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A Prediction-Guided and Local-Execution Collaborative MPPT Method for Dynamic Environments: Mechanism Insights and Performance Validation

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Abstract : *Dynamic irradiance variations, temperature disturbances, and partial shading conditions continuously shift the maximum power point (MPP) of photovoltaic (PV) systems, increasing the difficulty of maximum power point tracking (MPPT). Conventional MPPT methods mainly rely on real-time feedback and lack the ability to perceive MPP migration trends under dynamic environments, while existing intelligent MPPT studies primarily focus on prediction accuracy rather than the effective integration of predictive information into control processes. To address this issue, a collaborative MPPT method combining gated recurrent unit (GRU)-based prediction guidance and incremental conductance (INC)-based local execution is proposed. The GRU model provides operating-point trend information, while the INC algorithm ensures feedback-based regulation and stable convergence. The proposed method is evaluated under dynamic irradiance variations, temperature disturbances, partial shading conditions, and composite dynamic conditions. Results show that the GRU–INC framework achieves higher tracking efficiency, lower tracking error, and more stable operating trajectories than the conventional INC-based approach, particularly under partial shading and composite dynamic conditions. Ablation studies further demonstrate that the performance improvement mainly originates from the collaboration between prediction guidance and real-time feedback rather than from the prediction module alone. The results confirm the effectiveness of the proposed collaborative mechanism for MPPT under dynamic environments and highlight the benefit of integrating prediction guidance with feedback regulation*

Keywords : *Photovoltaic systems; Maximum power point tracking; Gated recurrent unit; Incremental conductance; Collaborative control; Dynamic environments*

1. Introduction

Maximum power point tracking (MPPT) plays a critical role in improving the energy utilization efficiency of photovoltaic (PV) systems. However, under dynamic irradiance variations, temperature disturbances, and partial shading conditions, the maximum power point (MPP) continuously shifts, making accurate tracking increasingly challenging [1]–[3]. Although conventional, intelligent, and hybrid MPPT methods have been extensively studied

[9], [19]–[20], most conventional approaches rely solely on real-time feedback and exhibit limited adaptability under rapidly changing operating conditions. Recent advances in machine learning have promoted the application of data-driven methods in PV systems and MPPT optimization [4]–[7], [22], [28]. Among them, gated recurrent units (GRUs) have shown strong capability in temporal prediction tasks. However, existing studies mainly focus on prediction accuracy and tracking performance, while the integration of predictive information into practical MPPT regulation remains insufficiently explored [8], [17]. To address this issue, a prediction-guided and local-execution collaborative MPPT framework is proposed by combining GRU-based prediction and incremental conductance (INC)-based regulation. The framework integrates predictive information with feedback regulation to improve the adaptability of MPPT under dynamic environments. The main contributions of this work are summarized as follows: 1）A prediction-guided and local-execution collaborative MPPT framework is proposed. 2）A collaborative mechanism is established to integrate predictive information with feedback regulation while maintaining control stability. 3）The proposed method is validated under dynamic irradiance variations, temperature disturbances, partial shading conditions, and composite dynamic conditions. Ablation studies are further conducted to investigate the source of performance improvement.

2 Prediction-Guided and Local-Execution Collaborative MPPT Method

To enhance MPPT performance under dynamic environments, a collaborative framework combining GRU-based prediction guidance and INC-based local execution is developed. The framework integrates operating-point trend information with feedback regulation. The GRU model provides prediction guidance, while the INC algorithm performs operating-point correction and stable convergence, enabling improved dynamic response and operational stability.

2.1 Overall Architecture of the Collaborative MPPT Framework

The proposed framework consists of dynamic environment inputs, a prediction-guidance module, a local-execution module, and a feedback regulation loop, as illustrated in Fig. 1.

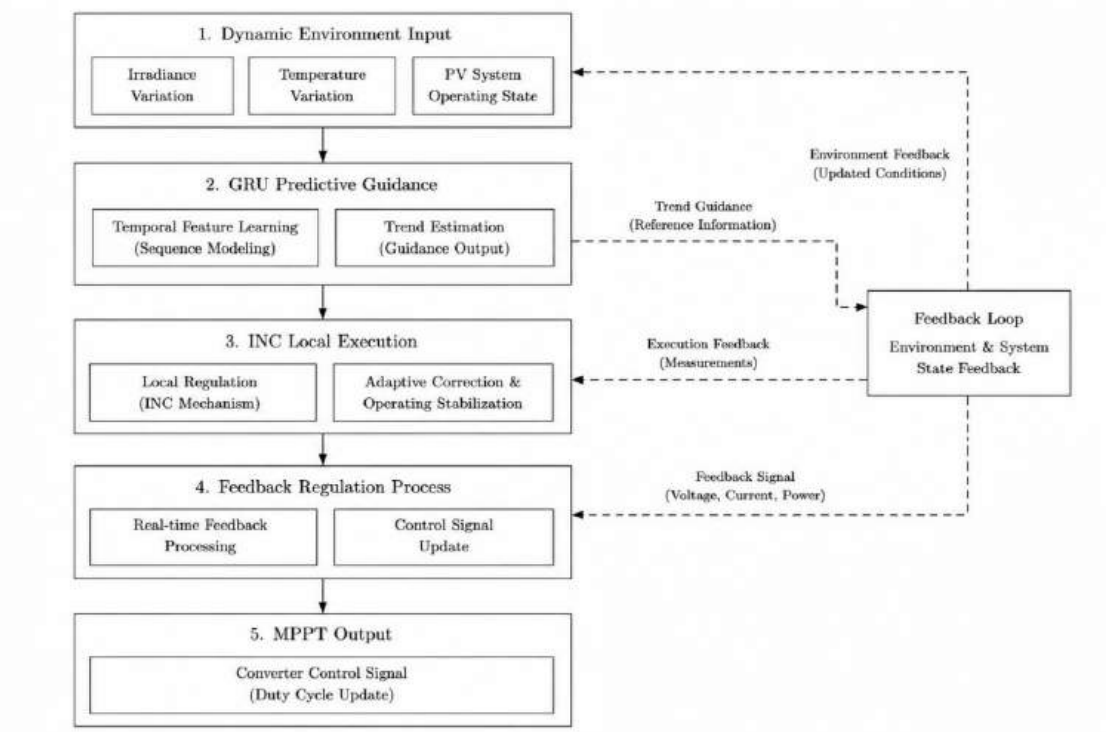


Fig. 1. Overall architecture of the GRU-based prediction-guided and INC-based local-execution collaborative MPPT framework

During operation, irradiance, temperature, and PV system operating states are fed into the prediction-guidance module. The GRU model extracts temporal features from historical data and generates operating-point trend information, which serves as a reference for subsequent

regulation. The local-execution module employs the incremental conductance (INC) algorithm to regulate the operating point. By combining prediction guidance with real-time measurements, the controller continuously updates the operating point and adjusts the converter control signal to track the maximum power point. Meanwhile, system states are fed back to support subsequent prediction and regulation. Unlike conventional MPPT structures that rely solely on local feedback, the proposed framework incorporates operating-point trend information into the regulation process. Prediction guidance provides directional information, while local execution ensures real-time adjustment and feedback correction, forming a collaborative regulation structure.

2.2 GRU-Based Prediction-Guidance Module

Under dynamic operating conditions, the maximum power point continuously shifts with variations in irradiance, temperature, and system states. Conventional MPPT methods mainly rely on instantaneous measurements and therefore have limited capability to exploit the temporal information contained in historical operating data. As a result, rapid environmental changes may lead to delayed responses and tracking deviations. To address this issue, a GRU-based prediction-guidance module is incorporated into the proposed framework to provide operating-point trend information. The GRU model takes irradiance, temperature, PV voltage, PV current, and output power as inputs, while the reference MPP voltage is selected as the prediction target. Historical data are organized using a sliding time window to preserve temporal correlations between environmental variations and operating-point migration. By learning the relationship between historical operating states and the reference MPP voltage, the GRU model generates a predicted operating-point trend under current conditions. The prediction result is not directly used for control computation but serves as guidance for the subsequent regulation process. Compared with conventional recurrent neural networks, GRUs are more effective in capturing long-term temporal dependencies while alleviating the gradient vanishing problem during training [11], [12]. In addition, their relatively simple structure and low computational complexity make them suitable for real-time MPPT applications. In the proposed framework, the GRU module is used to enhance environmental trend perception and operating-point prediction, rather than replacing the feedback-based regulation process.

2.3 INC-Based Local-Execution Module

In the proposed framework, the incremental conductance (INC) algorithm serves as the local-execution layer and is responsible for operating-point regulation through real-time feedback. Unlike the GRU module, which provides prediction guidance, the INC algorithm directly participates in the control process to ensure stable operation under dynamic conditions.

The INC algorithm determines the position of the operating point relative to the maximum power point based on the voltage–power relationship of the PV array and adjusts the control direction accordingly. Owing to its simplicity, reliability, and widespread engineering application, it remains one of the most commonly used MPPT techniques. In the proposed collaborative framework, the INC algorithm operates under the guidance of predictive information rather than as an independent controller. The GRU output provides operating-point trend information, while the INC algorithm performs local correction using real-time voltage and current measurements. By combining prediction guidance with feedback regulation, the controller utilizes both historical and real-time information for operating-point adjustment. When environmental conditions change, prediction guidance provides directional information for operating-point migration, reducing unnecessary local search. As the operating point approaches the target region, the INC algorithm further refines the operating point and ensures stable convergence through feedback regulation. Because the feedback loop is retained throughout the control process, system stability can be maintained even when prediction errors occur. Therefore, the primary role of the INC module is not only to perform local MPPT regulation but also to provide real-time feedback constraints and stability support

for the collaborative framework. Together, the GRU and INC modules form a prediction-guided and local-execution collaborative MPPT structure.

2.4 Prediction-Guided and Local-Execution Collaborative Mechanism

Conventional MPPT methods rely primarily on real-time feedback for operating-point regulation. Under dynamic environments, continuous MPP migration may lead to delayed responses and reduced tracking efficiency. Although prediction methods can provide information about future operating-point trends, prediction errors may compromise system stability when predictive outputs are directly used for control. To overcome these limitations, a prediction-guided and local-execution collaborative mechanism is developed by integrating GRU-based prediction with INC-based regulation. In the proposed mechanism, predictive information is not used as a direct control input. Instead, it serves as guidance for the local-execution process, while operating-point regulation remains governed by feedback measurements. This design enables the framework to incorporate trend information without sacrificing control stability. During operation, prediction guidance provides directional information for operating-point migration, whereas local execution continuously refines the operating point through feedback regulation. When environmental conditions change, prediction guidance helps reduce unnecessary local search. As the operating point approaches the target region, feedback regulation ensures accurate adjustment and stable convergence. The overall collaborative mechanism is illustrated in Fig. 2.

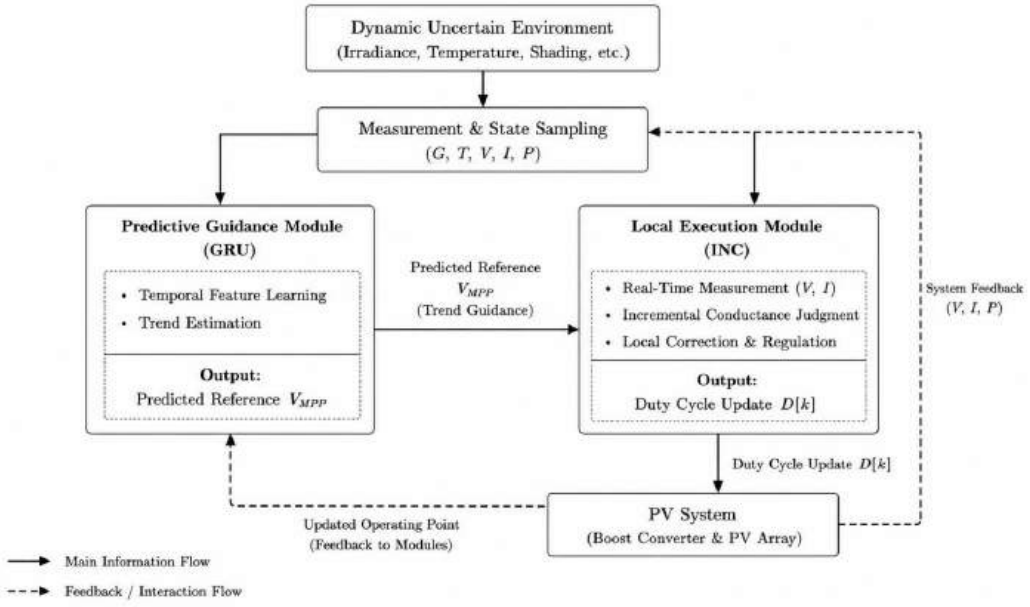


Fig. 2. Prediction–execution cooperative adaptive interaction mechanism

Compared with conventional local-search MPPT methods, the proposed mechanism enhances the perception of operating-point migration trends. Compared with purely prediction-based strategies, it preserves the robustness and stability of feedback regulation. Therefore, the performance improvement originates from the collaboration between prediction guidance and local execution rather than from the replacement of feedback control by predictive information.

3 Test Conditions and Evaluation Metrics

To evaluate the performance of the proposed prediction-guided and local-execution collaborative MPPT method under dynamic environments, a unified PV system model was established and tested under various operating conditions. The system consists of a PV array, a Boost DC–DC converter, and an MPPT controller. The PV array model was developed based on a classical PV modeling approach [31]. In the proposed framework, the GRU module provides prediction guidance, while the INC algorithm performs local execution and feedback regulation. The reference irradiance and temperature were set to 1000 W/m² and 25 °C, respectively. During operation, irradiance, temperature, PV voltage, PV current, and output power were continuously monitored under identical control settings. Four test

scenarios were considered: dynamic irradiance variations, temperature disturbances, partial shading conditions, and composite dynamic conditions. These scenarios were designed to evaluate dynamic response capability, temperature adaptability, tracking performance under multiple power peaks, and overall robustness under complex operating conditions. To quantitatively assess MPPT performance, tracking efficiency and tracking error were adopted as the primary evaluation metrics. Tracking efficiency measures the proximity between the actual output power and the theoretical maximum power and is defined as：

$$\eta=\frac{\sum_{k=1}^{N} P_{out}(k)}{\sum_{k=1}^{N} P_{MPP}(k)}\times 100\% \quad \text{（Equation } \mathbf{1}\text{）}$$

where $P_{out}(k)$ and $P_{MPP}(k)$ denote the actual output power and theoretical maximum power at the k-th sampling instant, respectively, and N is the total number of samples.

Tracking error evaluates the deviation between the operating voltage and the reference MPP voltage and is defined as：

$$E_{avg}=\frac{1}{N}\sum_{k=1}^{N}|V_{MPP}(k)-V(k)| \quad \text{（Equation } \mathbf{2}\text{）}$$

where $V_{MPP}(k)$ is the reference MPP voltage, V(k) is the operating voltage, and N is the total number of samples.

These metrics evaluate MPPT performance from the perspectives of energy harvesting capability and tracking accuracy.

4 Performance Analysis Under Dynamic Operating Conditions

To evaluate the proposed prediction-guided and local-execution collaborative MPPT method, experiments were conducted under dynamic irradiance variations, temperature disturbances, partial shading conditions, and composite dynamic conditions. Based on the evaluation metrics defined in Section 3, the GRU–INC and ONLY–INC structures were compared in terms of tracking efficiency, tracking error, and operating trajectories.

4.1 Performance Under Dynamic Irradiance Variations

Dynamic irradiance variations continuously shift the maximum power point and therefore require rapid and stable MPPT responses.

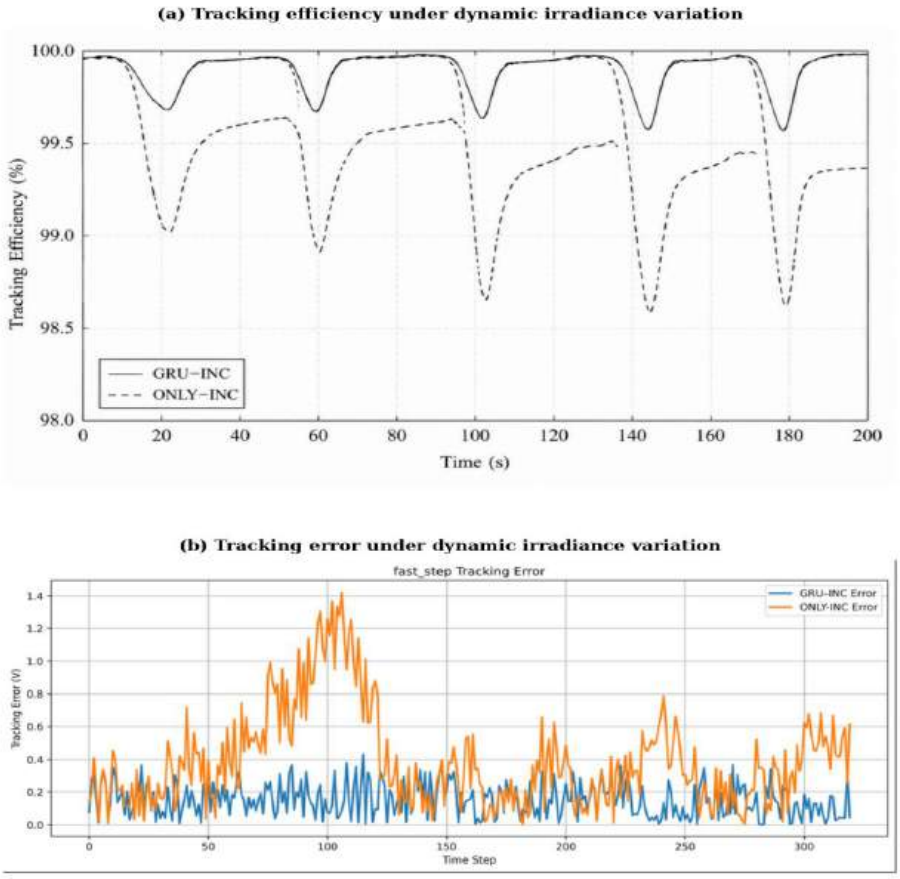


Fig. 3. **Comparison of tracking performance under dynamic irradiance variations.**

Figure 3 compares the tracking performance of the two methods under dynamic irradiance conditions. As shown in Fig. 3(a), the GRU–INC structure maintains consistently higher tracking efficiency with smaller fluctuations throughout the test. In contrast, the ONLY–INC structure exhibits a noticeable efficiency drop during irradiance transitions and requires a longer recovery period. The tracking error results shown in Fig. 3(b) further demonstrate the advantage of the GRU–INC structure. Lower tracking errors are observed throughout the test, whereas the ONLY–INC structure experiences larger error fluctuations during rapid irradiance changes. This indicates that prediction guidance helps reduce unnecessary operating-point adjustments when environmental conditions vary. Overall, the GRU–INC structure achieves higher tracking efficiency and lower tracking error under dynamic irradiance variations. The results demonstrate that integrating prediction guidance with feedback regulation improves MPPT performance under rapidly changing conditions.

4.2 Performance Under Temperature Disturbances

Temperature variations continuously affect PV output characteristics and gradually shift the maximum power point. Compared with dynamic irradiance variations, temperature disturbances typically evolve more slowly and are therefore suitable for evaluating long-term tracking stability.

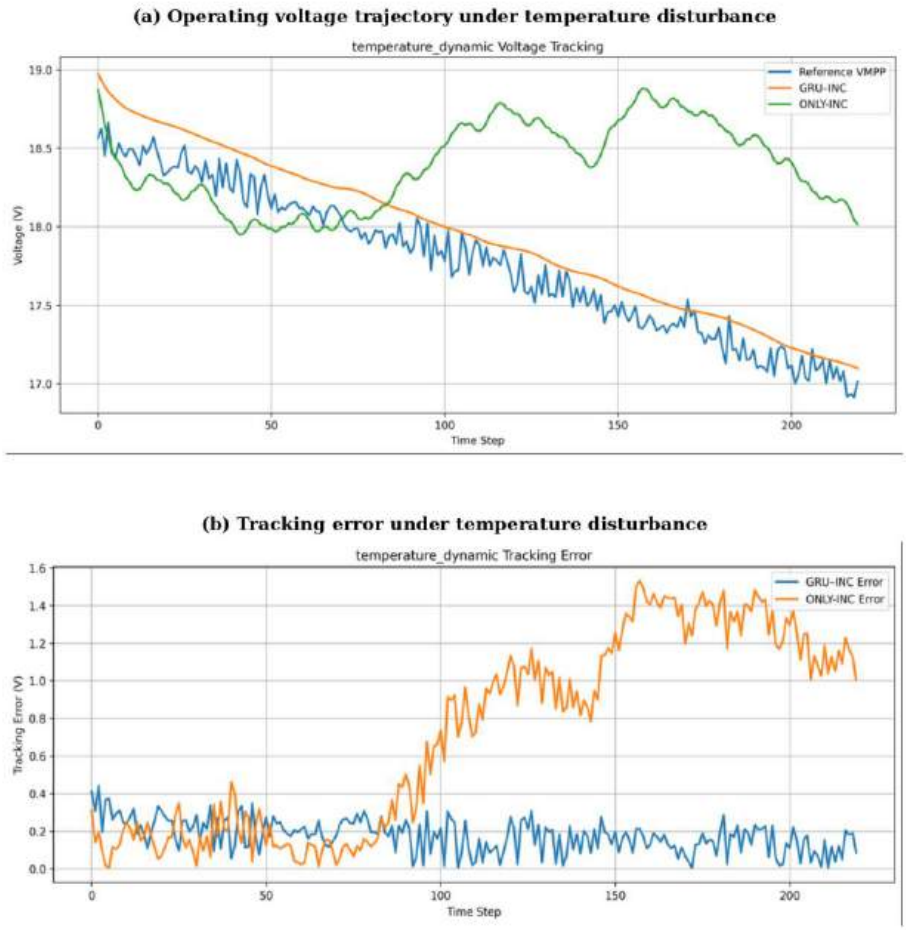


Fig. 4. **Comparison of performance under temperature disturbances.**

Figure 4(a) presents the operating-voltage trajectories under temperature disturbances. As the temperature changes, the reference MPP voltage gradually shifts toward a lower voltage region. The GRU–INC structure closely follows the reference trajectory throughout the test, whereas the ONLY–INC structure gradually deviates from the target operating point and exhibits noticeable cumulative deviation during the later stages.

Figure 4(b) compares the tracking errors of the two methods. The GRU–INC structure maintains consistently low tracking errors with limited fluctuations over the entire test period. In contrast, the tracking error of the ONLY–INC structure gradually increases as temperature variations accumulate, indicating reduced tracking accuracy under long-term operating-condition changes. Overall, the GRU–INC structure demonstrates superior tracking stability under temperature disturbances. The results indicate that integrating prediction guidance with feedback regulation effectively mitigates cumulative deviation and improves long-term tracking accuracy.

4.3 Performance Under Partial Shading Conditions

Partial shading conditions (PSCs) introduce multiple local power peaks into the PV power-voltage characteristic, increasing the risk of convergence to local optima. Consequently, numerous intelligent and swarm-based MPPT methods have been developed to enhance global tracking capability [18], [23]–[25]. PSCs therefore provide a challenging scenario for evaluating MPPT performance under complex operating conditions.

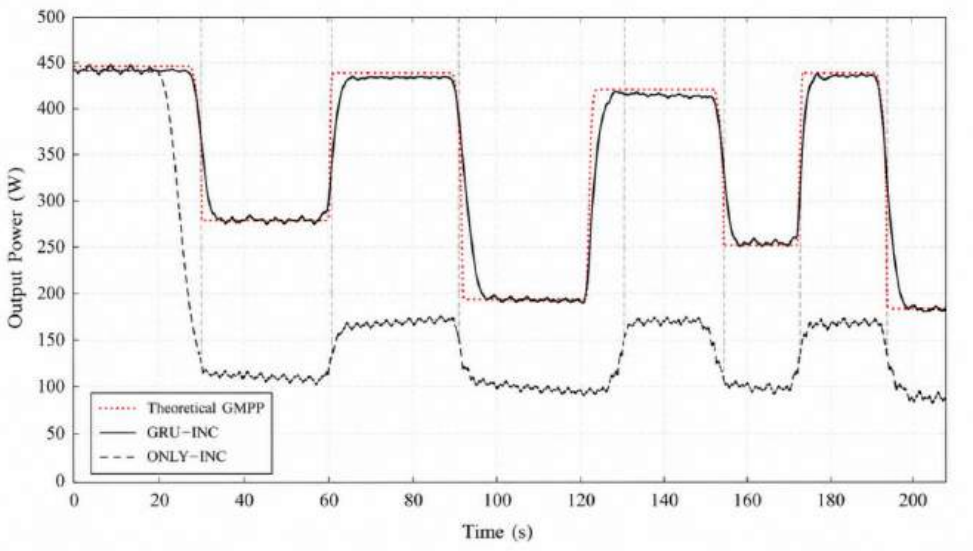


Fig. 5**. Comparison of output-power tracking performance under partial shading conditions**

Figure 5 shows the output-power responses of the two methods under PSCs. As shading patterns change, the theoretical maximum power exhibits multiple step variations. The GRU–INC structure closely follows the theoretical maximum power throughout the test, with only minor deviations during shading transitions. In contrast, the ONLY–INC structure experiences noticeable power losses during several operating periods. Following shading transitions, the output power deviates from the theoretical maximum and remains trapped in lower-power regions for extended periods. This behavior indicates that feedback-based local search alone is more susceptible to local optima under PSCs. The dynamic responses further show that the GRU–INC structure rapidly converges to the new operating region after shading changes, whereas the ONLY–INC structure exhibits slower recovery and prolonged tracking deviations. These results suggest that prediction guidance improves the ability to identify favorable operating regions, while feedback regulation ensures accurate local convergence. Overall, the GRU–INC structure demonstrates superior adaptability under PSCs. By combining prediction guidance with local execution, the proposed method improves global tracking capability and maintains operation closer to the global optimum, resulting in higher power extraction and improved tracking performance.

4.4 Performance Under Composite Dynamic Conditions

Composite dynamic conditions involve simultaneous irradiance variations, temperature disturbances, and partial shading effects, resulting in a more challenging operating environment for MPPT. Under such conditions, the controller must continuously track the operating point while maintaining stable performance in the presence of multiple disturbances.

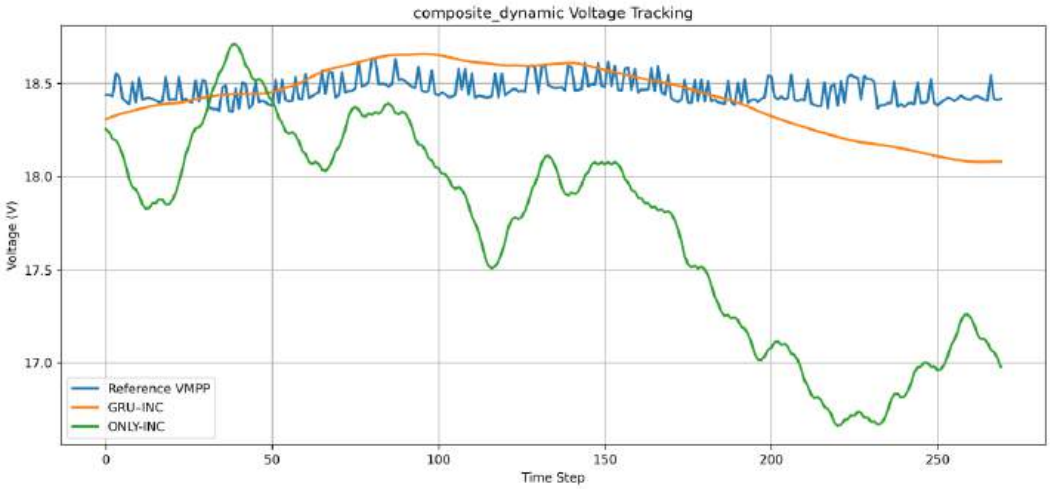


Fig. 6**. Comparison of operating-voltage trajectories under composite dynamic conditions**

Figure 6 compares the operating-voltage trajectories of the two methods under composite dynamic conditions. The reference MPP voltage represents the theoretical optimal operating trajectory. The GRU–INC structure remains close to the reference trajectory throughout the test and continuously adapts to environmental changes. In contrast, the ONLY–INC structure exhibits larger voltage fluctuations and gradually deviates from the reference trajectory as operating conditions become increasingly complex. At the beginning of the test, both methods exhibit similar operating behavior. However, as irradiance variations, temperature disturbances, and shading transitions accumulate, the ONLY–INC structure develops noticeable operating-point deviations from the reference trajectory. The GRU–INC structure, on the other hand, maintains closer trajectory tracking and more stable operating behavior throughout the test. These results indicate that feedback-based local regulation alone becomes increasingly susceptible to cumulative disturbances under complex operating conditions. By integrating prediction guidance with local execution, the proposed framework maintains more accurate operating-point tracking and improved stability in the presence of multiple environmental variations. Overall, the results under composite dynamic conditions further demonstrate the robustness of the proposed collaborative MPPT method. Compared with the conventional ONLY–INC structure, the GRU–INC framework achieves superior trajectory tracking and operating stability under coupled environmental disturbances.

5 Analysis of the Prediction-Guided and Local-Execution Collaborative Mechanism

The results presented in Section 4 indicate that the performance improvement achieved under dynamic environments cannot be attributed solely to the prediction model. Instead, it arises from the collaborative interaction between prediction guidance and local execution. Although the proposed method demonstrates superior tracking performance under dynamic irradiance variations, temperature disturbances, partial shading conditions, and composite dynamic conditions, the underlying mechanism requires further investigation. Therefore, the proposed collaborative framework is analyzed from the perspectives of functional roles, collaborative interaction, and practical applicability.

5.1 Analysis of the Source of Collaborative Performance Improvement

Under dynamic environments, the maximum power point continuously shifts with variations in irradiance, temperature, and operating conditions. Conventional MPPT methods rely primarily on feedback regulation and may experience delayed responses under rapidly changing conditions. In contrast, prediction models can capture operating-point migration trends from historical information but cannot independently guarantee control stability. As a result, neither prediction-based nor feedback-based approaches alone can simultaneously achieve fast adaptation and stable operation. Recent studies have therefore explored hybrid MPPT structures that combine predictive models with feedback regulation [26], [27].

In the proposed framework, the GRU-based prediction-guidance module and the INC-based local-execution module perform complementary functions. The GRU module provides operating-point trend information, while the INC algorithm ensures feedback-based correction and stable convergence. Their respective roles are summarized in Table 1.

Table 1. Functional roles of prediction guidance and local execution

Module	Primary Function	Contribution
GRU-based prediction guidance	Trend perception and operating-point prediction	Provides directional information and reduces unnecessary search
INC-based local execution	Feedback correction and stable convergence	Ensures operational stability and continuity
Collaborative mechanism	Integration of predictive and feedback information	Balances adaptability and stability

The role of prediction guidance is not to replace local execution but to provide directional information for operating-point adjustment. When operating conditions change, predictive information helps reduce unnecessary search efforts, while local execution continuously

refines the operating point through feedback regulation. This complementary interaction enables the framework to maintain both adaptability and stability.

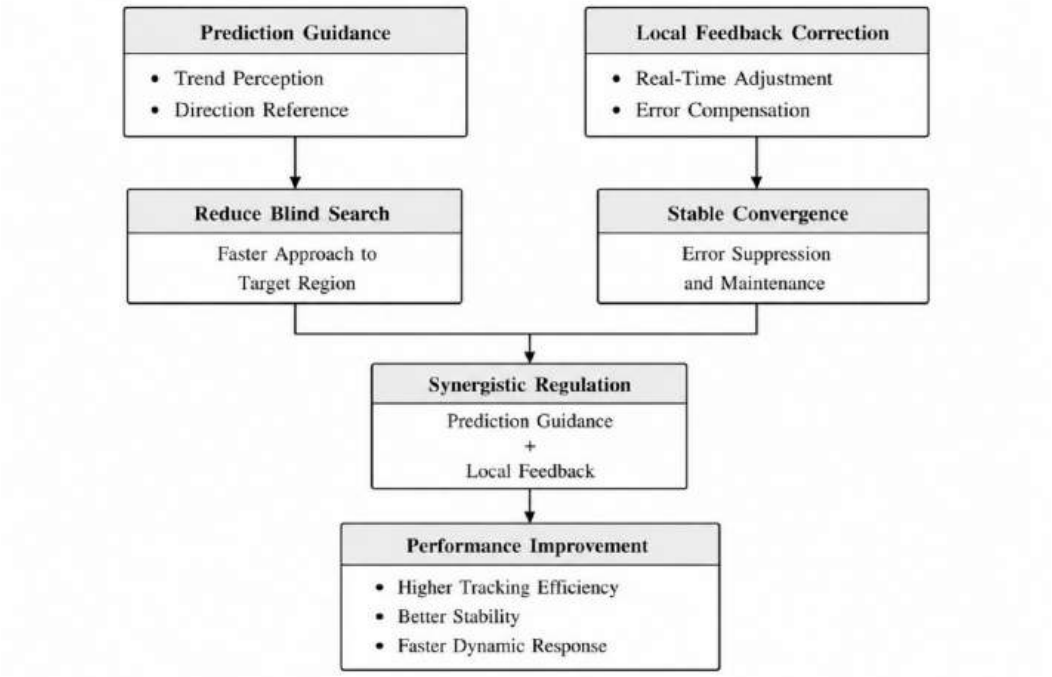


Fig. 7. **Schematic illustration of the collaborative performance enhancement mechanism**

Therefore, the observed performance improvement originates from the collaboration between prediction guidance and local execution rather than from either component individually. Prediction guidance enhances the perception of operating-point migration, whereas local execution ensures stable regulation. Their interaction constitutes the primary source of the performance gains observed in Section 4.

5.2 Ablation Study

To evaluate the contribution of prediction guidance within the proposed framework, the complete GRU–INC structure was compared with the ONLY–INC structure, in which the prediction-guidance module was removed. Figure 8 presents the tracking error and tracking efficiency results under different operating conditions.

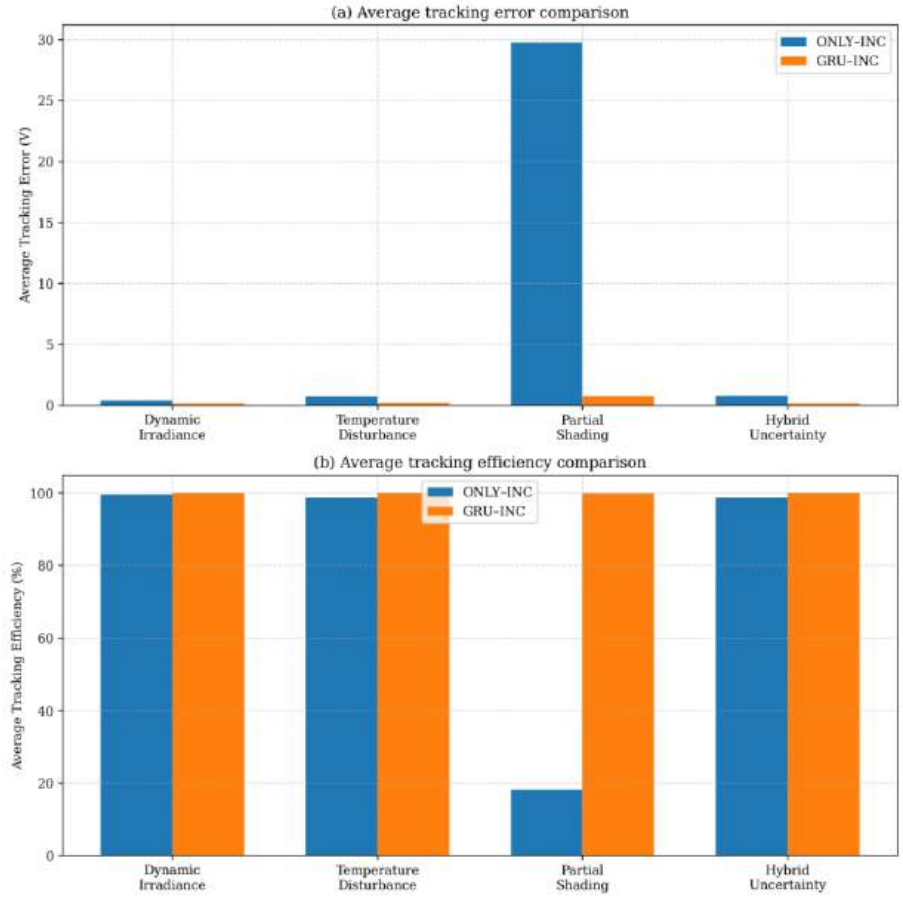


Fig. 8. Comparison of ablation-study results for different structures

As shown in Fig. 8(a), the GRU–INC structure achieves lower tracking errors across all test conditions. Under dynamic irradiance variations and temperature disturbances, both structures maintain acceptable tracking performance, whereas the GRU–INC structure consistently exhibits smaller errors. The difference becomes more pronounced under partial shading and composite dynamic conditions, where the ONLY–INC structure experiences a substantial increase in tracking error while the GRU–INC structure maintains relatively stable performance. Figure 8(b) further compares the tracking efficiency of the two methods. The GRU–INC structure achieves higher tracking efficiency under all operating conditions. The improvement is particularly evident under partial shading conditions, where the efficiency of the ONLY–INC structure decreases significantly. These results indicate that prediction guidance enhances the adaptability of the MPPT process under complex operating environments. The ablation results demonstrate that prediction guidance does not directly perform operating-point regulation. Instead, it improves the effectiveness of feedback-based regulation by providing additional operating-point trend information. Consequently, the performance gains achieved by the proposed method originate from the collaboration between prediction guidance and local execution rather than from either component alone.

5.3 Practical Implementation Analysis of the Collaborative Framework

In practical MPPT applications, tracking performance must be achieved without compromising operational stability and real-time capability. In the proposed framework, prediction guidance and local execution are functionally separated. The prediction module provides operating-point trend information, whereas the control process remains governed by feedback regulation. As a result, the framework enhances environmental awareness while preserving the stability characteristics of conventional feedback-based MPPT methods.

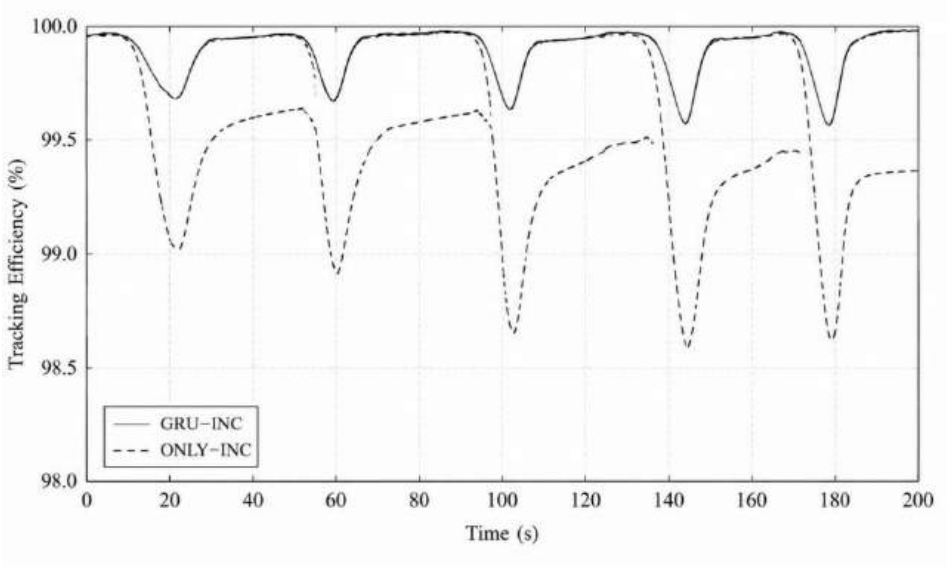


Fig. 9. Tracking-efficiency variation under continuous dynamic operating conditions

Figure 9 compares the tracking-efficiency variations of different structures under continuous dynamic conditions. The GRU–INC structure maintains consistently high tracking efficiency throughout the test and exhibits smaller performance fluctuations during environmental transitions. In contrast, the ONLY–INC structure experiences more pronounced efficiency degradation and requires a longer recovery period following disturbances.These results indicate that the proposed framework can maintain stable operation under continuously changing conditions. Prediction guidance provides additional operating-point information, while feedback regulation ensures reliable adjustment during online operation. Their combination improves operational robustness without sacrificing control stability.

Furthermore, the GRU module is used only for trend prediction and does not directly participate in control-signal updates. Consequently, the fundamental MPPT control structure remains unchanged, and the mature INC algorithm continues to govern operating-point regulation. This design facilitates practical implementation while retaining the advantages of conventional feedback-based control.

5.4 Applicability and Limitations of the Proposed Method

Although the proposed method demonstrates favorable performance under various dynamic operating conditions, its effectiveness remains influenced by environmental complexity and data coverage. Table 2 summarizes its applicability and potential limitations under different operating scenarios.

Table 2. Applicability and limitations of the proposed method

Operating Condition	Observed Performance	Potential Limitation
Dynamic irradiance variations	High tracking performance	Minor
Gradual temperature variations	Stable operation	Minor
Partial shading conditions	Effective global tracking	Increased regulation difficulty due to multiple power peaks
Composite dynamic conditions	Robust tracking performance	Increased prediction complexity
Unseen operating conditions	Dependent on feedback correction	Limited generalization capability

Because the GRU module learns environmental dynamics from historical data, its prediction capability depends on the coverage and representativeness of the training dataset. Previous studies have shown that data-driven models may experience performance degradation when operating conditions differ significantly from the training distribution. Under such

circumstances, prediction accuracy may decrease, reducing the effectiveness of prediction guidance. This limitation is common to many data-driven approaches operating in complex dynamic environments [15]. In the proposed framework, predictive information is used only to provide operating-point trend guidance rather than direct control actions. Therefore, prediction guidance cannot replace feedback-based regulation. Under complex or previously unseen operating conditions, the INC-based local-execution module remains responsible for operating-point correction and stable convergence. As a result, the feedback mechanism continues to provide a degree of robustness even when prediction errors occur. The proposed method is most suitable for environments characterized by continuous dynamic variations and operating conditions similar to those represented in the training data. Under extreme or unseen conditions, the contribution of prediction guidance may be reduced. Nevertheless, the local-execution mechanism can still maintain basic MPPT functionality. Therefore, the primary advantage of the proposed framework lies not in eliminating prediction errors but in improving adaptability through the collaboration between prediction guidance and local execution.

6 Conclusion

A prediction-guided and local-execution collaborative MPPT method was proposed by integrating GRU-based prediction guidance with INC-based feedback regulation. Experimental results under dynamic irradiance variations, temperature disturbances, partial shading conditions, and composite dynamic conditions demonstrated improved tracking efficiency, reduced tracking error, and enhanced operating stability compared with the conventional ONLY–INC structure. Mechanism analysis and ablation studies showed that the performance gains originate from the collaboration between prediction guidance and local execution rather than from the prediction module alone. Prediction guidance provides operating-point trend information, whereas feedback regulation ensures stable convergence and operational robustness. The main contribution of this work lies in the development and validation of a collaborative framework that integrates predictive information with conventional MPPT regulation. The proposed approach provides a practical reference for combining machine-learning-based prediction with feedback control in dynamic MPPT applications.

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