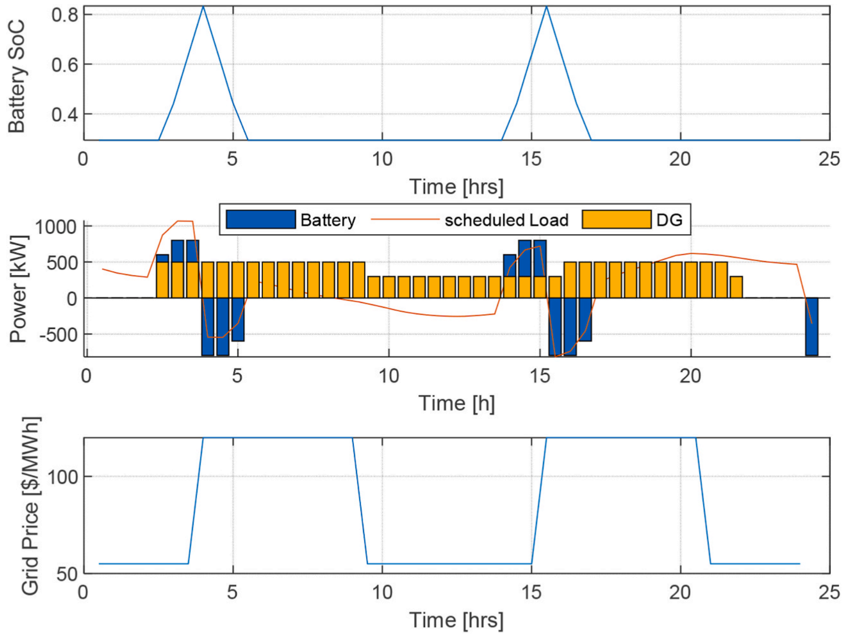

Fig. 6. The EMS optimal dispatch with the ToU pricing scheme.

energy forecasting accuracy levels would introduce fewer volatile variations in the ESS cost and DG cost. However, the controllable load is adjusted to compensate for the power mismatch, leading to higher grid costs. Notably, there is no significant change in either the DG cost or the ESS cost between the forecast accuracy levels of 0.8 and 0.9. The most significant cost reduction is observed at the 0.95 accuracy level, indicating the importance of more accurate renewable energy forecasts for achieving optimal system performance.

3) Different Model Parameters

To demonstrate the usefulness of the proposed online EMS and its adaptability to various settings, different model parameters such as DG start-up cost, and ESS degradation cost are considered. First, we specify two different values than the value presented in Table 2

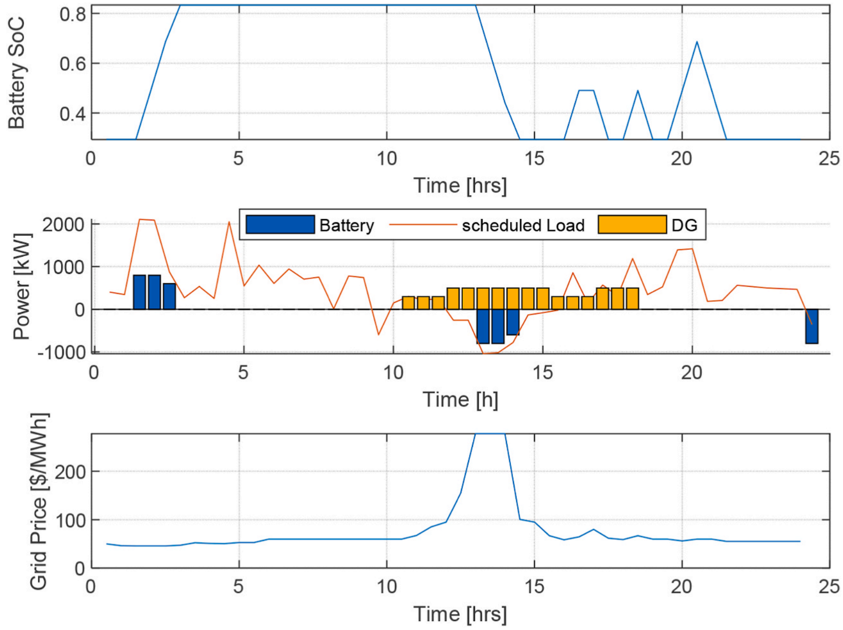

Fig. 7. The EMS optimal dispatch with a one-spike pricing scheme.

Table 3
Comparison between system costs based on different pricing scheme for one day.

Costs ($/day)	Electricity pricing schemes		
	RTP	ToU	One-spike
Grid cost	1379	1493	1798
ESS cost	1384	1498	1281
DG cost	1166	1380	985
Total system cost	3929	4371	4064

Table 4
System costs based on five scenarios with different forecast accuracy levels for one day.

Costs ($/day)	Forecast accuracy levels				
	0.8	0.85	0.9	0.95	0.98
Grid cost	1402	1388	1400	1362	1380
ESS cost	1343	1332	1343	1315	1315
DG cost	1205	1198	1205	1185	1205
Total system cost	3950	3918	3948	3862	3900

for the DG start-up cost. Fig. 8 shows the EMS solution for DG operating intervals along with the RTP. As observed, the EMS solution involves multiple generation intervals when the start-up cost is reduced. Second, the ESS degradation cost (C_t^{deg}) in (9) is eliminated to test the performance of the ESS. Fig. 9 presents the %SoC for two different cases with and without degradation cost along with the RTP. The case without battery degradation cost leads to the worst results as it has a higher discharge power ratio, putting the battery at risk of being misused. It has clearly shown that the proposed method is advantageous in all terms.

4) Different Weights Settings

Moreover, the simulations are conducted with varying weights assigned to each objective to understand the trade-offs and find the optimal balance for different system configurations. The assignment of weight values to each objective reflects their relative importance and directly influences the objective function presented in Equation (6). The adjustment of weight parameters offers valuable insights into the sensitivity of the EMS model to different objectives. It allows for an in-depth analysis of the trade-offs between minimizing operating costs, reducing ESS degradation, optimizing DG operation, and minimizing gas emissions. By varying the weights, decision-makers can prioritize specific objectives based on their preferences and system requirements. For instance, if

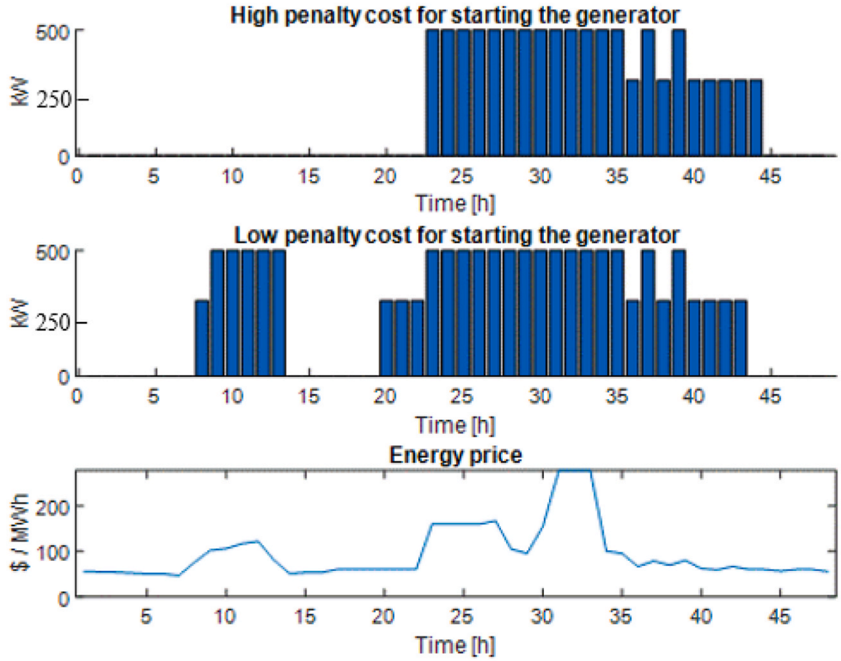

Fig. 8. Results for the scenario with high and low DG start-up cost.

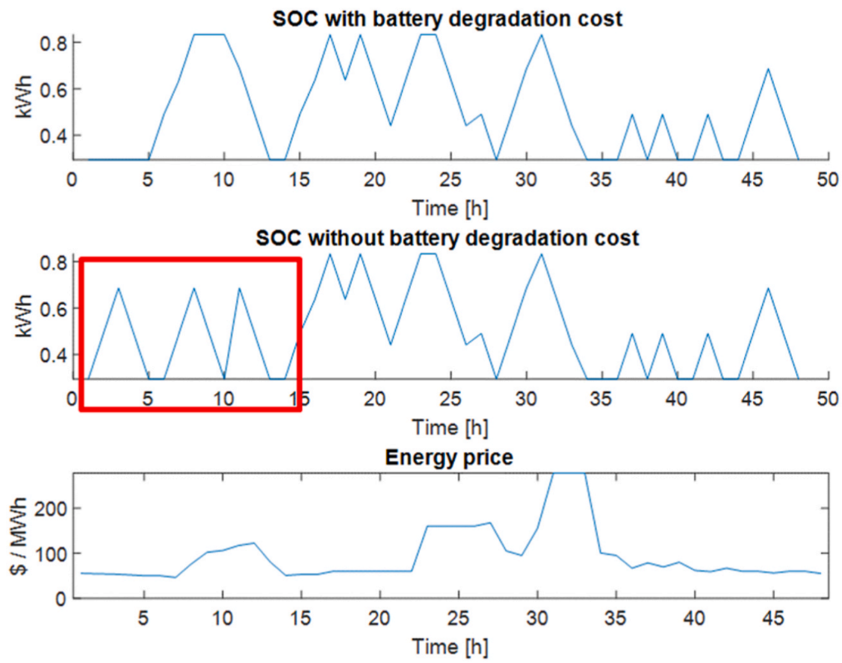

Fig. 9. Results for the scenario with and without battery degradation cost.

minimizing ESS degradation is of utmost importance, a higher weight can be assigned to the corresponding objective, resulting in a more conservative strategy for ESS operation. On the other hand, a lower weight on ESS degradation and a higher weight on minimizing gas emission costs may lead to a long-term degradation impact. In this paper, the gas emission cost function is multiplied by a weighting factor that is selected as the penalty cost factor in $/kg.

Table 5 provides a comprehensive summary of the variations considered for each objective function weight and gas emissions factor, allowing for a systematic analysis of their impact on the system's costs. The corresponding costs associated with the grid, ESS degradation, DG operation, and gas emissions are presented in Table 6 for all the scenario combinations, utilizing the RTP scheme.

Notably, cases with low weight settings (ρ = 0.3) demonstrate higher grid and total system costs, indicating limited potential for demand response. Conversely, cases with high weight settings (ρ = 0.8) exhibit increased gas emission costs but improved demand response capabilities. On the other hand, cases with ρ = 0.5 strike a balance by equally considering the system costs.

Furthermore, the choice of gas emissions factor plays a significant role in influencing the DG operating power levels. A lower gas emissions factor ($\xi_{gas} = 0.05$ $/kg) results in a lower penalty cost for the produced gas, leading to higher DG operating power levels. Conversely, as the gas emissions factor increases ($\xi_{gas} = 0.25$ $/kg), environmental concerns take priority, prompting the DG to adjust its power level to minimize diesel consumption while still meeting the operational requirements of the system. Additionally, Table 4 demonstrates that the battery degradation cost remains relatively stable, indicating the optimal utilization of the battery in both smoothing and energy arbitrage modes, with optimal DOD ratios.

By exploring the cost implications and performance outcomes under different weight parameter combinations, system operators and planners can identify the optimal balance that aligns with their specific goals and constraints. This flexibility in assigning weights allows for the customization of the EMS model to meet varying system requirements and stakeholder preferences. It provides valuable decision-making support in optimizing the trade-offs and achieving a sustainable and cost-effective operation of hybrid renewable power stations.

D. Challenges and Opportunities

The proposed EMS model opens up significant opportunities for enhancing the efficiency, reliability, and sustainability of hybrid power stations. By effectively integrating RES, ESS, and DGs, the EMS can optimize the utilization of these resources, leading to reduced operating costs and improved system performance. The EMS can facilitate the seamless transition between grid-connected and islanded modes, allowing the hybrid power station to operate in the most economically and environmentally favorable mode based on prevailing conditions. Furthermore, the proposed EMS model provides opportunities for demand response and load management. By incorporating demand-side flexibility and controllable loads, the EMS can optimize the scheduling of energy resources based on electricity pricing mechanisms. This enables the participation of consumers in load shifting and peak load reduction, leading to improved grid stability, reduced energy costs, and enhanced system resilience.

On the other hand, the proposed EMS model presents several challenges and opportunities. One of the main challenges is the accurate modeling and optimization of multiple components within the system. Integrating renewable energy sources, ESS, and DGs while considering their dynamic characteristics and operational constraints requires advanced modeling techniques and optimization algorithms. Ensuring the seamless coordination and control of these diverse components is a challenge that needs to be addressed for optimal system performance. Another challenge is the management of uncertainties associated with renewable energy generation and load forecasting. The intermittency and variability of renewable sources pose challenges in achieving reliable and cost-effective operation of the hybrid power station. Developing robust forecasting models and implementing adaptive control strategies that can dynamically respond to changes in renewable energy availability and load demand are crucial for maximizing the benefits of the proposed EMS model.

Addressing the challenges and leveraging the opportunities of the proposed EMS model requires further research and collaboration between academia and industry. Advances in mode-free algorithms, and real-time control strategies will contribute to the effective implementation of the proposed EMS model in practical hybrid power stations.

5. Conclusion

This paper has presented an EMS for hybrid renewable power stations, encompassing DG, ESS, and controllable loads. The primary objectives of this EMS are threefold: to minimize the overall operating cost associated with the various system components, to reduce pollutant gas emissions resulting from DG operation, and to ensure compliance with system operating constraints. A degradation cost model has been developed to account for long-term capital cost of the battery, enhancing its integration into short-term operational decision-making.

The implementation of the proposed EMS within a microgrid configuration, including an ESS, a PV source, a DG, and aggregate controllable loads, has been successfully demonstrated through simulation studies. These studies have showcased the adaptability of the EMS in utilizing various energy storage types, such as batteries and DG, to achieve multiple decision-making objectives. Additionally, we have considered diverse pricing schemes and model settings, thereby validating the effectiveness of the proposed EMS.

In future work, our objectives include exploring the integration of machine learning techniques into the EMS, allowing for enhanced decision-making capabilities. Furthermore, we aim to incorporate models that account for uncertainties in RES forecasting and RES generation output, enabling a more robust and accurate EMS performance.

Table 5
The parameter trade-offs and the variations we test in this paper.

Different objective function weights settings (ρ)	Different gas emissions factor settings ξ_{gas}
I: 0.3	A: 0.05 $/kg
II: 0.5	B: 0.15 $/kg
III: 0.8	C: 0.25 $/kg

Table 6
System costs based on different objective function weights and gas emissions factor settings for one day.

Costs ($/day)	I-A	I–B	I–C	II-A	II-B	II-C	III-A	III-B	III-C
Grid cost	1250	1357	1480	1379	1492	1585	942	1063	1184
ESS cost	1284	1234	1290	1304	1355	1301	1408	1438	1495
DG cost	1226	1093	742	1166	885	742	1292	1025	874
Total cost	3760	3684	3512	3849	3732	3628	3642	3526	3553
Gas emissions cost	1494	2090	2738	2597	3580	4178	4325	4925	5457

Data availability statement

All data supporting the findings of this study are included within the article.

CRediT authorship contribution statement

Aya Amer: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Ahmed Massoud:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization. **Khaled Shaban:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of Competing interest

The authors declare that they have no conflicts of interest regarding the research presented in this manuscript. Specifically, there are no financial interests or arrangements with any individuals, organizations, or entities that could be perceived as having influenced the research conducted or the content of this paper.

Furthermore, the authors declare that they have not received any financial support, funding, or grants from any sources that might have a vested interest in the outcomes or conclusions of this research. This research has been conducted with integrity and objectivity, and the results and interpretations presented herein are solely based on the data and analysis.The authors are committed to upholding the highest standards of transparency and ethics in their research endeavors.

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