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Phase Robust Optimization of PV-Energy Storage Microgrid Based on Deep Reinforcement Learning and Mixed Integer Constraint Model

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Abstract

The pronounced dependence of photovoltaic (PV) generation on meteorological conditions, coupled with substantial fluctuations in load demand, renders conventional deterministic optimization approaches inadequate. Addressing the need for robust multi-phase decision-making across temporal domains (e.g., day-ahead scheduling and real-time adjustment) and the coordinated optimization of continuous variables (such as energy storage charge/discharge rates) and discrete variables (such as unit commitment states), this research proposes a phased robust optimization strategy for PV-storage microgrids. This strategy integrates Deep Reinforcement Learning (DRL) with a Mixed-Integer Constrained Model (M-ICM). The methodology explicitly accounts for the coupling effects between irradiance intensity, temporal sequence efficiency, and the state-of-charge of energy storage systems. This ensures that the microgrid control system provides sufficient resilience mechanisms for dynamic energy allocation in practical applications, facilitating global optimization of microgrid energy utilization. The simulation results show significant improvements over conventional methods, which includes reduction in time-to-peak under dynamic balancing conditions, maintenance of lower output current-to-power ratios, and enhanced convergence speed of the neural network model.

Keywords: Photovoltaic microgrid, Energy storage regulation, DRO, DRL, M-ICM

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1. Introduction

With the increasing global market share of photovoltaic (PV) generation technology in renewable energy systems, continuous technological advancements are being made in PV microgrid optimization. The inherent temporal fluctuations of PV power generation have intensified the demand for responsive regulation in microgrid systems [1]. Unlike conventional renewable energy generation approaches, PV systems implement multi-layer coordination management through photoelectric conversion, energy storage, grid connection mechanisms within microgrid architectures. This interconnection establishes a correlation between reactive power output in distributed structures and grid system frequency. However, PV generation demonstrates limited capability to enhance power output when confronting uneven power supply conditions in grid systems, thereby compromising overall power system stability [2]. This limitation diminishes the potential coverage scope of secondary output variables in electrical systems.

1.1 Current research status

The distributed photovoltaic (PV)-energy storage system has the capability to inject active power into grid systems while providing frequency regulation in response to variations in grid power demand [3]. This operational characteristic proves instrumental in mitigating disturbances caused by renewable

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energy fluctuations, thereby enhancing power system security and stability through the implementation of adaptive control strategies that optimize energy storage utilization for output balancing [4]. The operational framework for phase regulation in PV microgrid-energy storage systems is illustrated in Figure 1.

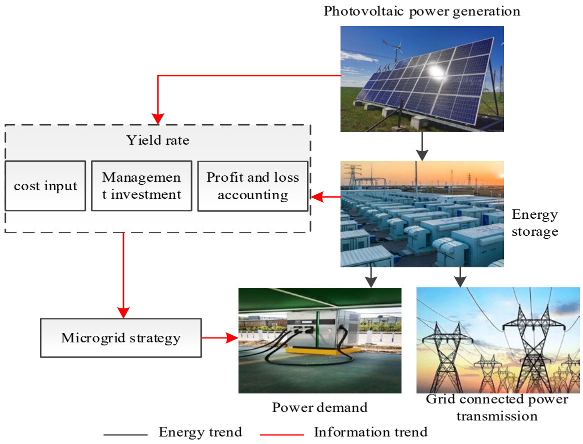

Figure. 1. PV-energy storage stage regulation and control process.

The generation-energy storage strategy of photovoltaic microgrid adopts a neural network model to deal with the problem of illumination uncertainty, thus improving the efficiency and accuracy of the solution more effectively [5]. Considering the randomness of PV microgrid output, its decision level depends on the preset probability distribution. When the data distribution changes (such as illumination data, temperature change, etc.), the regularization of the complete solution may require a new decision calculation method [6]. Although the optimization strategy is designed to cope with variable situations, in complex situations (meteorological data, etc.), the resulting scheme is still conservative and fails to fully reveal the physical characteristics of the abnormal distribution of data [7].

Photovoltaic energy storage microgrid is based on a distribution neural network model, which seeks the best solution in uncertainty [8]. This can not only adapt to the current robust optimization method of neural network models to find the optimal solution in the worst case, but also provide new technical support to solve its conservative problem [9]. Considering the multi-faceted impact of robust optimization and the conservative optimization of neural network models in three-dimensional space, the combination of the two has become the main direction of power research [10].

These technical challenges have garnered significant research attention. Petersen, H. R. et al. investigated the integration of multistage distributed neural network models with integer-zero programming design, where the probability distributions of uncertainties at each primary stage are influenced by decision-making processes from preceding stages [11]. The study further considered fuzzy set boundaries associated with first- and second-order moment decision processes, where these boundaries remain non-deterministic and decision-related empirical data are represented through weighted averages and coprobability distribution vector spaces. Besides, Ivanov, O., & Thompson, G. proposed a Wasserstein linear distance-based distributed neural network model employing fuzzy set deep learning algorithms [12]. This framework addresses critical challenges in renewable energy microgrid operations, which include real-time electricity pricing, renewable generation capacity, and load demand management. Experimental validation indicates that the proposed architecture effectively balances energy output between main grids and microgrids through dynamic pricing mechanisms, while the developed DRO minimum product method provides reliable energy dispatch instructions under uncertainty. Sanchez-Lopez, R., & Bertsekas, D. employed an imprecise Dirichlet model to construct fuzzy sets encompassing all possible probability distributions of PV system rated output power [13]. The critical challenge of accurately matching multi-vector spaces across primary operational stages can be formulated as a system of linear equations for resolution [14].

1.2 Technical analysis

M-ICM (Mixed-Integer Constrained Model) is a mathematical optimization problem in which the variables contain both continuous and integer variables, and are subject to linear or nonlinear constraints [15]. As an extended form of MIP (Mixed-Integer Programming), it is widely used in complex problems that requires the combination of discrete decision and continuous optimization [16]. Traditional mixed-integer linear programming (MILP) approaches exhibit significant computational inefficiency when applied to microgrid optimization problems. This time-intensive nature often renders them unsuitable for real-time dispatch scenarios requiring rapid responses. Particularly for microgrid optimization involving multiple periods and numerous variables, conventional MILP methods frequently entail substantial computational time. This characteristic hinders their applicability in the rapidly evolving operational dynamics of modern power systems.

In the field of PV-energy storage microgrid control, the goal is to obtain the optimal output solution under the most stable PV conditions. However, it is still a problem of probabilistic prediction to ensure the stable output of a photovoltaic microgrid. Considering the advantages and disadvantages of DRL in computing, the performance comparison between the mainstream fusion method and the traditional single method is listed in Table 1.

Table 1. Key issues and solutions.

Problems	Deficiencies of the existing methods [17]	The improved direction of fusion DRO
Over-conservatism	Traditional DRL tends to be a safe but sub-optimal strategy in three-dimensional space optimization.	Distribution perturbation via DRO explicitly optimizes the "worst case" rather than average, avoiding conservatism.
Compute efficiency	High computational cost	Adopt hierarchical optimization or approximate DRO.
Environmental uncertainty	DRL is sensitive to the distribution shift	Adversarial training explicitly models distributional uncertainty.
Training stability	The DRO target may cause a gradient explosion.	Update using a regularized or conservative strategy.

The optimization of neural network models in three-dimensional space is too conservative, and related research is devoted to the integration of the two. A method for distributing neural network models to optimize DRO is proposed. The comparison of mainstream fusion methods is shown in Table 2.

Table 2. Comparison of the fusion methods.

Methods	Core ideas	Advantages	Disadvantages	Applicable scenarios
DRL + DRO[18]	The DRO objective is directly embedded in the DRL policy optimization.	-Directly optimize the robustness - Adapt to dynamic environmental changes	- High computational complexity - Unstable training	High uncertainty environment
DRO-regularization strategy [19]	DRO constraints are added to the policy gradient (PG) or value function (Q-learning) of the DRL.	- Balance performance and robustness - The interpretability is strong.	- Hyperparameter sensitive - May be overly conservative	Tasks that require a trade-off between robustness and efficiency
Layered hybrid architecture	The bottom DRL is responsible for local decisions, and the top DRO adjusts the global policy distribution.	- Modular design is easy to expand - Reduce the computational burden	-Stratified training is complex. -Two-level optimization objectives need to be coordinated	Multiscale decision problem
Antagonism DRL [20]	Adversarial perturbations are introduced into the environment. Improve robustness through confrontation training.	- Proactively expose vulnerability - Improve the robustness of confrontation	-May deviate from the true distribution - The training is difficult.	Safety-critical areas

While Deep Reinforcement Learning (DRL) offers significant capabilities for real-time decision-making, its practical application often encounters substantial challenges in satisfying system constraints. DRL algorithms typically prioritize the optimization of the objective function during training, exhibiting a relative weakness in handling critical physical system constraints. These constraints include, but are not limited to, charge/discharge limits for energy storage devices and power balance requirements. Consequently, the resulting optimal control actions derived from DRL may violate the operational boundaries of the actual system, thereby compromising solution feasibility.

1.3 Research motivation and innovation

The core of the hierarchical hybrid architecture in this paper is to use the general form of data statistics to divide all possible data distributions (that is, non-deterministic sets), and to seek the best solution on this set to ensure that the decision-making process can maintain high quality and efficiency no matter how the data distribution changes [21].

Based on the reliable model of DERS (Distributed Energy Resources System), which is involved in the secondary regulation of the power grid system, this paper studies the adaptive control strategy, including the regulation of microgrid output [22]. Firstly, by introducing DRL (Deep Reinforcement Learning) control system design, the dynamic performance and quality of the control system are improved; Subsequently, DRO (Distributionally Robust Optimization) fuzzy computing control strategy is adopted to robustly optimize the proposed adaptive control strategy. Through the comparative analysis with the traditional model constraint strategy, it is proved that the technical method in this paper integrates the hierarchical hybrid model and has a good robust optimization effect on the constraints of photovoltaic energy storage, which solves the problem of poor effect of parameter gradient analysis in the traditional method and avoids the risk of gradient explosion caused by the target [23].

The main innovations of this study are listed below:

(1) Collaborative optimization of DRL and MILP is completed, which includes DRL providing a fast initial solution, MILP ensuring the feasibility and optimality of the solution, and balancing the speed and accuracy.

(2) Stage robustness mechanism is done. Distributed robust optimization is adopted according to the PV-energy storage stage, and model predictive control is used in the real-time stage.

(3) The hybrid Action Network is proposed to output continuous and discrete actions to avoid the dimension disaster caused by traditional discretization.

This paper proposes a hybrid optimization framework to address this critical limitation. By integrating the rapid response capabilities of DRL with the precise constraint-handling rigor of Mixed-Integer Linear Programming (MILP), the framework simultaneously ensures solution feasibility and meets the time-sensitive demands of real-time scheduling. This synergistic approach addresses the computational efficiency bottleneck inherent in traditional MILP while circumventing the constraint-handling deficiencies of standalone DRL. Consequently, it provides a more robust and reliable solution for the real-time optimal scheduling of microgrids.

2. Methodology

The main technical route of this study is shown in Figure 2.

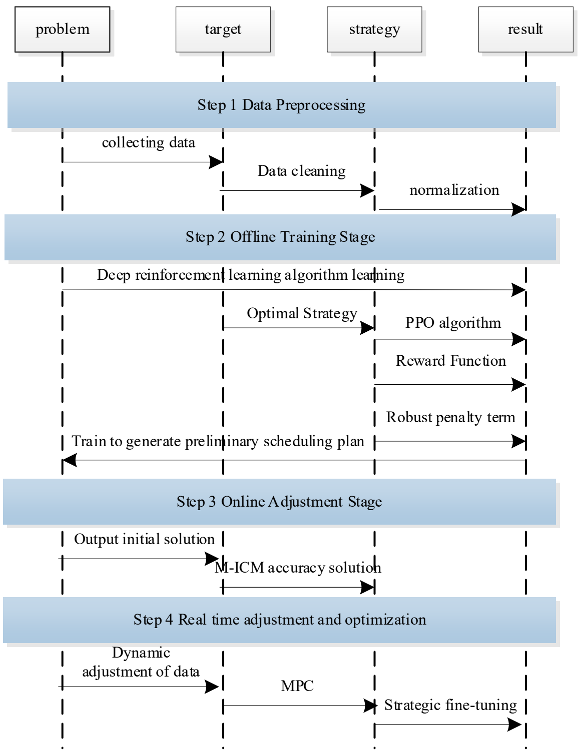

Figure. 2. Technical flow chart

(1) Data preprocessing, namely, cleaning, normalizing, and other preprocessing operations are carried out on the collected data of photovoltaic power generation, load demand, energy storage state, and the like.

(2) In the offline training stage, the DRL algorithm is used to learn the optimal strategy. The reward function of the improved PPO algorithm is designed, and the economic objective and the robust penalty term are considered comprehensively. A preliminary schedule scheme is generated through the train.

(3) In the online adjustment stage, the DRL output is used as the initial solution, and the accuracy is solved by M-ICM.

(4) Perform real-time adjustment and optimization, namely dynamically adjusting that schedule scheme according to the real-time data. MPC is used to adjust in real-time and fine-tune the strategy.

2.1 PV-energy storage control strategy

During the transmission of the system based on the operation of the photovoltaic microgrid, the grid considers the stability of the new energy, combines with the power consumption environment, and has a controllable principle for the output of the microgrid. Therefore, it is necessary for the new energy island to adapt to peak shaving to ensure the stability of the overall operation of the grid [24]. At present, the existing methods are limited to traditional robust optimization, which is highly conservative and may sacrifice economy; it is difficult to deal with high-dimensional nonlinear constraints. If pure reinforcement learning lacks an explicit constraint processing mechanism, it may violate physical constraints (such as energy storage SOC boundary). The output peak shaving model is displayed in Figure 3.

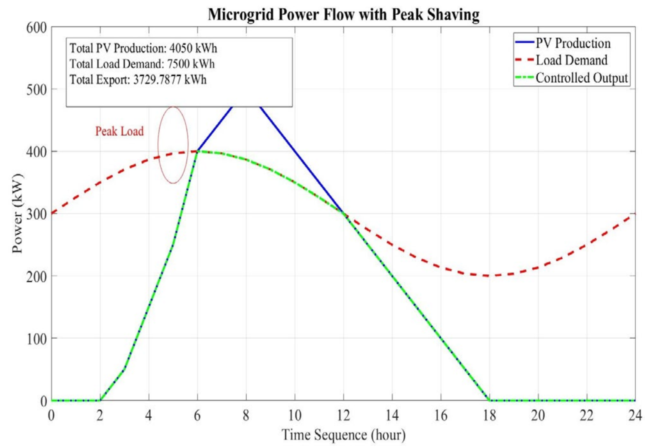

Figure. 3. Output peak regulation model of photovoltaic microgrid-This is based on simulation data. (Data from: SolarGIS dataset, https://solargis.com/).

In the proposed photovoltaic microgrid output peak shaving model, the red dotted line represents the traditional robust optimization boundary, and the blue solid line represents the multi-dimensional uncertainty description of M-ICM.

The emergence of microgrid technology has established a more efficient technical pathway for renewable energy generation [25]. To face the challenges posed by the inherent uncertainty of renewable energy output, this study investigates the application of hierarchical hybrid architecture neural network models in photovoltaic (PV) microgrid systems and proposes a dynamic load regulation strategy based on a mixed-integer constrained optimization framework. The regulatory model process is shown in Figure 4.

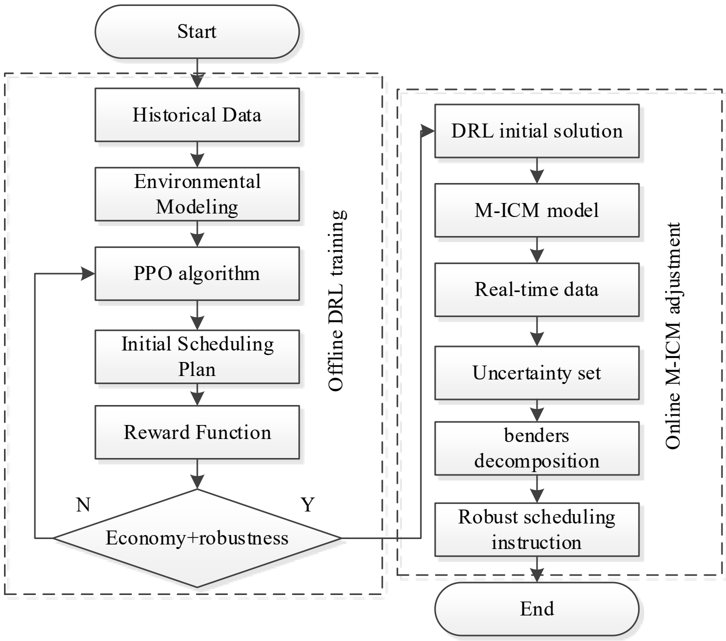

Figure. 4. PV-energy storage regulation and control model process

When resolving energy storage scheduling challenges in distributed neural network models for PV systems, the integration of enhanced Distributionally Robust Optimization (DRO) with hierarchical hybrid architecture presents complementary advantages in addressing multidimensional data challenges associated with probabilistic distributions:

(1) Offline training phase: The Proximal Policy Optimization (PPO) algorithm in Deep Reinforcement Learning (DRL) is utilized to learn optimal strategies under dynamic microgrid environments, generating preliminary scheduling schemes. The reward function incorporates economic objectives with robustness penalty terms through systematic design.

(2) Online adjustment phase: DRL outputs serve as initial solutions for the Mixed-Integer Constrained Model (M-ICM), with Benders decomposition employed for precision solution derivation. Robustness constraints are incorporated to mathematically characterize uncertainty sets encompassing PV generation and load fluctuations.

This methodology not only enhances operational accuracy but also demonstrates global optimality characteristics. To minimize equipment adjustment costs, policy-constrained fine-tuning of multidimensional models ensures secure and stable system operation under fuzzy distribution conditions [26]. Through the application of DRL duality principles, the multidimensional model is subsequently transformed into transfer functions, thereby streamlining the problem-solving process.

The proposed DRL model architecture incorporates predictive state-space representations of PV microgrids, accounting for critical operational indicators including load demand, energy storage state of charge (SOC), and electricity pricing mechanisms. Execution strategies are formulated for both continuous action spaces (energy storage charge/discharge operations) and discrete action domains (islanding mode transitions) [27].

2.2 Objective function framework

The objective composite function of PV energy storage-islanding includes two parts: minimizing the fluctuation of load capacity and minimizing the operation cost [28]. Robust optimization is introduced for specific analysis, and the implementation idea of robust optimization is shown in Figure 5.

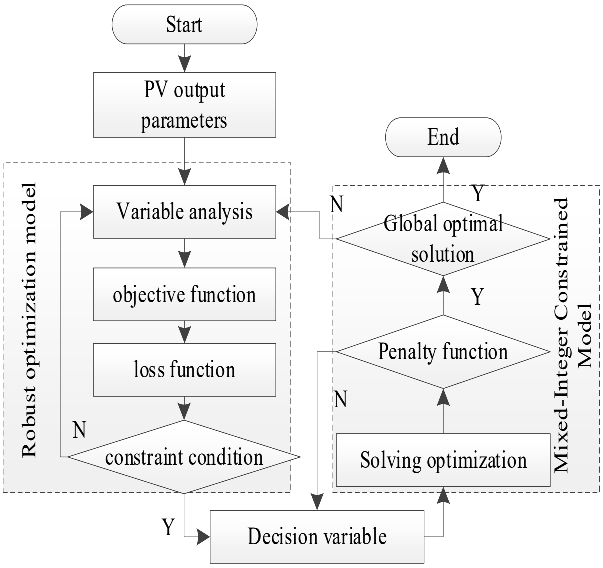

Figure. 5. Robust optimization model.

Penalize the violation of the running cost constraint through the adaptive weight coefficient of the reward function. Then, the mixed integer constraint is modeled, and the objective function is as follows:

$$\min \sum_{t=1}^{T} \left(c_i P_i + c_j P_j \right) + \gamma \cdot \mathrm{W} \tag{1}$$

In the formula, c is the reward function, p is the constraint objective, i, j are the reward and penalty weight coefficients respectively, and W is the conditional value to enhance the robustness.

Data-driven fuzzy set description is used to deal with the uncertainty of photovoltaic:

$$\mathrm{U} = \left\{ \tilde{P}_{PV,t} \middle| \left| \tilde{P}_{PV,t} - \hat{P}_{PV,t} \right| \le \Delta_{PV,t} \right\} \tag{2}$$

In the formula, u is the load uncertainty, and the robustness of the DRL strategy is enhanced through the countermeasure training $\tilde{P}_{PV,t}$.

Considering that the fluctuation of the load capacity is different from the function of reducing the operation cost, the formula of the overall target composite function is converted:

$$\begin{cases} u^{\min} \ge 0 \\ \Delta p_i > \Delta p_j \end{cases} \tag{3}$$

$$\delta_{v,s,q,r}^{i,j} = \begin{cases} \delta_v = \sum_{i,j} v_i^{\alpha \leftarrow \beta} + v_j^{\alpha \leftarrow \beta} \\ \delta_s = \sum_{i,j} s_i^{\alpha}(\phi) + v_j^{\beta}(\phi') \\ \delta_q = \sum_{i} q_i(\alpha) - q_j(\beta) \\ \delta_r = \sum_{i} r_i(\alpha, \beta) + r_j(\alpha, \beta) \end{cases} \tag{4}$$

In the formula, $\delta_{v,s,q,r}^{i,j}$ is the operation cost of distributed photovoltaic microgrid, where v is the cost of photovoltaic power generation, s is the cost of sales, q is the cost of energy storage, and r is the cost of operation and maintenance; α, β are the electricity prices of islanding and grid-connected respectively, and ϕ, ϕ' are the unit price of electricity purchase at the peak and valley of the grid respectively [29]. Simulation and performance verification

3. Simulation and performance verification

3.1 Simulation environment settings

The algorithm performance is verified by the simulation platform (OPAL-RT + MATLAB/Simulink), and the hardware configuration is shown in Table 3.

Table 3. Hardware environment configuration.

Components	Specification
Computing host	Intel Xeon W-2295 (18 cores, 36 threads) / NVIDIA RTX A6000 (48GB video memory)
Real-time simulator	OPAL-RT OP4510 + FPGA expansion module
Power hardware	Chroma 61845 PV array simulator + Keysight BT3554A Battery Tester
Monitoring equipment	NI PXIe-5171R High speed data acquisition card (1MS/s Sampling rate)

The simulation platform adopts Python + Pyomo for MIP solution, and the simulation environment is shown in Table 4:

Table 4. Configuration of the simulation environment.

Structural layer	Application	Indications
Hardware Layer	OPAL-RT	Real-time Linux
	NI LabVIEW 2023	Equipment control

Middleware Layer	Docker Container 1	Python 3.9 + Pyomo 6.4.3
		Gurobi 10.0 (MIP solver)
	Docker Container 2	PyTorch 2.1 + CUDA 12.1
		Custom Gymnasium 0.29
Application Layer	Scenario Generator	Wright-Fisher
	Hybrid Solver Router	MIP/DRL Dynamic switching logic
	Resilience Analyzer	Disturbance resistance evaluation

This study is based on a high-fidelity simulation environment (including real-time hardware-in-the-loop testing), and will be extended to the actual microgrid system verification in the future.

3.2 Experimental comparison test

(1) Algorithm performance comparison

To verify the optimization effect of M-ICM used in this paper on DRO, the Gurobi algorithm of a single MILP model [28], the DDPG algorithm of a DRL model [29] and the traditional TSRO (Two-Stage Robust Optimization) [30] are used for comparative testing. The comparison benchmark is calculated for the PV-energy storage DERS in the simulation model, and the calculation accuracy is obtained for comparison. The results are shown in Table 5 and Figure 6.

Table 5. Indicators' test results.

Indicators	Method in the study	Pure MILP	Pure DRL	TSRO
Average cost ($/day)	152.3	148.7	165.2	160.8
Constraint violation rate (%)	0	0	12.5	3.2
Calculation time (s/step)	1.8	45.2	0.3	30.1

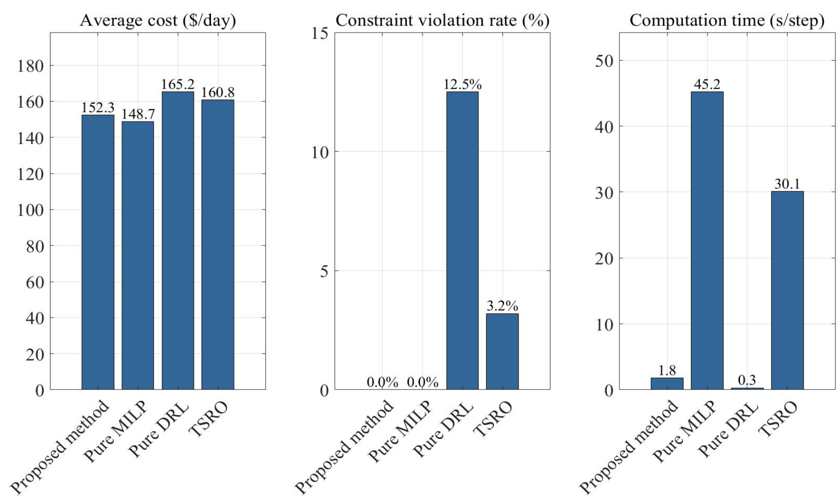

Figure. 6. Comparative analysis of the algorithm performance.

In the evaluation of the DERS metrics, the proposed DRO-integrated enhancement has shown a 20-fold improvement in computational efficiency compared to MILP while maintaining constraint-compliant execution strategies, coupled with an 8.25% cost reduction relative to pure DRL implementations. All results meet the criteria for the best global optimal solution, thus showing greater suitability for the phased robust operational demands of PV-ESS systems.

(2) System dispatch response test

To verify the technical advancement and DRO optimization level of the proposed M-ICM strategy, a PV-energy storage system model was constructed on the Simulink platform.

Comparative analyses of regulation performance among MILP, DRL, and TSRO methodologies are presented in Figure 7.

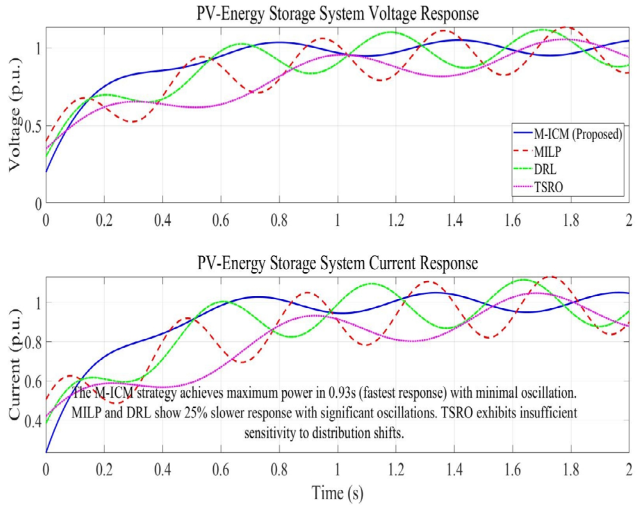

Figure. 7. System dispatch response test.

Through comparative analysis of voltage and current responses in PV-energy storage systems, it is evident that all control systems achieve dynamic equilibrium, successfully attaining maximum power output. The proposed methodology has shown superior performance with a 0.93-second transition from normal startup to maximum power output, exhibiting minimal overshoot and low-amplitude oscillations in photovoltaic voltage, current, and rated power output. This indicates enhanced dynamic equilibrium quality. Comparatively, MILP (Mixed Integer Linear Programming) and DRL (Deep Reinforcement Learning) methods exhibit over 25% inferior performance with significant oscillations, primarily attributable to training complexity and excessive conservatism in control strategies. Although TSRO (Two-Stage Robust Optimization) incorporates secondary dynamic adjustments, its insufficient sensitivity to distribution shifts results in suboptimal performance.

The operational principle of the Distributed Energy Resource System (DERS) architecture is elucidated through comparative analysis with conventional approaches. A three-dimensional coupled model of photovoltaic-energy storage DERS is established in MATLAB/Simulink simulation environment. Experimental verification confirms DERS' superior autonomous secondary output variable coverage compared with traditional grid-connected PV-energy storage systems. The developed three-dimensional model shows consistency with mechanistic analysis, achieving robust optimization across operational phases and validating adaptive control capabilities.

4. Conclusion

In this paper, according to the state of photovoltaic new energy and energy storage, it is divided into different zones, and a two-dimensional dynamic load reduction strategy is designed according to the zones to consider the state of different illumination stages. Based on the mixed integer constraint model, the coupling system of photovoltaic energy and model constraint strategy is designed, considering the discrete analysis of light intensity and time domain changes, as well as the evolution trend of energy storage charging and temperature variables. The model evolution effect is shown in Figure 8.

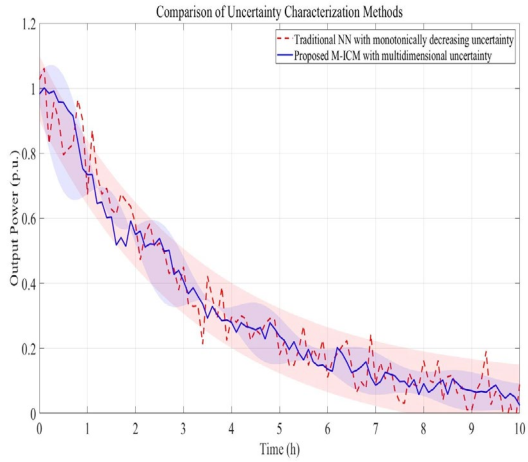

Figure. 8. M-ICM and effect of traditional model evolution-This drawing is based on simulation data. (Data from: SolarGIS dataset, https://solargis.com/)

In Figure 7 : (1) Traditional method with simple decreasing uncertainty (red dashed line with red shaded area); (2) The paper method with complex multidimensional uncertainty (blue solid line, blue shadow area)

This study integrates the deterministic characterization of monotonically decreasing sets into the M-ICM framework, which spatially represents the operational unpredictability and nuanced variations inherent to islanding operations. The proposed methodology empowers multidimensional modeling to delineate uncertainties embedded within multiple monotonically decreasing trends, thereby enhancing the precision in quantifying computational feasibility boundaries. Furthermore, through a comprehensive analysis of multi-source, intricate uncertainties arising during monotonic decay processes, decision-makers' adaptive capabilities are significantly strengthened through improved scenario awareness.

Future research directions will focus on game-theoretic interactions and cooperative optimization among multiple microgrids. Transfer learning techniques will be employed to adapt pre-trained control strategies to microgrids in diverse climatic zones. Real-time control validation will be conducted through RT-LAB platform integration to enhance photovoltaic microgrid robustness against environmental variability.

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