RESEARCH ARTICLE

A Digital-Twin-Driven Cyber–Physical Framework for Real-Time Energy Management and Secure Operation of Renewable Energy Systems

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Abstract

Real-time optimal operation and control acts as the intelligent core of renewable energy systems, yet intermittent generation and time-varying loads introduce uncertainties that hinder secure and efficient operation. To address this issue, this paper proposes a digital-twin-driven cyber–physical framework for real-time energy management and secure operation, enabling tight synchronization and closed-loop interaction between physical assets and their digital counterparts. A simplified multi-source data fusion Transformer is developed to improve forecasting accuracy by continuously integrating historical power data and key environmental factors (e.g., temperature, wind speed, and solar radiation). Based on the twin-enabled predictive information and state feedback, a Transformer–Adaptive Dynamic Programming (TM-ADP) method is further proposed for real-time optimal scheduling of grid-connected renewable energy systems. In addition, a YOLOv8-based multi-target detection module is incorporated to enhance operational safety through intelligent visual monitoring of photovoltaic panels. Experiments on a digital twin platform validate that the proposed framework improves operational efficiency, reliability, and safety under uncertain operating conditions.

Keywords: digital twins, cyber–physical fusion prediction, real-time management, secure operation.

1 Introduction

With the large-scale integration of intermittent renewable energy sources, dynamic loads, and energy storage systems, the energy flow and information flow in microgrids and integrated energy systems have become highly coupled. Related studies indicate

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that, for practical operation, energy management and control must simultaneously achieve economic efficiency and reliability under strong nonlinearity, stringent real-time requirements, and pervasive uncertainties, which continues to challenge accurate modeling, optimization, and control [1]. In broader contexts involving intelligent systems, energy management, and cyber–physical security, real-time scheduling often relies on sensing, communication, and data-driven decision-making, and adaptive dynamic programming methods have also been explored to improve real-time control performance and operational adaptability [2, 3] Meanwhile, digital twin techniques applied to renewable energy grids leverage artificial intelligence to enhance energy management, providing a virtual counterpart that continuously mirrors the physical system [4], while digital twin-based attack detection and mitigation for PV smart systems, enabled by hybrid machine learning algorithms, provides essential support for trustworthy operation [5] As a result, more adaptive learning- and data-driven methods are increasingly regarded as key choices for coping with operational fluctuations and uncertainty.

Data-driven forecasting networks can directly extract informative features from historical and real-time data, thereby providing prior knowledge for subsequent scheduling and control. Multifactor and multiscale load forecasting models can characterize load variation patterns in a finer-grained manner [6], and hourly rooftop photovoltaic (PV) power prediction that combines physical mechanisms with meteorological forecasting can improve responsiveness to external disturbances [7]. In the operational monitoring of photovoltaic systems, vision-based defect detection methods that combine infrared thermal imaging with deep learning object detection networks are able to accurately identify panel faults from image data [8] In addition, certain energy management systems adopt improved swarm-intelligence optimization to enable online decision-making, where forecasting modules are typically used to provide short-term trend information [9]. Nevertheless, such forecasting networks remain sensitive to data quality and exogenous factors; when operating conditions or data distributions shift, their performance may fluctuate, which in turn can weaken their coordination with real-time control.

Beyond accurate forecasting, real-time optimization and control are equally crucial to ensure the safe and economical operation of renewable-energy-based systems. Distributed robust model predictive control (MPC) has been applied to the energy management of islanded multi-microgrids with explicit consideration of uncertainty [10], and heuristic optimization methods tailored to digital-twin settings offer implementable pathways for control and dispatch [11]. From a data-driven perspective, reinforcement learning (RL) and approximate dynamic programming have been employed for microgrid real-time energy management and economic dispatch under uncertainty [12], while safe RL emphasizes satisfying operational constraints and security objectives at the distribution-network level [13]. However, to address the challenges arising from increasing system complexity and uncertainty on both the supply and demand sides, RL-based control still requires further improvements in both theoretical foundations and practical implementation.

To overcome these limitations, cyber–physical integration frameworks enabled by digital twins have emerged as a promising solution. By establishing real-time synchronization and closed-loop interaction between physical energy systems and their informational counterparts, digital twins provide a unified platform for perception, prediction, and control. Building on this paradigm, this paper proposes a Transformer-based Adaptive Dynamic Programming (TM-ADP) framework that integrates multi-source data fusion, real-time optimal scheduling, and operational monitoring within a digital twin environment. The proposed framework enables efficient and secure real-time energy management of renewable energy systems under uncertainty, as validated through a digital twin platform. The major innovations and contributions of this work are summarized as follows:

1. A Transformer-based adaptive dynamic programming (TM-ADP) scheduling framework is developed, which integrates cyber and physical factors to improve prediction accuracy and enhance the adaptability of real-time energy management under uncertain operating conditions.

2. A YOLOv8-based real-time monitoring strategy is proposed for anomaly detection, enabling timely identification of faults and ensuring the secure operation of PV systems.

3. A digital twin verification platform is constructed to validate the proposed framework, confirming its superiority in operational efficiency, reliability,

Table 1. List of Symbols.

Symbol	Description
k	Discrete time index.
$P_{\mathrm{PV},k}^{l}$	Power of the l-th PV unit at time k.
$P_{L,k}^{m}$	Power of the m-th load.
$P_{\mathrm{Ba},k}^{n}$	Charging/discharging power of the n-th battery.
x_k	State vector at time k.
x_{k+1}	State vector at time k+1.
$u(\cdot)$	Control policy.
$u^*(\cdot)$	Optimal control policy.
$\underline{\mathbf{u}}_k$	Control action at time k.
$E_{\mathrm{Ba},k}$	Battery energy at time k.
E_{B}	Baseline energy.
$E_{\mathrm{Ba}}^{\max}$	Rated maximum battery energy.
$E_{\mathrm{Ba}}^{\min}$	Rated minimum battery energy.
$J(\cdot)$	Performance index function.
$U(\cdot)$	Immediate cost function.
$f_{1,k},\ f_{2,k}$	Sub-terms of the performance index at time k.
$l_1,\ l_2,\ \varepsilon$	Weights in the performance index.
γ	Discount factor in ADP.
$\psi(\cdot)$	Initial value function.
L_{CIoU}	Complete IoU loss.
IoU	Intersection over Union.
$\mathbf{b}$	Predicted bounding box.
$\mathbf{b}^{gt}$	Ground-truth bounding box.
$\rho^2(\cdot)$	Squared center distance term.
c	Diagonal length of the smallest enclosing box.
α	Weight factor for the aspect-ratio term.
v	Aspect-ratio consistency term.

and system security.

The organization of this paper is as follows. Section II introduces the problem formulation. Section III presents the proposed TM-ADP framework. Section IV describes the digital twin platform and the YOLOv8-based monitoring mechanism. Section V provides the experimental analysis. Finally, Section VI concludes the paper.

2 Problem Statement

2.1 Descriptions of the Renewable System

As shown in Figure 1, the renewable energy system consists of solar generation, loads, the main grid, an energy storage system, and an energy management system. According to the law of energy conservation, it satisfies:

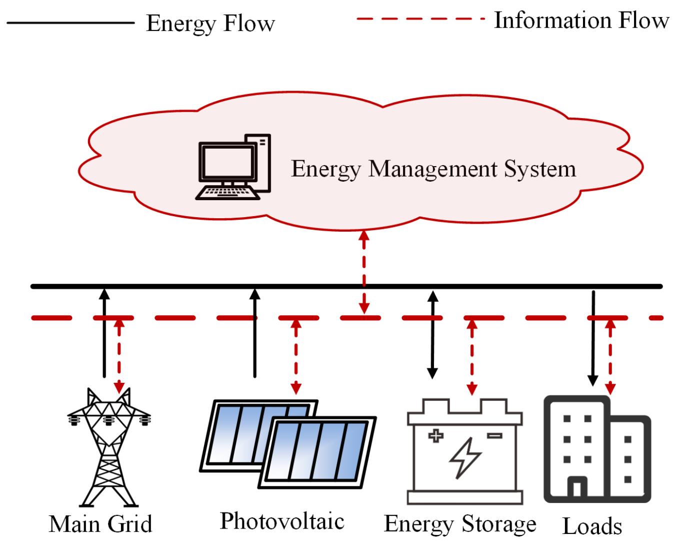


Figure 1. The architecture of renewable system.

$$\sum_{l=1}^{L} P_{\mathrm{PV},k}^{l} + P_{G,k} = \sum_{m=1}^{M} P_{L,k}^{m} + \sum_{n=1}^{N} P_{\mathrm{Ba},k}^{n}, \tag{1}$$

where $P_{\mathrm{PV},k}^{l}$, $P_{L,k}^{m}$, and $P_{\mathrm{Ba},k}^{n}$ denote the power of the l-th PV panel, the m-th load, and the n-th battery at time k, respectively. A positive $P_{\mathrm{Ba},k}^{n}$ indicates charging, and a negative value indicates discharging.

The statement of renewable system is as follows:

$$x_{k+1} = f(x_k, \underline{u}_k), \quad k = 0, 1, 2, \ldots, \tag{2}$$

with state vector $\mathbf{x}_k = [x_{1,k}, x_{2,k}]^T$ and control input $\underline{\mathbf{u}}_k = (u_k, u_{k+1}, \ldots)$. Specifically,

$$x_{1,k} = P_{G,k} = P_{\mathrm{L},k} + P_{\mathrm{Ba},k} - P_{\mathrm{PV},k}, \tag{3}$$

$$x_{2,k} = E_{\mathrm{Ba},k} - E_{\mathrm{B}}, \quad E_{\mathrm{B}} = \frac{1}{2}\left(E_{\mathrm{Ba}}^{\max} + E_{\mathrm{Ba}}^{\min}\right), \tag{4}$$

where $u_k = P_{\mathrm{Ba},k}$ is the battery charging/discharging action, $E_{\mathrm{Ba},k}$ denotes the battery energy at time k, and $E_{\mathrm{Ba}}^{\max}$ and $E_{\mathrm{Ba}}^{\min}$ are the rated maximum and minimum energy levels, respectively.

2.2 Optimization Objective and Performance Function

The performance function, denoted by J is mathematically defined as:

$$\begin{aligned} J(x_k, \underline{u}_k) &= \sum_{t=k}^{\infty} \gamma^{t-k}(f_{1,k} + f_{2,k} + \varepsilon \underline{u}_k^2) \\ &= \sum_{t=k}^{\infty} \gamma^{t-k}(l_1 x_{1,k}^2 + l_2 x_{2,k}^2 + \varepsilon \underline{u}_k^2) \\ &= \sum_{t=k}^{\infty} \gamma^{t-k} U(x_t, \underline{u}_t) \end{aligned} \tag{5}$$

where $x_{1,k} = P_{G,k} = P_{L,k} + P_{\text{Ba},k} - P_{\text{PV},k}$ represents the net power exchanged with the main grid, and $x_{2,k} = E_{\text{Ba},k} - E_{\text{B}}$ denotes the deviation of the battery energy from its reference. Here, l_1 and l_2 are weighting coefficients, and $\gamma \in (0, 1]$ is the discount factor.

The objective of $f_{1,k} = l_1 x_{1,k}^2$ is to maximize PV power utilization by minimizing the main grid output, while $f_{2,k} = l_2 x_{2,k}^2$ penalizes overcharging or over-discharging of the energy storage system.

3 Optimization of TM-ADP control methods

3.1 Transformer Model

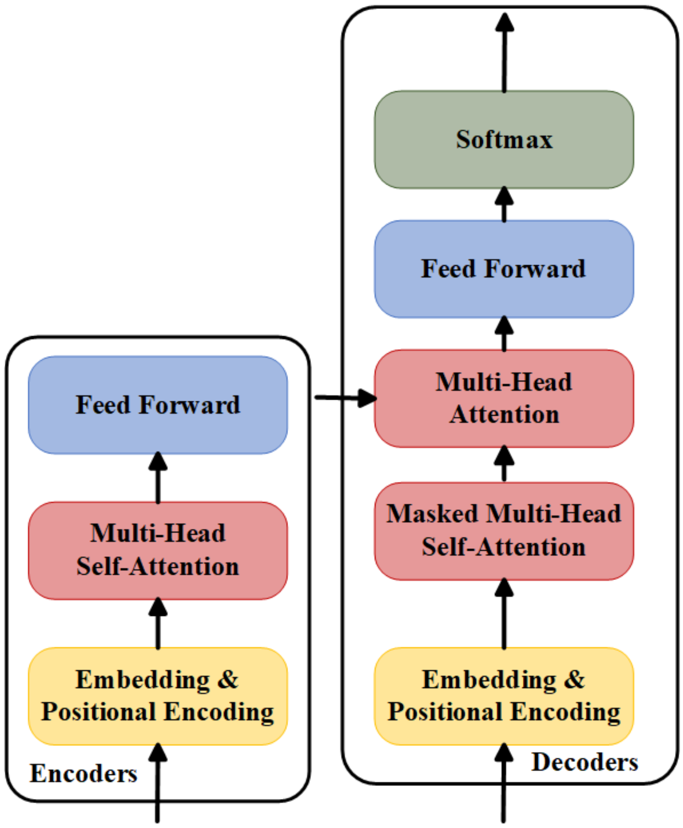


Figure 2. The architecture of Simple Transformer.

Solar generation and load electricity consumption are predicted using the Simple Transformer prediction network of the transformer paradigm. The Simple Transformer (TM) is a neural network architecture. The Simple Transformer replaces recurrent and convolutional operations with a self-attention mechanism, allowing each token to simultaneously consider all others. This design enables parallel computation and effectively captures long-range dependencies. As depicted in Figure 2, the architecture consists of two main modules: an encoder and a decoder. The encoder maps the input sequence to latent representations using multi-head self-attention and a feed-forward network, while the decoder generates the output sequence through masked self-attention, encoder-decoder attention, and a feed-forward network. The central operation is the scaled dot-product attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{6}$$

where Q, K, and V are the query, key, and value matrices, and d_k is the key dimension.

The key settings of the Transformer-based prediction tasks are summarized in Table 2.

Table 2. Input/output settings of the Transformer-based prediction tasks.

Task	Item	Description
PV	Input variables	Barometric pressure
		Global radiation
		Diffuse radiation
		Ambient temperature
		Historical PV generation
		year, month, day, hour, and minute
	Output variable	PV generation
	History length	16 steps (4 h)
	Forecast length	1 step ahead (15 min)
Load	Input variables	Ambient temperature
		Real-time electricity price
		Historical load consumption
		year, month, day, hour, and minute
	Output variable	Load consumption
	History length	16 steps (4 h)
	Forecast length	1 step ahead (15 min)

3.2 Transformer-based Adaptive Dynamic Programming

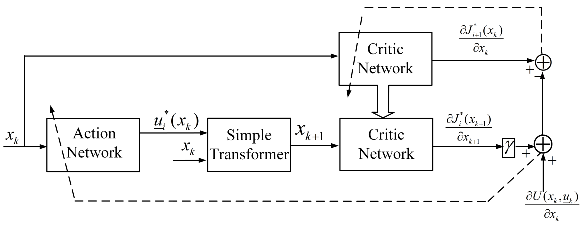


Figure 3. The iteration process of Simple Transformer Adaptive dynamic programming.

Transformer-based adaptive dynamic programming (TM-ADP) is an extension of the basic Adaptive Dynamic Programming (ADP). The ADP algorithm adaptively adjusts the control strategy to make it close to the optimal control strategy of the traditional dynamic programming method. With its strong advantages in solving nonlinear optimal control, it has received widespread attention in recent years in the optimization of energy management system operation control. The framework of TM-ADP is shown in Figure 3. It uses the function generalization ability of neural networks to estimate control performance indicators or their partial derivatives. In conventional ADP, the critic network approximates the value function, while action selection is handled via an external optimization procedure. TM-ADP improves this scheme by embedding the action variables directly into the critic's input, enabling joint evaluation of state-action pairs.

3.2.1 Critic Network Training

The critic network estimates performance function values through supervised learning. In this study, it is trained using the backpropagation algorithm, with a configuration of five input neurons, one output neuron, and 200 hidden neurons. The network output is formally defined as:

$$J_k^*(x_k) = W_{\mathrm{c},k}^T \phi_c(x_k), \tag{7}$$

where $W_{\mathrm{c},k}$ represents the weight coefficients of the Critic network, updated iteratively via the following formula:

$$W_{\mathrm{c},(k+1)} = W_{\mathrm{c},k} - \alpha_{\mathrm{c}} \frac{\partial e_{\mathrm{c},k}}{\partial W_{\mathrm{c},k}}. \tag{8}$$

α_{c} is the network learning rate, and $e_{\mathrm{c},k}$ is the network error, defined as:

$$\boldsymbol{e}_{\mathrm{c},k} = \frac{1}{2}[J_{(k+1)}^*(x_k) - J_{(k+1)}(x_k)]^2. \tag{9}$$

3.2.2 Action Network Training

Once the critic network is trained, the action network is subsequently optimized by minimizing $U(x_k + \gamma J^*(x_{(k+1)}))$ using BP, thereby approximating the optimal control policy $u^*(x_k)$. The action network consists of four input neurons, one output neuron, and 200 hidden neurons. Guided by the critic network's outputs, the action network parameters are updated via gradient descent as follows:

$$u^*(x_k) = W_{\mathrm{a},k}^T \phi_a(x_k). \tag{10}$$

The update formula for the execution network weights $W_{\mathrm{a},k}$ is:

$$W_{\mathrm{a},(k+1)} = W_{\mathrm{a},k} - \alpha_{\mathrm{a}} \frac{\partial e_{\mathrm{a},k}}{\partial W_{\mathrm{a},k}}, \tag{11}$$

where α_{a} is the learning rate of the execution network, and $\boldsymbol{e}_{\mathrm{a},k}$ is the execution network error, defined as:

$$\boldsymbol{e}_{\mathrm{a},k} = \frac{1}{2}[u^*(x_k) - u(x_k)]^2. \tag{12}$$

After completing the training of the critic network, the performance of the energy management system can be evaluated.

3.2.3 Value Iteration

In the TM-ADP algorithm, each iteration updates the value function and control rule. Let the initial value function be:

$$J^*(x_k) = \psi(x_k), \tag{13}$$

where $\psi(x_k)$ can be any positive semi-definite function. The iterative control policy $u_0^*(x_k)$ can be obtained by:

$$u_0^*(x_k) = \arg\min_{u_k} U(x_k, u(x_k)) + \gamma J_0^*(\hat{x}_{(k+1)}), \tag{14}$$

where $J_0^*(\hat{x}_{(k+1)}) = \Psi(\hat{x}_{(k+1)})$. The update formula for function J^* is given by:

$$J_1^*(x_k) = U(x_k, u^*(x_k)) + \gamma J_0^*(\hat{x}_{(k+1)}). \tag{15}$$

For $i = 1, 2, \ldots$, the iteration process for value iteration is

$$u_i^*(x_k) = \arg\min_{u(x_k)} U(x_k, u(x_k)) + \gamma J_i^*(\hat{x}_{(k+1)}). \tag{16}$$

$$J_{i+1}^*(x_k) = U(x_k, u^*(x_k)) + \gamma J_i^*(\hat{x}_{(k+1)}). \tag{17}$$

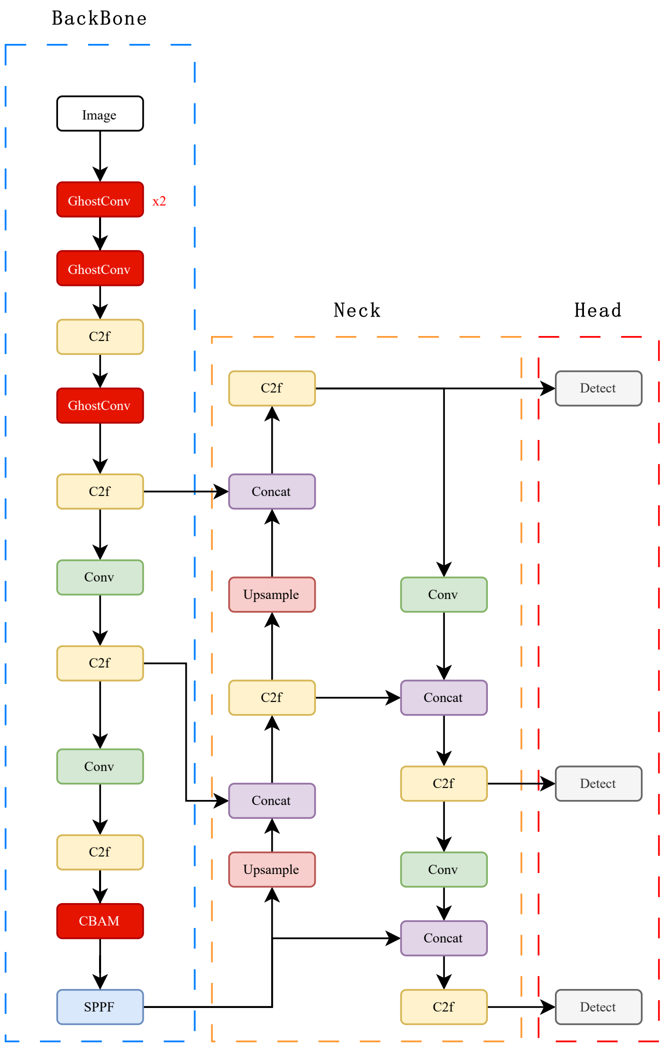


Figure 4. The structure diagram of YOLOv8.

4 Renewable Energy Management System

4.1 Digital Twin Platform

A Digital Twin is a virtual representation of a physical entity within a digital environment, integrating multi-source data, computational models, algorithms, and real-time interactions to enable comprehensive perception, simulation, prediction, and optimization of physical assets, processes, or systems. As shown in Figure 5, the renewable energy management system comprises three interconnected modules: prediction, control, and monitoring. The prediction module leverages a transformer-based model to fuse barometric pressure, global and diffuse radiation, ambient temperature, historical PV generation, and temporal features, providing accurate forecasts of PV output and load demand. The control module implements the TM-ADP algorithm for real-time energy scheduling, while the monitoring module employs the YOLOv8 model to visualize and detect defects in solar PV panels.

In the implemented digital twin platform, the physical layer consists of the renewable energy system, including PV generation units, load demand, the main grid, and the energy storage system, while the digital layer contains the corresponding data-driven prediction model, system state model, TM-ADP controller, and visual monitoring model. During operation, the platform acquires multi-source information from the physical side, including PV power, load power, battery charging/discharging power, battery energy/SOC, electricity price, meteorological variables, and PV panel images. These data are used to update the digital state vector and provide real-time inputs for the prediction, control, and monitoring modules.

The platform adopts a multi-time-scale communication mechanism. The control sampling period is set to 1 ms for fast dynamic variables, the communication period of the energy management layer is set to 100 ms for state updating, forecasting, optimization, and control decision-making, and the meteorological data are updated every 15 min. The digital model is updated through real-time state correction, rolling parameter updating, and event-triggered structural adjustment. At each energy management sampling period, newly collected measurements are uploaded to the digital layer to correct the current system state. The forecasting model then generates predictive information, which is combined with real-time state feedback and sent to the TM-ADP controller. The controller calculates the optimal battery charging/discharging command and feeds it back to the RT-LAB-based physical renewable energy system model for execution. When the system evolves to the next time step, newly collected measurements are again used to replace the predicted states and update the digital model, thereby avoiding open-loop drift between the physical system and its digital counterpart. Meanwhile, the YOLOv8-based monitoring module processes PV panel images in the digital layer and provides defect detection results for operational safety assessment. Through this repeated process of data acquisition, state updating, forecasting, control decision-making, and feedback execution, the platform realizes closed-loop real-time cyber–physical interaction at the energy management level.

4.2 YOLOv8-based monitoring strategy

The YOLOv8 model conceptualizes object detection as a single-stage regression task, simultaneously

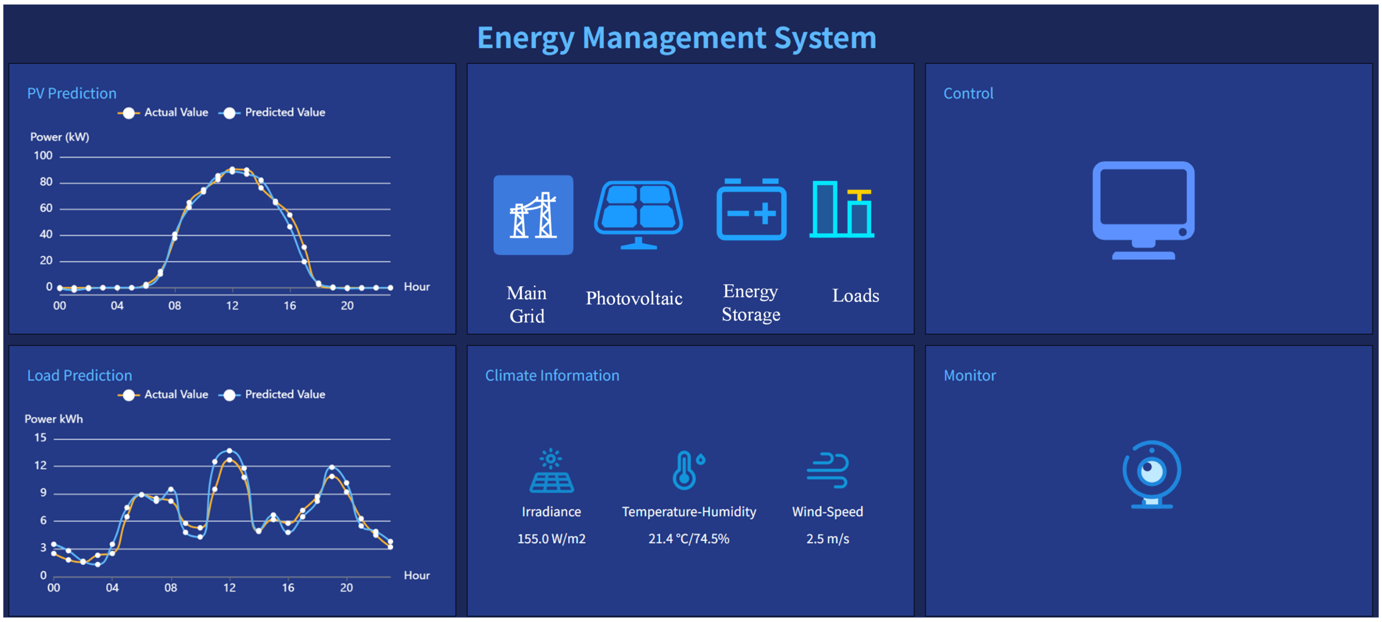


Figure 5. Renewable Energy Management System.

predicting bounding box coordinates, object classes, and associated probabilities, enabling fast and efficient detection. Building upon the strengths of previous YOLO architectures, YOLOv8 represents one of the most advanced object detection networks currently available. In this study, the model is applied to train, evaluate, and visualize a solar PV panel defect dataset, identifying six defect categories: bird droppings, clean panels, dirt accumulation, electrical damage, physical damage, and snow cover. Its stability, generalization ability, accuracy, and computational efficiency make YOLOv8 particularly suitable for PV panel defect detection. The detailed parameter settings are listed in Table 3.

Following the standard YOLO input resolution of 640 × 640, Figure 4 illustrates the YOLOv8 architecture, which comprises three primary components: the backbone, the feature fusion network, and the prediction head. The backbone contains five Convolution-Batch Normalization-SiLU (CBS) modules that downsample feature maps five times, with the C2F module serving as the main feature extractor. The neck adopts the PANet structure, performing bidirectional feature fusion from top-down and bottom-up, and is connected to the backbone via skip connections and the SPPF module. The head outputs objects at three scales—large, medium, and small—through Detect modules with varying receptive fields. Each Detect module employs an anchor-free, decoupled head design: one branch predicts the bounding box coordinates (top-left and bottom-right corners), and the other predicts class probabilities.

Bounding box regression is typically optimized using the Complete IoU (CIoU) loss, defined as:

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(\mathbf{b}, \mathbf{b}^{gt})}{c^2} + \alpha v \tag{18}$$

where IoU is the Intersection over Union between the predicted box $\mathbf{b}$ and ground truth $\mathbf{b}^{gt}$. ρ^2 is the squared Euclidean distance between box centers, c is the diagonal length of the smallest enclosing box covering both $\mathbf{b}$ and $\mathbf{b}^{gt}$. v quantifies aspect-ratio consistency, and α is a weighting factor for the aspect ratio term.

Table 3. Parameter settings of the YOLOv8 model.

Parameter	Value
Model variant	YOLOv8n (Nano)
Pre-trained weights	`yolov8n.pt`
Backbone C2f units	[1, 2, 2, 1]
Neck C2f units	[1, 1, 1, 1]
Input resolution	640 × 640
Epochs	400
Batch size	32
Learning rate	0.01
Weight decay	0.0005

5 Results

5.1 Prediction results

The PV and load data are obtained from the Photovoltaic Output Dataset (PVOD) and the Open Power System Data (OPSD) dataset, respectively.

The one-day prediction results for solar power and load power are presented in Figures 6 and 7, respectively, with a sampling interval of 15 minutes. In both figures, the blue curves represent the actual values, whereas the red curves represent the values predicted by our proposed model. In addition, the quantitative comparison results of different prediction models are summarized in Table 4. The visual and quantitative results demonstrate that our proposed model can accurately track the variations in both PV generation and load demand, thereby providing reliable prediction information for subsequent energy management and control.

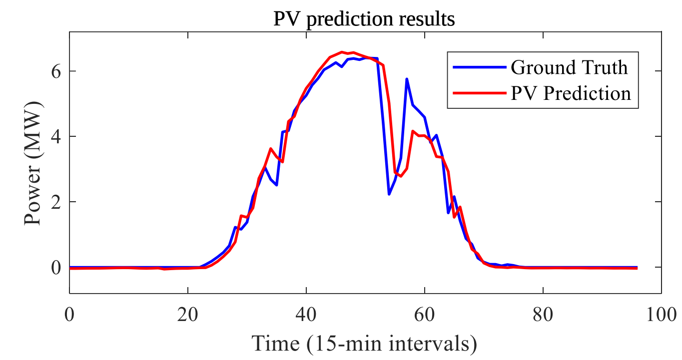


Figure 6. PV power prediction

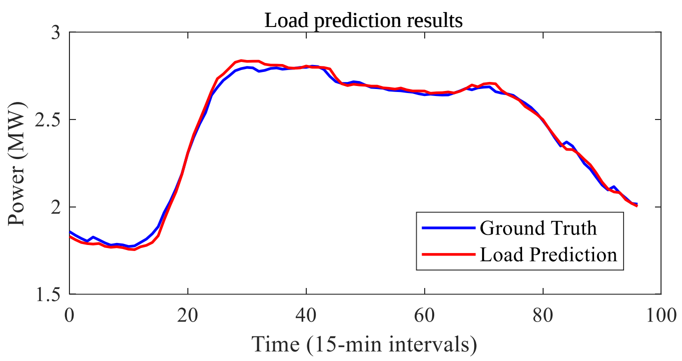


Figure 7. Load prediction

Table 4. Prediction results.

Model	LOAD		PV	
	MAE	MSE	MAE	MSE
CNN	0.1583	0.0438	0.3700	0.3666
LSTM	0.0641	0.0067	0.2160	0.2495
BiLSTM	0.0564	0.0053	0.2525	0.3329
GRU	0.0501	0.0043	0.2081	0.2144
Ours	**0.0416**	**0.0031**	**0.1774**	**0.1648**

5.2 Optimization control results

Figures 9 and 10 illustrate the performance of the proposed control strategy. In Figure 9, the blue line shows market electricity prices, the red line represents electricity costs under the ADP optimized control, and the green line corresponds to costs under the Constant Power Charging (CPC) strategy, demonstrating that the proposed strategy effectively reduces operational expenses. Figure 10 depicts the state variable dynamics: PV power generation (red), load consumption (green), and the energy storage State of Charge (SOC) trajectories (orange and blue). The results indicate that surplus PV generation during the day is utilized for charging the storage system, while discharging occurs at night to meet the load demand, ensuring efficient energy utilization and system operation. The quantitative optimization performance is summarized in Table 5.

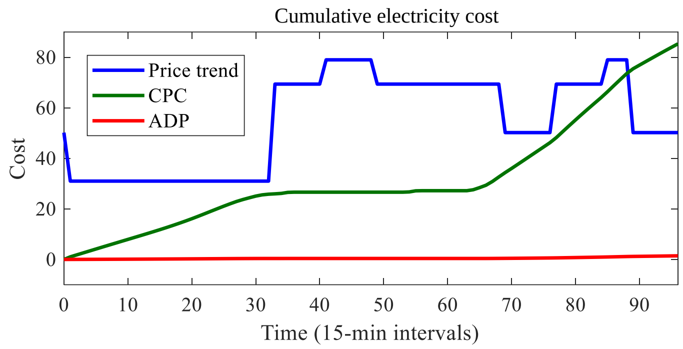


Figure 9. Cumulative electricity cost.

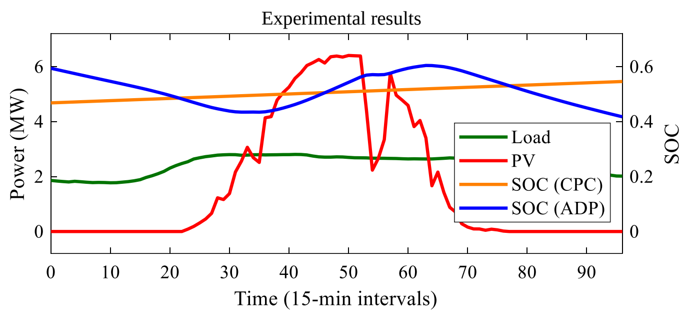


Figure 10. Experimental results.

Table 5. Optimization performance comparison.

Indicator	ADP	CPC	Comparison
PV utilization rate	99.31%	82.77%	+16.54 p.p.
Mean SoC	0.5148	–	–
Electricity cost	1.4321	85.3068	59.57× less

5.3 Safety monitoring results

The improved YOLOv8 model is employed in this study to perform multi-target detection on (PV) panels. The detection tasks include identifying various types of defects such as dust accumulation, physical damage,

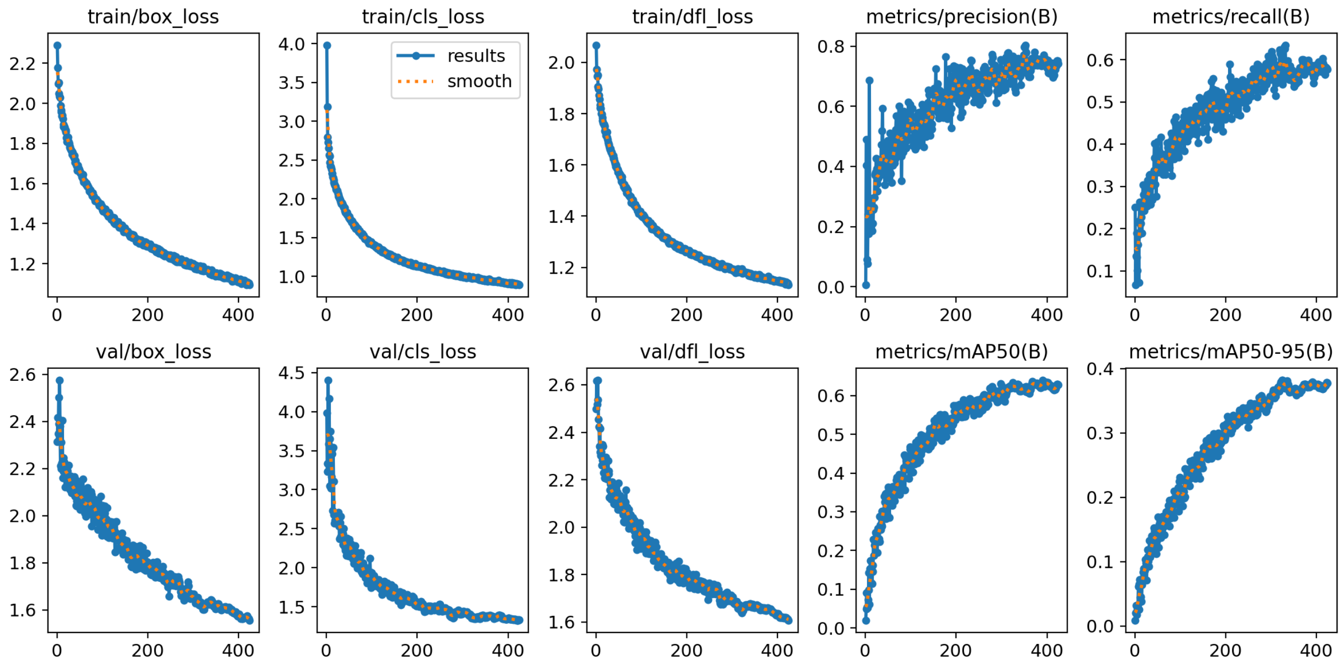


Figure 8. The results of YOLOv8.

snow cover, bird droppings, as well as distinguishing defect-free panels. In the network configuration, the number of $C2F_1$ bottlenecks in the backbone is set to 1, 2, 2, and 1, respectively, while the neck consistently employs a single $C2F_2$ bottleneck.

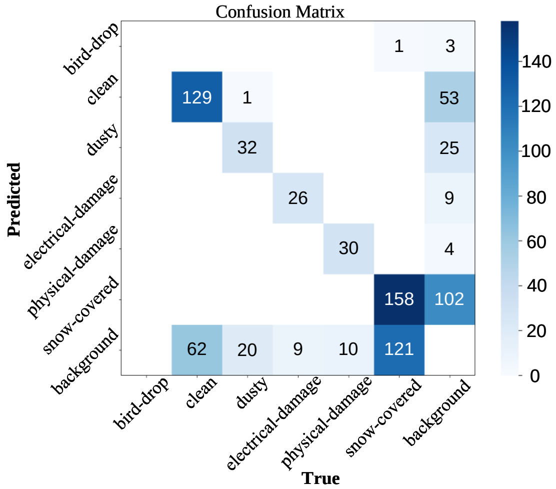


Figure 12. The confusion matrix of YOLOv8.

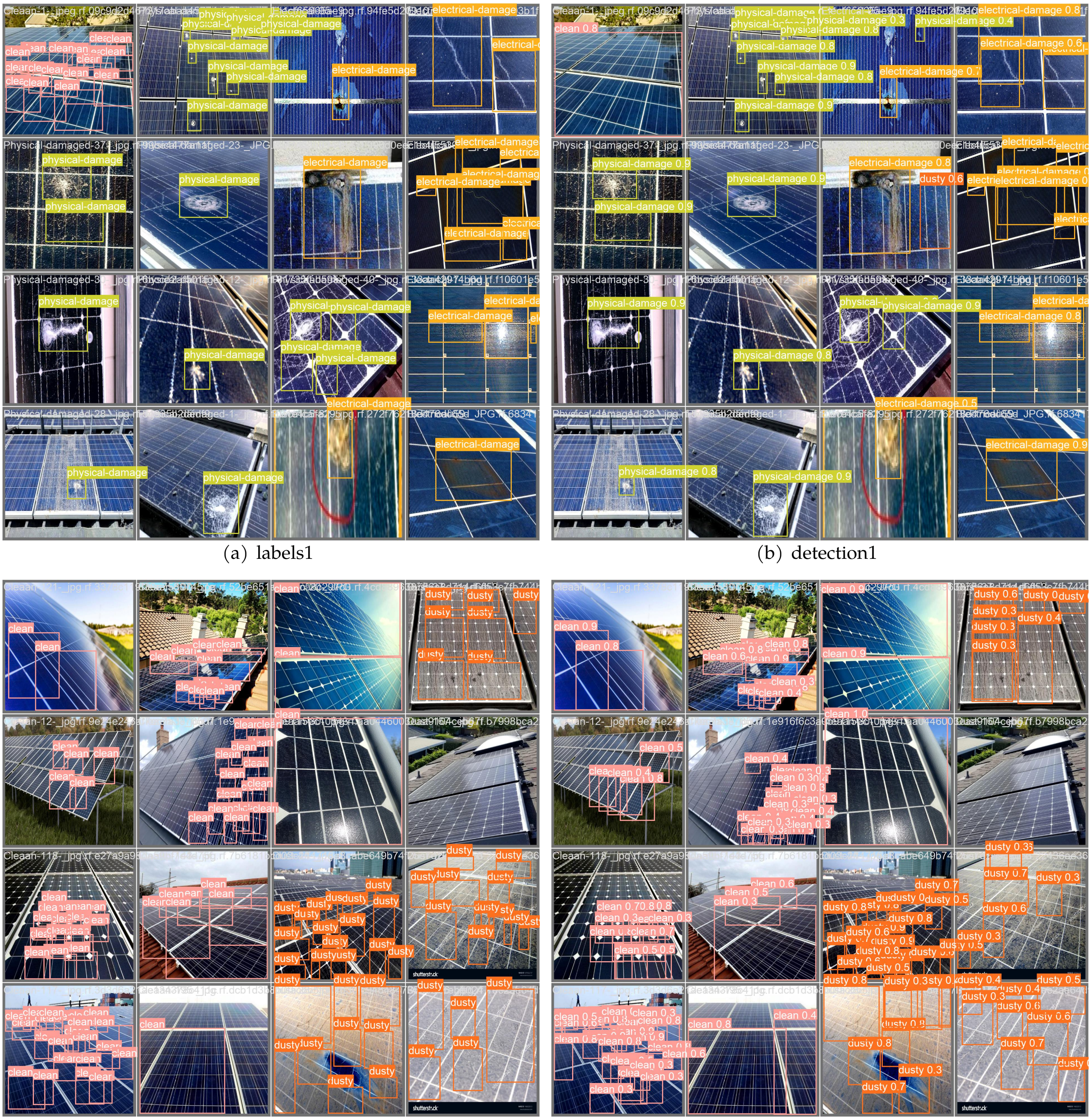
Figure 8 presents the training performance of the YOLOv8 model, where results are shown for both the training set (train) and validation set (val). The horizontal axis indicates the number of training epochs, and the vertical axis represents the variation of key performance metrics. The model achieves a mean Average Precision (mAP@0.5) of 0.7, demonstrating satisfactory detection accuracy and good convergence behavior.

As illustrated in Figure 12, the confusion matrix summarizes the classification performance, where the horizontal axis (True) denotes the actual class and the vertical axis (Predicted) indicates the model's predictions. Darker shades correspond to higher counts, with the matrix covering categories including bird-drop, clean, dusty, electrical-damage, and physical-damage.

The PV panel image data used in this experiment come from the "solar panel faulty od final dataset" on the Roboflow Universe platform. The YOLOv8 model was trained for 400 epochs with a batch size of 32 and three threads running simultaneously. The ground-truth labels and detection results of the YOLOv8 model are shown in Figure 11. This demonstrates that this model can effectively detect PV panel faults, thereby ensuring safe system operation.

6 Conclusion

In conclusion, this study developed a Transformer-based Adaptive Dynamic Programming (TM-ADP) framework for real-time optimal energy management and secure operation of renewable energy systems under uncertainty. By integrating a multi-source data fusion Transformer for accurate forecasting and a TM-ADP scheduler for adaptive control, coupled with a YOLOv8-based monitoring strategy for real-time anomaly detection



(a) labels1 (b) detection1

(c) labels2 (d) detection2

Figure 11. Labels and results of YOLOv8 model.

of photovoltaic panels, the proposed approach effectively enhanced both operational efficiency and system security. Validation on the digital twin verification platform confirmed the feasibility and effectiveness of the proposed framework. Translating digital-twin-enabled, data-driven cyber–physical energy solutions into large-scale deployments often involves additional system-level considerations beyond algorithmic design, such as scalability. Addressing such practical boundary conditions remains an important direction for deployment-oriented study. Future work will aim to scale the framework to larger renewable energy systems and incorporate market mechanisms for combined economic and security optimization while further improving deployment readiness through broader validation under diverse operating conditions.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Wen Yang served as an Associate Editor of the *Chinese Journal of Information Fusion* at the time of manuscript submission. To ensure the integrity of the peer-review process, Wen Yang was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Ahmad, S., Shafiullah, M., Ahmed, C. B., & Alowaifeer, M. (2023). A review of microgrid energy management and control strategies. *IEEE Access, 11*, 21729-21757. [CrossRef]

[2] Guo, C., Wang, X., Zheng, Y., & Zhang, F. (2022). Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning. *Energy, 238*, 121873. [CrossRef]

[3] Chen, R., Fang, Z., Yuan, J., Zhou, J., Liu, Q., Zeng, X., & Li, J. (2026). A smooth distributed and multi-objective ADP-based power system optimal operation control method. *Sustainable Energy Technologies and Assessments, 87*, 104903. [CrossRef]

[4] Fan, X., & Li, Y. (2023). Energy management of renewable based power grids using artificial intelligence: Digital twin of renewables. *Solar Energy, 262*, 111867. [CrossRef]

[5] Shen, Z., Xu, W., Li, W., Shi, Y., & Gao, F. (2023). Digital twin application for attach detection and mitigation of PV-based smart systems using fast and accurate hybrid machine learning algorithm. *Solar Energy, 250*, 377-387. [CrossRef]

[6] Zhang, Y., Liu, L., Yuan, F., Zhai, H., & Song, C. (2023). Multifactor and multiscale method for power load forecasting. *Knowledge-Based Systems, 268*, 110476. [CrossRef]

[7] Zhi, Y., Sun, T., & Yang, X. (2023). A physical model with meteorological forecasting for hourly rooftop photovoltaic power prediction. *Journal of Building Engineering, 75*, 106997. [CrossRef]

[8] Xie, H., Yuan, B., Hu, C., Gao, Y., Wang, F., Wang, C., ... & Chu, P. (2024). ST-YOLO: A defect detection method for photovoltaic modules based on infrared thermal imaging and machine vision technology. *PloS one, 19*(12), e0310742. [CrossRef]

[9] Majeed, M. A., Phichaisawat, S., Asghar, F., & Hussan, U. (2023). Optimal energy management system for grid-tied microgrid: An improved adaptive genetic algorithm. *IEEE Access, 11*, 117351-117361. [CrossRef]

[10] Zhao, Z., Guo, J., Luo, X., Lai, C. S., Yang, P., Lai, L. L., ... & Shahidehpour, M. (2022). Distributed robust model predictive control-based energy management strategy for islanded multi-microgrids considering uncertainty. *IEEE transactions on smart grid, 13*(3), 2107-2120. [CrossRef]

[11] Zhang, C., Zhou, Q., Shuai, B., Williams, H., Li, Y., Hua, L., & Xu, H. (2022). Dedicated adaptive particle swarm optimization algorithm for digital twin based control optimization of the plug-in hybrid vehicle. *IEEE Transactions on Transportation Electrification, 9*(2), 3137-3148. [CrossRef]

[12] Lin, Z., Song, C., Zhao, J., & Yin, H. (2022). Improved approximate dynamic programming for real-time economic dispatch of integrated microgrids. *Energy, 255*, 124513. [CrossRef]

[13] Ye, Y., Wang, H., Chen, P., Tang, Y., & Strbac, G. (2023). Safe deep reinforcement learning for microgrid energy management in distribution networks with leveraged spatial–temporal perception. *IEEE Transactions on Smart Grid, 14*(5), 3759-3775. [CrossRef]

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