Optimal Operation Strategy for Microgrid Systems under Renewable Energy Uncertainty

Nguyen Van Tan, Nguyen Van Cong, Ho Le Minh Dat, Le Nguyen Thanh Trung, Truong Thi Bich Thanh, Nguyen Hong Viet Phuong*
Faculty of Electrical Engineering
The University of Da Nang – University of Science and Technology
Da Nang, Viet Nam
tan78dhbk@dut.udn.vn, 105210142@sv1.dut.udn.vn, *105210143@sv1.dut.udn.vn*, *105210171@sv1.dut.udn.vn*, *nhvphuong@dut.udn.vn*,
*Corresponding author: ttbthanh@dut.udn.vn

***Abstract*— The uncertainty in solar photovoltaic (PV) and wind turbine (WT) power output, combined with two-settlement electricity market price fluctuations (Day-Ahead and Real-Time), presents significant challenges for cost-effective microgrid operation. This paper proposes a two-stage energy management strategy combining Quadratic Programming (QP) for Day-Ahead optimal scheduling and Model Predictive Control (MPC) with a receding horizon for Real-Time corrective dispatch, aiming to minimize total operational costs including electricity trading, diesel fuel, and BESS degradation costs. The QP stage establishes a 24-hour cost-optimal dispatch plan from forecast data, while the receding horizon MPC re-optimizes dispatch at each hourly interval to compensate for forecast deviations and reduce real-time imbalance penalties. The proposed strategy is expected to support more cost-effective microgrid operation compared to conventional Day-Ahead-only scheduling under realistic renewable uncertainty conditions.**

Keywords - Microgrid energy management; Model Predictive Control; Quadratic Programming; Day-Ahead scheduling; Real-Time dispatch

I. INTRODUCTION

In the context of ever-increasing global energy demand and the urgent imperative to reduce greenhouse gas emissions, the transition toward Renewable Energy Sources (RES) is becoming an inevitable trend. Alongside this development, the Microgrid model has emerged as a core technological solution. By integrating distributed energy sources such as photovoltaic (PV) solar power and wind energy, combined with Battery Energy Storage Systems (BESS) and conventional backup generators, Microgrids enable flexible electricity supply, enhance grid reliability, and strengthen energy autonomy for load areas[1][2][3].

Despite offering numerous superior advantages, the growing share of renewable energy in Microgrids also introduces significant operational challenges. The greatest difficulty stems from the uncertainty and intermittency of solar and wind power, as these sources are entirely dependent on actual weather conditions. The discrepancy between forecasted and actual power output can lead to the risk of supply-demand imbalance[4][5]. Furthermore, the economic operation of Microgrids is becoming increasingly complex due to the need to balance fluctuating Time-of-Use (TOU) electricity tariffs, generator fuel costs, and Battery Energy Storage System (BESS) degradation costs. When relying solely on single day-ahead energy management scheduling strategies, the system is highly susceptible to suboptimal operating conditions whenever actual conditions deviate from forecasts, resulting in increased operational costs, forced procurement of electricity at peak prices, higher fuel costs for backup generators, or accelerated battery lifespan degradation due to improper charge/discharge cycles[6][7].

To comprehensively address the aforementioned challenges, this paper proposes a two-stage hybrid energy management model, combining Quadratic Programming (QP) and Model Predictive Control (MPC) algorithms. The objective of this strategy is to minimize total system operational costs while satisfying stringent technical constraints.

Specifically, the main contributions of this paper include:

- Proposal of a two-stage QP–MPC hybrid control architecture: The paper develops a hierarchical management framework in which the Day-ahead scheduling stage employs the QP algorithm to establish an economically optimal power dispatch baseline based on forecast data, while the Real-time stage employs the MPC algorithm to continuously update system states and adjust power output, thereby eliminating deviations caused by the uncertainty of generation sources and load demand.
- Development of a comprehensive operational cost optimization model: The study formulates a total operational cost optimization problem for the Microgrid system. A key feature is that the model simultaneously incorporates three cost components: electricity transaction costs, backup generator operating costs, and battery degradation costs. This enables the system to strike a balance between immediate economic benefits and long-term equipment longevity.
- Enhancement of reliability and stability: Through simulation scenarios, the study demonstrates that the QP–MPC coordination enables the system to both closely track long-term cost optimization targets and maintain continuous stability in the face of real-world weather fluctuations, delivering superior operational performance.

II. MICROGRID COMPONENTS

As illustrated in Fig 1, the microgrid system investigated in this paper comprises a solar photovoltaic system with an installed capacity of 600 kWp, a wind turbine with a rated

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capacity of 200 kW, a Battery Energy Storage System (BESS), and a cluster of three diesel generators.

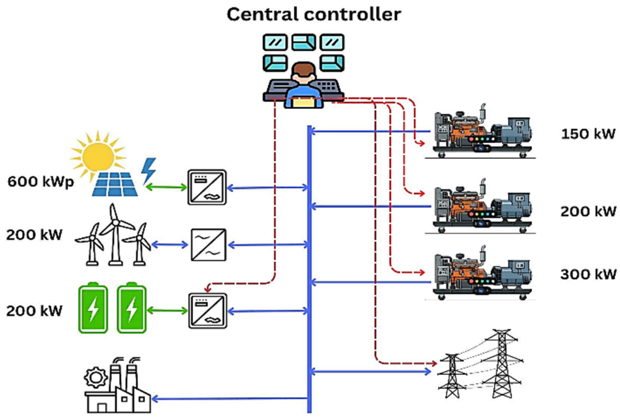

Figure 1. General schematic of the Microgrid

A. Renewable Energy Sources and Load

The output of both sources is weather-dependent and inherently variable.

The system load comprises residential and industrial loads within the area, with electricity consumption varying on an hourly basis throughout the day.

Hourly generation output data for the PV system, wind turbine, and load over a 24-hour cycle are obtained from the results of available forecasting models, such as machine learning methods including LSTM, CNN, and others[8][9].

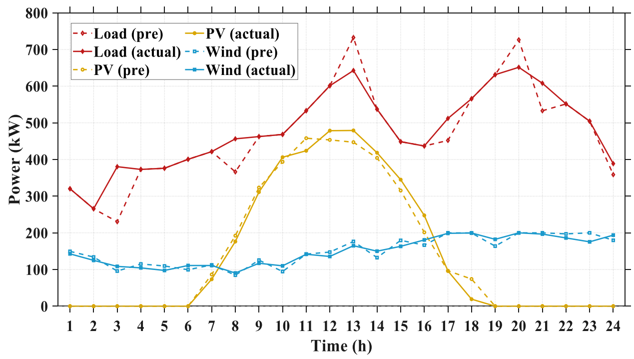

Figure 2. Output data for PV, Wind, and Load

B. Diesel generators

The system comprises three diesel generators (DG1, DG2, DG3) with rated capacities of 150 kW, 200 kW, and 300 kW, respectively. In this study, the three diesel generators are available for dispatch throughout the 24-hour scheduling horizon. Setting Pmin = 0 allows each unit to operate at zero output, enabling the QP solver to economically determine the optimal dispatch level for each generator at each time step based on actual system needs.

The operational cost of each generator is modeled using a quadratic fuel cost function with respect to the output power.

Table 1. Fuel cost function parameters of the diesel generators

DG	a [USD/kW^2]	b [USD/kW]	c [USD]	P_{min} [kW]	P_{max} [kW]
1	0.00016	0.06995	0.47619	0	150
2	0.00013	0.06065	0.79365	0	200
3	0.00012	0.05879	1.26984	0	300

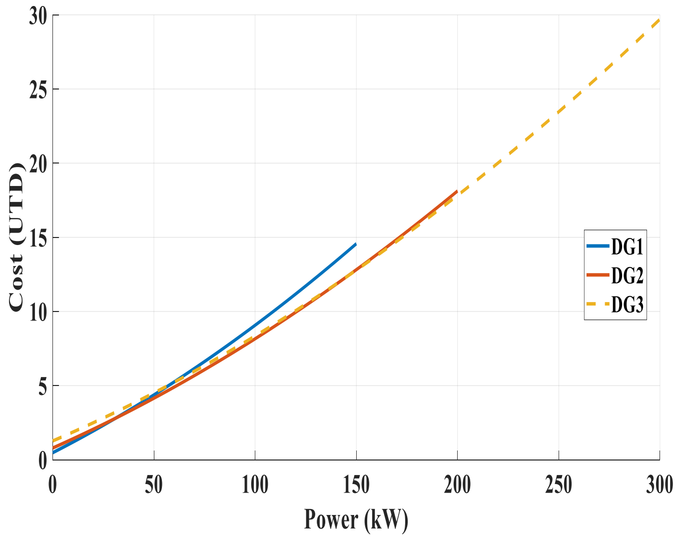

Figure 3. Cost curves of the diesel generators

Generation capacity constraints:

$$P_{dg\,\min}^{i} \le P_{dg}^{i,t} \le P_{dg\,\max}^{t} \quad (1)$$

Ramp rate constraints:

$$Ramp_{dg\,\min}^{i} \le P_{dg}^{i}(t+1) - P_{dg}^{i}(t) \le Ramp_{dg\,\max}^{i} \quad (2)$$

C. Battery Energy Storage System (BESS)

The Battery Energy Storage System (BESS) has a capacity of 200 kWh and is capable of flexibly operating in both charging and discharging modes in response to dispatch signals from the EMS.

The BESS plays a critical role in balancing power between generation sources and load, particularly during periods of significant renewable output fluctuation or peak load demand[10]. In addition, the BESS participates in the electricity trading strategy within the Microgrid, storing energy when prices are low and discharging when prices are high in order to minimize total operational costs[11].

Table 2. BESS cost function parameters

P_{cap} [kWh]	SOC max	SOC min	Efficiency	P_c [kW]	P_{disc} [kW]
200	0.95	0.2	0.95/0.95	90	74

$$0 \le P_c \le 90 \quad (3)$$

$$0 \le P_{disc} \le 74 \tag{4}$$

State of energy constraints:

$$0.2 \le SOC_{BESS}(t) \le 0.95 \tag{5}$$

Energy Storage State-of-Charge Evolution Constraint:

$$SOC_{BESS}^{t+1} = SOC_{BESS}^{t} + \frac{P_c(t) \times \eta_{BESS}^{c} \times \Delta t}{P_{cap}} - \frac{P_{disc}(t) \times \Delta t}{\eta_{BESS}^{disc} \times P_{cap}} \tag{6}$$

The input variables to the controller comprise forecast data for solar output, wind output, and load demand over the next 24 hours.

D. Utility Grid

The Microgrid system is connected to the utility grid, enabling bidirectional power exchange depending on the operating state. When internal generation is in surplus, the Microgrid can export electricity to the grid; conversely, it imports electricity from the grid when internal sources are insufficient to meet the load demand.

Electricity prices in this paper are determined according to two markets: the Day-Ahead (DA) market and the Real-Time (RT) market, where the RT market comprises separate buying prices (RT – Buy) and selling prices (RT – Sell). The price differentials between these levels are exploited by the EMS to optimize the operational schedule in order to minimize total system costs[12].

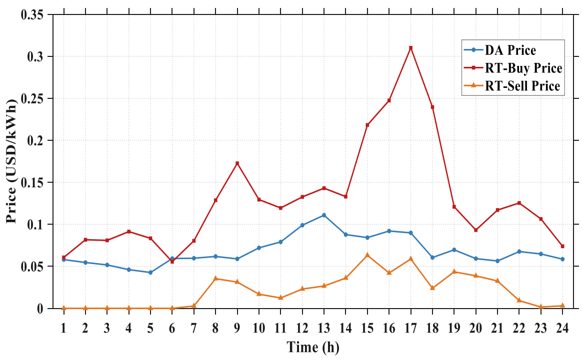

Figure 4. Day-ahead and Real-time electricity prices

III. RESEARCH METHODOLOGY

The energy management strategy proposed in this study is structured as a two-level hierarchy designed to ensure economical and stable operation of the microgrid under conditions involving the participation of renewable energy sources.

At the first level, the day-ahead scheduling problem is solved one day in advance based on PV power, wind power, and load forecast data, using the Quadratic Programming (QP) algorithm to determine the optimal operational schedule for the diesel generators, the BESS, and the power exchange with the main grid over the entire subsequent 24-hour period. The output of this stage is a reference dispatch schedule that serves as the baseline operational plan for the entire day[13].

However, due to the inevitable forecast errors between the predicted and actual values of PV output, wind output, and load, power balance deviations from the established schedule are unavoidable. Therefore, at the second level, a Model Predictive Control (MPC) controller is applied to continuously adjust the operating setpoints in real time: at each time step, the MPC utilizes actual measurement data in conjunction with the previously established operational schedule to solve an optimization problem and determine appropriate power correction adjustments, thereby ensuring power balance and maintaining economic efficiency in the face of system uncertainties.

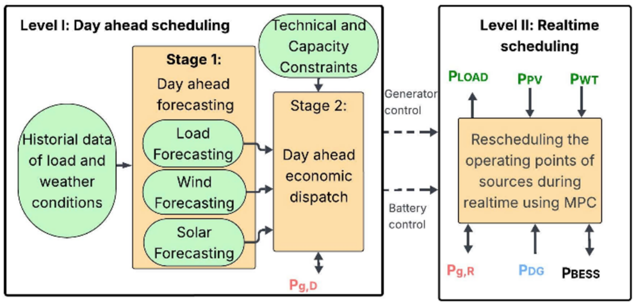

Figure 5. Two-level energy management strategy for microgrid operation

A. Quadratic Programming Algorithm

In this study, the optimization problem is formulated as a Quadratic Programming (QP) problem with a quadratic objective function and linear constraints. The problem is solved using the Quadprog solver in the MATLAB environment.

The general form of the QP problem is expressed as follows:

$$\min_{x \in \mathbb{R}^n} f(x) = \frac{1}{2} x^T Q x + c^T x \tag{7}$$

With constraints:

$$Ax = b \tag{8}$$

$$Dx \le g \tag{9}$$

Where $\mathbf{Q} \in \mathbb{R}^{n\times n}$ is a symmetric positive definite matrix ($Q \succ 0$), $\mathbf{c} \in \mathbb{R}^n$ is the linear cost coefficient vector. The matrices **A**, **D** and vectors **b**, **g** represent the linear constraints of the problem.

The algorithm for solving the QP problem is based on satisfying the Karush–Kuhn–Tucker (KKT) optimality conditions, in which the optimal solution is obtained by solving a system of linear equations derived from the KKT conditions, combined with updating the Active Set at each iteration. This process ensures that the obtained solution satisfies all constraints and attains the optimal value of the objective function.

- *Algorithm principle*

At each iteration step k, the algorithm identifies a set of active constraints W_k. The QP problem is then reformulated as a constrained problem of the following form:

$$\min_{d_k} \frac{1}{2} d_k^T Q d_k + g_k^T d_k \tag{10}$$

Subject to:

$$A_k d_k = 0 \tag{11}$$

Where:

$$g_k = Q x_k + c \tag{12}$$

The search direction d_k and the Lagrange multipliers λ are determined by solving the following system:

$$\begin{bmatrix} Q & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} d_k \\ \lambda \end{bmatrix} = \begin{bmatrix} -g_k \\ 0 \end{bmatrix} \tag{13}$$

- *Solution update*
  - If $d_k \neq 0$:

  Update the new iterate as follows:

$$x_{k+1} = x_k + \alpha_k d_k \tag{14}$$

Where α_k is the step size chosen to ensure that the new iterate x_{k+1} remains feasible with respect to all constraints.

  - If $d_k = 0$ and a blocking constraint is encountered, that constraint is added to the working set W_k.

- *Optimality condition check*
  - If $d_k = 0$:

    + If all Lagrange multipliers $\lambda_i \geq 0 \rightarrow$ The optimal solution is attained.

    + Otherwise $\rightarrow$ Remove the constraint with $\lambda_i < 0$ from the working set W_k.

- *Algorithm iteration*

The process is repeated until the optimality conditions are satisfied.

B. Day – Ahead Schedule

The day-ahead scheduling stage is executed one day in advance to determine the optimal operational plan for the entire subsequent 24-hour period. The input data comprises forecast values of solar irradiance, wind speed, and load demand, which are used to formulate an optimization problem with the objective of minimizing the total daily operational cost of the microgrid.

The objective function is formulated to include three principal cost components: the electricity transaction cost with the main grid, the fuel cost of the diesel generators, and the degradation cost of the BESS, expressed as follows:

$$\min \sum_{t=1}^{T} \begin{bmatrix} P_{g,D}^{t} \times C_{g,D}^{t} \\ + \sum_{i=1}^{n} (a_i \times P_{dg}^{i}(t)^2 + b_i \times P_{dg}^{i}(t) + c_i) \\ + C_{BESS} \times (P_c(t) + P_{disc}(t)) \end{bmatrix} \tag{15}$$

Where:

$P_{g,D}^{t}$: Power purchased from the system at time step t [kW]

$C_{g,D}^{t}$: Grid electricity price at time step t [USD/kW]

P_{dg}^{i}: Power output of diesel generator i at time step t [kW]

a_i, b_i, c_i: Coefficients in the quadratic fuel cost function of the generator (Table 1)

C_{BESS}: Unit degradation cost of the battery at time step t

$P_c(t)$: Charging power of the battery at time step t [kW]

$P_{disc}(t)$: Discharging power of the battery at time step t [kW]

The optimization problem must satisfy the following technical constraints:

Power balance:

$$\sum_{i=1}^{n} P_{dg}^{i,t} + P_{pv}^{t} + P_{wt}^{t} + (P_{disc}^{t} - P_{c}^{t}) + P_{g,D}^{t} = P_{load}^{t} \tag{16}$$

Where:

P_{pv}^{t}: Power of PV at time step t [kW]

P_{wt}^{t}: Power of wind turbine at time step t [kW]

P_{load}^{t}: Active power consumed by the load at time step t [kW]

With the constraints on the diesel generators (1),(2) and the energy storage system (3),(4),(5),(6) presented in Section II.

The day-ahead scheduling process is carried out according to the steps described in the flowchart of Figure 6. After receiving the forecast input data, the objective function and all constraints are defined and formulated in QP standard form. The problem is then solved using the quadprog solver in MATLAB with a time horizon of $T = 24$ hours and a time step of $\Delta t = 1$hour. The output is the optimal operational schedule $\{P_{dg}^{DA}, P_{BESS}^{DA}, P_{grid}^{DA}\}$ for each hour of the day, which simultaneously serves as the reference operational plan for the real-time control stage at the next level.

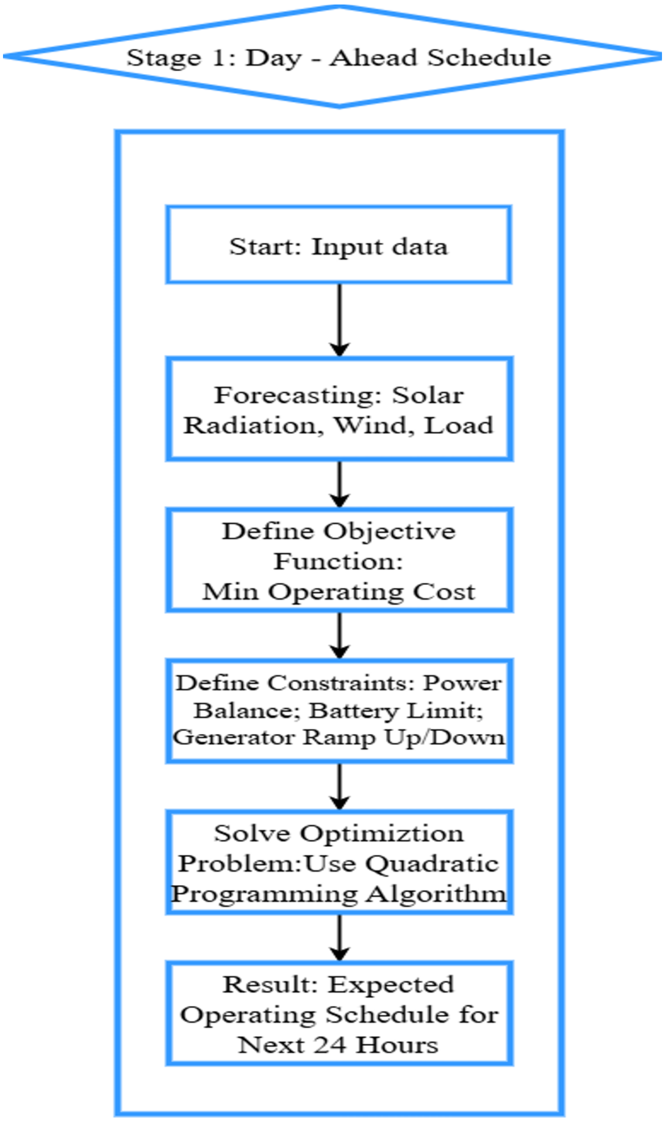

Figure 6. Flowchart of the day-ahead QP-based scheduling

C. *Real Time Schedule*

Although the day-ahead operational schedule provides an optimal plan based on forecast data, discrepancies between the predicted and actual values of PV output, wind power, and load demand are unavoidable, leading to power imbalances during real-time operation. To address this issue, the second stage employs a Model Predictive Control (MPC) algorithm to continuously adjust the operating setpoints of the generation sources at each time step, ensuring power balance and maintaining economic efficiency under real operating conditions[14].

At each time step t, the MPC controller solves an optimization problem over a shrinking prediction horizon of length $N_t = N_T - t + 1$, where $N_T = 24$ hours, spanning from the current step t to the end of the scheduling day. The objective function is:

$$\min \sum_{t=1}^{T} \left[\begin{array}{l} \sum_{i=1}^{n} \left(a_i \times P_{dg}^i(t)^2 + b_i \times P_{dg}^i(t) + c_i \right) \\ + C_{BESS} \times \left(P_c(t) + P_{disc}(t) \right) + C_{g,R}^{buy} P_{g,R}^{buy}(t) + C_{g,R}^{sell} P_{g,R}^{sell}(t) \end{array} \right] \qquad (17)$$

Where:

$C_{g,R}^{buy}$, $C_{g,R}^{sell}$: The electricity buying and selling prices with the main grid at time step t

$P_{g,R}^{buy}$, $P_{g,R}^{sell}$: The purchased and sold power exchanged with the main grid at time step t

Constraints for the Real-Time

Power balance:

$$\begin{array}{l} \sum_{i=1}^{n} P_{dg}^{i,t} + \left(P_{disc}^{t} - P_{c}^{t} \right) + P_{g,D}^{t} + P_{g,R}^{buy}(t) + P_{g,R}^{sell} \\ = P_{load}^{t} - P_{pv}^{t} - P_{wt}^{t} \end{array} \qquad (18)$$

A distinctive feature of the power balance constraint in the real-time stage is the deviation term that explicitly distinguishes between the actual component $P_{g,D}^t$ - the correction power adjusted relative to the day-ahead schedule - which serves as a fixed value that does not vary; whereas P_{pv}^t, P_{wt}^t are the actual PV and WT output powers at the current time step, replacing the forecast values used in the Day-Ahead stage. Any surplus or deficit in power generation relative to the day-ahead schedule is compensated through the adjustment of P_{dg}^t, P_c, P_{disc} and the grid power exchange $P_{g,R}^{buy}(t)$, $P_{g,R}^{sell}(t)$.

The technical constraints of the Diesel generators and BESS remain identical to those applied in the Day-Ahead optimization stage.

The real-time operation procedure is implemented iteratively based on the Receding Horizon mechanism, as illustrated in the flowchart in Figure 7. At each time step, the system acquires real-time measured data of PV output, wind power, and load demand, then computes the deviation relative to the forecast values used in the day-ahead schedule[15][16]. Based on this deviation together with the reference operational plan from Stage 1, the MPC controller solves the optimization problem and determines the optimal power correction actions for the Diesel generators, BESS, and grid exchange. Only the control action at the current time step is executed; at the next time step, the entire procedure is repeated with updated information until the 24-hour cycle is completed. This closed-loop mechanism enables the system to continuously adapt to real-world uncertainties, ensuring power balance and maintaining economic operation throughout the entire control process.

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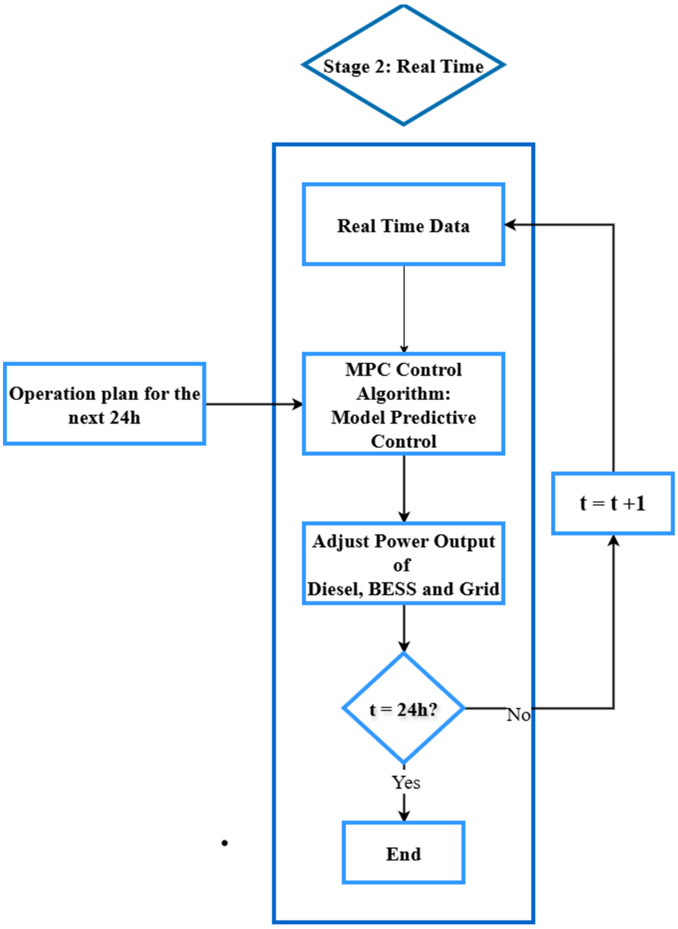

Figure 7. Flowchart of the real-time energy management strategy

IV. RESULTS

A. Day-Ahead Dispatch Results and Cost Analysis

Figure 8 presents the day-ahead power dispatch results over a 24-hour scheduling horizon. The dispatchable generation (DG) units are committed primarily during peak load hours, while photovoltaic (PV) and wind power resources serve the daytime load demand (hours 9–14). The battery energy storage system (BESS) undergoes charging during off-peak hours (hours 3–5) and discharges around hours 12–13, maintaining its state of charge (SOC) close to 20% throughout the scheduling period.

Figure 9 illustrates the hourly system operating cost throughout the day. The results indicate negative costs during approximately hours 11–15, attributed to surplus power generation and electricity export to the main grid, whereas operating costs rise sharply during hours 18–21 due to elevated load demand.

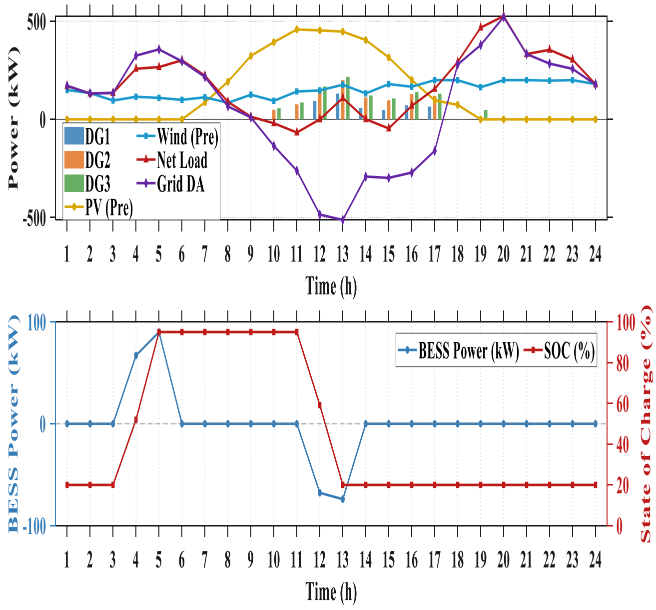

Figure 8. Day-ahead dispatch and BESS operation

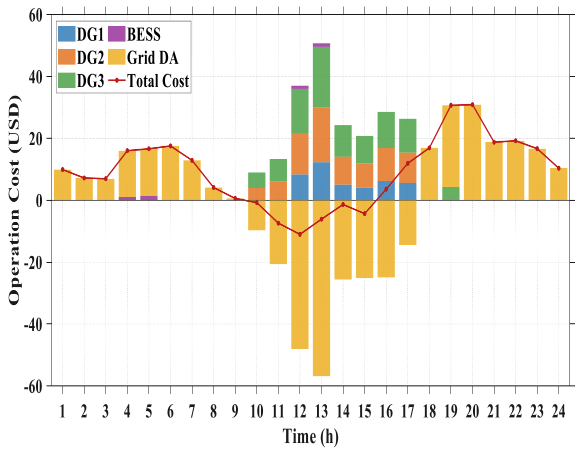

Figure 9. Day-ahead operation cost analysis

B. Real-Time Corrective Dispatch under MPC

Figure 10 presents the real-time power dispatch results under MPC control. The actual PV and wind power outputs exceed the day-ahead forecasts during hours 12–14. The MPC optimizes the power dispatch at each control interval to compensate for these forecast deviations while maintaining the BESS state of charge (SOC) within its permissible bounds.

Figure 11 reflects the flexible re-dispatching of the system relative to the day-ahead schedule. The operation cost drops significantly during hours 12–14 due to surplus generation and the exploitation of real-time electricity export opportunities, while considerable cost fluctuations appear in the remaining time intervals owing to forecast errors and load variability.

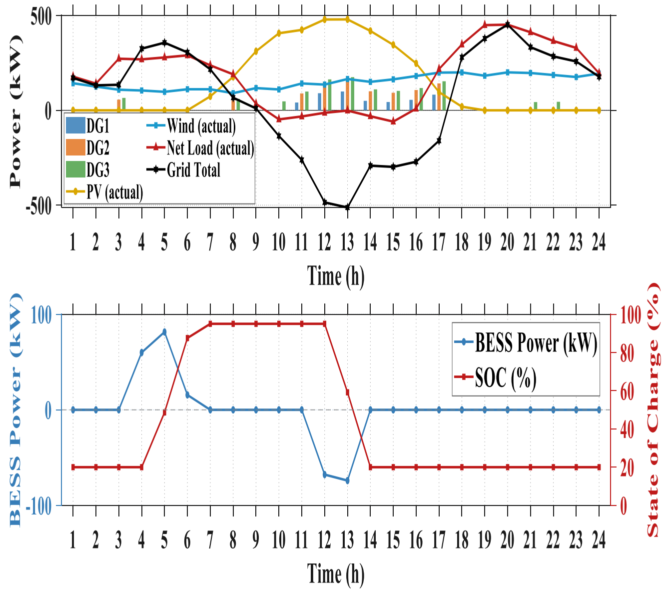

Figure 10. Real-time dispatch and BESS operation

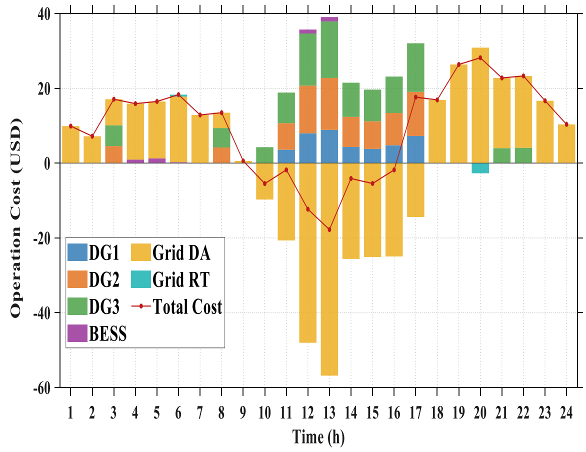

Figure 11. Real-time operation cost analysis (MPC)

C. *Performance comparison*

Figure 12 compares the hourly operation costs between the day-ahead (DA) and real-time (RT) dispatch schedules. The two cost curves closely track each other during off-peak hours but diverge significantly during hours 10–17, where the MPC achieves lower operation costs by exploiting additional surplus renewable generation.

Figure 13 shows that the real-time adjustments remain close to zero under normal operating conditions, the MPC performs minor corrective actions relative to the day-ahead schedule.

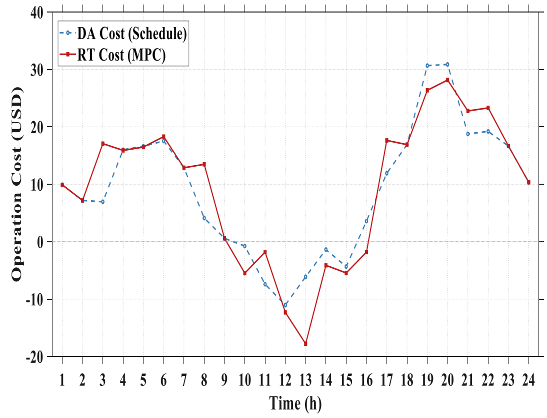

Figure 12. Hourly operation cost comparison DA - RT

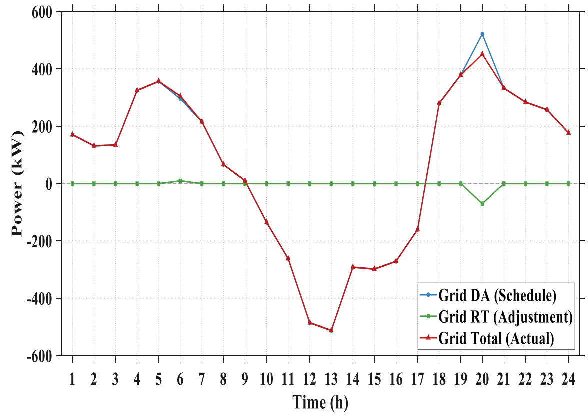

Figure 13. Grid power exchange: DA – RT – Total

V. Conclusions

This paper proposes a two-stage QP–MPC energy management strategy for microgrids to address the uncertainty of renewable energy sources. Simulation results indicate that the proposed framework is capable of reducing system operation costs while maintaining power balance across the scheduling horizon. The results also suggest that the combined day-ahead and real-time coordination has the potential to support more reliable and cost-effective microgrid operation under realistic renewable variability conditions.

In future research, the proposed framework will be further developed by incorporating advanced forecasting models, such as machine learning (ML) and deep learning (DL) techniques, to improve the prediction accuracy of renewable generation and load demand inputs. Furthermore, the proposed energy management strategy will be extended to multi-microgrid systems (MMS), enabling coordinated cross-microgrid energy exchange to enhance operational flexibility, system stability, and economic benefit maximization at a large-scale system level.

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