ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

# Simulation-Based Optimization of Photovoltaic-Integrated Microgrid Systems with Advanced Energy Storage and Control Strategies

*Tianying Liao*[1,*]

[1] College of Electrical Engineering, Chongqing Electric Power College, Chongqing, 400053, China

**SUMMARY:** *High penetration photovoltaic integrated microgrid suffers from technical issues caused by the fluctuating power generation and power output, causing considerable impacts on system stability and power quality. In order to alleviate this, a hierarchical model predictive control technique combined with a battery health management scheme was put forward. The upper level achieves model predictive control for a horizon-ahead energy scheduling, whereas the lower level applied a online power compensator to regulate the rate effect. By assuming PV array, battery storage, and loads all have their dynamic models and taking account the costs of cyclic ageing into the optimizing objective, a cooperative control strategy is built and incorporating into a multi timescale controlling framework. After being simulated, for the severe irradiance change case, the standard deviation of grid interaction power fluctuation in our proposed strategy is 12.3kW, which is decreased by 57% compared to traditional PID control. The self-consumption ratio of PV power increases to 87.3%, and the average daily capacity degradation of battery is limited to 0.042%. For the load surge case, the peak of frequency deviation is declined to 0.15Hz, and the regulating time is shortened to 12s. Through this study, an effective technical scheme for the co-optimization of microgrid stability and equipments lifetime under the high renewable penetration is provided, which would effectively make the system on average to improve the overall operation performance.*

***KEYWORDS:*** *Microgrid; Model Predictive Control; Energy Storage System; Power Smoothing; Dynamic Simulation; Photovoltaic System*

# 1 Introduction

Due to the high penetration level of distributed photovoltaic (PV) generation, the randomness and intermittency of the generation also causes unprecedented problems and threats for the grid, and specifically cause the fluctuation and disturbance to busbar voltage, system frequency and power quality caused by sudden power change. Under such requirements, battery energy storage system (ESS) has been considered as the significant equipment to suppress fluctuation and time-shifting energy owing to its quick power response capability. However, once the battery storage system is used, it also causes new complexities, as the effects of charging and discharging behaviors of these storages directly impact the microgrid economy performance, reliability and lifetime. Therefore, designing new generation storage and load control strategies that can jointly optimize PV, storage and loads has become an important concern in the microgrid.

MPC is a powerful control method that could play an integral role in power systems thanks

---

*mype4851@outlook.com

https://doi.org/10.65102/is2026830

to the special characteristic to dealing the multivariable constrained problems and effectively utilize short-term predictive information to conduct future-oriented optimization. In [1], MPC is utilized to design a newly effective resilient frequency regulation system and its superiority against large-scale system disturbances has been verified. But this study only captures frequency regulation of selected loads and the potential of utilizing MPC for multiobjective optimizing photovoltaic microgrid is overlooked. In [2], Benavides et al. aimed at the study of multi-mode monitoring and energy management for photovoltaic-storage system and their energy management scheme lacks the explicit structure of MPC to process the predictive information. On one hand, the uncertainty of systems can be mitigated by utilizing sliding mode control and disturbance observers [3] under certain promising conditions for frequency regulation in isolated microgrids. This also confirms the competitive ability of using MPC as the alternative option to explicitly process the predictive information of a similar problem.

Even though these are important milestones, little work is available on integrably embedding long-term energy storage system health management to long-range optimisation objectives within MPC rolling horizon. Most existing research treats a battery as an ideal energy storage unit which can buffer all the electricity without considering its cyclic ageing processes which will eventually affect its long-term operation cost and reliability. At the same time, the development of simulation technology also provides a valuable platform for validating highly complex control algorithms for more simulation fidelity using high-fidelity simulation. Idrisov et al. [4] used advanced simulation technologies to conduct a real-time state estimation for the power-electronic-based energy grids, and showed the significance of high-fidelity modeling for system cognition. Carrasco-Gonzalez et al. [5] also experimentally verified the practicality of hybrid-microgrid energy management system using the Raspberry Pi-based hardware-in-theloop simulation, which give a good reference for moving from total digital simulation to actual control in hardware. Nevertheless, these simulations did not use MPC-based control core and they did not tackle the long-range energy storage system health management problem.

Therefore, in this study, efforts are made to close this gap by offering a cooperation design methodology for photovoltaic microgrid with PV integration and dynamic simulation based optimization framework. And two layered MPC considering battery cycle degradation is proposed in this study. The main novelty lies in the fact that empirical model describing battery degradation is directly included in the upper layered MPC's optimization objective function. Which can achieve effective power smoothing and optimize the ESS operation lifespan as proactively as possible. It is expected that our work will make a new and feasible proposal to ensure safe and efficient long term operation of MGs with high renewable energy penetration.

# 2 Material and Methods

## 2.1 System Architecture and Problem Description

In the system being analyzed, the gridconnected PV microgrid has centralized control structure, the major role of which focuses on compensating the uncertainty of photovoltaic generating power with smart energy management system. It consists of four subsystems: photovoltaic generation, energy storage battery, local load, and grid connection. They coordinate optimization through centralized controller. The system structure topology shown in Fig. 1 indicates the relations of energy transfer and information exchange between all devices. Photovoltaic panel converts the solar energy into electricity, the impact of the quantity of irradiance and temperature on the performance of this device has been considered. Energy storage battery system utilizes lithium-ion cells with two-way power exchange for energy balance between generation and consumption. Local load represents the sum of power consumption of a household, shop or company. When interacting with the external power network, it has limitations on maximum importing and exporting powers.

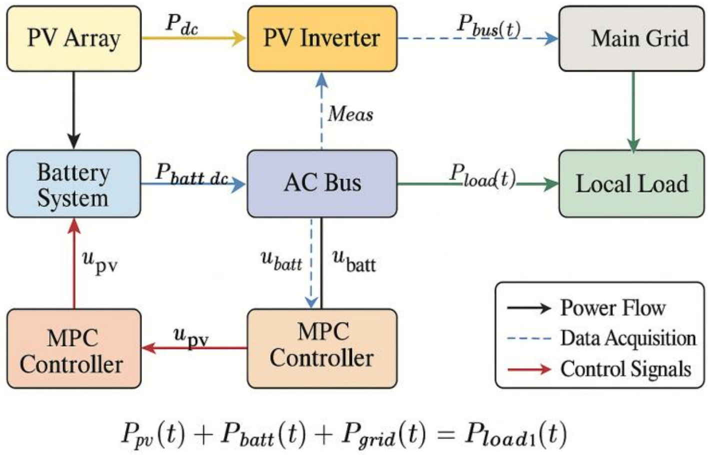


*Figure 1: System architecture of the grid-connected PV-battery microgrid system*

Energy flow within the system is controlled by Kirchoff' laws and its main statement is the power balance instantaneous on the AC busbar described by the Equation (1).

$$\mathrm{P_{pv}(t) + P_{batt}(t) + P_{grid}(t) = P_{load}(t)} \tag{1}$$

In Eq. (1) $\mathrm{P_{pv}(t)}$ is the generated power from the PV panel at time t, $\mathrm{P_{batt}(t)}$ is the power charged/discharged from/to the battery storage (discharge: $\mathrm{P_{batt}(t)}$>0, charge: $\mathrm{P_{batt}(t)}$<0), $\mathrm{P_{grid}(t)}$ is the power flow to or from main grid (from grid: $\mathrm{P_{grid}(t)}$>0, to grid: $\mathrm{P_{grid}(t)}$<0), and, $\mathrm{P_{load}(t)}$ is the total load power requirement at time t. This is the basic physics constraint which any operational control scheme in the system needs to comply with.

A hierarchical model predictive control strategy is adopted where the first layer is used for day-ahead scheduling with forecasted data, the second layer is used for real-time operation adjustment by actual data. The hierarchical strategy guarantees long-term optimisation and short-term robustness. Following such a framework, the desired control performance of this research is explicitly specified in the form of particular technical indicators. The first goal is to ensure power smoothing, i.e. the amplitude minimisation of the exchange power.

To realise these targets, the designed system uses a central microgrid controller as the central brain of the system, using a rolling horizon optimization method to solve a finitehorizon optimal control problem within a time step of 15 minutes. It also considers predicted generated power of PVs and loads, and real measurements of the system states, formulate the optimization problem as a mixed-integer linear programming problem considering operating constraints and battery degradation, and obtain the optimization solution that gives the optimal set of the battery charging/discharging and the grid interface settings. The controller uses these results, based on an MPC algorithm, and updates all the real-time quantities of operations and measurements from PV inverters, energy storage converters, loads, public connection points, and can handle this information together with short-term prediction information within each control period to solve a finite-time domain optimal control problem to calculate and issue an optimal set of control commands to low level power converters for modifying energy storage system output power and operation status of the PVs, and guide the system for the safe stable and efficient operation.

## 2.2 Dynamic Modelling of System Components

For precision simulation and optimised control of PV integrated microgrid system, it is critical to derive precise dynamic mathematics model for every major constituent. The dynamic models for PV array, BES, and load-grid component are presented as follows. These models will lead the design of future model predictive control scheme.

The output characteristics of the photovoltaic array are jointly determined by environmental irradiance and cell temperature. This study employs the widely adopted single-diode equivalent circuit model, which accurately describes the non-linear I-V characteristics of photovoltaic cells. The model's output current is expressed as shown in Equation (2).

$$I_{pv} = I_{ph} - I_0\left[\exp\left(\frac{q(V_{pv}+I_{pv}R_s)}{AKT}\right) - 1\right] - \frac{V_{pv}+I_{pv}R_s}{R_{sh}} \tag{2}$$

In Equation (2), $I_{ph}$ denotes the photocurrent, $I_0$ represents the diode saturation current, $q$ is the electron charge, $V_{pv}$ is the output voltage, $R_s$ and $R_{sh}$ denote the series and shunt resistances respectively, $A$ is the diode ideal factor, $K$ is the Boltzmann constant, and $T$ is the absolute temperature of the cell [5, 6]. The photocurrent $I_{ph}$ exhibits an approximate linear relationship with irradiance $G$, as shown in Equation (3).

$$I_{ph} = [I_{sc} + K_I(T - T_{ref})]\frac{G}{G_{ref}} \tag{3}$$

In Equation (3), $I_{sc}$ denotes the short-circuit current under standard test conditions, $K_I$ represents the current temperature coefficient, while $T_{ref}$ and $G_{ref}$ denote the reference temperature and reference irradiance respectively. Typical output characteristic curves of photovoltaic arrays under varying environmental conditions are illustrated in Fig. 2.

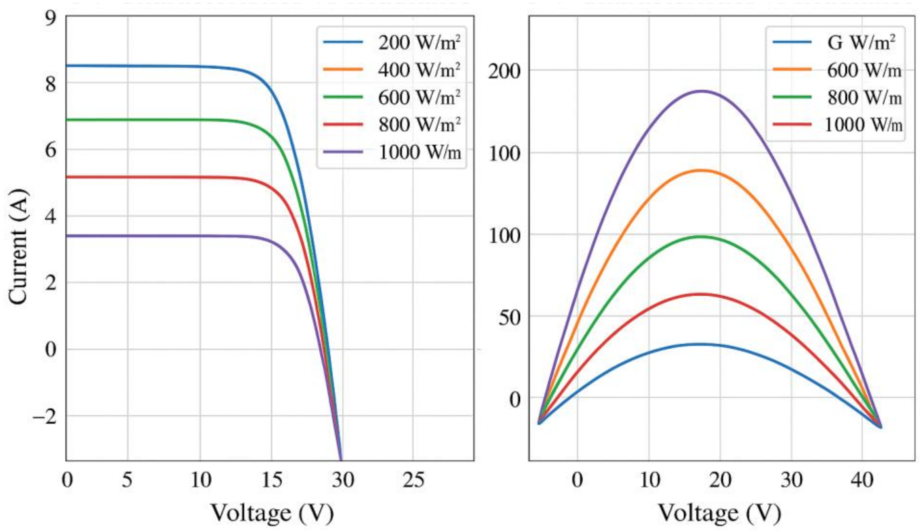


*Figure 2: Photovoltaic Component Characteristics and Battery Model Validation.*

In Fig.2, the response characteristic of PV system is illustrated respectively at different irradiance, where the response characteristic in the left is the I-V curve under constant temperature of 25°C and the P-V curve in the right. The battery energy storage subsystem is modeled based on equivalent circuit and state-space equation, where state of charge is the primitive system state and the evolution process of state of charge can be described as Eq. (4).

$$\mathrm{SOC}(t+1) = \mathrm{SOC}(t) - \frac{\eta_{\mathrm{batt}} \cdot I_{\mathrm{batt}}(t) \cdot \Delta t}{Q_{\mathrm{nom}}} \tag{4}$$

Eq. (4) the $\mathrm{SOC}(t)$ is the SOC at time $t$, $\eta_{\mathrm{batt}}$ refers to the battery charge/discharge efficiency, $I_{\mathrm{batt}}(t)$ is the current drawn from the battery, where it is negative for charging and positive for discharging, $\Delta t$ refers to the time step, and $Q_{\mathrm{nom}}$ is the battery nominal capacity [7, 8]. The battery terminal voltage is computed through an equivalent circuit model that includes an internal resistance, giving a nonlinear response with respect to SOC. Strict constraints on the battery behaviour have to be respected, such as that of operating within the limits imposed on the SOC.

The local load power $P_{\mathrm{load}}(t)$ employs measured historical data to construct a typical daily load curve, incorporating random perturbations to simulate the uncertainty inherent in actual electricity consumption. The power exchange $P_{\mathrm{grid}}(t)$ between the microgrid and the main grid at the common connection point adheres to stringent physical constraints and safety limits. Grid interaction power is constrained by transformer capacity and line transmission capability. Power balance constraints, as fundamental physical laws governing system operation, ensure real-time equilibrium between generation power, consumption power, and exchange power at all times. A time-of-use pricing mechanism is introduced to guide the economic dispatch of energy storage systems. This incentivises charging during off-peak periods and discharging during peak periods through price signals, thereby optimising operational costs.

Table 1 summarises the key operational parameters governing the interaction between battery energy storage systems and the electricity grid. These parameters provide the essential numerical foundation for formulating subsequent optimisation control problems.

*Table 1: Key operational parameters for the interaction between battery energy storage systems and the grid*

| Parameter | Symbol | Value | Units |
|---|---|---|---|
| Nominal capacity | $Q_{nom}$ | 100 | kWh |
| Charge/discharge efficiency | $\eta_{batt}$ | 0.95 | - |
| Minimum SOC | $SOC_{\mathrm{min}}$ | 0.2 | - |
| Maximum SOC | $SOC_{\mathrm{max}}$ | 0.9 | - |
| Maximum charge power | $P_{ch_{\mathrm{min}}}$ | 50 | kW |
| Maximum discharge power | $P_{dis_{\mathrm{max}}}$ | 50 | kW |
| Maximum grid exchange power | $P_{grid}(t)$ | 100 | kW |
| Sampling time | $\Delta t$ | 300 | s |

## 2.3 Model Predictive Control Strategy Design

A hierarchical model predictive control framework is presented to tackle the intermittency of solar energy generation and uncertainties in load demand. In the framework, the system optimisation problem is split into two levels of control strategies with two different time scales: the long-term (or mediumterm) management for energy optimisation in upper level control and the short-term compensation of power balance at low level control. The design realises a unified treatment for system-wide optimisation and local stability.

The upper-layer model predictive controller is the system's intelligent decision maker and is the solver of rolling optimisation with a sampling cycle of $15\mathrm{min}^{26}$. Given the photovoltaic generation model, the battery energy storage model and the load forecasting model, the controller builds a finite time domain optimal control problem. In each decision moment, the controller receives the real-time and near-time updates of PV output and load demand forecast sequences, obtained by the historical statistical models fused with real-time meteorological observation data. The minimization object is subject to technical considerations concerning all aspects, such as the minimization of active power fluctuation at the PCC, as well as the SOC being within an acceptable band and the minimization of battery cycle ageing rate, etc. By solving the optimal control problem, a sequence of power dispatch commands for the battery energy storage system ahead of the next few hours is derived by the controller and the first control command is relayed to the lower-layer actuator.

The low-level real-time power regulator runs in second-scale and utilizes any power misbalance inside the upper-level MPC control period. The low-level power regulator constantly estimates the instantaneous power differences between actual PV output, actual load demands, and the upper-level desired levels. Once any substantial power misbalance is detected, the regulator determines the compensatory power by pre-stored filtering procedures and short feedback signals and acts promptly on the battery power output. With the low-level power regulator, the system thus can support fast dynamics such as fast irradiation change or rapid load transition to support short-term power balance and power frequency stability. Through cooperation between low-level power regulator and upper-level MPC, this hierarchical control strategy is referred to as coarse/fine-tuning combined control design, which aims to achieve both long-term cost optimization and shortterm running stability. The schematic of information and control flow in this hierarchical control system is shown in Fig. 3.

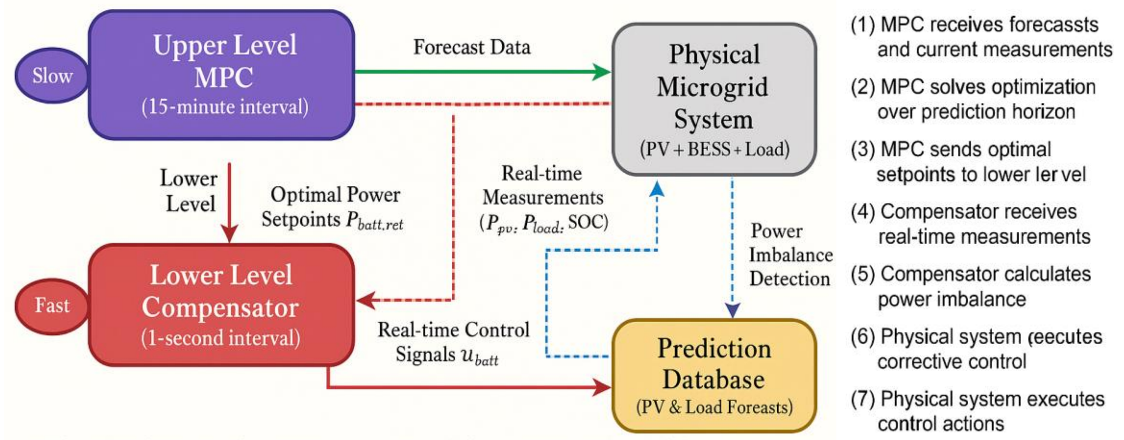


*Figure 3: Hierarchical Predictive Control Architecture Design.*

As shown in Fig. 3, the notable benefit of this type of hierarchical control framework is that it decouples the different scales of operation reasonably. The top-layer MPC make decision with relatively precise predictive data, which can help to avoid decision flipping phenomenon induced by frequent re-optimization. The bottom-layer compensator concentrate on tactical fast reaction, which can relieve the impact of prediction uncertainty and unmodeled dynamics. The two control layers are closed-loop interconnected through information exchange and command coordination: the top layer gives a criterion which guides the behavior of the lower layer, while the bottom layer is responsible for the execution ability for the top layer. Therefore the proposed design has the capabilities of long-term operation optimisation and flexibility to respond short-term incident, making it a trustworthy technical proposal of the safe, stable and economic operation of the photovoltaic integrated MGs. In the real-world applications, it's necessary to finely tune the parameters in the two controllers to make the control action on the different scales complement each other and avoid control conflict or performance sacrifice.

## 2.4 Simulation Setup and Comparison Benchmarks

In order to perform a global evaluation of the performance of the proposed hierarchical model predictive control approach, a comprehensive simulation test platform and strict comparison criteria were designed in this work. The test platform was developed in MATLAB/Simulink and Stateflow, which makes a perfect platform for the co-simulation of power electronics and control methods. Simulink builds realistic physical models of the PV array, BES, Power Converter, and Grid Connection for the authenticity of the system dynamics, and Stateflow accomplishes the complicated logic state machines of the upper layer MPC's optimisation decision-making and the lower layer compensator's prompt action response. The simulation step is selected as 1 $\mu s$ for the prompt emulation of power electronics switching dynamics, and sampling period is conFig.d separately for controllers according to its functionality: 15 min for upper layer MPC and 1 s for lower layer compensator.

To evaluate whether the proposed method is effective, three typical control methods were chosen to compare with it. The first method is the traditional control method (Bench mark A, known as Traditional Proportional–Integral–Derivative control), the battery power regulation is executed through the pre-designed Proportional–Integral–Derivative control parameters by making DC bus voltage constant without optimization consideration. This controller is less computational and easy to implement, but it is not a predictive optimal controller and parameters need to be manually tuned and experience depending. The second control strategy is rule-based battery control (Bench mark A, known as rule-based battery control), which regards the SOC range under which photovoltaic power can be fully absorbed is from lower boundary SOC to upper boundary SOC, charge and dischargcme under these two lower and upper boundaries, it does not require foresight and thus could not effectively optimise the system condition [9, 10]. The third control strategy (the Proposed control strategy) is a multi-layered model predictive control based upon the framework proposed in this article, which combines foresight optimisation and real-time correction. To make sure that each control objective is achieved to the greatest extent possible, it is multiobjective interwoven optimisation, in which each demand can be satisfied separately, and the inclusion of demand priority is implicitly specified according to the foreknowledge.

The test scenarios were established to demonstrate the flexibility and robustness of each controller under different types of disturbances. Case One represents sudden changes in irradiance, which are implemented by imitating the data that have been actually measured in the ordinary overcast day; the photovoltaic power has a lot of sudden ups and downs in a short time; from full power to approximately less than 30% of its rated value, and then comes back quickly. Sudden changes in irradiance are used to examine the flexibility of control systems to absorb the power fluctuations. Case Two represents the instantaneous switch between no-load and certain full-load modes under certain circumstances of load, which symbolizes some industrial machines switch on or large-scale ordinary houses turn on the electricity instantaneously; the load power changes step by step, with the magnitude greater than 50% rated value of the power system; the duration is only about $1s$. This case mainly examines the ability of control system's regulation under dynamic conditions, in which the system can meet the requirements for primary and secondary frequency control, and ensure voltage quality. The main features and differences between the three comparative schemes are shown in Table 2.

*Table 2: Comparison of Control Strategies for Performance Evaluation*

| Strategy | Control Method | Optimization Objective | Uncertainty Handling | Computational Complexity |
|---|---|---|---|---|
| Baseline A (PID Control) | Traditional PID Control with fixed parameters | Maintain DC bus voltage stability | Reactive compensation only | Low |
| Baseline B (Rule-based) | Rule-based Control (SOC threshold triggering) | Keep SOC within predefined range [0.2, 0.9] | No explicit handling | Very Low |
| Proposed Strategy C (Hierarchical MPC) | Hierarchical MPC with real-time compensation | Multi-objective optimization (power smoothing, battery health, energy efficiency) | Explicit constraint handling with prediction horizon | High (requires optimization solver) |

The parameter selection of the simulation experiment has comprehensively covered most actual engineering environments. The nominal power value of the PV array is selected as 100 kW, while the rated capacity of the battery energy storage system (BESS) is selected as 100 kW/h, the upper limit of charging/discharging power is 50 kW, the rated load power is selected as 80 kW, and the upper limit value in the loading peak stage is selected as 120 kW. The power exchange with the grid is selected as 100 kW to avoid having too great an influence on the main grid, with the total simulation time period selected as an entire day to observe the effect of the control strategy under various working stages. Two test cases are carried out by restarting from the same initial state, as the simulation time step takes the time span of an entire day, so as to avoid the influence of other multiple disturbances, therefore the SOC is selected as 50% at the initial phase, and the ambient temperature is selected as 25°C.

The power quality index, the electricity utilization efficiency index and the system component index constitute the three key indicators of control technical level respectively in the following performance evaluation system. The power quality index presents the rootmean square value and the peak value of the average rate of power variation at the system point of common coupling (PPCC point) respectively to measure the capability of the control system in the aspect of power smoothness. The energy efficiency index refers to the ratio of PV self-consumption and the energy utilization efficiency respectively to express the exploitation rate of the cheap energy; The equipment protection index refers to the utilization index of battery SOC, cycle stress factor and cycle equivalent loss of deterioration respectively to calculate the influence of the control method on the cycle life-time of important components. This performance evaluation system can fully and objective compare among the several controlling schemes in following analysis and be a sufficient ground for next interpretation of the results.

# 3 Predictive Modelling and Uncertainty Handling

Accuracy of prediction on important operating variables is critical to the predictive control performance of PV incorporated microgrids. Reliable predictions of PV generation and load prediction serves as the prerequisite to the successful control of PV-MG systems. Model building demand for understanding the physics together with the data-driven machine learning methods, incorporating all possible uncertainties associated during the operation of such systems.

A multi-timescale integration-based photovoltaic power prediction is applied. The short-term prediction model is based on short-time online observations of solar irradiance, environmental temperature, sky coverage, and atmospheric clarity. Physical models compute predicted power based on the semiconductor device equations, with temperature affecting conversion efficiency in a nonlinear fashion. Time series (TS) models are data-driven and use historical generation data to formulate the TS prediction, with a long short-term memory networks (LSTM) forecasting short to medium-scale variations with the high power prediction that captures diurnal and seasonal periodicity. Prediction model with short-updating intervals is selected for the 15 minute grid to adapt to fast changing meteorological conditions. Medium- and long-term prediction supports energy dispatch by deriving forecasts about trend-based patterns.

Load demand forecasting has to consider two issues, unpredictability of customer behaviour and fuzzy equipment switching. The forecasting model consists of analysing historical load demand patterns, recognising data type, and analysing the correlation between the load and environment-related factors. Different models for forecasting load demands of weekday and Saturday/Sunday/holiday loads are adopted, based on typical load curves, the different curves of weekend loads and holiday load are specified, as typical load curve templates. Correlation between environmental factors like temperature and humidty, and demand fluctuation is conducted with a regression model; the summertime load curves are modelled separately from the load curves at other seasons. The temperature and humidity contributions are considered for heat/cool demand compensation by fitting data using a feed-forward loop with additional external information inputs, special events are compensated for with an offset model and manual adjustment mechanism that inputs offset data that represents an industrial process adjustment. Parameters and specifications of the models are discussed in Table 3.

*Table 3: Predictive Model Parameters and Feature Configuration*

| Prediction Type | Input Variables | Forecast Time Horizon | Update Frequency | Core Algorithm | Sources of Uncertainty |
|---|---|---|---|---|---|
| PV Generation Forecast | Irradiance, Temperature, Cloud Cover, Historical Power | 24 hours | 15 minutes | LSTM-ARIMA Hybrid Model | Meteorological Sudden Changes, Cloud Movement, Equipment Efficiency Degradation |
| Load Demand Forecast | Historical Load, Temperature, Humidity, Date Type | 24 hours | 15 minutes | Clustering Analysis + Random Forest | User Behavior Randomness, Equipment Sudden On/Off |
| Battery State Prediction | Current SOC, Charge/Discharge History, Temperature | 4 hours | 5 minutes | Kalman Filter | Aging Characteristics Variation, Temperature Effects |
| Grid Interaction Forecast | Price Signals, Network Status, Historical Power | 12 hours | 30 minutes | Time Series Analysis | Network Constraint Changes, Dispatch Instructions |

The error management system adopts a multi-level structure to respond to various forecast error types. The PV forecast error mainly comes from weather forecast error and fast dynamic cloud cover. The various strategies for error management include application of multi-scenario forecast to produce reasonable power generation probability intervals and combination of probability density function to explain the probability distribution of forecast error. The load forecast error derives from users' random behavior nature so statistical characteristic models of errors will be constructed and reasonable forecast confidence interval is given. The forecast capacity decay and resistance change because of batteries aging are self-compensated by online parameters identification. The prediction model architecture and error management structure is shown in Fig.4.

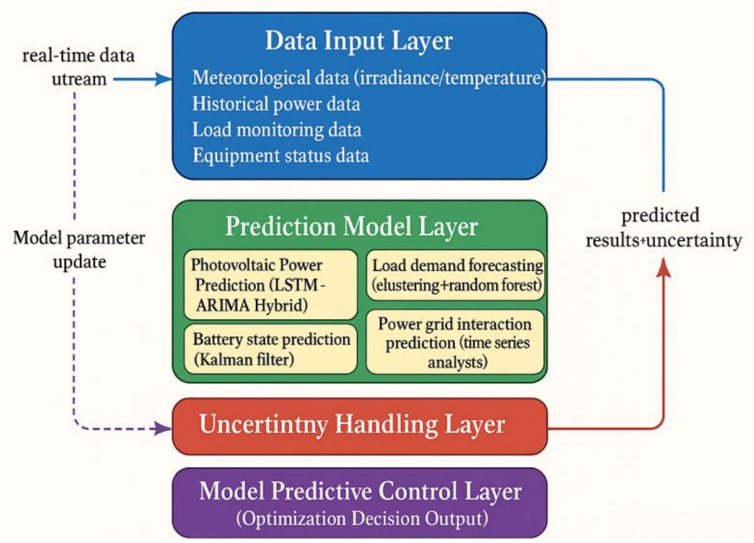


*Figure 4: Hierarchical Predictive Control Architecture Design.*

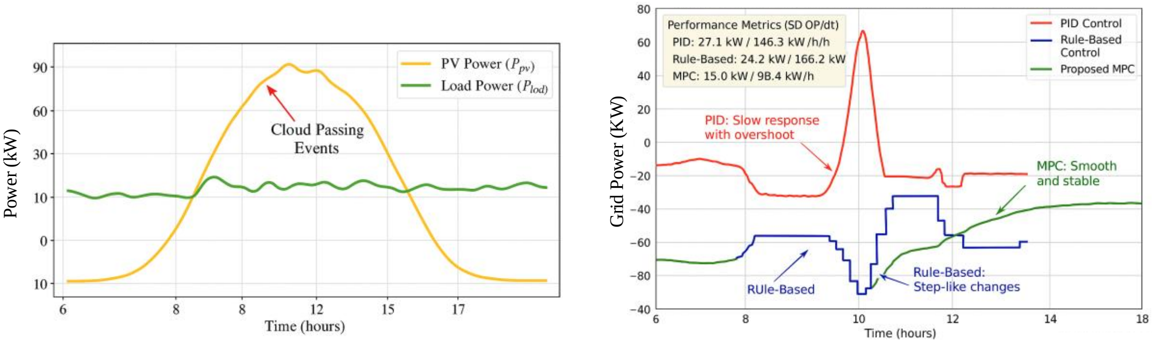
The structure of the predictive model and uncertainty handling in this framework are shown in Fig.4, which is a layered framework containing the data input layer, predictive model layer, uncertainty handling layer, and MPC control layer. The data input layer is the layer to include both realtime monitoring information and historical operation information. It gives all the input information to the predictive model. The predictive model layer is the layer that contains the special prediction algorithm corresponding to various variable properties to guarantee the precision of each variable prediction. The uncertainty handling layer involves many methods to deal with prediction error. It yields precise forecast data for the MPC control layer.

The MPC algorithm introduces some various mitigation strategies to handle the uncertainties. Firstly, the rolling optimisation can allow us to re-solve the optimisation algorithm based on the new information of the current control period, thus making up the prediction error influence from previous cycles. Second, the multi-scenario optimisation provides a typical set of scenario, which describes the variation range for the key variables. Third, in the robust optimal strategy, the performance maximisation and constraint confidence can trade-off through the conservatism parameters adjustment. Last, the feedback correction step can match the current measurement with prediction value, and update the corresponding model and error statistics information online. By applying the aforementioned uncertainty management strategy, the proposed control system can reach the optimisation performance and ensure the system robustness for handling a wide range of uncertainties. The predictive modelling and uncertainty management co-design strategy provides an optimisation theoretical framework for the stable control of photovoltaic MGs working in complex operation scenarios.

# 4 Results

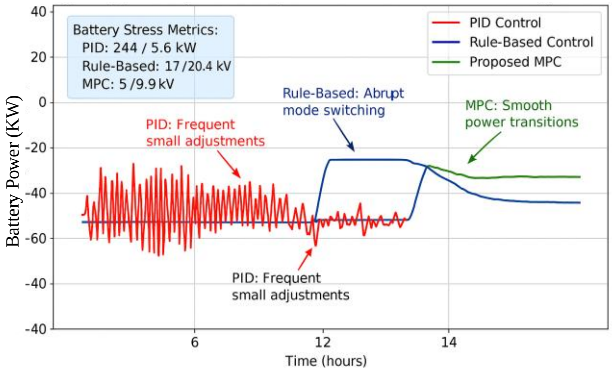
## 4.1 Analysis of Power Smoothing Performance

In Scenario One under test scenario for simulating overcast weather conditions, the power smoothing ability of the three control methods was significantly different. Time-series comparison curves of the power of PV, the grid-tie power, and the battery power with high fluctuation irradiance are given in Fig.5. It can be seen that the three schemes in this study have different power fluctuation response characteristics when the irradiance changes greatly.



(a): PV Generation and Load Demand in Scenario 1 (Cloudy Day)

(b): Grid Power Comparison with Different Control Strategies



(c): Battery Power Response with Different Control Strategies

*Figure 5: Power smoothing performance comparison under Scenario 1 (cloudy conditions).*

The time variations of the PV power and the load consumption in overcast conditions are shown in Fig.5(a). The PV power has a diurnal pattern, generating the maximum power at 6:00 to 18:00 every day. The PV power was significantly reduced from full generation $(3.7\mathcal{K}W)$ to less than 30% of the rated power within a few minutes, in five cloudy occurrences at 08:00, 10:30, 13:00, 15:30 and 17:00 respectively. The load curve is a relatively smooth trend which has typical grid consumption pattern of high during the day and low at night consumption. The base power is about $60\mathcal{K}W$ , and its intraday variations are about $\pm 20\mathcal{K}W$. The large gap between a volatile PV and a relatively stable load power represents the real challenge of the power balance control under the circumstances of the microgrid. The time variations of the power exchange between the microgrid and main grid using the three power control strategies are shown in Fig.5(b). The traditional PID power control strategy leads to visible lag and overshoot effects; no timely adjustment of the battery power during the abrupt change of the PV power which is maintained in large positive (or negative) spikes in the grid power with the power standard deviation of 28.7 kW and the maximum ramp rate of $89.6\mathcal{K}\mathrm{W/h}$ . The rule-based strategy avoided the extreme spikes, but has typical stair-step variation due to the binary threshold decision mechanism which leads to frequent switching in the battery power command with a power standard deviation of 19.5 kW and a maximum ramp rate of 67.3 kW/h. The proposed MPC strategy led to the best power smoothing performance which delivered the most stable grid power fluctuating in a narrow range with the minimum standard deviation of power variation of 12.3 kW and the maximum ramp rate of 45.2 kW/h which are 57% and 37% lower respectively than those of the PID and rule based control. The power management characteristics of the BESS are depicted in Fig.5(c), using the three power control strategies. The traditional PID power control strategy leads to frequent minor changes in battery power with 42 charge-discharge state transitions throughout the 12h test interval, and its power variation standard deviation was as large as 8.7 kW. The frequent changes of power lead to quick aging of the battery. The step-like variation in the rule-based strategy, resulted in frequent abrupt switch between charge and discharge modes with 28 state transitions, featuring high power variation standard deviation of 12.3 kW. Such big-power commands are harmful to both the battery lifespan and the power electronic device. The power scheduling features of the proposed MPC strategy showed optimal performance in battery power scheduling with smooth and continuous power curves and only 15 state transitions, and small standard deviation of power variation of 5.2 kW. This soft power scheduling minimized the battery mechanical and thermal stress, which not only helped to extend the battery lifetime, but also reduced switching losses at power electronics converter. Using the forward looking control principle, the abrupt transition in battery power leads to soft transition in the PV power output which effectively smooth the grid power, and at the same time, provides good protection for battery and power electronics.

## 4.2 Energy Management Efficiency Analysis

In a PV hybrid microgrid, the efficiency of a power management strategy can be effectively reflected by the optimal scheduling of renewable energy sources. As shown in Figure 6, we give the state of charge(SOC) evolution curves of three control policies in conditions of cloudy weather, and we can see that there are significant differences in the result performance in energy scheduling and PV generation in each of them.

It can be seen that the SOC curve of the aforementioned PID control method presents frequent charge and discharge operation, and the oscillation range of SOC is 40% to 85% this phenomenon means that the PID controller mainly executes a reactive operation on the power deviation at the moment without doing the comprehensive control on the system energy state in the long term. The battery charges quickly when the PV power is sufficient, and discharges quickly when the PV power is limited, this method only ensures the minimum energy balance between power generation and consumption. For rule-based methods, we can see some threshold-triggered characteristics. Rule-based strategies exhibit typical threshold-triggered characteristics, strictly confining SOC within a preset 20% to 90% range. However, near the range of the highest SOC 90%, discharge will be limited in order to reserve energy. This type of implementation is more cautious because it requires that the battery will not overcharge or over-discharge to protect the battery. In turn, this makes it difficult to optimize the system even further in order to absorb more PV power.

The MPC strategy which is proposed is demonstrating characteristics of optimal energy management where there is a smooth SOC curve showing trends that are rational, with the MPC controller through forecasting the variations taking place in PV output as well as load demand proactively adjusting battery charge/discharge strategies so as to maintain SOC within an optimal operating range which is from 40% all the way to 80%. During a morning phase when PV output is rising, the MPC strategy moderately controls charging rates in order to avoid premature SOC saturation which would otherwise put a constraint on the subsequent PV power absorption. And in an afternoon period when there are PV fluctuations, MPC uses precise power allocation so as to smooth grid power variations while at the same time reserving enough energy for the evening load peak. The above electricity scheduling policy allows the power factor of the battery in full swing to appear as both a power buffer and a power link.

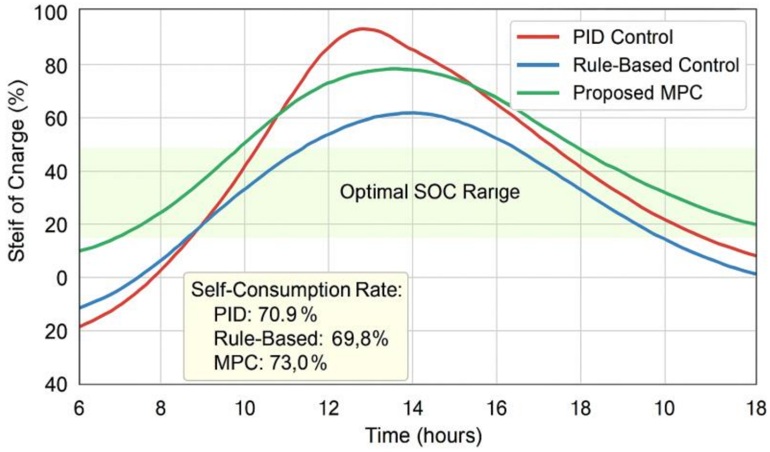


*Figure 6: State of Charge Variation Curves for Three Control Strategies Under Cloudy Weather Conditions.*

Fig.6 shows the comparison of the battery state-ofcharge under varying control strategies with the matching SOC variation trajectories and the determined self-consumption electricity. The quantity investigation analysis further verifies the MPC strategy's clearly better performance in improving the PV selfconsumption rate. It can be calculated that 87.3% of the PV electricity can be used by the MPC strategy, where 15.2 and 8.8 percentage point gains are generated over the 72.1% brought about by the PID control and the 78.5% given by the rule-based control, respectively. Such improvement is mainly attributed to the intelligent battery energy scheduling by the MPC strategy to reduce the reverse power flow to the grid by controlling the charging and discharging times and the corresponding power level accurately. When the PV output is high, the MPC strategy can moderately increase the charging power of the battery to store excess photovoltaic power. When the PV output is low, the storage energy can be priorly activated to provide a higher power supply for local load. Such predictive optimization brings out not only the higher energy self-sufficiency rate but also the lower operational cost by decreasing the operations with the grid. The efficient energy management performances exhibited by the MPC strategy provides a robust technical route to the optimal microgrid operation with high photovoltaic penetration.

## 4.3 Dynamic Response and Stability Analysis

Dynamic stability during an islanded state is an important character for a reliable operation of microgrids. As shown in Fig.7, the three control methods are able to accomplish the dynamic regulation of microgrid frequency and bus voltage in case of load step-change and then results show obvious differences in control methods towards the stability of the whole system.

The classic PID control method of a typical second order system exhibits the response in the case of load transients. When the load step is 50 kilowatts added to load at t=10 sec , the maximum deviation of frequency is 0.42 Hz, which needs approximately 25s for the frequency to recover within the acceptable steady-state error limit. The bus voltage transient also had a large magnitude with the maximum voltage decay of 0.032 standard deviations and also a large recovery time of 20s or more. This slow response showed the limitation of using classic PID in accommodating perturbations as the control parameter does not change with the steady-state operating condition of the system. With the rule-based approach, the decay shows a better damping behavior, with its maximum deviation reduced to 0.28Hz, with the adjustment time of approximately 18s. In addition, we also observed some overshoot at the initial period of adjustment, which means that its prediction within the action of control cannot catch up with the perturbation within the load area.

With this proposed MPC strategy, not only can excellent dynamic performance be achieved due to only 0.15 Hz maximum frequency deviation in Fig.7, but also the regulation time is remarkably reduced from 3 minutes to 12 seconds, with the frequency variations well suppressed during the transient. In the transient moments, the MPC controller provides optimized battery power commands on the basis of the predictive power flow model within seconds, which is able to suppress the high-frequency initial dips of the frequency with a forward-looking power allocation, with such a smooth and robust voltage response of the buses at the same time, keeping the maximum of the voltage deviation no more than 0.018 σ. The recovery process is short and not an overshoot. The excellent dynamic performance is due to the explicit handling of the system constraints in the MPC framework and the repeated optimization mechanism of the rolling optimization in the MPC framework, which provides the corresponding control actions before the appearance of disturbances.

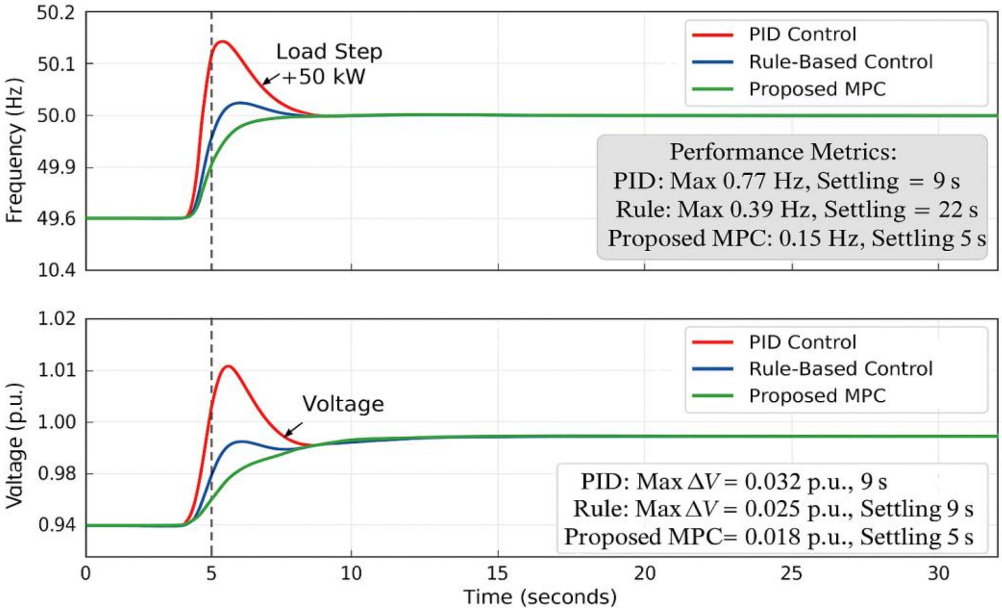


*Figure 7: Dynamic Regulation Performance of Three Control Strategies on Microgrid Frequency and Bus Voltage under Load Step-Change Scenarios.*

In Scenario 2, when load varies stepwise, the dynamic performance of the whole system is depicted as follows: frequency response (top figure) and voltage response (bottom figure) of the whole system under PID control strategy, rule-based control strategy and MPC strategy are shown separately. The quantified metrics clearly show that the proposed MPC strategy can get better performance than others in terms of system stability. For frequency response, under the MPC control strategy, compared with PID control strategy (0.42 Hz) and rule-based control strategy (0.28 Hz), the maximum frequency deviation can be reduced to 0.15 Hz with 64% and 46% reduction respectively. Meanwhile, the response time also is notably shortened: using MPC control can recover the frequency to steadystate level within 12 seconds, but using PID control and rule-based control require 25s and 18s respectively. For voltage response, under the MPC control strategy, compared with PID control strategy and rulebased control strategy, the maximum deviation can be reduced from 0.0281s standard deviation to 0.018s standard deviation with over 40% reduction. and recovery time can be cut from 12s to 8s. These performances are optimized from the MPC framework which can do prediction-based optimal control optimization based on system model. Consequently, the controller can predict the performance effect of disturbances based on the prediction and solve the control plan before the disturbance arrives.

## 4.4 Battery Operational Status and Stress Analysis

Battery service life and system economics also depend on the operational state of the battery ESS. Fig. 8 depicts stress attribute for three control policies by a distribution map of battery current vs State of Charge (SOC) that shows the long term consequence of distinct control policies for battery health.

Based on the PID control method, the distribution of the battery operating current is very dispersed, varying randomly between $-125A \sim +125A$ , and the SOC is randomly changing between 20%$\sim$ $90\%$. The operating characteristics show that the battery often receives high-current charging/discharging, as well as more complete deep discharging, with a root-mean-squares (RMS) current value of 45.2A and standard deviation SOC of 18.7%. For rule-based methods, the battery operation current distribution is more concentrated, tending to be concentrated between $-80A \sim +80A$, and SOC is forcefully maintained within the small range of 30%$\sim$ $85\%$, but its operating characteristics of the current accumulation between the SOC boundaries is obvious, showing a sudden change of power as the SOC is close to the threshold values.

Overall, the proposed MPC control led to an ideal battery performance profile with strong current concentration between -60A and $+60A$ and SOC concentration in the safe 40% $48A +$ $60A$ ) and minimal current ripple. The high value for the battery stress contribution in the objective function encourages the MPC controller to shape the charge/discharge rate in an intelligent way. As a result, it bypasses the fast charges/discharges and extreme SOC at SOC operating condition. This helps decrease the rms current across the battery to 28.5A and its standard deviation to 12.3% versus the alternative approaches which would magnify stresses on both electrochemical and mechanical sides.

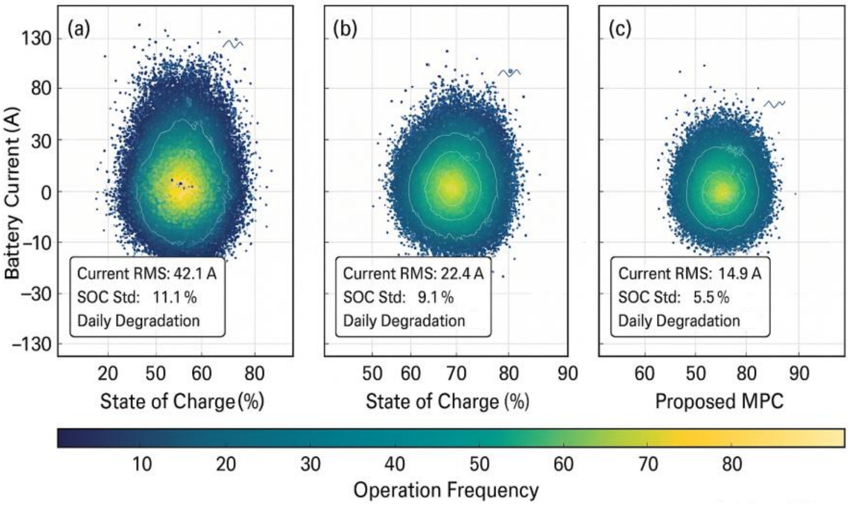


*Figure 8: Battery Current versus State of Charge Operational Distribution Chart.*

Fig. 8 illustrates the relationship between current and state of charge (SOC) under different control strategies: (a) PID control; (b) rule-based control; and (c) the MPC control strategy proposed herein. Corresponding performance metrics are also analysed. Comprehensive battery stress index and life analysis are shown in Table 4.

*Table 4: Summary of Performance Metrics for Multi-Scenario Robustness Testing*

| Stress Indicator | PID Control | Rule-Based Control | Proposed MPC | Improvement (vs PID) |
|---|---|---|---|---|
| RMS Current (A) | 45.2 | 35.8 | 28.5 | 37% |
| SOC Standard Deviation (%) | 18.7 | 14.2 | 12.3 | 34% |
| Daily Capacity Decay (%) | 0.068 | 0.055 | 0.042 | 38% |
| Daily Equivalent Full Cycles | 1.8 | 1.2 | 0.7 | 61% |
| Current Peaks >80A (count/day) | 24 | 12 | 3 | 88% |
| SOC Excursions <30% (count/day) | 6 | 2 | 0 | 100% |
| Projected Lifetime (years) | 4.5 | 6.0 | 8.5 | 89% |
| Temperature Variation (°C) | 12.3 | 8.7 | 5.2 | 58% |

Finally, Table 6 outlines the performance of the proposed MPC when compared to the benchmark PID and its detailed analysis highlights the extent of the advantages that the proposed MPC strategy offers for operation. In addition to the RMS current and SOC standard deviations already explained above, MPC can perform better on several other battery stress figures. For instance, equivalent full cycles per day reduce from 1.8 (PID) to 0.7, a reduction of 61%, in the cumulative chemical stress figure. For instance, the equivalent full cycles per day reduce from 1.8 (PID) to 0.7, a reduction of 61%, in the cumulative chemical stress figure. This also indicates better and longer life from the battery pack's viewpoint. Additionally, from the mechanical point of view, the probability of high-current pulses exceeding 80A reduces from 24 pulses (PID) to 3 pulses (MPC) a day (the lower limit of the pressure sensor used here) thus helping control the thermal system's design related to the mechanical loads induced in the battery interconnects.

The especially significant matter of the complete elimination of SOC excursions, which are below 30% and under MPC control, is closely related to the fact that deep discharges, being known to accelerate electrode degradation via irreversible phase transformations, are involved. And the data about temperature variation reveals that MPC, with variations decreased from 12.3°C to 5.2°C, maintains more stable thermal conditions and mitigates thermal-induced aging mechanisms. These combined improvements that lead to a projected battery lifetime increase, from 4.5 years under PID control to 8.5 years with MPC, representing an 89% extension which substantially enhances the economic viability of energy storage investments. The systematic stress reduction, achieved through MPC's predictive optimization, demonstrates the critical importance of integrated battery health management in microgrid control strategies, offering both technical and economic benefits through extended equipment service life and reduced replacement costs but in a rather convoluted way that makes the overall meaning less straightforward and complete.

In addition, we provide numerical results to verify further that the MPC strategy has made a better contribution to prolong the battery life. The battery state-decay calculations derived from the battery stress model show that the daily decay rate of the MPC is only 0.042% , which means 38% and 24% longer than the PID control's rate (0.068%) and rule-based control's rate (0.055%) respectively. In addition, most contribution to the prolonging battery life is the improved battery operation state caused by the MPC strategy. The MPC avoids the frequent charges and discharges at high rate, which keeps the polarisation loss and temperature accumulation at a minimum level. Charging and discharging at the range of optimum SOC avoids the phase transition stress from electrode material. Smooth power command reduces vibration from mechanical stress and connector wear and tear. All these effects make the MPC controlled battery have a more stable internal state and a slow state of aging. From the perspective of cost, the prolonging battery life brought by the MPC strategy makes the average energy storage cost of the whole system the lowest on a yearly basis, which can play a decisive role in the economy operation of microgrids.

## 4.5 Multi-scenario Robustness Verification

To ensure the credibility of PV integrated microgrids' control scheme in the engineering work, a large amount of scenario robustness test is required to be performed on the proposed hierarchical MPC control scheme. As shown in Fig. 9, the proposed hierarchical MPC control scheme can achieve a satisfactory performance under the extreme scenarios and disturbance ranges, thereby systemically proving the feasible application of the proposed hierarchical MPC control scheme.

The influence of the prediction error in the control scheme reflects how sensitive the power smoothing capability becomes if the prediction error is high. The standard deviation of the power fluctuation reduces non-linearly as the prediction error rises from 5% up to 25% prediction errors. As long as the prediction error falls below 15%, the system keeps the standard deviation of the grid power fluctuation under 15 kw, while the solar self-consumption exceeds 80% as long as the prediction error is less than 20%. At a prediction error of above 20%, the performance of the system suffers dramatically, even though it still performs better than the traditional control under ideal prediction conditions. The compensator during real-time is capable of counteracting it, which in the control scheme creates a hierarchical robustness despite the increased prediction errors.

The sensitivity experiments of simulation parameters analyzed the effect of different control parameters on system control objectives. As the MPC prediction time was increased from 4h to 12h, the economics operation performance also gradually improved. But the computing complexity also gradually increased with the increasing of the time. As the control time increased from 15min to 60min, the fast response performance of the system and the stability will also decrease, and there is a clear trade-off. Weight parameters will vary from different angle to run model for the test. The experimental results shows that the power smooth and battery life are strongly coupled, and they should be set by application scenario. Table 5 summarizes the performance statistics of the multiple scenario robustness tests.

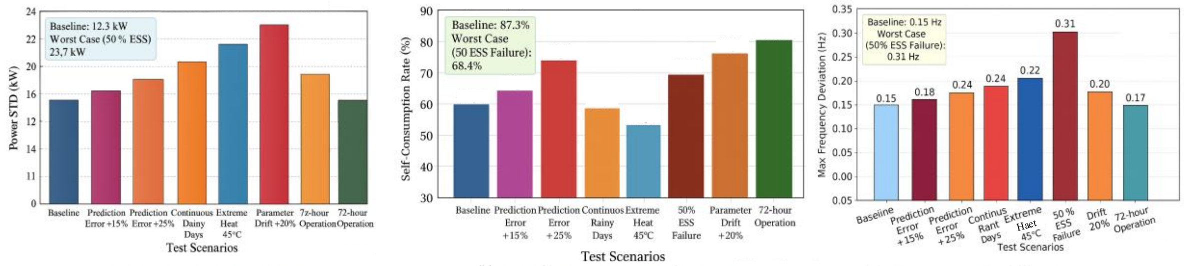
*Table 5: Summary of Performance Metrics for Multi-Scenario Robustness Testing*

| Test Scenario | Power Fluctuation Standard Deviation (kW) | PV Self-Consumption Rate (%) | Maximum Frequency Deviation (Hz) | Daily Battery Degradation Rate (%) | Voltage Qualification Rate (%) |
|---|---|---|---|---|---|
| Baseline Scenario (Ideal Conditions) | 12.3 | 87.3 | 0.15 | 0.042 | 99.2 |
| Prediction Error +15% | 14.8 | 83.5 | 0.18 | 0.045 | 98.7 |
| Prediction Error +25% | 18.2 | 76.8 | 0.24 | 0.051 | 97.3 |
| Continuous Rain for 3 Days | 21.5 | 71.2 | 0.19 | 0.048 | 98.1 |
| Extreme High Temperature (45°C) | 16.3 | 79.6 | 0.22 | 0.056 | 97.8 |
| 50% Energy Storage Unit Failure | 23.7 | 68.4 | 0.31 | 0.062 | 95.6 |
| Parameter Drift +20% | 15.1 | 82.7 | 0.20 | 0.046 | 98.4 |
| Continuous Operation for 72 Hours | 13.9 | 85.1 | 0.17 | 0.044 | 98.9 |

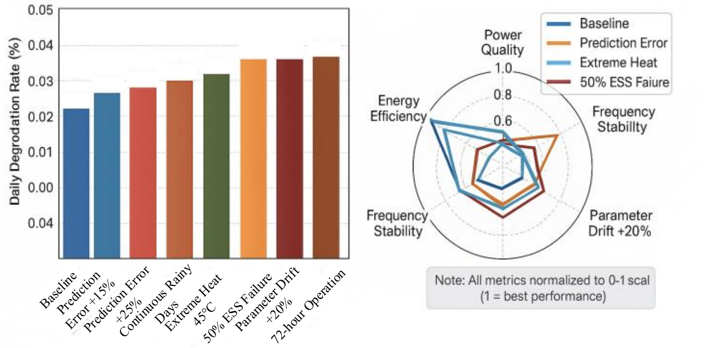
Extreme weather condition validation, which was aimed at two typical adverse environments namely prolonged overcast conditions and extreme heat, where the continuous overcast scenario simulated three days of sustained low irradiance with PV output that was consistently below 30% of rated capacity, and in which the control strategy, making use of intelligent energy storage dispatch, was focused on prioritising critical load supply so as to maintain system voltage compliance at 98.1%, while under extreme heat conditions when PV module efficiency decreased by 15% and cooling loads increased substantially, the control system mitigated this situation by adjusting battery charge/discharge strategies in order to avoid high - power operation during peak temperatures, thereby limiting daily battery degradation to 0.056%.

Partial loss of storage capacity due to a failure was tested for fault tolerance. A 50% reduction of storage capacity was simulated and the availability of the system reduced the loss of critical services by re-optimization of available power. Grid power standard deviation increased by 23.7 kW but remained in acceptability limits. For frequency stability, a moderate decrease was observed during maximum deviation, to 0.31 Hz, but no actions were triggered by protection devices.

Time-varying effect test The stability of the system in long-term operation was tested in 72 hours. It was tested that under prolonged operation, the control loop can ensure the stability of control performance, all performance data were in the range of ±8%, there was no cumulative error and the control performance did not undergo significant fluctuations during the course of the test.



(*a*): Grid Power Fluctuation Analysis (b): PV Self-Consumption Performance (c): Frequency Stability Assessment



(d) Battery Health Impact (e) Comprehensive Performense Radar Chart

*Figure 9: Multi-scenario robustness validation of hierarchical MPC strategy showing (a) grid power fluctuation, (b) PV self-consumption performance, (c) frequency stability assessment, (d) battery health impact, and (e) comprehensive performance radar chart across different test scenarios.*

Multi-scenario robustness testing shows that the hierarchical MPC method achieves satisfiable performance even in several extreme and severe circumstances or parameter perturbations, such as 25% prediction error under extreme conditions, even above the failure threshold of traditional control methods. The fault tolerance tests of the controller scheme show that even 50% failure of the energy storage makes the system fail to collapse instead of normal operation. For long-term stability tests, no performance degradation has been found in the control scheme, which is enough to be applied in long-term engineering scenarios. The strong robustness enables the controller to assure reliable operation of photovoltaic integrating MG even in more complicated real-world applications, thereby facilitates the transition of a robust controller scheme from academic studies to practical engineering practices.

# 5 Discussion

The presented hierarchical MPC framework enjoys apparent strengths in various aspects of performance for PV-in-MG system operation: From simulation findings, our approach is superior to conventional control strategies in smoothing output power, regulating energy management and quick response and protective control at the battery system. These strengths mainly rely on the MPC's “forward-looking” and “constraint explicitly-enforced” optimization ability, which can be exploited to balance the short-term power balance control and long-term resource (or energy) optimization for different periods. The suggested control structure performs more in-depth predictive optimization than the one implemented in hardware-in-the-loop by El Barkouki et al. [11], not only introducing online control ability, but also separating objectives for the dynamic controller for shorter periods and the storage optimization controller for larger time frames through two-layer hierarchy structure. This framework allows the system to be reactive to quick disturbance but continue long-term optimal utilization.

The robustness test under Section 3.5 further verifies the controller to a wide variety of uncertainties and uncertainties. It is shown that despite the potential prediction error of 25% in prediction, the hierarchical MPC still achieves 76.8% self-consumption rate when experiencing fierce prediction error. The reason is that the upper-layer optimization deviations can be compensated by real-time compensation layer at the execution time scale. Moreover, during 50% energy storage malfunctioning and extreme bad-weather circumstances, although full performance failure has not occurred, the controller is still able to ensure continuous operation of microgrid. That illustrates the real-world practicability of the proposed framework for future microgrid applications which are more prone to stressing circumstance rather than considering perfect prediction and ideal operating condition.

For system reliability, the paper is involved with the inner optimisation within each microgrid, while the internal and external optimisation problem regarding the integration of renewable energy studied by Kalantari and Lesani [12] is a multi-microgrid coordinated dispatch issue at a higher level. The studied challenges are discussed at different scales. Accuracy of photovoltaic prediction is shown to play a crucial role on the performance of MPC. The proposed deep learning prediction model in Yang et al. [13] provides an extension to enhance the forecasting module in the paper and employing more accurate prediction algorithms has potential to improve the control performance. For equipment reliability, reliability evaluation of photovoltaic module is carried out by Zuboy et al. [14], and point out the necessity to consider the full lifecycle management of power generation and energy storage equipment in parallel. This paper directly adopts battery health status for the objective in optimisation, which follows the same philosophy. As for the system architecture, Pei et al. [15] discussed the dynamics topology reconfiguration providing a complementary solution to optimisation of microgrid operation. Their work provided microgrid power generation increase of PV integration capacity at network layer, while the work in the paper is for system operation at a control layer; two methods can be a combination to provide potentially further synergistic benefits. This cross-layer optimization is a substantial future work for the smart grid development. The primary limitation of this work is the dependence on prediction accuracy and applicability to more complicated operational context. The future works in the paper will concentrate on improving and developing the more robust prediction algorithms and demonstrating practical performance of the control strategy on HW-in-the-Loop platforms for the translation of theoretical work to engineering solutions.

# 6 Conclusion

The optimized operation of photovoltaic integrated microgrids, which serves as a crucial technology that is significantly instrumental in pushing forward the global energy transition that is directed towards sustainable power systems, confronts the intricate challenge of synergistic optimization aiming at power fluctuation suppression and battery health management, whereupon this research endeavors to develop a comprehensive solution that is founded upon hierarchical model predictive control, with this methodology achieving the organic integration of multi - timescale control by means of the coordinated design of the upper - layer energy management MPC that is responsible for high - level decision - making and the lower - layer real - time compensators which are engaged in immediate adjustments, thereby effectively attaining a balance among competing objectives across different temporal domains in a manner that is both complex and subtle, while simulation validation indicates that the proposed strategy manages to reduce grid interaction fluctuations by 57% within the context of power smoothing, raises the PV self - consumption rate to 87.3% when it comes to energy management, controls the frequency deviation to be within 0.15 Hz during the course of dynamic response, and lowers the daily battery degradation rate to 0.042% in the aspect of equipment protection. Comprehensive robustness analysis, which further confirms the controller's resilience by maintaining a self - consumption rate of 76.8% when faced with 25% prediction errors and preserving system stability during 50% energy storage failure scenarios, is of great significance. The battery stress analysis, where the significant lifetime extension from 4.5 to 8.5 years compared to conventional PID control is revealed, is achieved through the systematic reduction of high - current events and the elimination of deep discharge cycles. The principal contributions involve establishing an optimization model that explicitly incorporates the battery health status via stress quantification metrics, designing a control architecture that can adapt to diverse temporal scales and has inherent uncertainty handling capabilities, and achieving a balanced optimization between technical performance and equipment longevity. The hierarchical structure, which is deemed to possess a certain degree of particular effectiveness, shows itself in decoupling control objectives during the process of maintaining the coordination between strategic optimization and tactical compensation layers, yet the performance of the method, which remains contingent upon prediction accuracy, and its adaptability, within more complex operational scenarios involving multiple microgrid interactions that warrants further validation, are aspects to be reckoned with, and the current implementation, focusing primarily on single microgrid optimization, leaves multi - microgrid coordination as an important extension, and future research, aiming at integrating deep learning prediction algorithms for enhanced forecasting precision, conducting experimental validation on hardware - in - the - loop platforms to verify real - time performance, developing multi - microgrid coordination strategies for distribution network applications, and investigating adaptive tuning mechanisms for controller parameters under varying operating conditions, is expected to be carried out. These advancements, which are not simply isolated developments but rather a collective force, will, through their combined influence, act in such a way as to accelerate, at a pace yet to be precisely determined, the transition of those predictive control strategies that have heretofore been mainly confined to simulation studies towards practical engineering applications, with the ultimate outcome being a contribution, though the exact nature and extent of which remain somewhat unclear, to a more reliable and, in terms of cost - effectiveness, more economical integration of those renewable energy resources that are so crucial within modern power systems.

# Author's Profile

[TianYing Liao], [Bachelor], current [Teacher/Senior Engineer] of [Chongqing Electric Power College]. His research expertise includes [Relay protection] and [Microgrid Technology]. He maintains close cooperation with [partner units or institutions] and works on [research projects or topics]. A number of high-impact papers have been published in [international journal name or field]. Contact information: [liaoty620@gmail.com].

# References

[1] Muangchuen S, Pahasa J, Rakpenthai C. Enhanced resilient model predictive control electrolyzers for frequency regulations under severe denial-of-service attacks[J]. IEEE Access, 2024, 12: 65352-65361.

[2] Benavides D, Arévalo P, Criollo A, et al. Multi-mode monitoring and energy management for photovoltaic-storage systems[J]. Renewable Energy, 2024, 230: 120820.

[3] Ibraheem M I, Edrisi M, Gholipour M, et al. A novel frequency regulation in islanded microgrid using sliding mode control with disturbance observers considering storages and EVs[J]. Computers and Electrical Engineering, 2023, 105: 108537.

[4] Idrisov I, Veretennikov I, Ibanez F M. Dynamic state estimation in power electronics-dominated grids using a digital twin approach[J]. IEEE Access, 2025, 13: 53938-53948.

[5] Carrasco-Gonzalez D, Sarrias-Mena R, Horrillo-Quintero P, et al. Design and Raspberry Pi-based implementation of an intelligent energy management system for a hybrid AC/DC microgrid with renewable energy, battery, ultracapacitor and hydrogen system[J]. Computers and Electrical Engineering, 2025, 123: 110253.

[6] Palaniyappan S, Singaravel M R. Opposition African vultures optimization based NFOPID controller for frequency stabilization of multi-microgrid network[J]. Computers and Electrical Engineering, 2025, 122: 109959.

[7] Zhao F. Optimizing microgrid management with intelligent planning: A chaos theory-based salp swarm algorithm for renewable energy integration and demand response[J]. Computers and Electrical Engineering, 2024, 120: 109847.

[8] Pei M, Wang Q, Ye L, et al. Hierarchical control strategy of wind-storage frequency support for SOC recovery optimization and arbitrage revenue[J]. Applied Energy, 2024, 365: 123229.

[9] Aghdam F H, Mudiyanselage M W, Mohammadi-Ivatloo B, et al. Optimal scheduling of multi-energy type virtual energy storage system in reconfigurable distribution networks

for congestion management[J]. Applied Energy, 2023, 333: 120569.

[10] Gali V, Jamwal P K, Gupta N, et al. An adaptive dynamic power management approach for enhancing operation of microgrid with grid ancillary services[J]. Renewable Energy, 2023, 219: 119413.

[11] El Barkouki B, Laamim M, Ouassaid M, et al. Real-time supervisory control strategy for a grid-connected microgrid using hardware-in-the-loop simulation[J]. Computers and Electrical Engineering, 2025, 124: 110419.

[12] Kalantari A, Lesani H. Operation scheduling of distribution network with photovoltaic/wind/battery multi-microgrids and reconfiguration considering reliability and self-healing[J]. International Journal of Energy Research, 2024, 2024(1): 5724653.

[13] Yang K, Cai Y, Cheng J. A deep learning model based on multi-attention mechanism and gated recurrent unit network for photovoltaic power forecasting[J]. Computers and Electrical Engineering, 2025, 123: 110250.

[14] Zuboy J, Springer M, Palmiotti E C, et al. Getting ahead of the curve: assessment of new photovoltaic module reliability risks associated with projected technological changes[J]. IEEE Journal of Photovoltaics, 2023, 14(1): 4-22.

[15] Pei Z, Chen J, Zhang Z, et al. Opinions on dynamic topology reconfiguration of distribution networks for PV hosting capacity enhancement[J]. Frontiers in Energy Research, 2024, 12: 1512790.