IECO International Journal Of Industrial Electronics Control and Optimization
Print ISSN: 3517-2645
Online ISSN: 3568-2645
Homepage: https://ieco.usb.ac.ir/

A Study on Optimal Energy Management of a Renewable-Based Microgrid: A Model Predictive Control Approach

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Article Info

Article type:
Research Article

Article history:
Received: 08-December-2025
Received in revised form: 03-February-2026
Accepted: 25-February-2026
Published online: 22-Dec-2026

Keywords:
Energy Management,
Energy Storage Systems,
Microgrid,
Model Predictive Control,
Quadratic Interpolation Optimization.

ABSTRACT

Effective energy management in renewable-based microgrids demands advanced optimization and forecasting strategies capable of addressing the intrinsic uncertainties of solar generation and load demand. This paper proposes a comprehensive day-ahead scheduling framework based on Model Predictive Control (MPC) to enhance the operational efficiency of a grid-connected microgrid comprising photovoltaic units, microturbines, fuel cells, and battery energy storage. The MPC structure incorporates 24-hour-ahead forecasts of load and solar irradiance generated through multiple deep learning architectures, enabling dynamic adaptation to rapidly changing environmental and consumption conditions. To solve the underlying optimization problem, a novel Quadratic Interpolation Optimization (QIO) algorithm is employed, offering improved convergence behavior and robustness in comparison with conventional metaheuristic methods. The integrated forecasting–optimization methodology ensures optimal dispatch of distributed resources, effective utilization of storage systems, and economically efficient power exchange with the utility grid. Extensive simulations validate the superiority of the proposed MPC-QIO framework in reducing operational costs, enhancing renewable energy penetration, and maintaining system reliability even under forecasting uncertainties. The results confirm that the synergy between deep learning-based prediction and advanced optimization significantly strengthens the controllability and resilience of modern microgrids, highlighting the method's strong potential for real-world deployment.

I. Introduction

The proliferation of Distributed Energy Resources (DERs) has positioned microgrids as a cornerstone of modern, decentralized power systems, offering a pathway to enhanced resilience, cost efficiency, and localized energy control [1-3]. These systems are instrumental in harnessing Renewable Energy Sources (RES) like solar and wind power, thereby accelerating the global transition to a sustainable energy paradigm [4-6]. By decentralizing electricity generation and alleviating strain on traditional transmission networks, microgrids present a viable solution to pressing issues such as energy poverty, transmission congestion, and volatile electricity pricing [7]. Nevertheless, the integration of RES introduces significant operational complexities. The innate intermittency and stochastic nature of solar irradiance and wind speed pose substantial threats to the power balance and operational reliability of microgrids. To counteract these challenges, Energy Storage Systems (ESS) are increasingly employed to mitigate power fluctuations, enhance energy time-shifting, and guarantee a reliable power supply. Concurrently, sophisticated Energy Management (EM) strategies now play a pivotal role in achieving optimal, safe, and economical microgrid operation under uncertainty [8, 9].

To address this challenge, researchers have recently developed efficient methodologies for solving the EM problem in microgrids. For example, reference [10] proposes a hybrid dynamic demand response program using the Pelican Optimization Algorithm for microgrid EM, effectively reducing peak demand and operating costs while maintaining system reliability. Additionally, reference [11] proposes a multi-layer optimization framework for integrated energy systems management. The first layer performs single-objective optimization to minimize operational costs, while the second layer employs multi-objective optimization to simultaneously reduce environmental emissions and groundwater extraction. The third layer enhances system independence from the main grid through technical improvements in power loss reduction and voltage profile optimization. Expanding on this, Reference [12] introduces a hybrid optimization framework that merges metaheuristic algorithms with conventional power flow analysis for microgrid economic dispatch. The study implements a comprehensive parameter optimization strategy to evaluate five metaheuristic algorithms, identifying the most effective one for minimizing levelized energy costs. Reference [13] proposes an intelligent Golden Jackal Optimization algorithm to address distributed-generation EM in battery storage systems and hybrid energy sources. The method aims to minimize operating costs while considering constraints such as power balance, generation capacity, consumer loads, and energy storage dynamics. Additionally, reference [14] develops a quantum-enhanced particle swarm optimization approach for optimal microgrid EM, focusing on minimizing operational costs and emissions. The study formulates a deterministic scheduling model and applies QPSO to improve search performance in multi-objective dispatch.

Existing metaheuristic optimization approaches can provide acceptable solutions for day-ahead microgrid scheduling under deterministic conditions. However, modelling uncertainties in solar irradiance and load profiles using predefined scenarios or probabilistic assumptions does not offer a fully reliable representation of real-world behavior, as these approaches often fail to capture the stochastic and time-varying nature of distributed energy resources. To overcome these limitations, MPC has emerged as an effective solution, as it can learn the behavioral patterns of historical data and use this knowledge to predict future system behavior. Consequently, MPC provides a more robust and accurate framework for EM in microgrids, improving both operational efficiency and reliability under uncertain conditions [15].

For the aforementioned reasons, researchers have gradually turned to using MPC for microgrid EM. For instance, the authors in [16] apply MPC in an AC/DC microgrid as a solution for EM. The approach formulates a receding-horizon optimization problem that considers short-term predictions of load and renewable generation to schedule storage and load operations in real time. MPC explicitly handles system constraints and updates control actions dynamically to adapt to changing conditions. Furthermore, reference [17] implements a two-level hierarchical MPC for EM in a microgrid, where the high level performs long-term economic optimization and the low level carries out short-term economic optimization to manage storage and load operations efficiently. Additionally, reference [18] proposes an MPC-based EMS for an isolated electro-thermal microgrid, aiming to minimize operating costs, reduce battery degradation, and ensure reliable energy supply. The approach incorporates an estimated State of Health model for the ESS to extend its lifespan, while MPC optimizes the scheduling of PV, diesel generator, battery, and thermal loads. Reference [19] presents an MPC-based EMS for cooperative optimization of interconnected grid-connected microgrids. The approach formulates scheduling and power exchange among distributed energy resources as a mixed-integer quadratically constrained programming problem, using forecasted inputs to optimize operations across multiple microgrids efficiently. In addition, the authors in [20] develop a hybrid constrained Particle Swarm Optimization–MPC algorithm for storage EM in a microgrid. The method formulates the operational scheduling problem as a constrained optimization, and uses a modified PSO, with constraint handling via Deb's rule, embedded in MPC to produce feasible, cost-effective control decisions. In a related study, the authors in [21] formulate and solve the optimization problem using quadratic programming, integrating a control penalty mechanism for battery and PEV state-of-charge (SoC) management and employing Monte Carlo simulation with scenario reduction to handle renewable generation uncertainties within an MPC framework. The authors in [22] formulate a MILP-based MPC optimization for islanded microgrids, integrating dynamic load shedding with time-of-use pricing and solving it via the CPLEX solver.

Although the aforementioned MPC and hybrid-based EMS approaches effectively mitigate some of the limitations in previous studies, they generally do not investigate different deep learning techniques for the prediction module and often rely on a single forecasting method. In many cases, the prediction model is treated as a black box, without providing explicit details, or when its structure is specified, no comparison with alternative predictive models is performed. Moreover, in the EM optimization stage, many studies either employ outdated linear programming formulations or fail to introduce novel optimization strategies, and seldom benchmark their results against standard or state-of-the-art solvers.

Additionally, a significant challenge and limitation of optimization algorithms, particularly conventional methods, lies in their susceptibility to converging to local minima. This phenomenon hinders the ability to identify the globally optimal solution, as the algorithm becomes trapped within a suboptimal configuration, preventing further improvement.

To address the limitations of previous EMS studies, this work integrates a comparative evaluation of multiple deep learning architectures to generate 24-hour-ahead forecasts for both load and solar irradiance generation within the MPC framework. For EM optimization, a novel Quadratic Interpolation Optimization (QIO) algorithm is employed, providing enhanced convergence, robustness, and solution quality compared with conventional metaheuristics. Comparative simulations against PSO and GA indicate that QIO consistently achieves lower operational costs and more stable scheduling outcomes, highlighting the effectiveness of combining deep learning-based forecasting with an advanced optimization engine for reliable and economical microgrid operation.

The contributions of this study are detailed as follows:

1. The research systematically compares multiple deep learning architectures for 24-hour ahead forecasting within an MPC framework.
2. A novel Optimization algorithm is developed for day-ahead microgrid scheduling, offering enhanced convergence speed and solution quality relative to conventional metaheuristics.
3. The proposed integrated framework combining deep learning forecasts with MPC-QIO is benchmarked against PSO and GA, evidencing substantial reductions in operational costs and improved reliability of microgrid operations.
4. Battery health is explicitly managed through the enforcement of upper and lower SoC limits, mitigating the risks of overcharging and deep discharge and thereby extending battery lifespan.

The remaining sections of this paper are structured as follows: Section 2 presents the detailed modelling of the microgrid components and their operational constraints. Section 3 introduces the MPC framework along with the training of the deep learning-based forecasting models. Section 4 describes the proposed EM System integrated with the QIO algorithm. Section 5 reports the simulation results, performance comparisons, and discussion of the EMS under different scenarios. Finally, Section 6 concludes the study and highlights potential directions for future research.

II. Modelling of microgrid

Microgrids are localized power grids that offer enhanced reliability, resilience, and potential cost savings compared to traditional grid systems. This paper investigates a grid-connected microgrid designed to provide a stable and economical power supply to a local community. The microgrid under investigation operates in grid-connected mode and incorporates a photovoltaic (PV) system, battery energy storage (BESS), micro turbine (MT), and fuel cell (FC) as primary energy resources. This configuration enables the system to satisfy local electricity demand through an optimal combination of renewable generation and dispatchable units, while maintaining the capability to exchange power with the main grid to enhance operational flexibility and economic performance. The schematic diagram of the proposed microgrid architecture is presented in Fig 1.

A. Objective function

This paper formulates a day-ahead EM model for the microgrid with the primary objective of minimizing total operational costs under normal operating conditions. The optimization problem is mathematically expressed through the following objective function:

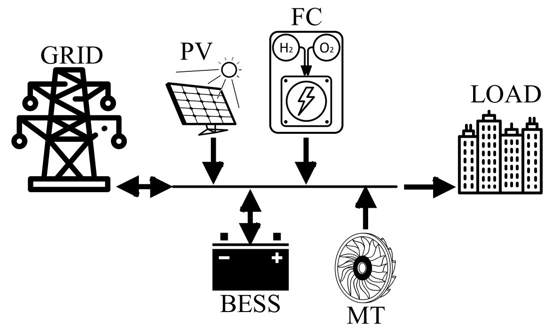

Fig. 1. diagram of the grid-connected microgrid configuration.

$$\min \left(\sum_{t=1}^{N_t} Cost_t^{BESS} + \sum_{t=1}^{N_t} Cost_t^{FC} + \sum_{t=1}^{N_t} cost_t^{MT} + \sum_{t=1}^{N_t} Cost_t^{PV} + \sum_{t=1}^{N_t} Cost_t^{GRID} \right) \quad (1)$$

The objective function minimizes the total operational cost of the microgrid over the 24-hour scheduling horizon. It includes the costs associated with energy supply from the BESS($Cost_t^{BESS}$), FC($Cost_t^{FC}$), MT($cost_t^{MT}$) and PV($Cost_t^{PV}$), along with the costs of power exchange with the main grid($Cost_t^{GRID}$). The complete formulation of each cost component is provided below:

$$Cost_t^{BESS} = \lambda^{BESS} \times P_t^{BESS} \quad (2)$$

$$Cost_t^{FC} = \lambda^{FC} \times P_t^{FC} \quad (3)$$

$$Cost_t^{MT} = \lambda^{MT} \times P_t^{MT} \quad (4)$$

$$Cost_{t,s}^{PV} = \lambda^{PV} \times P_{t,S}^{PV} \quad (5)$$

$$Cost_{t,s}^{GRID} = Market\ Price_t \times P_t^{GRID} \quad (6)$$

The operation and maintenance costs (λ) for each energy source are adopted from [23], while market price data are obtained from [24].

B. Problem Constraints

To ensure reliable microgrid operation, the power balance constraint must be strictly maintained at each time step. This fundamental requirement, expressed in Equation (7), guarantees that the total power generation from all sources exactly matches the total load demand, accounting for both local consumption and power exchange with the main grid [24].

$$P_t^{LOAD} = P_t^{GRID} + P_t^{BESS} + P_t^{FC} + P_t^{MT} + P_t^{PV} \quad (7)$$

The operational constraints for each distributed generation unit are defined by their minimum and maximum output limits, as specified in Equations (8) through (12). These technical constraints ensure that all components operate within their safe operational boundaries while maintaining system reliability and efficiency [24].

$$P_{Min}^{GRID} \leq P_t^{GRID} \leq P_{Max}^{GRID} \quad (8)$$

$$P_{Min}^{BESS} \leq P_t^{BESS} \leq P_{Max}^{BESS} \quad (9)$$

$$P_{Min}^{FC} \leq P_t^{FC} \leq P_{Max}^{FC} \tag{10}$$
$$P_{Min}^{MT} \leq P_t^{MT} \leq P_{Max}^{MT} \tag{11}$$
$$P_{Min}^{PV} \leq P_t^{PV} \leq P_{Max}^{PV} \tag{12}$$

Furthermore, to maintain battery health and ensure operational reliability, the SoC is constrained within specified minimum and maximum thresholds. These limits prevent overcharging and deep discharging, thereby extending the battery's lifespan and maintaining its performance throughout the scheduling horizon [2].

$$SoC_{Min}^{BESS} \leq SoC_t^{BESS} \leq SoC_{Max}^{BESS} \tag{13}$$

The proposed optimization framework ensures strict adherence to the equality and inequality constraints outlined in Equations (8-12) throughout the solution process. To further reinforce compliance with the SoC limitations specified in Equation (13) and maintain grid interconnection standards, a penalty-based mechanism is implemented. This approach assigns additional cost components for constraint violations, effectively steering the optimization toward feasible and physically realizable operating conditions while preserving system integrity.

C. Modelling of PV

The photovoltaic system's power generation is determined by incident solar irradiance, ambient temperature conditions, and the panel's rated characteristics. The relationship between these parameters and the resulting electrical output is mathematically represented as follows [25]:

$$P_{PV}(S_i(t)) = PV^{array}.Df^{PV}.\left(\frac{S_i(t)}{S_{i,\mathrm{STC}}}\right). \tag{14}$$
$$[1 + \alpha p.(T_c - T_{c,\mathrm{STC}})]$$

where $S_i(t)$ represents the solar irradiance at time t, $S_{i,\mathrm{STC}}$ denotes the irradiance under standard test conditions, T_c and $T_{c,\mathrm{STC}}$ are the cell temperature and its reference value under standard conditions, respectively. PV^{array} indicates the rated capacity of the PV system, Df^{PV} is the derating factor accounting for losses, and αp is the temperature coefficient of power.

The power outputs of the BESS, FC, and MT are directly derived from the proposed algorithm's solution, and are constrained within pre-defined operational ranges. The algorithm effectively coordinates the power generation of these distributed energy resources to simultaneously satisfy the load demand, minimize grid energy procurement costs, and, when feasible, inject surplus power into the grid during periods of peak pricing. Crucially, the proposed methodology ensures that these achievements are consistently realized while rigorously satisfying all defined constraints.

III. Model predictive control

This research implements a Model Predictive Control (MPC) framework to effectively manage uncertainties inherent in

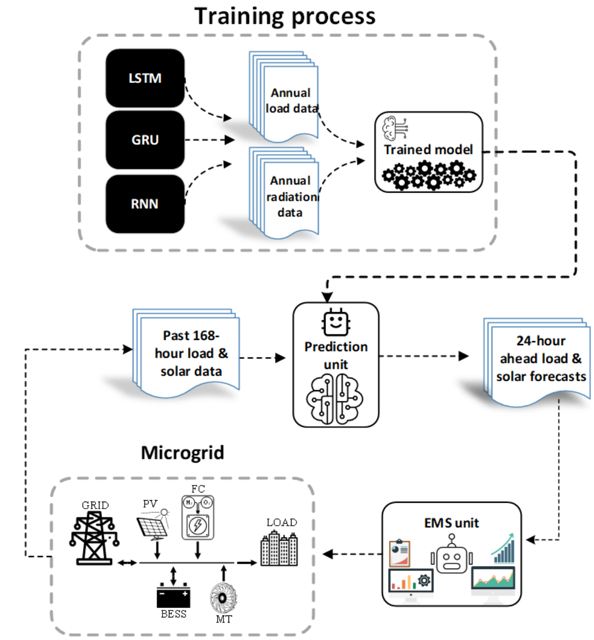

Fig. 2. Schematic of the predictive control methodology.

load demand and solar irradiance within microgrid operations. The proposed MPC methodology adopts a rolling horizon strategy that integrates real-time forecast updates with dynamic optimization of control actions. A comprehensive historical dataset, encompassing one full year of recorded load consumption and solar irradiation measurements, serves as the foundation for developing the prediction models. This extensive data collection captures critical seasonal fluctuations, recurring daily patterns, and anomalous operational scenarios, thereby establishing a robust basis for constructing reliable forecasting models.

The predictive component of the MPC architecture employs a sliding window mechanism that processes historical observations over a 168-hour window (equivalent to seven days), formulated as:

$$\mathrm{X}_t = (x_{t-167}, x_{t-166}, \ldots, x_t) \tag{15}$$

to generate 24-hour-ahead forecasts for both electrical load and solar irradiance. The forecasting process is mathematically represented as:

$$f_\theta(\mathrm{X}_t) = \hat{\mathrm{Y}}_{t+1:t+24} \tag{16}$$

where f_θ denotes the trained forecasting model with parameters θ, mapping the historical input sequence to future predictions. This architectural design facilitates the identification of weekly cyclical patterns while ensuring computational tractability. The forecasting engine transforms historical observation sequences into future projections through sophisticated deep learning structures, with these predictions subsequently informing the optimization module responsible for day-ahead scheduling decisions. The receding horizon implementation guarantees continuous controller adaptation to evolving operational conditions through the integration of the most recent measurements at each optimization interval.

A. Comparative Analysis of Deep Learning Forecasting Architectures

A systematic evaluation of three advanced deep learning architectures, Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Gated Recurrent Unit (GRU), was conducted to determine the optimal forecasting methodology for integration within the MPC framework. To ensure equitable comparison, all models were standardized with identical input configurations, processing 168 historical time steps to generate 24-step-ahead forecasts, thereby maintaining consistency in architectural constraints and learning capabilities across the experimental framework.

The overall flowchart of the proposed methodology, which integrates the forecasting process and optimization framework, is illustrated in Fig 2.

IV. Energy management system

The Energy Management System (EMS) constitutes the decision-making core of the proposed framework, where the 24-hour-ahead load and solar irradiance forecasts, generated by the deep learning models in the preceding stage, are transformed into optimal operational schedules for all microgrid assets. These forecasted profiles provide the temporal structure within which the EMS determines the charging-discharging strategy of the BESS, the dispatch levels of distributed generation units, and the interaction with the utility grid. Given the inherently nonlinear and constrained nature of microgrid scheduling, the performance of the EMS critically depends on the selection of a robust and computationally efficient optimization algorithm capable of navigating a highly complex search space. To address these challenges, this study adopts the Quadratic Interpolation Optimization (QIO) algorithm as the core optimization engine. QIO leverages the mathematical rigor of the Generalized Quadratic Interpolation mechanism to achieve an effective balance between global exploration and local exploitation, thus preventing premature convergence and improving solution quality compared with conventional metaheuristics. Owing to its demonstrated superiority in solving engineering optimization problems, the QIO algorithm is introduced here as the recommended optimization method. A detailed description of the algorithmic structure and its integration within the EMS is presented in the subsequent section.

A. Quadratic Interpolation Optimization

The QIO algorithm is a mathematically-driven metaheuristic that builds its search strategy upon the concept of Generalized Quadratic Interpolation (GQI). The fundamental idea is that, instead of randomly exploring the search space or relying solely on evolutionary operators, QIO continuously constructs local quadratic models using triplets of candidate solutions. For any three sampled points in the decision space, the algorithm fits a quadratic curve that approximates the underlying cost function in that region. The estimated minimizer of this quadratic model is then used as a directional indicator to generate new candidate solutions.

Unlike classical quadratic interpolation, which only works properly when the three points satisfy specific geometric orderings, GQI expands the method to all possible point configurations. The algorithm systematically analyzes every case in which three points may be located relative to each other and reconstructs the quadratic model in a way that always produces a valid minimizer. This guarantees that the search direction is meaningful, even in irregular or high-dimensional landscapes where traditional interpolation fails or produces a maximizer instead of a minimizer.

QIO incorporates these interpolated minimizers into two complementary search modes:

Exploration Phase (Global Search):

Random individuals are selected from the population to generate interpolation-based candidate points. The algorithm uses the minimizer obtained from the GQI curve to jump into unexplored regions of the search space. When QIO performs exploration, the position of the current individual is updated as:

$$v_i(t+1) = x^*_{i,rand1,rand2}(t) + \omega_1.\left(x_{rand3}(t) - x^*_{i,rand1,rand2}(t)\right) + round\left(0.5.(0.05 + r_1)\right).\log\left(\frac{r_2}{r_3}\right) \tag{17}$$

$$x^*_{i,rand1,rand2}(t) = GQI(x_i(t), x_{rand1}(t), x_{rand2}(t), fit(x_i(t)), fit(x_{rand1}(t)), fit(x_{rand2}(t))) \tag{18}$$

where x_{rand1}, x_{rand2}, and x_{rand3} represent the positions of randomly chosen individuals from the current population, r_1, r_2, and r_3 are random numbers between 0 and 1, fit() denotes the fitness function value and $GQI()$ is the GQI function. Weight ω_1, which can be modified using an adaptive coefficient b, is expressed as follows:

$$\omega_1 = 3n_1 b \tag{19}$$

$$b = 0.7a + 0.15a\left(\cos\left(\frac{5\pi t}{T}\right) + 1\right) \tag{20}$$

$$a = \cos\left(\frac{t\pi}{2T}\right) \tag{21}$$

where n_1 follows the standard normal distribution, t is the number of current iteration, and T is the maximum number of iterations. This prevents the algorithm from getting trapped too early in local minimum.

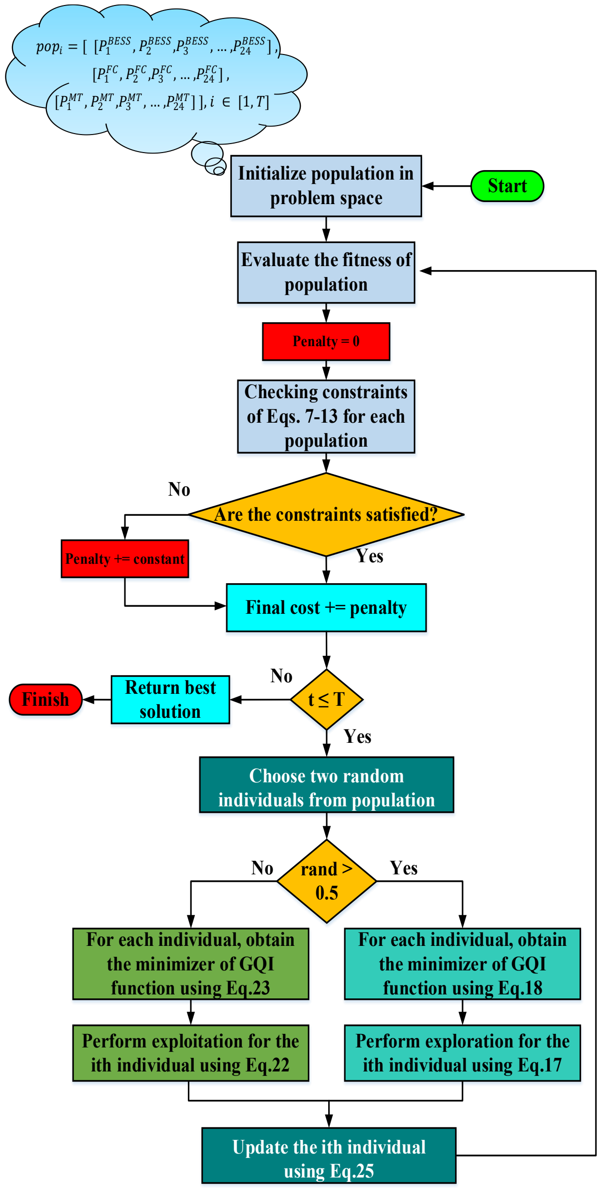

Fig. 3. flowchart detailing the implementation of the proposed method.

Exploitation Phase (Local Refinement):

The best individual found so far is combined with other population members to construct a new quadratic interpolation model. The resulting minimizer leads the search toward areas close to the current optimum, enhancing convergence speed and precision. When QIO performs exploitation, the position of the current individual is updated as:

$$v_i(t+1) = x^*_{best,rand1,rand2}(t) + \omega_2.(x_{best}(t) - round(1+rand).\frac{ub-lb}{ub^{r\,D} - lb^{r\,D}}.x_i^{r\,D}(t)) \tag{22}$$

$$x^*_{best,rand1,rand2}(t) = GQI(x_{best}(t), x_{rand1}(t), x_{rand2}(t), fit(x_{best}(t)), fit(x_{rand1}(t)), fit(x_{rand2}(t))) \tag{23}$$

$$\omega_2 = 3\left(1 - \frac{t-1}{T}\right)n_2 \tag{24}$$

where n_2 follows a standard normal distribution and rD is a random integer within the range [1, d], $lb^{r\,D}$ and $ub^{r\,D}$ represent the lower and upper boundaries at the rDth dimension. ω_2 serves as the exploitation weight, functioning as an adaptive coefficient.

According to Eq. (23), the best individual found so far (x_{best}) and two randomly selected individuals (x_{rand1} and x_{rand2}) are utilized within the GQI method to generate a minimizer ($x^*_{best,rand1,rand2}$), which typically outperforms the original three individuals. Based on Eq. (22), the ith individual is updated by exploring the neighborhood of $x^*_{best,rand1,rand2}$ relative to x_{best}, incorporating a random perturbation from $x_i^{r\,D}$. This search facilitates efficient exploitation and prevents stagnation within the algorithm.

After the exploration and the exploitation strategies are achieved, the position of the ith individual is updated according to the following equations:

$$x_i(t+1) = \begin{cases} x_i(t), & fit(x_i(t) \le fit(v_i(t+1)) \\ v_i(t+1), & fit(x_i(t) > fit(v_i(t+1)) \end{cases} \tag{25}$$

If the fitness value at the candidate position of the ith individual is superior to its current fitness, the individual's position is updated to the candidate position. Otherwise, the individual's position remains unchanged.

Through alternating these two mechanisms, QIO adaptively adjusts between exploration and exploitation without requiring gradient information, penalty parameters, or complex control coefficients. The method benefits from the accuracy of local quadratic models while maintaining the stochastic diversity of metaheuristic search. As a result, QIO exhibits strong performance across nonlinear, constrained, and multi-modal optimization problems, including microgrid energy scheduling.

Given the considerable mathematical complexity of the full GQI derivations, spanning multiple interpolation cases and detailed analytical constructions, the present paper focuses on describing the conceptual workflow of QIO rather than reproducing its extensive formulation. For readers interested in the complete mathematical development, the full derivations are comprehensively presented in reference [26]. Fig 3 illustrates the complete flowchart detailing the implementation of the proposed method, including the QIO algorithm, as well as how the problem is modeled and constraints are considered.

V. Simulation and Results

To evaluate the performance of the proposed methodology, comprehensive simulations were conducted on a grid-connected microgrid configuration, illustrated in Fig. 1. All numerical experiments were developed using Python and executed on a desktop computer equipped with an Intel Core i5 processor (1.60 GHz) and 16 GB of RAM. The technical specifications and rated parameters of the PV subsystem are reported in Table 1, while Table 2 summarizes the operational constraints and bidding prices associated with the distributed generation units participating in the scheduling process.

The historical data utilized in this study was obtained from the Renewable Ninja website, focusing on Denmark for the year 2022. To ensure a fair and unbiased comparison among the three forecasting architectures, LSTM, RNN, and GRU, all models were trained under identical experimental settings and hyperparameter configurations. Each network received the same input structure, was optimized using the same learning strategy, and was trained for an equal number of epochs to eliminate any performance variations arising from unequal training conditions. The complete set of training hyperparameters employed for all three models is summarized in Table 3.

TABLE I Numerical parameter values of the PV system

Variable	value
PV^{array}	15 kW
Df^{PV}	80 %
$S_{i,\mathrm{STC}}$	1 kW/m^2
αp	-0.5 %/°C
T_c	60 °C
$T_{c,\mathrm{STC}}$	25 °C

TABLE II Data of DG units and main grid

Type of Source	Min power (kW)	Max power (kW)	Bid (€ct/kWh)
PV	0	15	2.584
MT	6	30	0.457
FC	3	30	0.294
BESS	-30	30	0.380
Main Grid	-30	30	----------

As presented in Table 4, LSTM consistently provides the most accurate and stable forecasts for both solar irradiance and load demand, followed closely by GRU, while RNN shows comparatively lower precision, particularly for the more variable solar irradiance data. This comparison clearly demonstrates the relative effectiveness of the LSTM in capturing temporal patterns within the datasets. Therefore, the forecasts produced by the LSTM model are fed into the EMS, which utilizes the QIO algorithm to perform day-ahead scheduling. This integration ensures that the optimization algorithm has accurate and timely predictions, allowing for more efficient planning and reliable operation of the microgrid.

Figs 4&5 present the outcomes of the QIO algorithm for scenario 1 and 2 respectively. These figs show that the FC and MT units, driven by their competitive bid prices and high economic efficiency, frequently operate at or near their maximum output capacities. the results demonstrate that the energy resources are dispatched efficiently to meet the demand while optimizing operational costs. Priority is given to units with higher economic efficiency, reducing reliance on the main grid during peak pricing periods. Moreover, any surplus generation is exported to the grid, providing additional revenue and enhancing the overall economic performance of the microgrid.

A critical aspect of battery EM is maintaining the SoC within defined boundaries to ensure safe and efficient operation. Fig 6 depicts the SoC evolution over the 48-hour scheduling horizon. As illustrated, the battery strategically charges during periods of low electricity prices (00:00-08:00) to ensure adequate SoC for subsequent discharge during peak price hours (09:00-16:00), thereby minimizing reliance on the grid. Furthermore, the battery demonstrates effective responsiveness to price fluctuations, as evidenced by its reaction to the price surge around 21:00. Starting from an initial SoC of 20%, the proposed algorithm consistently regulates the battery state within the permissible range across both days, supporting reliable performance and longevity.

TABLE III Training hyperparameters

Parameter	Value
Optimizer	Adam
Learning rate	0.002
Batch size	128
Epochs	50
Loss function	Mean Squared Error

TABLE IV Comparison of Forecasting Performance of Algorithms

Algorithm	Dataset	R^2	RMSE	MAE
LSTM	Solar Irradiance	**0.99**	15.06	11.09
GRU		0.98	17.22	12.64
RNN		0.97	25.74	17.35
LSTM	Load Demand	**0.988**	1.94	1.56
GRU		0.984	2.23	1.82
RNN		0.97	2.56	1.97

Table 5 presents a comparison of the objective function values achieved by the tested algorithms over two consecutive days. The results indicate that the QIO algorithm consistently obtains superior solutions, with lower mean and worst-case values, as well as reduced variability compared to other methods. This demonstrates the effectiveness and stability of QIO in optimizing the system's performance across different daily scenarios.

To enable a clearer comparison, convergence curves for both scenarios are presented in Figs 7 and 8. These figs illustrate the progression of the algorithms toward optimal solutions across iterations in each scenario. By examining the convergence behavior, the relative speed, stability, and consistency of the methods can be more accurately assessed.

As illustrated in Fig 9, the costs achieved by each of the three algorithms are presented to compare their efficiency in reducing microgrid operational costs.

TABLE V Objective Function Comparison for the Tested Algorithms

Scenario	Algorithm	Best	Mean	Worst	SD
Day 1	**QIO**	**57.19**	65.33	77.36	5.17
	PSO	81.69	205.76	424.22	98.07
	GA	125.58	151.48	166.95	13.57
Day 2	**QIO**	**81.04**	88.47	97.17	5.04
	PSO	160.29	285.07	477.91	99.20
	GA	172.81	194.22	229.89	15.30

QIO results for Scenario 1.

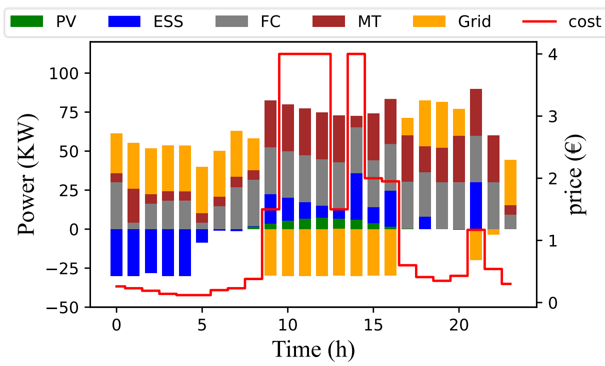

Fig. 4. QIO results for Scenario 2.

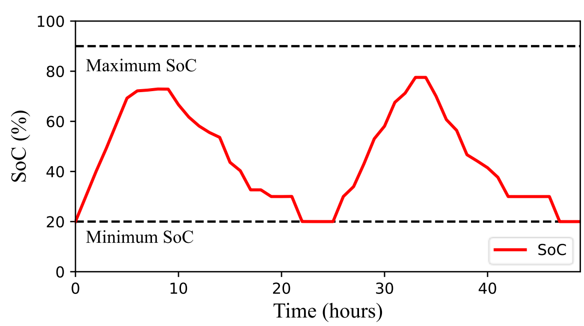

Fig. 5. SoC profile of test days.

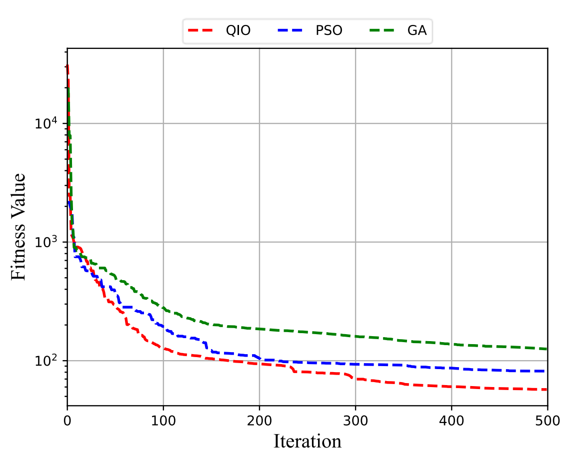

Fig. 6. Convergence curves of the algorithms for Scenario 1.

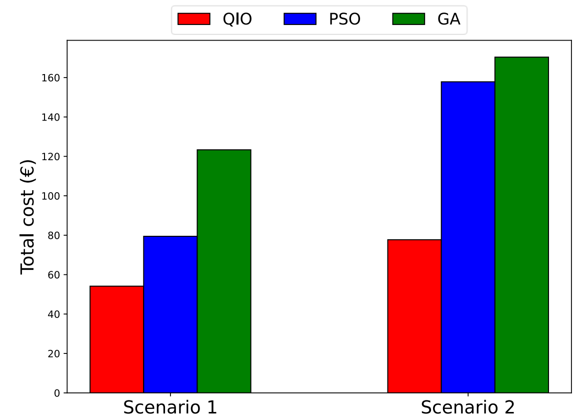

Fig. 7. Convergence curves of the algorithms for Scenario 2.

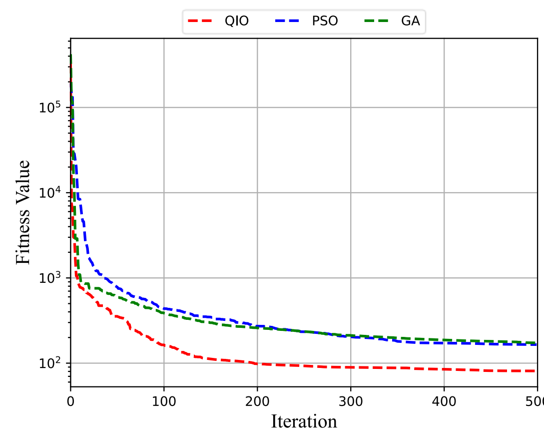

Fig. 8. Operational cost reductions achieved by algorithms.

The results demonstrate that the proposed algorithm reduced costs by 1.78% compared to the PSO and 4.88% compared to the GA in the first scenario. Furthermore, in the second scenario, this algorithm achieved a greater reduction in overall microgrid costs, decreasing them by 5.45% and 6.30% compared to PSO and GA, respectively.

VI. Conclusion

This paper has presented a comprehensive MPC framework for the optimal EM of a grid-connected, renewable-based microgrid. The primary objective was to minimize total operational costs while effectively addressing the inherent uncertainties of photovoltaic generation and load demand. The proposed strategy leverages a rolling-horizon approach, integrating real-time updated forecasts from a deep learning model to solve the day-ahead scheduling problem.

Simulation results demonstrate the efficacy of the MPC-based approach in significantly reducing operational costs and enhancing the utilization of renewable energy compared to traditional methods. Notably, the proposed MPC method achieved a forecast accuracy of 99% for predicting the next day's solar irradiance and load demand. Furthermore, numerical results indicate that the proposed QIO algorithm achieved cost reductions of 1.78% and 4.88% in the first scenario, and 5.45% and 6.30% in the second scenario compared to PSO and GA respectively, demonstrating a significant improvement in overall microgrid operational costs. The framework's inherent robustness to forecasting errors confirms its practical applicability for ensuring reliable and economically efficient microgrid operation.

Future work will focus on integrating additional renewable energy sources, evaluating the model's performance within a multi-microgrid environment, and incorporating electric vehicles with vehicle-to-grid capability.

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