DLINE JOURNALS

Signals and Telecommunication Journal

Print ISSN: 2278 – 6449
Online ISSN: 2278 – 6457

STJ 2025: 14 (1)
https://doi.org/10.6025/stj/2025/14/1/1-8

Signal Optimization and Control Strategy for New Energy Hybrid Power Generation System Based on Deep Learning

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ABSTRACT

By combining various renewable energy sources, new hybrid power generation technologies can significantly improve energy utilization efficiency and reduce environmental impact. However, due to the uncertainty and intermittent nature of this technology, signal optimization and control become particularly important. In this study, we use advanced techniques to enhance the performance of hybrid power generation systems. Our work involves utilizing deep learning to analyze and predict various factors, thereby finding the optimal operating mode. The conclusions of this work will have a positive impact on future energy management and dispatching. Additionally, the methods proposed in this article can provide valuable references for research in other related fields.

Keywords: Deep Learning, New Energy, Hybrid Power Generation, Signal Optimization, Control

Received: 19 October 2024, Revised 5 December 2024, Accepted 18 December 2024

1. Introduction

Given the various challenges the world faces today, people are increasingly focusing on replacing traditional energy sources, leading to growing attention to the research and application of new energy. Among them, new hybrid power technologies, including solar energy, ground temperature control, hydropower, aerodynamics, ocean dynamics, land dynamics, hydrology, surface temperature control, underground temperature control, ocean temperature control, have attracted significant interest [1]. Despite the significant progress in new energy hybrid power generation technology, it still faces many challenging issues. For example, due to the uncertainty and variability of new energy sources, their energy consumption fluctuates dramatically, affecting the overall economic benefits of the industry. Furthermore, the imbalanced ratio of supply and consumption of new energy leads to large-scale resource depletion and high operating costs. With technological advancements, the operation and management of new energy hybrid power generation systems still present numerous challenges. Therefore, adopting effective signal optimization and control strategies is essential to achieve better energy utilization and reliable results [2]. Compared to previous traditional optimization and control methods, automated operations can be more efficiently achieved. With advances in science and technology, in recent years, deep learning has been successfully applied in signal optimization and control of hybrid power generation systems, significantly improving the efficiency of traditional methods [3]. This machine learning method utilizes the principles of neural networks to learn various patterns from massive data and has good capabilities such as nonlinear fitting and generalization, thus greatly improving the operating status of hybrid power generation systems [4]. Through the application of deep learning techniques, we can analyze and learn from signal data of hybrid power generation systems, enabling better prediction and optimization of future power generation systems and effectively adjust operating strategies and output power to improve energy utilization efficiency and stability[5]. Additionally, deep learning can help us better understand the patterns and characteristics of signals, thereby implementing signal optimization and control strategies more effectively. The application of deep learning in the field of new energy hybrid power generation is becoming increasingly widespread, with a major research focus being signal optimization and control. By combining this technology with energy systems, we can better manage and dispatch new energy. This research not only provides references for other related topics but also contributes to the progress and widespread application of new energy technologies.

2. Related Work

In recent years, signal optimization and control strategies based on deep learning have received widespread attention in the field of new energy hybrid power generation systems. Models based on long short-term memory networks (LSTM) can perform long-term dependency modeling of new energy production, thereby improving prediction accuracy [6]. Deep learning-based energy optimization models: Energy optimization is another important aspect of signal optimization in hybrid power generation systems. By using deep learning models, researchers can optimize the scheduling of energy supply and demand to improve the energy utilization efficiency and stability of the system. For example, methods based on deep reinforcement learning can optimize system control strategies through learning and optimizing control policies in real-time operations to maximize energy utilization efficiency [7]. By applying deep learning techniques, researchers can effectively monitor and diagnose the status of hybrid power generation systems, ensuring their stable operation. This technology can analyze and learn from various sensor data to better understand the operation of the system and take effective measures to address issues promptly. By adopting these methods, operations and maintenance personnel can quickly identify and efficiently handle problems, greatly improving the reliability and stability of the system [8]. Through deep learning techniques, researchers can better understand the energy requirements of hybrid power generation systems and predict the trading situation in the electricity market more accurately. To this end, they have developed some effective trading strategies to meet the energy demands of hybrid power generation systems. By using deep learning techniques, we can effectively improve the economic benefits of hybrid power generation systems. Among them, energy storage is a key link that can help optimize scheduling and achieve effective balance between energy supply and demand. By analyzing and predicting changes in the energy market trend, we can use energy storage technology more effectively to enhance system efficiency and performance [9].

Through deep learning techniques, signal optimization and control strategies for new energy hybrid power generation systems have been widely applied, including energy prediction, optimization, system status monitoring, fault diagnosis, electricity market transactions, and energy storage management. Through research on hybrid power generation systems, we have discovered new ideas and methods that contribute to improving the energy utilization efficiency and stability of the system [10]. However, we have also found that there are challenges to be overcome, such as data collection and processing, model interpretability, and real-time performance.

3. Design of LSTM-Based Multi-Channel Convolutional Autoencoder LSTM Prediction Model

By adopting variational mode decomposition and dual thresholding, it is possible to effectively separate the effective patterns of the original vibration signal and achieve the partition of feature states. To better extract features, we can use multiple contracted autoencoder channels, which can synchronously extract continuous feature vectors at uniform sampling time intervals and fuse the features extracted by multiple parallel contracted autoencoders at different times [11-13]. This allows the final extracted features to have stronger temporal information, better reflecting the actual situation of the vibration signal. Compared with traditional CNN prediction models, the LSTM-based multi-channel convolutional autoencoder LSTM prediction model has higher accuracy, with a precision improvement of 9.8%. Ma et al. proposed an LSTM-based transformer health status prediction method, which can effectively reduce the loss caused by misjudgment of transformer health status. The loss weight value can be represented as follows:

$$\frac{\mathrm{e}\left|1-p_i^s\right|}{\mathrm{e}^{\left|1-p_i^s\right|}} s = n_i \tag{1}$$

In Equation (1), n_i is the state label of the i-th training sample; pi is the probability of the sample being in misjudgment state. Based on obtaining the loss weight value, a cross-entropy loss function with variable threshold and dynamic weight is constructed:

$$L_{\mathrm{al}} = \eta_i^{ni} E_{\mathrm{al}} \tag{2}$$

Where Eal represents the cross-entropy loss. The purpose of establishing the cross-entropy loss function is to reduce the error propagation in the residual contraction network and improve the network's sensitivity to normal and abnormal transformer states. Experimental results show that the average error of the proposed prediction model can be maintained within 0.3%.

Through in-depth research on the signal data of hybrid power generation systems, we can extract effective features, including but not limited to common statistical, frequency-domain, and time-domain models. Additionally, we can utilize convolutional neural networks and recurrent neural networks to achieve precise learning from start to finish. Carefully selected features are grouped into one training set, while another set is considered as the testing set. This categorization can effectively achieve multidimensional generalization, ensuring the accuracy of the model.

To meet different application scenarios, we should combine various neural network technologies, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and multilayer perceptrons (MLPs), to construct a complete deep neural network system capable of effectively recognizing complex information.

Through model training, deep learning models can achieve optimal performance. At this stage, we use loss functions, optimization algorithms, etc., to continuously adjust the basic parameters of the model and apply regularization techniques such as dropout and L2 to effectively avoid over fitting of the model. When the energy function of GBRBM is displayed, and the values of its visual components vi and hidden components hi are (v, h), the probability distribution is as follows:

$$E(v, h|\ \theta) = -\sum_{i=1}^{m} \frac{(v_i - a_i)^2}{2\sigma_i^2} \qquad (3)$$

In the equation, θ = {W, a_i, b_i} represents the structural parameters of GB-RBM. W denotes the connection weights between v*i* and h*i*; ai represents the bias of v*i*; b*i* represents the bias of h_i; σ_i is the standard deviation of Gaussian noise corresponding to v*i*. Through error constraint and unsupervised learning in hybrid pre-training, the output of GB-RBM can achieve a high fitting accuracy. Through practical application, the average relative error of this method is controlled within 0.9% to 3.7%. To more effectively evaluate the performance of the trained model, we will adopt various methods to measure its performance, including precision, recall rate, F1 score, and other aspects. We will use these values to assess the model's generalization ability and improve its performance accordingly. By optimizing several key factors of the model, such as learning rate, batch size, and grid architecture, we hope to significantly improve its performance [14,15]. With the use of advanced classification algorithms, we can effectively identify signals from the hybrid power generation system, better evaluate the current power generation efficiency, and predict future power generation demand according to market requirements, providing strong technical support for optimizing the operational strategy and power generation of the hybrid power generation system.

4. Experimental Design and Analysis

Through comparative analysis, we found that using deep learning technology to improve signal processing in hybrid power generation systems can better meet user needs. Therefore, we propose to conduct an experiment to evaluate the effectiveness of this technology. In the case of 12 sequences, we use RMSprop as the optimization algorithm and study the differences in mean squared error (MSE) and root mean squared error (RMSE) under different learning rate conditions, and the results are shown in Figure 1. Additionally, we used simulation techniques to provide relevant information.

In the 12 sequences, each batch contains 64 samples, and we use RMSprop for optimization. It can be observed from Figure 1 that with an increase in the learning rate, there is a significant improvement in both mean squared error (MSE) and root mean squared error (RMSE).

Based on Figure 2, we observed significant variations in the photovoltaic power generation of a 20kW power station in Shaoxing, Zhejiang, between October 2014 and February 2018. By examining the relationship between the power generation in March 2017 and climate factors at the power station, we found that the power generation showed a continuous increasing trend with the influence of climate. However, with an improvement in the climate, the power generation started to decrease. According to the research results, it can be concluded that there is a significant positive correlation between power and temperature, with a correlation coefficient of 0.5539. Therefore, for a more refined management of solar power generation, we not only need to use the power information of photovoltaic generation but also require more detailed temperature information to achieve the goal of efficient solar power generation.

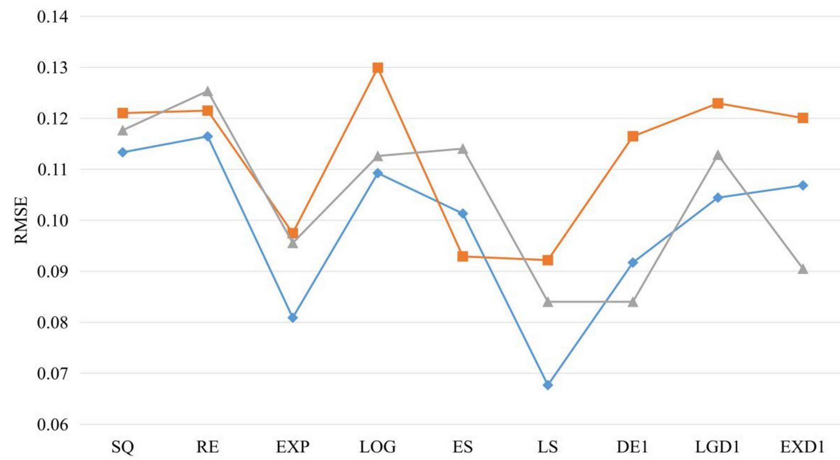

Figure 1. Changes in MSE and RMSE under different learning rates

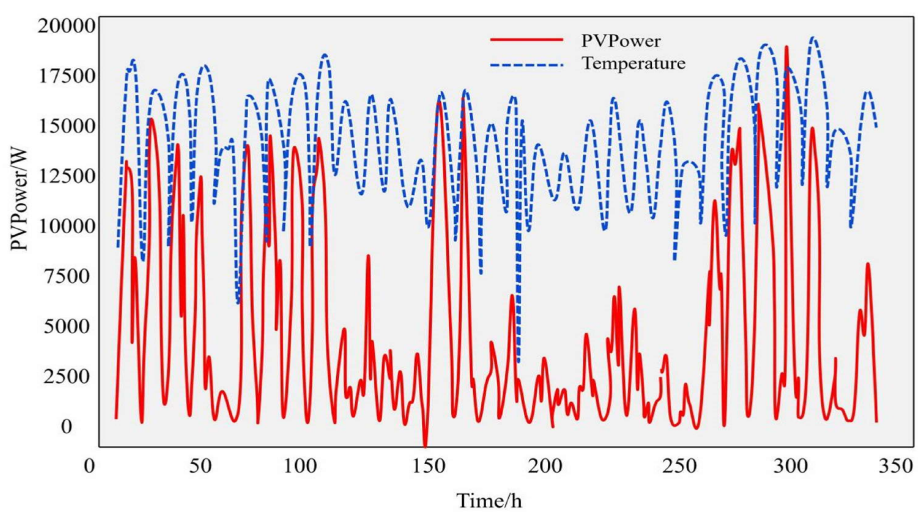

Figure 2. Photovoltaic Output Power and Temperature Variation Curve

By preprocessing the data analysis, we can divide them into two groups: one for training data analysis used for modeling and the other for testing data analysis used for modeling. During the modeling training, appropriate loss functions can be used to adjust the performance of the model. From Figure 3, we can clearly see that when CNN and LSTM are at 7.5 minutes and 15 minutes, respectively, their MAAPE, RMSE, and MAE curves perform optimally. However, when their processing speed exceeds these two thresholds, their MAAPE, RMSE, and MAE curves show a decreasing trend. Conv-LSTM is a more efficient mathematical modeling technique that significantly reduces errors compared to traditional mathematical modeling techniques like CNN, Conv-LSTM, and MLP, especially when the mathematical modeling period exceeds 15 minutes, its performance is more outstanding. Based on the statistical analysis of MAAPE, RMSE, MAE, and other indicators, it is evident that Conv-LSTM's accuracy is far superior to traditional mathematical modeling techniques like MLP. In conclusion, Conv-LSTM outperforms the other three models in the three different error indicators (MAAPE, RMSE), displaying excellent performance.

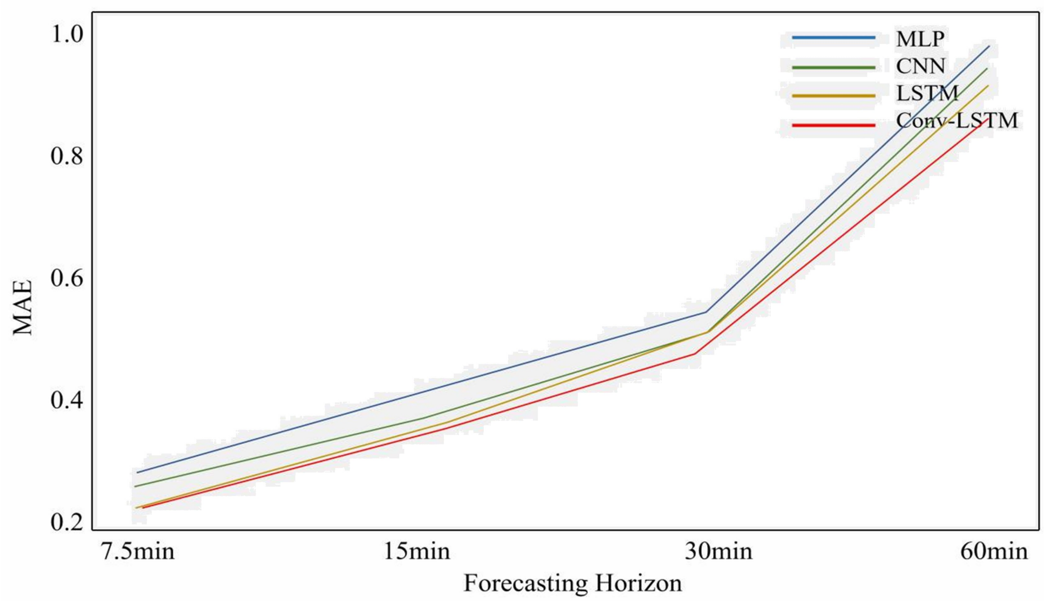

Figure 3. Evaluation Metrics of Four Models: (a) MAAPE value; (b) RMSE value; (c) MAE value

By combining CNN and LSTM, we can better build a high-precision, highly reliable, operationally efficient, scalable, and robust model to cope with the complex and variable environment in the field of photovoltaic power generation. The application of the CNN layer is not limited to extracting valuable information from time series data but also has the effect of noise suppression. Combining the CNN layer with the LSTM layer can greatly enhance the accuracy of photovoltaic power generation prediction. In order to comprehensively evaluate the performance of the trained model, we will use multiple methods to measure its performance. These methods will cover prediction accuracy, regression accuracy, energy consumption efficiency, and other aspects. We will assess the model's generalization ability and its practical application value from these aspects. By applying advanced deep learning techniques, we can effectively optimize and control the signals of the new energy hybrid power generation system and adjust the operating strategy and output power of the power generation system flexibly based on real-time energy consumption, load changes, and market dynamics to achieve the optimal energy utilization effect. Through the analysis and comparison of experimental results, we can better understand the application of deep learning techniques in signal optimization and control, thereby evaluating their advantages more effectively. Additionally, we can assess the application value of the model by evaluating its stability, robustness, and real-time performance.

Through detailed experimental design and analysis, we can demonstrate the feasibility and practicality of deep learning-based signal optimization and control strategies for new energy hybrid power generation systems, providing strong scientific evidence and technical support for the actual operation and management of hybrid power generation systems.

5. Conclusion

The use of deep learning methods to improve the new generation of hybrid power generation systems can not only greatly improve their energy efficiency but also significantly enhance their operational performance. Through multiple pilot studies, the success of this method has been proven, and it shows great potential for widespread application. Using deep learning methods, we can effectively improve the performance of hybrid power generation systems, master key parameters, and adjust them to achieve the best results, thereby achieving resource conservation. In addition, this method has multiple applications, such as teaching, simulation, and prediction, which helps improve the performance of power generation systems. Research shows that adopting deep learning-based information processing techniques helps greatly improve the energy utilization efficiency of hybrid power generation systems and has good operability. The application of this technique, whether in meeting specific market requirements or satisfying the increasing energy consumption, helps achieve better power generation, thereby greatly improving the stability and economy of the entire system. Through research, we find that adopting in-depth understanding-based methods to improve the signals of hybrid power generation systems not only has good operability but also has strong stability, greatly enhancing the energy utilization efficiency. Although this strategy has certain potential, it also faces some challenges, such as cumbersome procedures for data collection and analysis, simulation difficulties, and iteration challenges. Future research will delve deeper into exploring and optimizing deep learning models, expecting them to better support new energy hybrid power generation systems and have higher reliability.

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