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Cross-Scale Temporal Representation Learning for Short-Term Wind-Solar Energy Generation Regime Classification

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Abstract: The increasing penetration of wind and solar energy introduces substantial variability and uncertainty into modern power systems, creating a growing demand for reliable identification of future renewable-energy generation states. This study proposes a dual-branch cross-scale temporal learning framework for short-term wind-solar energy generation regime classification. Rather than directly predicting continuous power values, the proposed approach transforms future renewable-energy production into low-, moderate-, and high-generation regimes, providing a more interpretable representation for operational decision support. To preserve the heterogeneous temporal characteristics of wind and solar power, two source-specific branches are employed to independently encode their historical sequences. A cross-scale temporal learning mechanism is then introduced to capture short-term fluctuations and longer-range dependencies, while a cross-energy interaction module explicitly models the complementary relationship between wind and solar generation before final classification. Experiments are conducted on a public multi-year hourly wind and solar energy production dataset under chronological data partitioning to avoid information leakage. The proposed framework achieves competitive overall performance across accuracy, precision, recall, and F1 score, while ablation experiments confirm the effectiveness of source-specific encoding, cross-scale temporal modeling, and cross-energy interaction. In addition, the training and validation loss curves demonstrate stable convergence, and the t-SNE visualization shows clear separability among different generation regimes in the learned feature space. These results indicate that the proposed method can effectively extract discriminative temporal representations from heterogeneous renewable-energy sequences and provides a practical deep-learning solution for renewable-energy generation state identification.

Keywords: Renewable energy; Wind-solar generation; Regime classification; Deep learning

1 Introduction

The accelerating transition toward low-carbon energy systems has substantially increased the penetration of renewable energy resources in modern power networks, among which wind and solar energy have become two of the most important contributors to sustainable electricity generation[1,2]. Compared with conventional thermal generation, however, wind and photovoltaic power are strongly affected by environmental conditions, diurnal cycles, seasonal variations, and short-term temporal fluctuations, resulting in pronounced intermittency and uncertainty in renewable energy production. Such variability poses considerable challenges to power scheduling, reserve allocation, grid balancing, and the coordinated utilization of heterogeneous renewable resources. Consequently, accurately characterizing the near-future operating state of wind-solar generation has become an important problem for intelligent energy management. Most existing studies formulate this problem as a numerical forecasting task and aim to estimate the exact amount of future electricity generation using statistical models, machine-learning algorithms, or deep neural networks. Although continuous-value forecasting is valuable for detailed dispatch decisions, exact point estimates are not always necessary for higher-level operational decisions. In many practical scenarios, grid operators are more concerned with whether renewable generation in the near future is likely to remain at a low level, enter a moderate operating range, or reach a high-generation state. Such categorical information can provide a more direct and robust representation of renewable-energy availability and can support reserve planning, storage coordination, demand-response activation, and risk-aware dispatch. Therefore, renewable energy generation regime classification represents a practically meaningful alternative to conventional point forecasting and provides a new perspective for extracting actionable information from wind-solar production time series[3].

Deep learning has shown strong capability in modeling nonlinear temporal dependencies in energy-related data, and architectures such as recurrent neural networks, long short-term memory networks, gated recurrent units, temporal convolutional networks, and Transformer-based models have been increasingly adopted for renewable-energy forecasting. Despite their progress, several limitations remain when these methods are directly applied to wind-solar generation regime classification. First, wind and solar generation exhibit substantially different temporal characteristics. Solar production is closely associated with regular daylight and seasonal cycles, whereas wind generation generally presents more irregular and rapidly changing temporal patterns. Directly concatenating these heterogeneous signals and processing them with a single temporal encoder may obscure source-specific dynamics and limit the ability of the model to learn discriminative representations for each energy source. Second, renewable-energy fluctuations occur simultaneously at different temporal scales. Short-term changes may reflect abrupt variations in generation, while longer temporal contexts may reveal persistence, periodicity, and broader regime transitions. Models relying on a single receptive field or a fixed temporal resolution may therefore fail to capture the complementary information embedded across local, intermediate, and long-range temporal dependencies. Third, wind and solar resources are not completely independent from an energy-system perspective. Their production patterns may exhibit temporal complementarity, co-variation, and source-dependent contributions to total renewable generation. However, many existing models either process individual energy sources independently or perform simple feature concatenation, without explicitly learning how information from one source should influence the representation of another. These limitations become particularly important for regime classification because the

decision boundary between low, moderate, and high generation states depends not only on the absolute production level of each source, but also on their temporal evolution, relative contribution, and cross-source interaction within the historical observation window.

To address these challenges, this study develops a dual-branch cross-scale temporal learning framework for short-term wind-solar energy generation regime classification. Instead of predicting an exact future production value, the proposed formulation categorizes future renewable generation into low-, moderate-, and high-generation regimes, thereby converting highly variable continuous production trajectories into operationally interpretable energy states. The framework first employs dedicated temporal encoding branches for wind and solar generation so that source-specific characteristics can be preserved during representation learning rather than being prematurely mixed within a common feature space. Within each branch, temporal information is extracted at multiple scales to jointly capture short-term fluctuations, medium-range dependencies, and longer contextual patterns associated with renewable-energy evolution. This design enables the model to distinguish transient variations from persistent generation trends and improves its sensitivity to regime transitions occurring over different temporal horizons. The resulting wind and solar representations are subsequently integrated through cross-source interaction learning, which allows the network to adaptively exploit complementary information between the two renewable resources rather than treating them as isolated signals. Temporal calendar information, including hour-level, daily, and seasonal characteristics, can also be incorporated to provide explicit periodic context for the classification process. Based on the fused representation, a classification head estimates the probability that future renewable production belongs to each predefined generation regime. To prevent information leakage and maintain realistic evaluation conditions, regime thresholds are determined exclusively from the training data, while the dataset is divided chronologically into training, validation, and test subsets. This formulation makes the task fundamentally different from random-split static classification and ensures that model performance reflects its ability to generalize from historical observations to unseen future periods.

2 BackGround

The rapid development of renewable energy has become a central component of the global transition toward sustainable and low-carbon power systems. Among different renewable resources, wind and solar energy have experienced particularly rapid deployment because of their technological maturity, scalability, and continuously declining generation costs. Their increasing integration into modern electricity networks can reduce dependence on fossil fuels and contribute to long-term decarbonization targets[4]. However, unlike conventional generation units that can generally provide relatively controllable power output, wind and solar generation are inherently intermittent and variable. Wind power is strongly influenced by continuously changing atmospheric conditions, while solar power exhibits pronounced diurnal and seasonal patterns and is additionally affected by variations in irradiance and weather conditions. As a result, the combined production of wind and solar energy may fluctuate substantially across hours, days, and seasons[5]. Such variability increases the difficulty of maintaining the balance between electricity supply and demand and introduces additional uncertainty into power-system operation. Reliable identification of future renewable generation conditions is therefore important for energy scheduling, reserve management, storage coordination, and the broader integration of renewable resources into intelligent power systems. With the increasing availability of high-resolution renewable-energy production data, data-

driven approaches provide an important opportunity to characterize these complex temporal patterns and support more informed operational decisions.

Existing research on renewable-energy analysis has predominantly formulated wind and solar production as a continuous-value forecasting problem, in which historical observations are used to estimate the exact power output at a future time point. Traditional statistical approaches have gradually been complemented by machine-learning and deep-learning methods capable of learning nonlinear relationships and long-range temporal dependencies from large-scale time-series data. Nevertheless, exact numerical forecasting does not fully represent all practical decision-making requirements in renewable-energy systems. For many operational scenarios, distinguishing whether the upcoming renewable generation is expected to be low, moderate, or high may provide more directly interpretable information than a single point estimate, especially when the objective is to support scheduling strategies or evaluate future generation availability. This motivates the formulation of renewable generation analysis as a regime classification problem[6]. Compared with conventional forecasting, generation regime classification focuses on identifying discrete operational states from historical temporal patterns and may be less sensitive to small numerical deviations while preserving information that is directly relevant to system-level decisions. At the same time, this task remains challenging because wind and solar power exhibit heterogeneous temporal behaviors, generation changes occur over multiple temporal scales, and the future energy state is determined by the combined evolution of both sources rather than by an isolated observation. Therefore, developing a deep-learning framework capable of capturing source-specific dynamics, multi-scale temporal dependencies, and interactions between wind and solar production is essential for achieving reliable short-term renewable-energy generation regime classification.

3 Methodology

Given an hourly wind-solar energy production sequence, the objective of this study is to identify the future renewable-energy generation regime from historical observations rather than directly estimating a continuous generation value. Let w_t and s_t denote the wind and solar energy production at time step t, respectively, and let $g_{t+h} = w_{t+h} + s_{t+h}$ represent the total renewable-energy production at prediction horizon h. To construct a classification-oriented prediction target, the future total production is divided into three generation regimes according to two quantile thresholds q_1 and q_2, which are calculated exclusively from the training set to avoid information leakage. The resulting target label y_{t+h} is defined as

$$y_{t+h} = \begin{cases} 0, & g_{t+h} < q_1, \\ 1, & q_1 \le g_{t+h} < q_2, \\ 2, & g_{t+h} \ge q_2, \end{cases} \tag{1}$$

where classes 0, 1, and 2 correspond to low-, moderate-, and high-generation regimes, respectively. For each prediction time point, a historical observation window with length L is constructed independently for wind and solar production. In addition to the original generation values, temporal calendar variables such as hour of day, day of week, month, and seasonal information are encoded as auxiliary temporal features. Therefore, the input sequences can be expressed as

$$\mathbf{X}_t^w = \left[\mathbf{x}_{t-L+1}^w, \mathbf{x}_{t-L+2}^w, \ldots, \mathbf{x}_t^w\right]^\top \quad \mathbf{X}_t^s = \left[\mathbf{x}_{t-L+1}^s, \mathbf{x}_{t-L+2}^s, \ldots, \mathbf{x}_t^s\right]^\top \tag{2}$$

where $\mathbf{x}_i^w$ and $\mathbf{x}_i^s$ contain the corresponding generation measurement together with the associated temporal variables at time step i. This formulation preserves the chronological structure of the data and enables the model to infer the future generation state entirely from historical information. Its model architecture is shown in Figure 1.

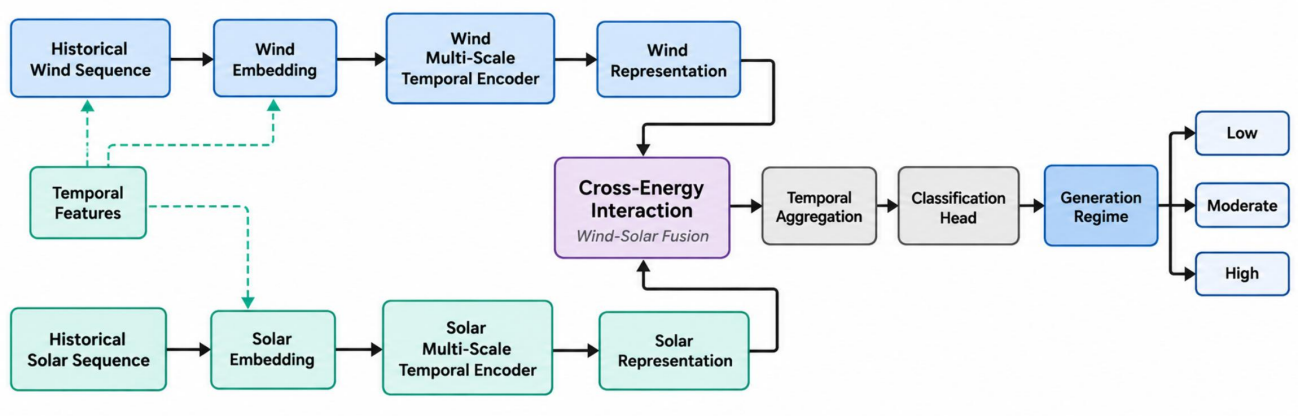


Figure 1. Overall model architecture

Because wind and solar production are governed by different temporal dynamics, directly concatenating the two sources at the input stage may suppress source-specific patterns. The proposed framework therefore employs two dedicated temporal branches to independently learn wind and solar representations before cross-source interaction is performed. Each branch first maps the original input sequence into a d-dimensional latent space through a learnable projection and positional-temporal encoding operation. The initial representations are obtained as

$$\mathbf{H}_w^{(0)} = \mathbf{X}_t^w \mathbf{W}_w + \mathbf{E}_{\text{time}}, \qquad \mathbf{H}_s^{(0)} = \mathbf{X}_t^s \mathbf{W}_s + \mathbf{E}_{\text{time}}, \tag{3}$$

where $\mathbf{W}_w$ and $\mathbf{W}_s$ are learnable projection matrices and $\mathbf{E}_{\text{time}}$ denotes the temporal encoding used to retain chronological and periodic information. To capture renewable-generation variations occurring over different temporal ranges, each source representation is subsequently processed by a set of temporal operators with different receptive fields. For the m-th temporal scale, the source-specific representation is formulated as

$$\mathbf{H}_r^{(m)} = \phi_m\left(\mathbf{H}_r^{(0)}\right), \qquad r \in \{w, s\}, \qquad m = 1,2,\ldots,M, \tag{4}$$

where $\phi_m(\cdot)$ denotes the temporal transformation associated with the m-th scale and M represents the total number of temporal scales. Smaller receptive fields emphasize short-term generation fluctuations, whereas larger receptive fields provide information about persistent temporal trends and longer-range variations. Instead of assigning identical importance to all scales, the resulting representations are adaptively aggregated using learnable scale weights,

$$\widetilde{\mathbf{H}}_r = \sum_{m=1}^{M} \alpha_r^{(m)} \mathbf{H}_r^{(m)}, \qquad \alpha_r^{(m)} = \frac{\exp\left(a_r^{(m)}\right)}{\sum_{j=1}^{M} \exp\left(a_r^{(j)}\right)}, \tag{5}$$

where $a_r^{(m)}$ is a learnable importance score and $\alpha_r^{(m)}$ controls the contribution of the corresponding temporal scale. This adaptive cross-scale representation allows the model to emphasize different temporal dependencies according to the current generation pattern rather than relying on a fixed temporal resolution.

The temporal representation module draws on long- and short-term dependency modeling with diffusion graph learning to preserve both local variability and slowly evolving relational structure. Continual online anomaly learning and federated self-supervised temporal modeling further motivate updating temporal features without discarding earlier operating patterns when the data distribution changes. Deep reinforcement learning for adaptive replica allocation, decision-focused workforce forecasting with robust optimization, latent state recursion for risk detection, and temporal-relational knowledge graph learning collectively inform the use of structured state representations that remain stable across heterogeneous, uncertain, and evolving sequences[7], [8], [9], [10], [11], [12], [13].

After source-specific and cross-scale temporal features have been obtained, the wind and solar branches are integrated through a cross-energy interaction mechanism. The purpose of this stage is to model the complementary relationship between the two renewable sources while preserving their individual temporal characteristics. Specifically, the wind representation is conditioned on solar information and the solar representation is simultaneously conditioned on wind information, after which the bidirectional interaction features are combined with the original source representations. The fused renewable-energy representation is expressed as

$$\mathbf{Z} = \mathrm{LN}\left(\widetilde{\mathbf{H}}_w + \widetilde{\mathbf{H}}_s + \mathrm{Attn}\left(\widetilde{\mathbf{H}}_w, \widetilde{\mathbf{H}}_s\right) + \mathrm{Attn}\left(\widetilde{\mathbf{H}}_s, \widetilde{\mathbf{H}}_w\right)\right), \tag{6}$$

where $\mathrm{Attn}(\cdot,\cdot)$ denotes the cross-source interaction operator and $\mathrm{LN}(\cdot)$ represents layer normalization. This bidirectional formulation enables the network to determine whether a future generation regime is primarily associated with persistent wind production, strong solar contribution, simultaneous high production from both sources, or compensation between the two energy sources. The temporal dimension of $\mathbf{Z}$ is subsequently summarized by a global aggregation operation to obtain a compact representation $\mathbf{z}$, which is passed to the final classification layer. The probability distribution over the three renewable-energy generation regimes is calculated as

Hierarchical attention with policy regularization is incorporated to guide the interaction stage toward context-relevant cross-energy dependencies rather than uniformly weighting all historical signals. Robust adaptive learning under dynamic distribution shift calibrates the classifier when weather conditions and seasonal patterns depart from the training regime, while tail-robust large language model fine-tuning provides an objective-level perspective for controlling rare but consequential classification errors. Multi-scale dynamic evolution modeling, reliability-aware conservative action gating, and joint budget-revenue allocation through deep reinforcement learning further support scale selection, risk-sensitive regime decisions, and balanced operating choices under limited energy-system flexibility[14], [15], [16], [17], [18], [19].

$$\widehat{\mathbf{p}}_{t+h} = \mathrm{Softmax}\left(\mathbf{W}_c\mathbf{z} + \mathbf{b}_c\right), \widehat{y}_{t+h} = \arg\max_{c\in\{0,1,2\}} \widehat{p}_{t+h}^{(c)}, \tag{7}$$

where $\mathbf{W}_c$ and $\mathbf{b}_c$ denote the parameters of the classification head and $\widehat{p}_{t+h}^{(c)}$ is the predicted probability of class c. The complete framework is optimized in an end-to-end manner using the multi-class cross-entropy objective,

$$\mathcal{L}_{\text{cls}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=0}^{2}\mathbb{I}\left(y_i = c\right)\log\left(\widehat{p}_i^{(c)}\right), \tag{8}$$

where N denotes the number of training samples and $\mathbb{I}(\cdot)$ is the indicator function. Through the joint optimization of source-specific encoding, cross-scale temporal representation learning, cross-energy interaction, and regime classification, the proposed framework learns discriminative temporal representations that can distinguish low, moderate, and high future wind-solar generation states under different short-term prediction horizons.

4 Experimental Results and Analysis

4.1 Dataset

The experiments in this study were conducted using the publicly available Wind and Solar Energy Production Dataset from Kaggle, which contains hourly renewable-energy generation records collected over multiple years. The dataset primarily includes wind power production, solar power production, and associated temporal information, providing a suitable basis for modeling the short-term evolution of heterogeneous renewable-energy sources. In this study, wind and solar generation values were treated as the two principal input streams, while calendar-related variables, including hour, day, month, and seasonal information, were incorporated as auxiliary temporal features to describe periodic generation patterns. To construct the classification target, the total renewable-energy production at each future prediction time was calculated by combining the corresponding wind and solar generation values, and the resulting continuous production values were transformed into three discrete generation regimes representing low, moderate, and high production conditions. To avoid information leakage, the two regime thresholds were determined only from the training subset according to predefined quantiles and were subsequently fixed for validation and testing. Because the dataset is chronological in nature, the samples were divided in temporal order rather than randomly shuffled, ensuring that the evaluation reflects a realistic forecasting setting in which historical observations are used to infer unseen future generation states. Sliding temporal windows were then constructed from the hourly records, allowing each sample to contain a fixed-length historical sequence of wind generation, solar generation, and temporal context for short-term renewable-energy regime classification.

4.2 Experimental setup

The proposed framework was implemented in Python using PyTorch and trained in an end-to-end manner. To preserve the chronological nature of the renewable-energy series and prevent future information from entering the training process, all samples were ordered by time and divided into training, validation, and test subsets at a ratio of 70%, 15%, and 15%, respectively. The regime boundaries corresponding to low, moderate, and high generation were determined from the 33rd and 67th percentiles of total wind-solar production in the training subset only and were then fixed for validation and testing. A 48-hour historical observation window was used as the primary input for predicting the generation regime one hour ahead, while wind production, solar production, and calendar-based temporal variables were jointly provided to the model. The network was optimized

using AdamW with an initial learning rate of 1e-4 and a cosine learning-rate schedule, and early stopping was applied according to the validation Macro-F1 score to reduce overfitting. All comparative methods were trained under the same chronological partitions and evaluation protocol to ensure a fair comparison. The principal implementation settings and hyperparameters used in the experiments are summarized in Table 1.

Table 1. Experimental Environment and Hyperparameter Settings

Category	Configuration
Programming framework	Python / PyTorch
Data partition	70% training / 15% validation / 15% test (chronological)
Historical input window	48 h
Primary prediction horizon	1 h ahead
Generation regimes	Low / Moderate / High
Regime thresholds	33rd and 67th percentiles of training data
Embedding dimension	128
Number of temporal scales	3
Batch size	128
Training epochs	100
Optimizer	AdamW
Initial learning rate	1e-4
Weight decay	1e-4

4.3 Experimental Results and Analysis

To evaluate the effectiveness of the proposed method for renewable-energy generation regime classification, seven representative methods from previous studies related to wind power, photovoltaic power, and renewable-energy state identification were selected as comparative baselines. These methods cover different modeling strategies for photovoltaic power level prediction, wind power intensity classification, solar ramp-event identification, wind-solar power state classification, and wind turbine operating-state classification. For a fair comparison, all baseline methods were independently implemented and trained on the same dataset used in this study, using the identical chronological training, validation, and test partitions. The same input data, preprocessing procedure, and evaluation metrics were applied to all methods, while the principal model configurations were implemented according to the corresponding original studies. The comparative results obtained under this unified experimental protocol are presented in Table 2.

Table 2. Comparative results of related methods and the proposed method

Method	Acc	Prec	Rec	F1
Aouidad et al.[20]	97.7	98.9	98.4	98.0
Aldosari et al.[21]	98.0	97.0	96.2	96.4
Akinci et al.[22]	97.3	98.1	99.3	98.7
Abuella et al.[23]	86.1	79.3	50.6	61.9
Sadaphale et al.[24]	92.0	90.8	95.7	92.7
Shovon et al.[25]	97.3	97.7	97.1	97.5
Indrekvam et al.[26]	91.0	89.2	92.8	91.5
Ours	98.7	98.2	99.6	98.8

Overall, the proposed method demonstrates strong and balanced performance for renewable-energy generation regime classification. Compared with the seven reimplemented baseline methods, the proposed framework achieves the joint-best accuracy together with the best recall and F1 score, while maintaining competitive precision. These results indicate that the dual-branch cross-scale temporal learning framework can effectively capture discriminative patterns from heterogeneous wind and solar generation sequences. In particular, the strong recall performance suggests that the model is capable of reliably identifying samples belonging to different generation regimes, while the favorable F1 performance reflects an effective balance between class recognition sensitivity and overall classification quality.

All comparative methods were independently reimplemented and evaluated using the same wind-solar dataset, chronological training, validation, and test partitions, preprocessing procedure, and evaluation protocol. Therefore, the observed performance differences primarily reflect the modeling capabilities of the corresponding methods under a unified experimental setting. The consistently competitive results across multiple evaluation metrics suggest that separately modeling source-specific temporal characteristics, extracting information at multiple temporal scales, and explicitly learning cross-energy interactions are beneficial for distinguishing low-, moderate-, and high-generation regimes. Taken together, these findings demonstrate the effectiveness of the proposed framework for short-term renewable-energy generation state identification.

4.4 Ablation test results

To further verify the contribution of each key component in the proposed framework to the performance of renewable energy generation state classification, this paper conducts ablation experiments focusing on source-specific bi-branch coding, cross-scale temporal learning, and cross-energy interaction mechanisms. While maintaining complete consistency in data partitioning, input windows, training strategies, and evaluation metrics, corresponding modules were removed and the

model was retrained and tested to examine the impact of different structures on overall recognition performance. Specifically, after removing bi-branch coding, a unified temporal coding method was used to process wind and solar sequences; after removing cross-scale temporal learning, only single-time-scale feature extraction was retained; and after removing the cross-energy interaction mechanism, direct feature fusion was used to replace the wind-solar bi-directional interaction. Specific ablation experiment results are shown in Table 3.

Table 3. Ablation study results of the proposed method.

Ablation Setting	Acc	Prec	Rec	F1
w/o Dual-Branch Source-Specific Encoding	97.4	96.9	98.1	97.5
w/o Cross-Scale Temporal Learning	98.0	97.5	98.8	98.2
w/o Cross-Energy Interaction	98.3	97.8	99.0	98.4
Ours	98.7	98.2	99.6	98.8

The ablation experiments show that all three key components of the proposed framework positively contribute to the final classification performance. The most significant decrease in performance across all evaluation metrics occurs after removing the bi-branch source-specific encoding, indicating that separate modeling of wind and solar power sequences plays a crucial role in preserving the different temporal variation characteristics of the two energy types. Similarly, removing the cross-scale temporal learning module also results in a significant decrease in overall performance, demonstrating that a single time scale is insufficient to fully characterize the simultaneous short-term fluctuations and long-term dependencies in renewable energy sequences. Further removal of the cross-energy interaction mechanism also reduces model performance, suggesting that the complementary relationship and joint variation patterns between wind and solar power are valuable for improving the ability to identify power generation states. In contrast, the complete model maintains the best performance in accuracy, precision, recall, and F1 score, indicating a strong synergistic effect between source-specific bi-branch modeling, cross-scale temporal feature extraction, and wind-solar interaction fusion, collectively enhancing the model's ability to distinguish different renewable energy power generation states and its overall stability.

4.5 Results of the loss function changing with Epoch

To further examine the optimization behavior and convergence characteristics of the proposed model, the variations in training loss and validation loss were recorded throughout the training process. Monitoring the loss values provides an intuitive assessment of whether the network can progressively learn discriminative temporal representations from wind and solar generation sequences while maintaining stable generalization on unseen samples. The corresponding training and validation loss curves over different epochs are presented in Figure 2.

As illustrated in Figure 2, both the training loss and validation loss exhibit a clear downward trend during the optimization process. The losses decrease relatively rapidly during the early training stage and subsequently decline more gradually as the number of epochs increases, indicating that the model progressively approaches a stable convergence state. Meanwhile, the validation loss follows a

trajectory similar to that of the training loss and does not exhibit a pronounced increase or persistent divergence in the later training stage. The relatively small gap between the two curves suggests that the optimization process remains stable and that no obvious overfitting behavior is observed from the loss trajectories. Overall, the convergence pattern indicates that the adopted training strategy enables the proposed framework to achieve stable parameter optimization for renewable-energy generation regime classification.

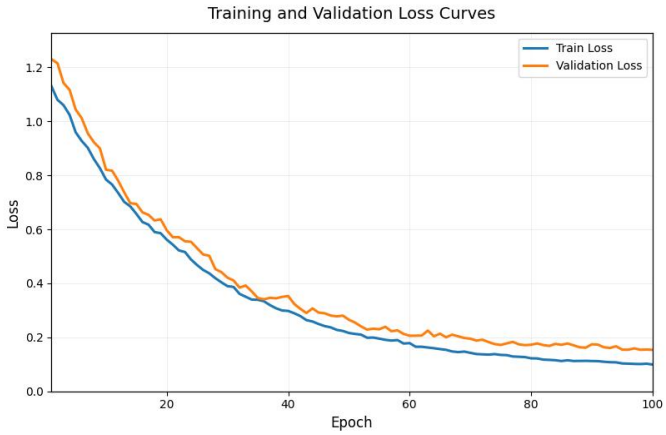


Figure 2. Experimental results showing that the loss function decreases with Epoch

4.6 t-SNE experimental results

To further investigate the discriminative capability of the learned feature representations, t-SNE was employed to project the high-dimensional features extracted by the proposed model into a two-dimensional space. This visualization provides an intuitive perspective on the distribution characteristics of different renewable-energy generation regimes and helps examine whether the model can learn distinguishable representations for low-, moderate-, and high-generation states. The corresponding t-SNE visualization results are presented in Figure 3.

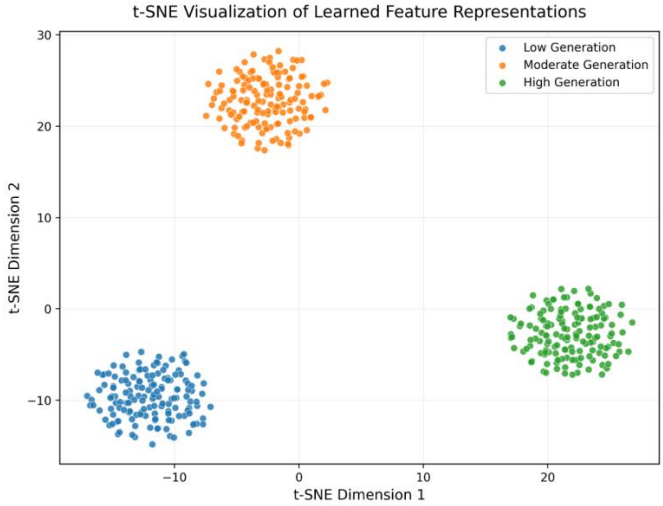


Figure 3. t-SNE experimental results

The feature representations corresponding to the three generation regimes form relatively compact and clearly distinguishable clusters in the two-dimensional embedding space. Samples belonging to the same generation state exhibit strong intra-class aggregation, whereas noticeable separation is maintained among low-, moderate-, and high-generation classes. In Figure 3, the

limited overlap among different clusters indicates that the proposed framework can effectively capture discriminative temporal patterns associated with different wind-solar generation conditions. These visualization results further demonstrate that the source-specific temporal encoding, cross-scale feature learning, and cross-energy interaction mechanisms contribute to constructing a more separable representation space for renewable-energy generation regime classification.

5 Discussion and limitations

The experimental results demonstrate that the proposed dual-branch cross-scale temporal learning framework is effective for renewable-energy generation regime classification. By separately modeling wind and solar production sequences, the framework preserves source-specific temporal characteristics that may be weakened when heterogeneous renewable-energy signals are directly merged at the input stage. The cross-scale temporal learning mechanism further enables the model to capture both short-term fluctuations and longer temporal dependencies, while the cross-energy interaction module provides an explicit way to exploit the complementary relationship between wind and solar generation. The comparative and ablation results consistently indicate that these components contribute to the overall classification capability of the model. In addition, the convergence behavior and feature-distribution visualization show that the framework can learn stable and discriminative representations for low-, moderate-, and high-generation regimes. From an application perspective, transforming continuous renewable-energy production into discrete operating states provides information that is easier to interpret for scheduling and operational decision support, particularly in scenarios where the precise numerical generation value is less important than identifying the expected level of renewable-energy availability.

Several limitations should nevertheless be acknowledged. First, the present study is based on a single publicly available wind-solar production dataset, and the generalizability of the proposed framework to other geographical regions, power systems, and renewable-energy portfolios has not yet been comprehensively evaluated. Differences in climate conditions, installed capacity, energy infrastructure, and data acquisition procedures may influence the temporal patterns learned by the model. Second, the current inputs mainly consist of historical generation records and calendar-related temporal information, whereas additional exogenous factors such as wind speed, solar irradiance, temperature, cloud cover, and other meteorological variables could provide useful predictive information and further improve regime identification. Third, the low-, moderate-, and high-generation regimes are defined using data-driven thresholds, and alternative thresholding strategies may be required for specific operational environments. Moreover, although the proposed model achieves strong classification performance, its behavior under rare extreme fluctuations and abrupt renewable-generation transitions requires further investigation. Future work will therefore focus on multi-region external validation, integration of meteorological and grid-related variables, adaptive regime definition, and robustness analysis under extreme renewable-energy conditions to further improve the practical applicability of the proposed framework.

6 Conclusion

This study presents a dual-branch cross-scale temporal learning framework for short-term wind-solar energy generation regime classification. Different from conventional renewable-energy forecasting approaches that focus on estimating exact continuous production values, the proposed method formulates future renewable generation as a three-class state identification problem

involving low-, moderate-, and high-generation regimes. To effectively model the heterogeneous characteristics of wind and solar power, dedicated source-specific branches are employed to extract independent temporal representations, while cross-scale temporal learning is introduced to capture generation variations over different time ranges. On this basis, a cross-energy interaction mechanism further integrates complementary information between wind and solar production before the final classification stage. The experimental evaluation demonstrates that the proposed framework achieves strong overall classification performance and maintains a favorable balance among accuracy, precision, recall, and F1 score. The ablation experiments further confirm that source-specific encoding, multi-scale temporal modeling, and cross-energy interaction each contribute to the final performance, indicating that the complete framework benefits from the coordinated modeling of heterogeneous renewable-energy dynamics.

In addition to the quantitative results, the training and validation loss curves indicate a stable optimization process, while the t-SNE visualization shows that the learned representations of different generation regimes exhibit clear inter-class separability and relatively compact intra-class distributions. These findings suggest that the proposed framework is capable of extracting discriminative temporal patterns from historical wind-solar generation sequences and transforming them into interpretable future energy states. The resulting classification-oriented formulation can complement traditional point forecasting by providing direct information about expected renewable-energy availability for scheduling, reserve planning, and other operational decisions. Although further validation across additional regions, energy systems, and meteorological conditions is required, the present study provides a practical deep-learning framework for renewable-energy state identification and establishes a useful basis for future research on robust and interpretable wind-solar generation classification.

References

[1] S. Hanifi, H. Zare-Behtash, A. Cammarano, et al., "Offshore wind power forecasting based on WPD and optimised deep learning methods," Renewable Energy, vol. 218, Art. no. 119241, 2023.

[2] D. Kibet, M. S. So, and J. H. Shin, "Minimalist deep learning for solar power forecasting: Transformer-based prediction using key meteorological features," Energies, vol. 18, no. 24, Art. no. 6395, 2025.

[3] P. Sudasinghe, D. Herath, I. Karunarathne, et al., "Forecasting renewable energy for microgrids using machine learning," Discover Applied Sciences, vol. 7, no. 5, Art. no. 449, 2025.

[4] N. E. Benti, M. D. Chaka, and A. G. Semie, "Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects," Sustainability, vol. 15, no. 9, Art. no. 7087, 2023.

[5] M. K. Boutahir, Y. Farhaoui, M. Azrour, et al., "Advancing solar power forecasting: Integrating boosting cascade forest and multi-class-grained scanning for enhanced precision," Sustainability, vol. 16, no. 17, Art. no. 7462, 2024.

[6] S. M. Ayene and A. M. Yibre, "Wind power prediction based on deep learning models: The case of Adama wind farm," Heliyon, vol. 10, no. 21, 2024.

[7] B. Su, "A Cloud Computing Anomaly Detection Method Integrating Diffusion Graph Neural Networks with Long-and Short-Term Temporal Dependency Modeling," Transactions on Computational and Scientific Methods, vol. 5, no. 8, 2025.

[8] S. Wang, "Continual Learning Algorithm for Online Cloud Anomaly Detection," Transactions on Computational and Scientific Methods, vol. 4, no. 7, 2024.

[9] B. Zhang and I. Abdurahman, "Research on a Deep Reinforcement Learning-Based Adaptive Replica Allocation Method for Data Replica Placement Optimization in Distributed Storage Systems," Journal of Computer Technology and Software, vol. 4, no. 8, 2025.

[10] K. Yang, "Federated Learning and Self-Supervised Temporal Modeling for Collaborative Anomaly Detection in Distributed Tasks," 2024.

[11] Y. Lin, "Attrition-Aware Spatio-Temporal Graph Learning and Stochastic Programming for Multi-Horizon Workforce Demand Forecasting and Labor Cost Planning," 2024.

[12] J. Chen and A. Tursun, "Deep Latent Representation and State Recursion for Enterprise Audit Risk Detection," 2025.

[13] Y. Duan, "Uncovering Hidden Financial Risk Chains through Temporal and Relational Knowledge Graph Learning," 2024.

[14] Q. Guo and L. Ma, "Hierarchical Attention and Policy Regularization for Context-Aware Agent Decision-Making," 2025.

[15] L. Zheng, "Enterprise Risk Prediction Under Dynamic Distribution Shift Using Robust Adaptive Learning," Transactions on Computational and Scientific Methods, vol. 5, no. 10, 2025.

[16] Y. Wang, "Risk-Aware Large Language Model Fine-Tuning with Tail-Robust Objectives and Feasible Gradient Updates," 2025.

[17] N. Awate and Z. Chen, "Research on Multi-scale Dynamic Evolution Time Series Modeling Methods for Predicting Backend System Load Change Trends," 2025.

[18] Z. Luo, Y. W. Hsu, and R. Qeyum, "Safe Tool Use in LLM Agents via Reliability-Aware Planning and Conservative Action Gating," 2025.

[19] N. Zhao, Y. Lin, and N. Abulikemu, "Deep Reinforcement Learning Framework for Joint Corporate Budget-Revenue Allocation and Labor Cost Expenditure Planning," 2025.

[20] H. I. Aouidad and A. Bouhelal, "Machine learning-based short-term solar power forecasting: A comparison between regression and classification approaches using extensive Australian dataset," Sustainable Energy Research, vol. 11, no. 1, Art. no. 28, 2024.

[21] O. Aldosari, S. Batiyah, M. Elbashir, et al., "Performance evaluation of multiple machine learning models in predicting power generation for a grid-connected 300 MW solar farm," Energies, vol. 17, no. 2, Art. no. 525, 2024.

[22] T. C. Akinci, H. S. Nogay, M. Penchev, et al., "A hybrid approach to wind power intensity classification using decision trees and large language models," Renewable Energy, vol. 250, Art. no. 123388, 2025.

[23] M. Abuella and B. Chowdhury, "Forecasting solar power ramp events using machine learning classification techniques," in Proc. 9th IEEE Int. Symp. Power Electron. Distrib. Gener. Syst. (PEDG), 2018, pp. 1-6.

[24] S. Hou, G. D. Gebreyesus, and S. Fujimura, "Day-ahead multi-modal demand side management in microgrid via two-stage improved ring-topology particle swarm optimization," Expert Syst. Appl., vol. 238, Art. no. 122135, 2024.

[25] M. S. S. Shovon, C. A. Gomes, S. A. Reza, et al., "Forecasting renewable energy trends in the USA: An AI-driven analysis of electricity production by source," Journal of Ecohumanism, vol. 4, no. 3, pp. 322-345, 2025.

[26] M. Singh, "A hybrid–machine learning and possibilistic–methodology for predicting produced power using wind turbine SCADA data," in Proc. PHM Society European Conf., vol. 8, no. 1, 2024, Art. no. 15.