

A Photovoltaic Inverter Attenuation Prediction Method based on Computer Simulation and Transformer Algorithm

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Abstract

To address the difficulty of timely assessment of photovoltaic (PV) inverter degradation during power-station operation and maintenance, this paper proposes a degradation prediction method that combines mechanism-based simulation data generation with Transformer-based time-series forecasting. First, a PV inverter operation simulation model is developed that considers irradiance, ambient temperature, module temperature, dust accumulation, baseline module degradation, and shading and temperature effects. The model is used to generate long-term samples under multiple operating conditions. Second, daily aggregated features and the performance ratio (PR) are adopted as key health indicators, and a multivariate Transformer forecasting model is constructed to capture long-range dependencies among historical operating states, environmental disturbances, and degradation trends. Simulation results show that, for the 200 h ahead output-power prediction task, the proposed method achieves a mean relative error of 2.64% and a standard deviation of 1.18%. The predicted curve closely follows the trend of power fluctuations. These results indicate that combining simulation data with a Transformer model provides a low-cost, scalable technical approach for PV inverter condition assessment and preventive maintenance. Further validation using real power-station data is still required before engineering deployment.

Keywords

photovoltaic inverter, degradation prediction, computer simulation, transformer, preventive maintenance

1. Introduction

As the global energy structure transitions and the “dual carbon” targets continue to advance, the installed capacity of photovoltaic (PV) power generation has been growing rapidly. In 2024, the global PV market grew to at least 520 GWp, with PV systems' share of the power mix steadily increasing [1]. In PV systems, the inverter performs critical functions including DC-AC conversion, grid connection control, and operational protection. Compared with conventional power plants, PV plants are more susceptible to environmental factors and more prone to faults. Therefore, identifying trends in inverter performance degradation before faults occur is a key issue for the refined operation and maintenance (O&M) of PV plants [1].

The combined effects of environmental, electrical, and thermal stress typically drive the degradation of PV inverters. High PV penetration can induce thermal cycling and voltage instability. Thermal cycling leads to

wear of the thermal management system and intensified component overheating, increasing the risk of material fatigue and thermal runaway; voltage instability may cause insulation breakdown and component overheating, weakening grid stability and increasing inverter trip risks. Overvoltage conditions directly accelerate power transistor degradation and reduce capacitor lifetime, while increasing short-circuit risks. Reactive power regulation generates electrical stress on components and induces switching losses in electronic devices, causing capacitor and inductor degradation and increased harmonic distortion, thereby reducing power conversion efficiency. Thermal stress manifests as material fatigue and thermal runaway risks, leading to solder joint cracking, semiconductor or material degradation, and ultimately catastrophic component failure and fire hazards. These mechanisms are mutually coupled, collectively exacerbating thermal stress on components and significantly affecting inverter reliability and service life [2].

However, current PV inverter maintenance largely relies on traditional approaches, such as periodic inspection and post-failure repair, which are inefficient and costly, hindering the stable and efficient operation of PV systems [3]. Therefore, establishing an automated, intelligent degradation-prediction model for PV inverters is of practical significance for preventive maintenance, spare parts planning, and O&M cost control.

Existing approaches to inverter degradation prediction include physics-based and data-driven methods.

Physics-based methods generally start from the failure mechanisms of critical components and use models such as the Arrhenius model and the Coffin-Manson relationship to describe the lifetime degradation processes of electrolytic capacitors, IGBT modules, and other devices. The advantage of such methods lies in their strong physical interpretability and extrapolation capabilities, but parameter calibration often relies on accelerated aging tests, and it is difficult to fully cover complex field operating conditions.

Data-driven methods, on the other hand, establish mapping models using historical inverter monitoring data and meteorological data. Common inputs include operating parameters such as voltage, current, and power, as well as environmental parameters such as irradiance and ambient temperature for time-series analysis and prediction. For example, some studies have employed LSTM for PV power forecasting [4], while others have combined CNNs with LSTMs, using CNNs to extract local features and LSTMs for sequence modeling [5]. These methods have strong fitting capability for complex nonlinear relationships but are sensitive to data volume, data quality, and model architecture design.

In practice, data-driven prediction methods are widely applied; however, sequence prediction models, such as LSTMs, struggle to handle long sequences of plant operational, meteorological, and environmental data. Their serial computation leads to long computation times that may affect prediction timeliness, and they also suffer from high computational resource requirements and structural complexity, which are unfavorable for large-scale deployment in industrial scenarios. The Transformer architecture models relationships between arbitrary time steps in a sequence in parallel through the self-attention mechanism, making it suitable for processing long-time-scale, multivariate degradation sequences [6].

Based on the above considerations, this paper proposes a PV inverter degradation prediction method using simulation data and a Transformer. The main contributions of this paper include: (1) constructing a simulation model that integrates environmental factors and inverter operating parameters to generate multi-condition historical data for model training; (2) establishing a Transformer multi-step prediction model with daily aggregated features and performance ratio as core indicators; and (3) validating the prediction accuracy of the model through a 200 h ahead output power prediction experiment and analyzing the error distribution and limitations of the method.

2. SIMulation Model for Training Data

To obtain the training samples required by the Transformer prediction model, this paper employs a computer simulation approach to construct mathematical models of PV inverter operating parameters and environmental indicators. The simulation model comprises two parts: an environmental parameter model and an inverter operating parameter model. The former describes the variations of irradiance, ambient temperature, and module temperature, while the latter describes dust accumulation, module degradation, and DC-side output characteristics.

2.1 Environmental Parameter SIMulation Model

A sinusoidal function is adopted to describe the diurnal variation of solar radiation, where sunrise time and sunset time are set to 6.5 and 18.5, respectively:

$$x(h) = \frac{h - h_{\text{sunrise}}}{h_{\text{sunset}} - h_{\text{sunrise}}} \cdot \pi \quad (1)$$

$$S_{\text{diurnal}}(h) = \begin{cases} \sin(\min(\max(x(h), 0), \pi)), & h_{\text{sunrise}} \leq h \leq h_{\text{sunset}} \\ 0, & \text{Otherwise} \end{cases} \quad (2)$$

Similarly, a sinusoidal function can be used to further construct a seasonal factor to describe the seasonal distribution of sunlight:

$$f_{\text{season}}(d) = 0.75 + 0.25 \cdot \sin(2\pi \cdot (\frac{d}{365} - 0.2)) \quad (3)$$

From this, the irradiance under ideal meteorological conditions can be constructed:

$$G_{\text{clear}}(h, d) = 1000 \cdot f_{\text{season}}(d) \cdot S_{\text{diurnal}}(h) \quad (4)$$

On this basis, the influence of cloud cover is considered, and a cloud noise factor is introduced to represent the random fluctuations in irradiance:

$$T_{\text{base}}(d) = 15 + 10 \cdot \sin(2\pi \cdot (\frac{d}{365} - 0.2)) \quad (5)$$

A cloud shading factor is applied over random time intervals to simulate short-term cloud shading effects:

$$f_{\text{cloud}_{\text{mask}}} = 1.0 \cdot r_2, \text{ where } r_2 \sim U(0.45, 0.85) \quad (6)$$

Thus, we obtain the actual irradiance model after meteorological correction:

$$G_{\text{poa}} = \min(\max(G_{\text{clear}} \cdot f_{\text{cloud}_{\text{noise}}} \cdot f_{\text{cloud}_{\text{mask}}}, 0), 1100) \quad (7)$$

Next, we model the ambient temperature, using a sinusoidal function to represent the seasonal variation of baseline temperature:

$$T_{\text{base}}(d) = 15 + 10 \cdot \sin(2\pi \cdot (\frac{d}{365} - 0.2)) \quad (8)$$

A sinusoidal function is used to represent the effect of diurnal solar motion on temperature:

$$T_{\text{diurnal}}(h) = 5 \cdot \sin(2\pi \cdot \frac{h - 6}{24}) \quad (9)$$

The two components are added to obtain the composite ambient temperature, as shown in Eq. (10):

$$T_{\text{amb}}(h, d) = T_{\text{base}}(d) + T_{\text{diurnal}}(h) + \epsilon_2, \text{ where } \epsilon_2 \sim N(0, 1.5) \quad (10)$$

Combining ambient temperature and irradiance, the module temperature can be modeled, as shown in Eq. (11):

$$T_{\text{cell}} = T_{\text{amb}} + 0.03 \cdot G_{\text{pos}} + \epsilon_3, \text{ where } \epsilon_3 \sim N(0, 1.2) \quad (11)$$

2.2 Inverter Operating Parameter Model

As shown in Eq. (12), the dust factor is constructed, where $d(t)$ is the number of operating days from the start of simulation to time t , $I_{\text{no_wish}}$ is an indicator function representing whether cleaning is performed on the i -th day, and D_{daily} is the daily dust accumulation rate (set to 0.0008 in this paper).

$$f_{\text{dust}}(t) = 1 - \min\left(\sum_{i=1}^{d(t)} D_{\text{daily}} \cdot I_{\text{no_wish}}(i), 0.08\right) \quad (12)$$

Next, the PV module operating parameters are modeled. First, three correction factors are considered: baseline module degradation, shading, and temperature effects.

$$H(d) = \min(\max(1.0 - d_{daily} \cdot d, 0.5), 1.05) \quad (13)$$

$$f_{shade} = \min(\max(1.0 - 0.01 \cdot \epsilon_4, 0.96), 1.0), \text{ where } \epsilon_4 \sim N(0,1) \quad (14)$$

$$f_{temp}(T) = \min(\max(1.0 + \gamma \cdot (T - 25), 0.6), 1.2) \quad (15)$$

Under the specified module parameters: rated voltage $V_0 \sim U(650, 850)$, rated power $P_{stc} \sim U(4000, 6000)W$; temperature coefficient $\gamma \sim U(-0.0045, -0.0030) ^\circ C^{-1}$; annual decrease rate $d_{year} \sim U(0.5, 2.0)\%/year$; daily decrease rate $d_{daily} = d_{year}/100/365$; other loss coefficient $f_{loss} \sim U(0.92, 0.98)$.

The DC power and voltage output of the PV inverter are given by:

$$P_{dc} = P_{stc} \cdot \frac{G_{poa}}{1000} \cdot f_{temp}(T_{cell}) \cdot H(d) \cdot f_{loss} \cdot f_{dust} \cdot f_{shade} \cdot (1 + \epsilon_5) \quad (16)$$

where $\epsilon_5 \sim N(0, 0.015)$.

$$V = V_0 \cdot [1.0 - 0.0012 \cdot (T_{cell} - 25)] \cdot (0.98 + 0.02 \cdot H(d)) \cdot (1 + \epsilon_6) \quad (17)$$

where $\epsilon_6 \sim N(0, 0.004)$.

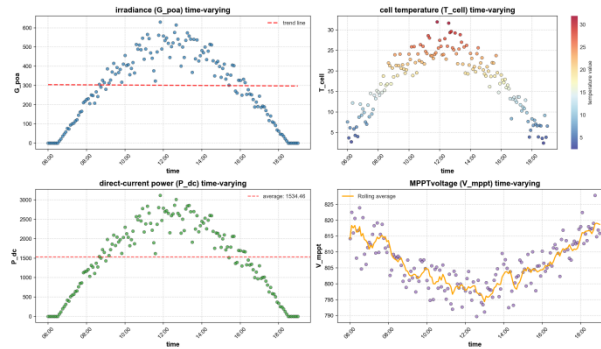
From this, the DC is expressed through DC power and voltage:

$$I = \begin{cases} \frac{P_{dc}}{V} \cdot (1 + \epsilon_7), & V > 10^{-6} \\ 0, & V \leq 10^{-6} \end{cases}, \text{ where } \epsilon_7 \sim N(0, 0.012) \quad (18)$$

In addition, this paper sets an operating status indicator. If the irradiance falls below the threshold of $20W/m^2$, the PV inverter is considered non-operating, and the corresponding time period is excluded from the effective power generation statistics.

The above simulation model can generate training data featuring intraday periodicity, seasonal variation, random cloud disturbances, and long-term degradation trends. Figure 1 shows the irradiance, module temperature, DC power, and DC voltage of PV inverter ID_001 on a given day from 6:00 to 19:00. It can be seen that the model reasonably reflects the influence of irradiance variation on module temperature and DC-side output, and can serve as the foundational data for subsequent Transformer model training.

Figure 1: Selected simulation data of photovoltaic inverter ID_001



3. Transformer-Based Prediction Model

3.1 Data Preprocessing

In PV inverter degradation prediction, the key challenge is to identify degradation trends from long-term, multivariate operating sequences. Traditional recurrent architectures such as RNNs and LSTMs are susceptible to gradient decay and to limitations in serial computation efficiency on long sequences. In contrast, the Transformer leverages the self-attention mechanism to capture dependencies across time steps in parallel,

making it better suited to modeling long-term operating states. This paper formulates inverter degradation prediction as a multivariate time-series multi-step forecasting problem, achieving future performance indicator predictions through temporal feature engineering, positional encoding, and sequence-to-sequence modeling.

First, the raw PV monitoring data are aggregated daily to remove noise from intraday fluctuations. For each inverter, the normalized DC power P_{norm} is calculated as a basic indicator, defined as the ratio of the current power to the historical maximum power, to eliminate capacity differences between devices. The calculation method of normalized DC power is given in Eq. (19).

$$P_{t_norm} = P_t \div P_{history_max} \quad (19)$$

On this basis, a daily feature set is constructed, including daily maximum power P_{max} , daily average power P_{mean} , power standard deviation P_{std} , daily irradiance G_{poa} maximum, daily total irradiance, daily mean irradiance, daily average module temperature T_{cell} , and daily maximum module temperature. This paper adopts the performance ratio (PR) as the core health indicator, defined as the ratio of actual maximum generated power to theoretical maximum generated power, clipped to the range [0, 1.2]. The PR can intuitively characterize the performance degradation trends of the inverter and PV modules during long-term operation.

$$PR = \frac{P_{max}}{(G_{max}/1000) \times 0.85} \quad (20)$$

To smooth out weather fluctuations and measurement noise, a 7-day moving average is applied to the PR indicator, and the smoothed value PR_{smooth} is used as the model prediction target. The moving average calculation formula is shown in Eq. (21), where $n = \min(7, t+1)$, $k = \min(6, t)$. A 30-day moving average is also calculated as a long-term trend reference. In addition, temporal features such as day-of-year, month, and cumulative operating days are introduced to encode seasonal patterns and operating duration effects.

$$PR_{smooth} = \frac{1}{n} \sum_{i=0}^k PR_{t-i} \quad (21)$$

3.2 Model Training

The model architecture uses a Transformer-encoder-based time-series predictor, as shown in Figure 2. The input sequence is mapped to a high-dimensional space through a linear projection layer and augmented with sinusoidal-cosine positional encodings, enabling the model to retain day-order information. The positional encoding formula is given in Eq. (22), where the position index represents the time step, i is the dimension index, and d_{model} is the feature dimension.

$$\begin{aligned} PE_{(pos,2i)} &= \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \\ PE_{(pos,2i+1)} &= \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \end{aligned} \quad (22)$$

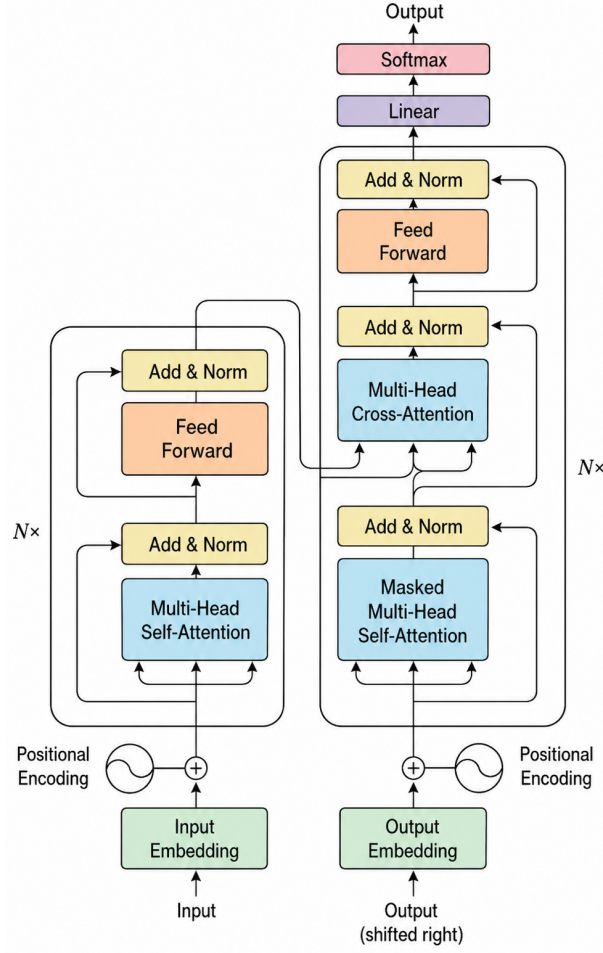
The encoder consists of a stack of multiple Transformer encoder layers, each containing a multi-head self-attention sublayer and a feed-forward neural network sublayer. The self-attention mechanism dynamically assigns weights to different days in the historical sequence, thereby capturing the nonlinear relationships among environmental disturbances, operating states, and degradation trends. The encoder output undergoes global average pooling and is then mapped through a fully connected network to the future smoothed PR sequence. During the training phase, samples are constructed using a sliding window approach, where each input sequence contains 90 consecutive days of multivariate features, and the output corresponds to the subsequent 30-day smoothed PR sequence. The normalized samples use mean squared error (MSE) as the loss function, defined in Eq. (23).

$$L_{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (23)$$

Here, y_i denotes the true PR sequence, $\hat{y}_i$ denotes the model-predicted sequence, and N is the number of samples. The MSE amplifies larger errors through the squared term, making the model more sensitive to

predictions that deviate significantly from the true values, which helps accurately capture key inflection points in degradation trends.

Figure 2: Transformer structure



Parameter updates use the AdamW optimizer, which decouples the weight decay (L2 regularization) term from the gradient update, as in traditional Adam, resulting in a more stable regularization effect. Its core lies in maintaining two first- and second-order moment estimate variables m_t and v_t , and updating according to the following rules:

$$\begin{aligned}
 m_t &= \beta_1 m_{t-1} + (1 - \beta_1) g_t \\
 v_t &= \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \\
 \hat{m}_t &= \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \\
 \theta_t &= \theta_{t-1} - \eta \left(\frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} + \lambda \theta_{t-1} \right)
 \end{aligned} \tag{24}$$

where g_t is the gradient of the current loss function with respect to the model parameters, θ_{t-1} is the model parameter vector, η is the global base learning rate, and λ is the weight decay coefficient used to penalize large parameter values. The hyperparameters β_1 , β_2 , and ϵ are empirically set to 0.0, 0.999, and 10^{-8} , respectively.

To further balance convergence speed and final performance, a cosine annealing learning rate scheduling strategy is adopted. As shown in Eq. (25), this strategy dynamically decays the learning rate from the initial value η_{max} to η_{min} using a cosine function.

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min}) \left(1 + \cos \left(\frac{T_{cur}}{T_{max}} \pi \right) \right) \quad (25)$$

where the current training epoch T_{cur} and the total number of training epochs T_{max} jointly determine the learning rate variation. This strategy enables the model to maintain a relatively fast convergence speed in the early training stage and perform fine-grained search with a smaller learning rate in the later stage, thereby improving convergence stability.

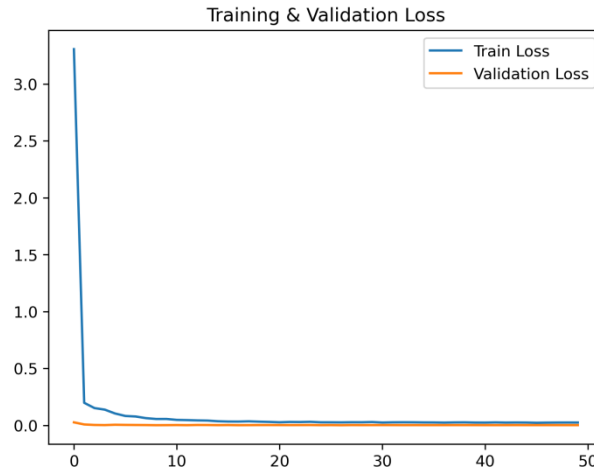
To prevent overfitting and training instability, early stopping and gradient clipping techniques are introduced. The early stopping mechanism continuously monitors the validation set loss; if it does not decrease for 20 consecutive training epochs, training is terminated and the model is rolled back to the checkpoint with the lowest validation loss. Gradient clipping is applied after each backpropagation and before parameter update, constraining the $L2$ norm of the gradient vector to no more than a preset threshold of 1.

In summary, the proposed method transforms the PV inverter degradation prediction problem into a multivariate time-series forecasting task. Positional encoding preserves temporal order information; the multi-head attention mechanism can automatically learn the contribution degrees of different meteorological factors and operating parameters to performance degradation; and the global pooling and fully connected layers compress the historical context into future PR sequence predictions, providing a quantitative basis for preventive maintenance and degradation assessment of PV plants.

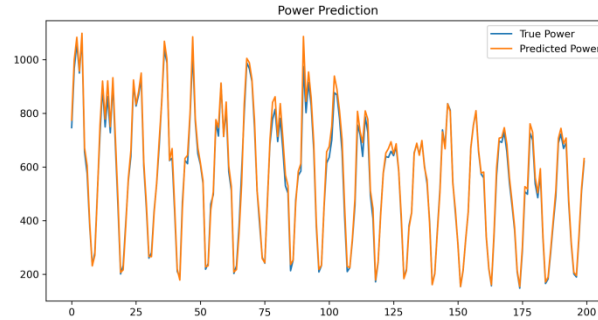
4. Results and Discussion

This study utilizes historical data generated by the simulation model to train the Transformer model and predicts the output power of a single inverter for the next 200 hours. The loss variation during model training is shown in Figure 3. Both the training loss and validation loss decrease rapidly with increasing training epochs and stabilize after approximately 10 epochs. The two curves do not show significant divergence, indicating that the model has converged sufficiently on the current simulation dataset and no significant overfitting is observed. It should be noted that, since the test and training data both originate from the simulation model, these results demonstrate only that the model has good fitting and generalization capabilities with respect to the simulation data distribution.

Figure 3: training & validation loss



The model's prediction performance is shown in Figure 4. The figure compares the simulated reference power and the model-predicted power over a 200-hour prediction horizon. Over the entire time span, the predicted curve maintains high consistency with the reference curve. During periods of rapid power increases and decreases, and pronounced intraday fluctuations, the predicted values closely track the fluctuations in the true values. This indicates that the Transformer model can effectively extract power temporal features and nonlinear variation patterns.

Figure 4: True power vs predicted power

To quantitatively evaluate prediction accuracy, this paper computes the distribution of prediction relative errors, as shown in Figure 5. The errors are mainly concentrated within a small range, with a mean relative error of only 2.64% and a standard deviation of 1.18%. These results indicate that, under simulation data conditions, the model can perform short-term power prediction with low error and has the potential to serve as an auxiliary assessment tool for degradation trends.

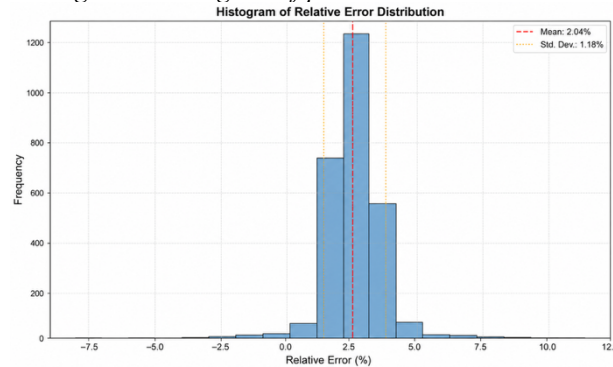
Figure 5: Histogram of prediction relative errors

Figure 6 shows the trend of the relative error over time. The error curve fluctuates around the 2.64% mean line without prolonged or large-magnitude deviations, indicating good model prediction stability. At the same time, errors in some periods are predominantly in the positive error region, suggesting a slight systematic overestimation tendency. This systematic error can be further reduced in the future by introducing bias correction, retraining with real data, or ensemble models.

Figure 6: Variation trend of prediction relative errors

In summary, the Transformer model presented in this paper can accurately predict the short-term output power of PV inverters in simulation. Its advantages primarily stem from the self-attention mechanism's global modeling of long-sequence dependencies and the smoothing effect of daily-aggregated features on weather noise. Compared with methods that rely solely on empirical thresholds or short-sequence models, the proposed approach can simultaneously leverage environmental variables, operational variables, and long-term degradation trends to provide more continuous quantitative information for inverter condition assessment.

Nevertheless, this paper still has several limitations. First, both training and test data are generated by the simulation model. Although this facilitates low-cost sample construction, factors such as sensor errors, equipment differences, communication failures, and abnormal shutdowns in real power plants have not been fully accounted for. Second, the experiment primarily validates the short-term power-prediction capability, and further research is needed for longer-term degradation prediction and remaining useful life estimation. Third, the current Transformer architecture is relatively simplified and lacks a systematic comparison with baseline models such as LSTM, CNN-LSTM, and Informer. Future research should introduce real operational data for transfer learning and robustness testing, and supplement ablation studies and multi-model comparisons to enhance the engineering credibility of the conclusions.

5. Conclusion

This paper proposes a PV inverter degradation prediction method based on simulation data and a transformer, and implements a preliminary model. The feasibility of generating datasets via computer simulation models for Transformer training has been demonstrated, and the model's predictions show a certain level of accuracy. This provides a technical pathway for achieving efficient, low-cost preventive maintenance of PV plants, thereby reducing costs and improving efficiency. Future work will need to expand the training dataset further, collect real operational parameters and environmental parameters across the full life cycle of PV plants, and train the Transformer model with greater computational power.

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Conflicts of Interest

The authors declare no conflict of interest.

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