sustainability

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Application of Fuzzy Control and Neural Network Control in the Commercial Development of Sustainable Energy System

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Abstract: Sustainable energy systems (SESs) occupy a prominent position in the modern global energy landscape. The purpose of this study is to explore the application of fuzzy control and neural network control in photovoltaic systems to improve the power generation efficiency and stability of the system. By establishing the mathematical model of a photovoltaic system, the nonlinear and uncertain characteristics of photovoltaic system are considered. Fuzzy control and neural network control are used to control the system, and their performance is verified by experiments. The experimental results show that under the conditions of low light and moderate temperature, the fuzzy neural network control achieves a 3.33% improvement in power generation efficiency compared with the single control strategy. Meanwhile, the system can still maintain relatively stable operation under different environmental conditions under this comprehensive control. This shows that fuzzy neural network control has significant advantages in improving power generation efficiency and provides beneficial technical support and guidance for the commercial development of SESs.

Keywords: sustainable energy system; photovoltaic system; fuzzy control; neural network control; generating efficiency; system stability

Citation: Xie, F.; Guan, X.; Peng, X.; Zeng, Y.; Wang, Z.; Qin, T. Application of Fuzzy Control and Neural Network Control in the Commercial Development of Sustainable Energy System. *Sustainability* **2024**, *16*, 3823. https://doi.org/10.3390/su16093823

Academic Editor: Idiano D'Adamo

Received: 24 March 2024
Revised: 28 April 2024
Accepted: 30 April 2024
Published: 2 May 2024

1. Introduction

Under the urgent global demand for sustainable development and environmental protection, sustainable energy systems (SESs), as a key means to realize clean and efficient energy utilization, have attracted extensive attention and investment [1–3]. This trend is tied to the worldwide concern about dependence on fossil fuels, the threat of climate change and the recognition of the limited resources [4]. Therefore, the SES is not only a technical challenge but also a strategic undertaking for the sustainable development of global society and the economy [5]. Thanks to continual advancements in science and technology, sustainable energy technologies have evolved rapidly, and solar energy, wind energy, and bioenergy have gradually become the main energy sources [6,7].

However, the uncertainty and fluctuation of these energy sources bring new challenges to the operation and management of energy systems [8]. In this context, optimizing the control system becomes paramount becomes very important to ensure that the SES can achieve efficient, stable, and sustainable operation under changing conditions [9–11]. With the wide application of renewable energy technology, people have witnessed the vigorous development of solar photovoltaic and wind power generation [12,13]. Nonetheless, the characteristics of these technologies, particularly the influence of weather changes on solar and wind energy productivity, have greatly reduced the predictability of energy, thus introducing new complexity and uncertainty [14]. This fluctuation of energy not only challenges the stability of the power system but also puts forward higher requirements for real-time operation and management of energy. In this context, the traditional control method of energy system seems inadequate. Therefore, the demand for the further optimization and intelligence of the control system is highlighted.

The significance of this study is to fill the research gap in the field of control optimization of SES. SES refers to a system that can supply energy stably for a long time without damaging future generations to meet their own needs. This system tends to use clean and renewable energy and helps to reduce environmental pollution and greenhouse gas emissions. This study specifically targets photovoltaic system as an important part of SES, aiming at improving the efficiency and system stability of photovoltaic power generation through the application of fuzzy control and neural network control algorithms, thus promoting the commercial development of SES.

By discussing the integration of fuzzy control and neural network control in depth, this study aims to provide innovative solutions for improving the control efficiency of SESs. In addition, by investigating the impact of this technology on business development, this study also provides substantive strategic suggestions for promoting the sustainable development of the sustainable energy industry. The research motivation stems from a deep understanding of the current challenges in the control of SESs. Traditional control methods exhibit limitations in the face of energy fluctuation and system complexity. By introducing the fusion of fuzzy control and neural network control, this study seeks to break the shackles of traditional control and improve the adaptability and performance of the system. Meanwhile, it pays urgent attention to the potential driving force of this technology to the shaping and innovation of sustainable energy business models. Through in-depth discussion of these issues, it is expected to provide forward-looking research results for promoting the intelligent control and commercial development of SESs. Firstly, this study explores the application of fuzzy control and neural network control algorithm in photovoltaic system and shows their remarkable potential in improving the efficiency and stability of photovoltaic power generation. Secondly, the mathematical model of photovoltaic system is established and verified by experiments, which verifies the effectiveness of the integrated control strategy in different environmental conditions. In addition, this study also analyzes the dataset in detail, which provides a reliable basis for the follow-up research. On the whole, this study provides new ideas and methods for the application of intelligent control technology in SES and makes positive contributions to the realization of a clean and efficient global energy future. The novelty of this study is that fuzzy control and a neural network control algorithm are applied to photovoltaic system for the first time, thus improving the efficiency and system stability of photovoltaic power generation. Fuzzy control considers the fuzzy relationship between input and output and can flexibly deal with uncertain factors such as illumination intensity and temperature. Neural networks can learn and simulate the complex nonlinear relationship of photovoltaic system to realize accurate prediction of photovoltaic system. Through the combination of these two advanced control algorithms, one can not only improve the system power but also optimize the running state of the system. Meanwhile, this method also provides beneficial technical support and feasible scheme for commercial development of photovoltaic systems.

2. Literature Review

Traditional proportional integral derivative (PID) control methods have been widely used in many industrial fields, but they gradually show some limitations in dealing with the uncertainty and complexity of SESs. These methods often cannot effectively deal with energy fluctuation and system nonlinearity. Fuzzy control has attracted much attention because of its adaptability to fuzzy information and uncertainty. Simon and Sánta [15] combined renewable energy (such as solar energy or geothermal energy) with a fuzzy control system which adjusted heating power according to indoor and outdoor temperature, humidity, and occupancy rate. Balakishan et al. [16] put forward the intelligent viewpoint of the photovoltaic–wind hybrid power generation system by realizing fuzzy logic at the stage required for the maximum efficiency of renewable energy system. The extracted power was processed by the secondary boost converter and multilevel inverter to effectively maintain the power quality and stability of the power grid. Ibrahim et al. [17] proposed a fuzzy logic control integrated energy management system for commercial loads with a hybrid grid–solar photovoltaic/battery energy system. Based on a novel metaheuristic particle swarm optimization technique, Afolabi and Farzaneh [18] determined the optimized configuration of the proposed off grid system by considering local meteorological and power load data as well as details of the technical specifications of the main components of renewable energy systems, while minimizing the cost of levelling electricity. Reddy [19] proposed a new variable fuzzy membership function island detection method for inverter integrated renewable energy systems composed of distributed generation or microgrid units. Based on a case study, Aghaloo et al. [20] proposed a fuzzy logic method based on spatial geographic models to select the optimal location for a solar–wind hybrid renewable energy system.

Conducted by D'Adamo et al. [21], this research utilizes a combination of long short-term memory (LSTM) neural networks and multi-criteria decision analysis (MCDA) to provide robust predictions for EUA pricing and suggests strategic policy enhancements. Neural network algorithm was employed by Wang et al. [22] to model project characteristics, user behavior characteristics, and content characteristics, thereby constructing a model for entrepreneurial project recommendation and resource optimization. Through the evaluation and analysis of the model, the results showed that the entrepreneurial project recommendation and resource optimization model can significantly improve the recognition accuracy and reduce the prediction error, which provided experimental reference and contribution for the sustainable development of social economy and the optimization of entrepreneurial resources. A network public opinion (NPO) risk management system was constructed by Wang et al. [23] through smart contracts, enabling public opinion to be tracked via smart books utilizing risk correlation tree technology. The research of Wang and Zhang was helpful to optimize the control measures of network environment. The economic growth of coal resource-based cities under low-carbon economic growth was evaluated by Deng et al. [24]. By promoting public participation mechanisms and increasing government policy intervention, the vitality of economic market in resource-based cities has been enhanced. Their research has important reference value for promoting urban resource management and economic efficiency. Li et al. [25] discussed the development path of clean energy and related issues of sustainable development in the ecological environment of mining projects driven by big data. Based on big data technology, the corresponding development path of clean energy and the sustainable development analysis model of ecological environment were constructed, and the feasibility and potential benefits of popularizing and applying clean energy in mining projects were evaluated. Through this study, it provided empirical support and decision-making reference for the development of mining projects in the field of clean energy, promoted the sustainable development of mining industry and realizes a win–win situation of economic and ecological benefits. This was of great significance to protect the ecological environment and realize the sustainable utilization of resources. Li et al. [26] found that digital finance can significantly alleviate the financing constraints of enterprises, and the impact on small and medium-sized enterprises and private enterprises was more significant. Li et al. [27] found that continuously eliminating the mismatch between internal and external resources was helpful to alleviate the adverse impact of climate change on environmental, social and governance (ESG) performance. Their research enriched the research on the influence of climate change on ESG performance of enterprises and provided a reference for enterprises to deal with climate risks.

The power management of isolated hybrid microgrid, especially the management of battery pack through fuzzy control, was discussed by Hosseinzadeh and Salmasi [28] in their research. The study emphasized how to effectively use the battery pack to balance the fluctuation of renewable energy and ensure the stable operation of the system in microgrid operation. Similarly, Derbeli et al. [29] improved the efficiency of a commercial photovoltaic system by integrating a fuzzy logic control mechanism for maximum power point tracking (MPPT), which was validated using the dSPACE platform. Their approach significantly improves steady-state oscillations, response time, and overshoot by 73.2%, 81.5%, and 52.9%, respectively, and offers significant advantages over conventional incremental conductance algorithms in optimizing solar energy conversion. The research of Al Sumarmad et al. [30] focused on energy management and voltage control in microgrid, and adopted artificial neural network (ANN) and fuzzy logic controller. Their study compared the performance of these three control methods in microgrid balance through simulation, especially when the weather conditions change, showing their respective advantages and limitations. Their work provided a comprehensive optimization method for the energy management system of microgrid, aiming at reducing operating costs and improving the overall efficiency of the system. An intelligent adaptive switching module architecture utilizing fuzzy logic technology for the efficient integration of renewable energy sources was proposed by Oprea et al. [31] in another study. Through a case study, their findings showed how the adaptive switching module architecture could optimize the operation of the module through fuzzy logic according to the uncertain values of various input parameters (such as weather parameters, power prediction, and battery level), thus improving efficiency and accelerating the return on investment. The design of adaptive switch module architecture took into account the battery packs of different sizes and how to protect the battery packs from over-discharge by controlling the relationship between load and available renewable power generation. Compared to conventional methods, Kalaiselvi et al. [32] enhance power quality control in hybrid renewable energy systems with their development of an enhanced proportional resonant second-order general integrators (EPR-SOGI) method combined with fuzzy logic control. In addition, Mbey et al. [33] address the challenges posed by the intermittent nature of solar photovoltaic (PV) generation and fluctuating electrical demands in smart grids by developing a novel hybrid deep learning model. Combining feed-forward neural networks, long short-term memory networks, and multi-objective particle swarm optimization, their approach significantly outperforms traditional models in forecasting, demonstrated by superior performance metrics on datasets from Douala, enhancing both accuracy and integration within smart grid systems. These studies showed that fuzzy logic and other intelligent control technologies played an important role in the energy management and voltage control of microgrid. They can not only improve the response speed and stability of the system but also optimize the energy use under complex environmental conditions, thus supporting the sustainable development goal.

Previous studies have successfully applied fuzzy control and neural network control in the field of energy systems, but the research on SES is relatively few. The existing research mainly focuses on the control of traditional energy systems, but there is still a knowledge gap for emerging renewable energy systems. In the aspect of business development, the past research mainly focused on market mechanisms, investment strategy and so on, and the research on control systems was relatively less. Therefore, understanding the specific role and potential contribution of control systems in business development is of great significance for promoting the business model innovation of sustainable energy industry. Therefore, this study aims to fill this gap, and provide new theoretical and empirical support for promoting the control and commercial development of SES by deeply studying the application of fuzzy control and neural network control in SES and the potential role of this fusion technology in commercial development. Although fuzzy control and neural network control have their own unique advantages, they also have some limitations and challenges. Previous studies often focused on the application of a single technology, lacking in-depth discussion on the integration of multiple technologies. In addition, existing research often lacks the full consideration of the practical application in commercial development, which leads to a certain disconnect between the research results and the actual needs. Therefore, this study aims to explore the comprehensive application of fuzzy control and neural network control in photovoltaic system to improve the power generation efficiency and stability of the system and provide technical support and guidance for the commercial development of SES. By establishing the mathematical model of photovoltaic system and carrying out the experimental verification of fuzzy control and neural network control, it is expected to fill the scientific gap in the existing research and promote progress and innovation in related fields.

3. Research Methodology

3.1. Establishment of Photovoltaic System Model

The photovoltaic system is a key component in the field of sustainable energy, with remarkable environmental protection and renewable energy characteristics. With the global pursuit of sustainable development, photovoltaic systems are increasingly widely used in the energy industry. A photovoltaic system takes solar energy as the source and does not produce harmful gases such as carbon dioxide, which conforms to the concept of environmental protection and sustainable development. The photovoltaic system involves many factors such as illumination and temperature and has nonlinear and time-varying properties. Therefore, its control and optimization have certain technical challenges. With the rapid development of the renewable energy market, photovoltaic systems have great potential in the commercial field. By optimizing the control algorithm of the photovoltaic system, the energy output can be increased and the operating cost can be reduced, thus promoting its wide application in commercial applications.

It is very important to understand the current–voltage characteristics of photovoltaic cells when analyzing and designing photovoltaic systems. These characteristics can be described by mathematical models based on physics, among which the most commonly used is the single diode equivalent circuit model. The model considers the nonlinearity and uncertainty of photovoltaic cells and simulates the current generation process of photovoltaic cells under the changes of illumination and temperature through the interaction of circuit elements [34]. Equation (1) is based on the single diode model, which integrates factors such as photovoltaic current, reverse saturation current, and series resistance, and is used to calculate the current of photovoltaic cells at a specific voltage. Equation (2) describes the relationship between current and illumination intensity, which is very important for understanding the performance of photovoltaic system under different illumination conditions. The current generation process of photovoltaic system can be described by a single diode equivalent circuit model. Considering the nonlinearity and uncertainty of the system, a general single diode equivalent circuit model is adopted, including factors such as photovoltaic current, reverse saturation current, series resistance, etc., as shown in Equation (1):

$$I_{\mathrm{pv}} = I_{\mathrm{ph}} - I_0\left(\exp\left(\frac{qV}{nKT}\right) - 1\right) - \frac{V}{R_{\mathrm{s}}} - I_{\mathrm{pv}} \tag{1}$$

In the equation, I_{ph} is the photogenerated current. I_0 is the reverse saturation current. q is the electron charge, V is the voltage, n is the destruction factor, K is the Boltzmann constant, and R_{s} is the series resistance. The relationship between current and light intensity is shown in Equation (2):

$$I_{\mathrm{pv}} = \mathrm{G} \times I_{\mathrm{ph}} - I_0\left(\exp\left(\frac{qV}{nKT}\right) - 1\right) - \frac{V}{R_{\mathrm{s}}} \tag{2}$$

In Equation (2), I_{pv} is the output current of the photovoltaic system. G is the light intensity factor, which indicates the influence of light intensity on photovoltaic current. The I_{ph} photogenerated current is the current generated by a photovoltaic system under given illumination conditions. I_0 is the reverse saturation current, which represents the reverse current under the condition of zero bias. Exp is the natural exponential function. q is the electron charge. V is the voltage, which represents the output voltage of the photovoltaic system. n ideal factor reflects the degree of non-ideal of photovoltaic devices. K is the Boltzmann constant. T is the temperature. R_{s} series resistance means the series resistance inside the photovoltaic system.

The photogenerated current represents the current generated by the photovoltaic system under illumination conditions, which is directly related to the illumination intensity and is one of the important outputs of the system. Reverse saturation current describes the reverse current caused by the characteristics of the material itself in the photovoltaic cells. This item is particularly critical in low light conditions, which affects the stability of the system. The series resistance takes into account the influence of the internal resistance of the photovoltaic system, which is an important parameter in the system and affects the response time and stability of the system. By introducing these parameters, people can more accurately capture the influence of illumination, temperature, and other factors on the current in photovoltaic system, which provides an experimental basis for subsequent fuzzy control and neural network control. In order to better understand the model structure, Figure 1 shows a schematic diagram of the photovoltaic system model:

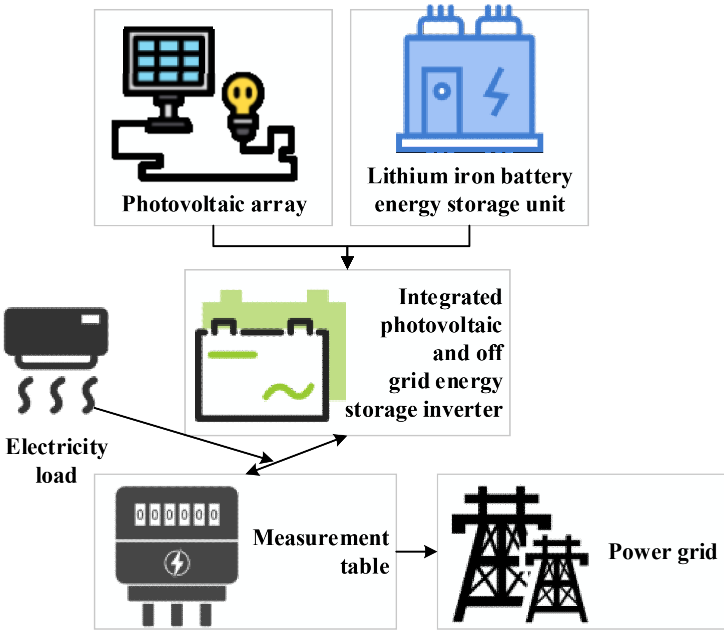

Figure 1. Photovoltaic system model structure.

Figure 2 shows the structural diagram of the photovoltaic system experimental device used in this study. As shown in the figure, the experimental system mainly includes the photovoltaic panel, data acquisition module, environmental condition simulator (used to simulate different lighting and temperature conditions), and control system unit (including fuzzy controller and neural network controller).

The main equipment specifications used in the experiment are shown in Table 1 below:

Table 1. Main equipment specifications used in the experiment.

Device Name	Model	Specifications
Photovoltaic panel	PV-X100	Maximum power 100 W, size 1230 mm × 530 mm.
Data acquisition module	DAQ-200	Support a variety of sensor inputs, sampling frequency up to 1 kHz.
Temperature sensor	TS-10	The measuring range is −20~80 °C, and the accuracy is ±0.5 °C.
Illumination sensor	LS-100	The measuring range is 0~1200 Lux, and the accuracy is ±15 Lux.
Control system unit	CSU-1	Integrated fuzzy controller and RNN controller, programmable, supporting real-time parameter adjustment.

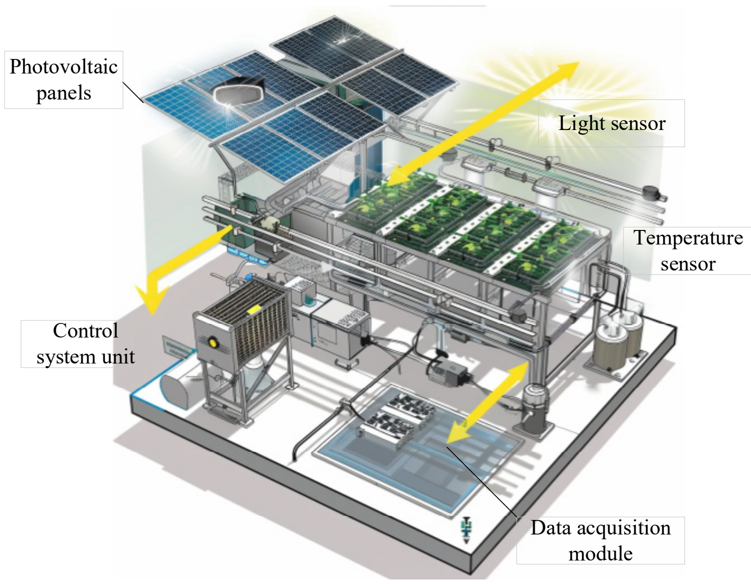

Figure 2. The structure of the experimental device of photovoltaic system.

3.2. Selection of Fuzzy Control and Neural Network Control Algorithm

In order to cope with the complexity and uncertainty of the photovoltaic system, two advanced algorithms, fuzzy control and neural network control, are selected to improve their practicability in commercial development. Among them, fuzzy control can deal with the fuzzy relationship between the input and output of the system through fuzzy logic. The fuzzy control algorithm is based on the Mamdani model, which aims to deal with the fuzziness and uncertainty of environmental factors, such as light intensity and temperature change. The following steps are followed in the process of establishing the model. Firstly, a set of fuzzy rule bases is established through expert experience and system response requirements. Secondly, the triangular membership function is used to divide the fuzzy set of input variables. Specifically, in the fuzzification stage, each input parameter (such as light intensity and temperature) is transformed into the corresponding membership degree, then fuzzy inference is carried out by using a fuzzy rule base to produce fuzzy output. Finally, in the deblurring stage, the fuzzy output is converted into specific control actions. In this experiment, the fuzzy controller sets 20 fuzzy rules, and the number of membership functions is 3 for each input variable. The algorithm realizes the fuzzy reasoning of the system state by establishing a fuzzy rule base, and adaptively adjusts the system parameters according to the expert experience in the rule base and the dynamic adjustment requirements of the system to optimize the power generation efficiency and stability of the photovoltaic system. Specifically, the fuzzy control algorithm converts the input variables into fuzzy sets through the triangular membership function, and then uses the fuzzy rule base for fuzzy reasoning, and finally uses the center of gravity method to calculate the specific control actions, thus achieving effective control of the photovoltaic system. The fuzzy control algorithm is applied to the photovoltaic system to realize adaptive control of uncertain factors such as light intensity and temperature fluctuation. Specifically, the fuzzy control algorithm establishes the fuzzy rules between the operating parameters of photovoltaic system (such as power generation, current, etc.) and external environmental factors (such as light intensity and temperature). These fuzzy rules are based on expert experience and the need for system dynamic adjustment. For example, when the light intensity is low and the temperature is moderate, the system rules may include the following: if the light intensity is low and the temperature is moderate, increase the power; if the light intensity is moderate and the temperature is high, reduce the power. By considering factors such as illumination and temperature, the fuzzy control algorithm can adaptively adjust the control parameters and optimize the power generation efficiency and stability of photovoltaic system.

In order to realize the guidance of SES, it is inseparable from the key role of the fuzzy controller (structure organization is shown in Figure 3). Fuzzy controllers can adaptively adjust the working state of the photovoltaic system by considering the fuzzy rules of environmental variables such as illumination and temperature to optimize its power generation efficiency and stability. As an important form of sustainable energy, the performance improvement of photovoltaic systems is very important for the sustainability of the whole energy system.

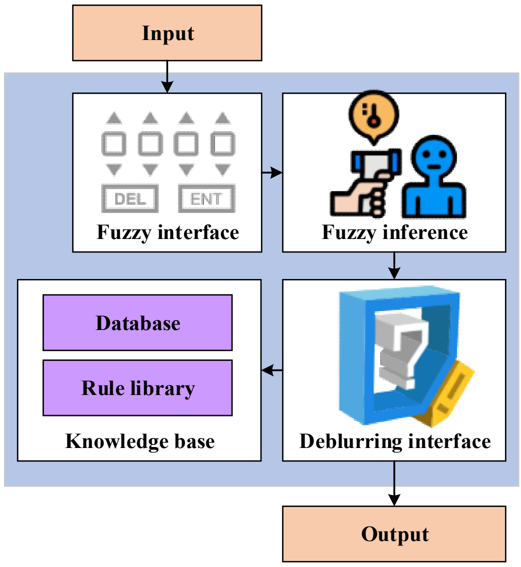

Figure 3. Structure of fuzzy controller.

In Figure 3, in the process of fuzzy control implementation, fuzzy control interface, fuzzy reasoning, and fuzzy interface are the key steps to building an effective control system. The performance and effect of the fuzzy controller are directly affected by these steps. The fuzzy control interface is responsible for transforming specific input variables (such as light intensity and temperature) into fuzzy membership functions. This process reflects the fuzziness and uncertainty in the real world. Through the carefully designed membership function, the system can capture the fuzzy characteristics of input variables more accurately and provide effective input for subsequent fuzzy reasoning. Fuzzy reasoning is an important process in fuzzy logic. At this stage, the fuzzy controller infers the fuzzy membership of the input according to a series of set fuzzy rules and produces fuzzy output results. The formulation of these rules is usually based on the experience of domain experts and the requirements of system performance. The accuracy of fuzzy reasoning directly affects the stability and adaptability of the control system.

Deblurring interface is the process of transforming the fuzzy output obtained by fuzzy reasoning into specific control actions or parameter adjustment. This step is to clarify the output result of the fuzzy controller, so that it can be directly applied to the actual system control. The design of the deblurring interface needs to consider the actual application scenario of the system and ensure that the influence of the output of the controller on the photovoltaic system is feasible and explainable. The performance of the fuzzy controller also depends on a knowledge base, which includes the definition of fuzzy rules, the selection of membership function and the method of resolving fuzzy. Knowledge base is a key part of fuzzy controller learning and adaptation. Through continuous updating and optimization, the fuzzy control system can better adapt to different working environments and requirements.

The neural network control algorithm is used to learn and simulate the complex nonlinear relationship of the photovoltaic system. By training the neural network, the system can understand the mapping relationship between the output power of photovoltaic cells and input parameters such as illumination and temperature. In real-time operation, the neural network will predict the output of the system and make adjustments according to the predicted results to ensure that the photovoltaic system can operate efficiently and stably under different working conditions.

In the selection of neural network control algorithm, the recurrent neural network (RNN) is adopted to better process the time series data of photovoltaic system. The recurrent neural network (RNN) model is adopted in the neural network control algorithm, aiming at simulating the complex nonlinear relationship of photovoltaic system and realizing the prediction and real-time control of the system state. The algorithm learns the mapping relationship between output power and input parameters (such as light intensity and temperature) of the photovoltaic system by training the neural network to realize the prediction of system state. Specifically, the neural network control algorithm specifies the parameters and hyperparameters of the RNN model, including training rounds, activation function, loss function, and optimization algorithm. Through the back propagation and optimization on the training dataset, the neural network can continuously improve the modeling and prediction ability of the system, thus realizing the real-time control of the photovoltaic system. The RNN introduces cyclic connections into the neural network, which enables it to process sequence data and retain the memory of past information. For a time-dependent photovoltaic system, the RNN can better capture the dynamic relationship between input parameters and improve the accuracy of system modeling. The specific structure is shown in Figure 4:

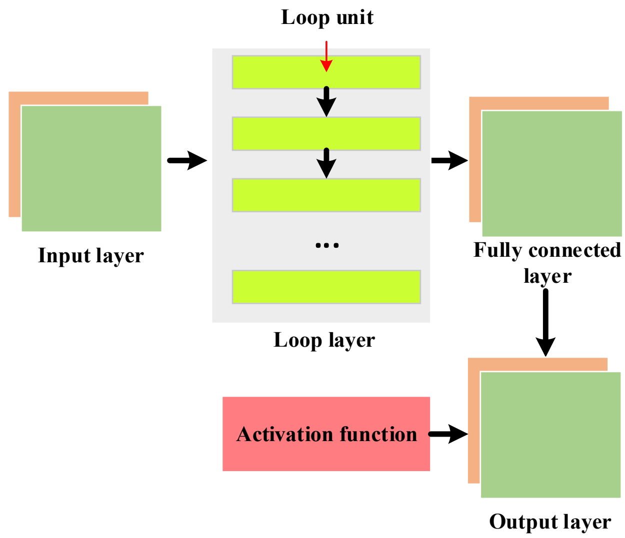

Figure 4. RNN network structure.

In Figure 4, the input layer receives external environmental parameters such as light intensity and temperature as the input of the network. Each input node represents a specific environment variable. The circulation layer is the core part of RNN, which contains many circulation units. There is a circular connection among these units, which allows the network to retain past information when processing sequence data. Each cycle unit contains multiple neurons. By learning historical data, the network can adaptively adjust the weight and capture the complex relationship between the output power of photovoltaic cells and input parameters such as illumination and temperature. The output layer generates the predicted output power of the photovoltaic system. The number of output nodes corresponds to the system output variables. In order to enhance the expressive ability of the network, several fully connected layers are introduced between the loop layer and the output layer. These layers allow the network to learn the nonlinear relationship between input parameters more flexibly and improve the modeling ability of the network to the dynamic characteristics of the system. Meanwhile, after the output of each neuron, the activation function ReLU is introduced to increase the nonlinear expression ability of the network.

The training process of the neural network is based on a large amount of photovoltaic system operation data. Through supervised learning, the network can learn the mapping relationship between input and output. Finally, the back propagation algorithm and gradient descent method are used to optimize the weight and bias of the neural network continuously, so that it can achieve higher prediction accuracy on the training set. The trained neural network is applied to real-time operation. Real-time input parameters (such as illumination and temperature) of the photovoltaic system are input into the neural network, and the predicted output power is obtained through forward propagation. The system adjusts the control parameters in real time according to the prediction results of the neural network to ensure that the photovoltaic system can operate efficiently and stably under different working conditions.

The details of the implementation of fuzzy control and neural network control algorithm in photovoltaic control system are as follows. Fuzzy controller: Based on expert system, according to two input parameters of illumination and temperature, the running state of photovoltaic system is adjusted through 20 fuzzy rules to optimize power output. The fuzzy member function adopts triangular distribution to ensure that the fuzzification of input parameters can cover a wide range of operating conditions. RNN controller: The structure of circulating neural network (RNN), the input layer receives illumination and temperature as network inputs, and the output layer generates the predicted power value of photovoltaic system through the processing of two circulating layers are adopted. The training of RNN model adopts back propagation algorithm, and the learning rate is set to 0.001. After 100 rounds of training, the model can accurately predict the power output under different environmental conditions.

3.3. Experimental Verification

The purpose of this experiment is to verify the application effect of the proposed fuzzy control and neural network control algorithm in the photovoltaic system to improve the power generation efficiency, stability, and adaptability of the system. On the one hand, it verifies the control effect of fuzzy control algorithm on the photovoltaic system through changes in light intensity and temperature. It is also necessary to evaluate the ability of neural network control algorithm to model and predict the dynamic characteristics of the photovoltaic system. Finally, the system performance of fuzzy control combined with neural network control is analyzed to improve the stability of the system in a complex environment.

In the data acquisition process, professional data acquisition equipment, such as illuminance sensor, temperature sensor, ammeter, and voltmeter, is used to monitor the running state of the photovoltaic system in real time. These sensors provide input parameters (light intensity, temperature) and output parameters (current, voltage, power generation) needed for the experiment. The acquisition frequency occurs once every minute to ensure that the changes of photovoltaic system under different illumination and temperature conditions are fully covered. Data are collected for one week in each season to cover the changes in different weather, seasons, and time periods. In the process of data collection, quality control is carried out, and possible abnormal values or data missing are checked and handled. The quality of the collected data is representative of the experimental results. The experimental dataset includes photovoltaic system data collected at different time periods throughout the year. The specific statistical information is as follows. Total data: 28,800 data points (collected once every minute for 4 weeks). Light intensity range: 100 Lux to 1000 Lux. Temperature range: 10 °C to 30 °C. Main statistical information: average value, standard deviation, minimum value and maximum value for light intensity, the average value is 550 Lux and the standard deviation is 258 Lux. For temperature, the average value is 20 °C and the standard deviation is 5 °C. In data processing, this study uses standardized processing methods to eliminate the dimensional influence of data and make the data more suitable for mathematical analysis. In addition, this study also sets the parameters of fuzzy control and RNN neural network in detail, such as the number of fuzzy rules, the selection of membership function, the number of layers and neurons of circular neural network, learning rate, and so on, to ensure the optimal operation of the algorithm. In this study, in order to evaluate the accuracy of neural network control algorithm in the output power prediction of photovoltaic system, two statistical indicators, root mean square error (RMSE) and determination coefficient (R^2), are adopted. RMSE is a measure of prediction error, which calculates the root of the average square of the deviation between the model prediction value and the actual observation value, and can reflect the accuracy of model prediction [35]. R^2 measures whether the model fits the data well, and its value is between 0 and 1. The closer the value is to 1, the stronger the explanatory power of the model is and the better the fitting effect is. These two indexes are used to evaluate the prediction ability and fitting degree of neural network model, which provides an important reference for model selection and optimization. The mathematical equations for RMSE and R^2 are shown in Equation (3) and Equation (4), respectively:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{3}$$

P_i represents the predicted value of the model. O_i indicates the actual observed value, and n represents the number of samples.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} \tag{4}$$

$\overline{O}$ represents the average of actual observed values. In addition, in the research, the design of fuzzy controller is aimed at the nonlinear and uncertain factors in photovoltaic system, such as light intensity and temperature change. Fuzzy controller deals with the fuzzy relationship between input and output through fuzzy logic to optimize the power generation efficiency and stability of photovoltaic system. The core components of fuzzy controller include membership function, membership parameters, and fuzzy rules. Membership functions are used to describe the fuzzy characteristics of input variables, and they usually take the form of triangle or Gaussian distribution. In the fuzzy controller, these functions convert the accurate input values into membership degrees in fuzzy sets to reflect the uncertainty and fuzziness of input data. For example, light intensity and temperature can be used as input variables, which can be converted into different levels in fuzzy sets through membership functions, such as "low light", "medium light", or "high temperature" and "low temperature". Membership parameters are the parameters used when defining membership functions, which determine the shape and distribution of fuzzy sets. The setting of these parameters is usually based on expert experience and the actual operation requirements of the system, and it needs to be adjusted through experiments or simulations to obtain the best control effect. Fuzzy rules are a series of logical statements based on expert experience, which defines the relationship between fuzzy sets of input variables and output control actions. For example, the fuzzy rule may include: "If the light intensity is low and the temperature is high, increase the power output of the photovoltaic system". In a fuzzy controller, these rules are used to infer specific control behaviors from fuzzy sets to adapt to environmental changes and optimize system performance. To sum up, the design of the fuzzy controller needs to comprehensively consider the selection of membership function. The adjustment of membership parameters and the formulation of fuzzy rules also need to be considered to ensure effective control and optimization in the face of uncertainty and nonlinearity in photovoltaic system operation.

The experimental process consists of three parts. The first is the experiment of the fuzzy control algorithm: firstly, the knowledge base and fuzzy rules of the fuzzy control system are established by using the collected data. Then, the operation of the photovoltaic system under different illumination and temperature conditions is simulated on the experimental platform, and real-time control is carried out through the fuzzy control algorithm. Finally, the response data of the system are recorded, including the changing trend of power generation and system stability. The second is the experiment of neural network control algorithm. Firstly, the collected data are divided into a training set and a test set. Then, the RNN neural network is trained by the training set, and the network weights and parameters are optimized. Finally, the prediction accuracy of the neural network on the output power of the photovoltaic system is verified on the test set. The neural network control algorithm is applied in real time on the experimental platform to record the actual response of the system. Thirdly, the experiment of combining fuzzy control with neural network control: the fuzzy control and neural network control algorithm are applied simultaneously on the experimental platform to observe the response of the system in a complex environment. The parameter settings are shown in Tables 2 and 3. RNN model adopts two-layer structure and introduces recurrent connection between hidden layers to capture the dependence of time series data. Rectified linear unit (Relu) is selected as the activation function of the neural network because it can increase the network's ability to deal with nonlinear problems. Mean squared error (MSE) is used as the loss function and the Adam optimizer is used as the optimization algorithm. In this study, the number of training iterations of the network is 100 rounds and the learning rate is set to 0.001. The proportion of training set and test set is 80% and 20%. This study uses triangular membership function to describe the fuzzy properties of input variables and captures the nonlinear characteristics of input variables through Gaussian membership function. Gaussian membership function is used to describe the uncertainty of input variables such as light intensity and temperature. Gaussian membership function can better reflect the fuzzy properties of input variables when processing smooth data and can effectively reduce the computational complexity. In addition, through expert opinions and system simulation analysis, combined with the actual operation experience of photovoltaic system, people have determined 20 fuzzy rules. These rules consider the dynamic relationships between light intensity, temperature, photovoltaic current, and voltage and can respond to environmental changes more flexibly, thus optimizing the power output of the system. Examples of input and output data are shown in Table 4:

Table 2. Experimental environment settings.

Experimental Environment	Setting
Illumination condition	Cloudy days: 100 Lux; sunny days: 1000 Lux; and the range of change: 100–1000 Lux
Temperature condition	Summer: 30 °C; winter: 10 °C; range: 10–30 °C
Data acquisition frequency	Data are collected once every minute
Experimental duration	Four weeks, ensuring different seasons and weather coverage

Table 3. Parameter settings.

Fuzzy control parameters	Number of fuzzy rules: 20 Number of membership functions: 3 Fuzzy control period: 1 min
Neural network structure	RNN
RNN layer number	2 layers
Number of neurons per layer of RNN	The first layer: 50, the second layer: 30
Learning rate	0.001
Number of training rounds	100 rounds
Proportion of training set and test set	Training set: 80%, test set: 20%

Table 4. Examples of input and output data.

Time Stamp	Illumination Intensity (Lux)	Temperature (°C)	Actual Power Output (W)	Predicted Power Output (W)
01-04-2023 08:00	200	15	150	145
01-04-2023 09:00	400	16	300	295
01-04-2023 10:00	600	17	450	445
01-04-2023 11:00	800	18	600	595
01-04-2023 12:00	1000	19	750	745
01-04-2023 13:00	900	20	700	695
01-04-2023 14:00	700	21	550	545
01-04-2023 15:00	500	22	400	395
01-04-2023 16:00	300	23	250	245
01-04-2023 17:00	100	24	100	95

4. Result and Discussion

4.1. Experimental Results of Fuzzy Control Algorithm

Through the experiment of fuzzy control algorithm, this study aims to evaluate its influence on the power generation efficiency and stability of photovoltaic systems under different illumination and temperature conditions. Figures 5 and 6 show the comparison between the actual generated power and the predicted power of fuzzy control under different environmental conditions, as well as the response time and stability score of the system. These data help the in-depth understanding of the performance of the fuzzy control algorithm.

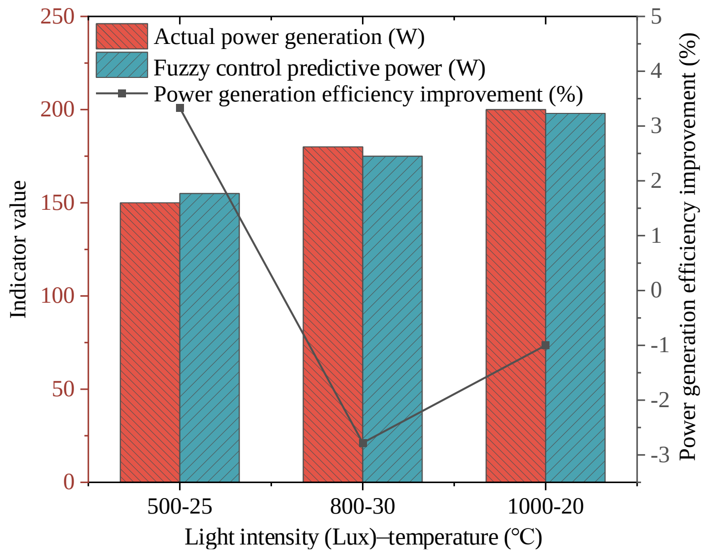

Figure 5. Power generation efficiency of the photovoltaic system.

By analyzing the data in Figure 5, the following conclusions can be drawn. When the light intensity is 500 Lux and the temperature is 25 °C, the actual power generation of photovoltaic system is 150 W. After fuzzy control algorithm prediction, the predicted power of photovoltaic system is 155 W. Compared with the actual power generation, the predicted power has increased by 3.33%. This shows that the fuzzy control algorithm has improved the power generation efficiency of photovoltaic system in this case. When the light intensity is 800 Lux and the temperature is 30 °C, the actual power generation of photovoltaic system is 180 W. However, through fuzzy control algorithm prediction, the predicted power generation is 175 W. Compared with the actual power generation, the predicted power is reduced by 2.78%. This means that in this case, the fuzzy control algorithm cannot effectively improve the power generation efficiency of photovoltaic system but leads to a certain degree of reduction. When the light intensity is 1000 Lux and the temperature is 20 °C, the actual photovoltaic system generates 200 W. After fuzzy control algorithm prediction, the predicted power generation is 198 W. Compared with the actual power generation, the predicted power is reduced by 1%. In this case, the fuzzy control algorithm has little influence on the power generation efficiency of photovoltaic system, and the difference between the predicted power and the actual power is small. On the whole, the fuzzy control algorithm has different effects on the power generation efficiency of photovoltaic system under different light intensity and temperature conditions. In some cases, the algorithm can effectively improve power generation efficiency, but in other cases, it may lead to a slight decrease in power generation efficiency. This shows that the effect of fuzzy control algorithm is affected by environmental factors such as light intensity and temperature, and it needs to be further optimized and adjusted to improve its application effect in photovoltaic system.

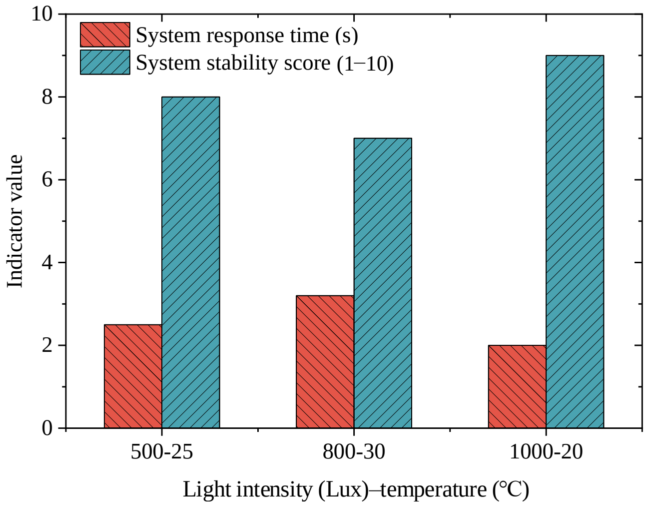

Figure 6. System stability evaluation.

The data in Figure 6 show the response time and stability scores of the system under different light intensities and temperature conditions. First, when the light intensity is 500 Lux and the temperature is 25 °C, the response time of the system is 2.5 s and the stability score is 8. This shows that under these conditions, the response speed of the system is moderate and the stability is good, but there is still room for improvement. Secondly, when the light intensity increases to 800 Lux and the temperature rises to 30 °C, the response time of the system slightly increases to 3.2 s, while the stability score drops to 7. This may be because higher light intensity and temperature have a greater impact on the system, resulting in a slight slowdown in the response speed of the system and a decline in stability. Finally, when the light intensity reaches 1000 Lux and the temperature is 20 °C, the response time of the system is the shortest, which is 2 s, and the stability score is the highest, which is 9 points. This shows that under the conditions of high light intensity and moderate temperature, the system has fast response speed and good stability, and can cope with external environmental changes more effectively. Taken together, these data provide people with the basis for evaluating the stability of the system under different environmental conditions, which is helpful to optimize the control algorithm to improve the stability and performance of the system.

4.2. Experimental Results of Neural Network Control Algorithm

Through the experiment of the neural network control algorithm, the purpose is to evaluate its prediction accuracy and real-time control effect in the photovoltaic system. Figures 7 and 8 show the comparison between the predicted results of the neural network and the actual output power on the test set, and the response of the system when the neural network control algorithm is applied in real time.

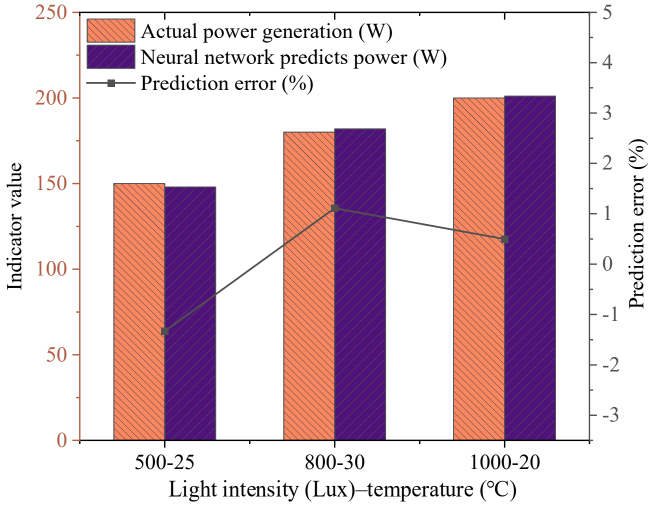

Figure 7. Prediction accuracy evaluation.

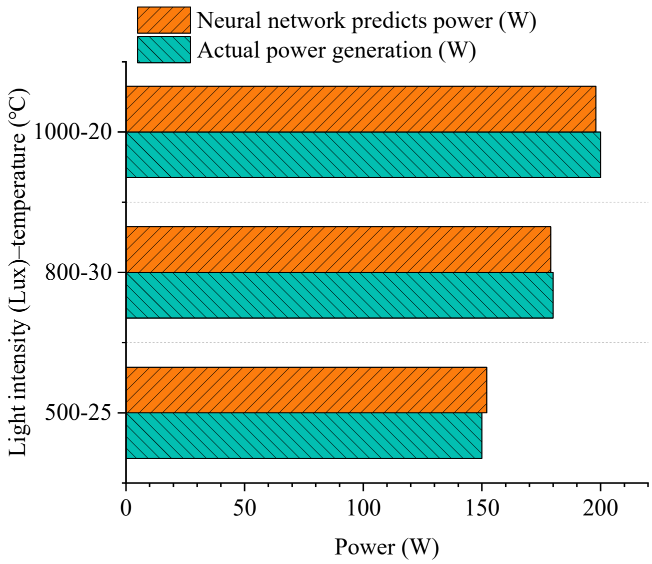

Figure 8. Real-time control effect.

According to the data in Figure 7, the prediction accuracy of neural network control algorithm can be evaluated. Firstly, the light intensity and temperature are used as input variables, and the actual power generation is used as output variables to predict. Taking the first row of data as an example, when the light intensity is 500 Lux and the temperature is 25 °C, the actual power generation is 150 W. The power predicted by neural network is 148 W, and the prediction error is −1.33% compared with the actual power. This means that the neural network underestimates the power output of the system but the error is small. Then, observing the data in the second row, when the light intensity is 800 Lux and the temperature is 30 °C, the actual power generation is 180 W. The power predicted by neural network is 182 W, and the prediction error is 1.11% compared with the actual power. In this case, the neural network overestimates the power output of the system, but the error is also small. Finally, taking the data in the third row as an example, when the light intensity is 1000 Lux and the temperature is 20 °C, the actual power generation is 200 W. The power predicted by neural network is 201 W, and the prediction error is 0.5% compared with the actual power. In this case, the neural network slightly overestimates the power output of the system, but the error is very small. To sum up, the neural network control algorithm shows high accuracy and stability in forecasting the power generation of photovoltaic system, and the prediction errors are within a small range, which shows that the algorithm has a good application prospect in practice. According to the data in Figure 8, the real-time control effect of neural network control algorithm can be observed under different light intensity and temperature conditions. Firstly, when the light intensity is 500 Lux and the temperature is 25 °C, the actual power generated by the photovoltaic system is 150 W, while the power predicted by the neural network is 152 W, which indicates that the neural network can relatively accurately predict the power generated by the system under this condition and achieve good real-time control effect. Secondly, when the light intensity increases to 800 Lux and the temperature rises to 30 °C, the actual power generated by photovoltaic system is 180 W, while the power predicted by neural network is 179 W, which is very close. This shows that the neural network can still accurately predict the power generation of the system under high illumination and high temperature conditions, and the real-time control effect is good. Finally, under the conditions of light intensity of 1000 Lux and temperature of 20 °C, the actual power generated by photovoltaic system is 200 W, while the power predicted by neural network is 198 W, and there is little difference between them. This further proves that the neural network control algorithm can effectively predict the power generation of the system under different illumination and temperature conditions and achieve reliable real-time control effect. Therefore, the tabular data reflect the good real-time control ability of neural network control algorithm in photovoltaic system, which provides strong support for the stable operation of the system.

Figures 7 and 8 show that the neural network control algorithm shows relatively low prediction error and high prediction accuracy for the output power of photovoltaic system on the test set. When the neural network control algorithm is applied in real time, the actual response power of the system is consistent with the expected value, showing a good real-time control effect. The neural network control algorithm is excellent in dealing with the time series data and complex relations of the photovoltaic system and has good modeling and forecasting ability for the dynamic characteristics of the system.

The root mean square error (RMSE) and determination coefficient (R^2) are used to evaluate the accuracy of the neural network model. RMSE reflects the deviation between the predicted value and the actual value of the model, and R^2 indicates the goodness of fit of the model to the data. The calculation result of RMSE is about 1.04, which means that the deviation between the predicted value and the actual value of the model is relatively small. The calculation result of R^2 is about 0.99744. This means that the model has a very high goodness of fit to the data and can almost perfectly explain the changes of the actual data. Taken together, these evaluation results prove the high accuracy and reliability of neural network model in the output power prediction of photovoltaic system.

Figure 9 shows the downward trend of model error during training, and it shows that the prediction performance of the model is gradually improved with the increase in training rounds. After 100 rounds of training, the average prediction error of RNN model on the test set is reduced to 2%, which shows that the model has high prediction accuracy.

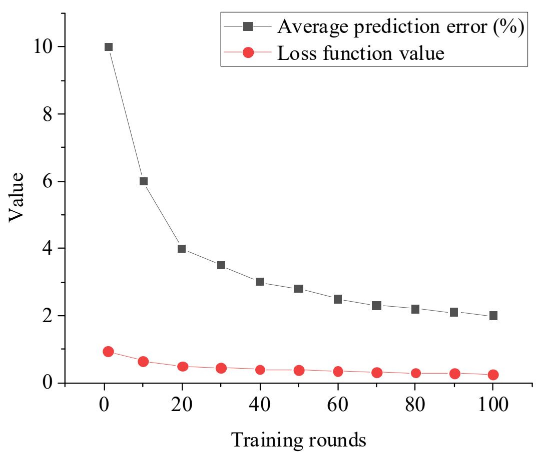

Figure 9. A downward trend of training error of RNN model.

4.3. Experimental Results of Fuzzy Control Combined with Neural Network Control

In order to evaluate the performance of the model under typical environmental conditions that may be encountered in the actual operation of photovoltaic system, two parameters, light intensity, and temperature, are selected in this study, which are tested under the conditions of low light (100 Lux) and moderate temperature (about 20 °C) to evaluate the adaptability and efficiency improvement ability of the model under poor light conditions. Meanwhile, the tests under the conditions of high illumination (1000 Lux) and high temperature (30 °C) are used to verify the stability and efficiency of the system under the operating conditions close to the limit. Through these specific interval settings, people can comprehensively evaluate the overall performance and adaptability of the model under different environmental conditions. Through the experiment of combining fuzzy control with neural network control, the purpose is to explore their synergistic advantages and improve the power generation efficiency and stability of the photovoltaic system. Figure 10 shows the system performance data of combining fuzzy control and neural network control under different lighting and temperature conditions, as well as the improvement effect compared with using fuzzy control or neural network control alone.

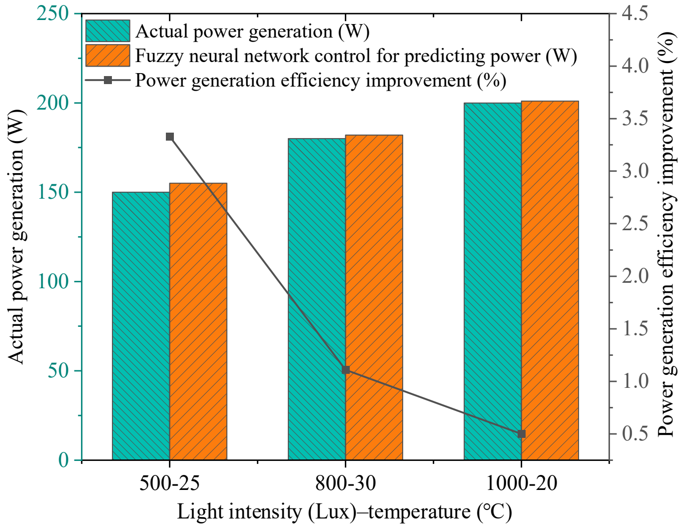

Figure 10. Comprehensive performance evaluation.

According to the data in Figure 10, taking 500 Lux and 25 °C as examples, the actual power generation of photovoltaic system is 150 W. After applying fuzzy neural network control, the predicted power output is 155 W, which is 3.33% higher than the actual power. Then, when the light intensity increases to 800 Lux and the temperature rises to 30 °C, the actual power generation increases to 180 W. However, the predicted power output after fuzzy neural network control is 182 W, which increases by 1.11%. Finally, under the conditions where the light intensity reaches 1000 Lux and the temperature is 20 °C, the actual power generation is 200 W, while the power output predicted by fuzzy neural network control is 201 W, which is only increased by 0.5%. From these data, it can be clearly seen that fuzzy neural network control has improved the power output of photovoltaic system in different environmental conditions, especially at 500 Lux and 25 °C, which reaches 3.33%. This shows that fuzzy neural network control is effective in optimizing the power generation efficiency of photovoltaic system, and it is expected to provide technical support for the commercial development of SES. In Figure 10, combining fuzzy control and neural network control, the system has achieved remarkable improvement in power generation efficiency under the conditions of low light and moderate temperature, showing the advantages of their synergy. Under the conditions of high illumination and high temperature, the power generation efficiency of the system is slightly improved compared with the single control strategy, but the improvement range is relatively small.

However, in comprehensive performance evaluation, fuzzy neural network control has obvious advantages over single control strategy in improving power generation efficiency. Meanwhile, it is worth emphasizing that the system can still maintain relatively stable operation under different environmental conditions under this comprehensive control, which provides strong support for the efficient performance of the photovoltaic system.

4.4. Discussion

For the control and optimization of the photovoltaic system, the fuzzy control algorithm and neural network control algorithm have been widely studied and applied in recent years. Giurgi et al. [36] found that the fuzzy control algorithm can effectively improve the power generation efficiency of photovoltaic system under certain lighting and temperature conditions, but in some cases, there were also cases of power output reduction. This is consistent with the conclusion of this study, which shows that the fuzzy control algorithm has a certain universality in different environmental conditions. On the other hand, research on the neural network control algorithm has also attracted much attention. For example, Derbeli et al. [29] discussed the joint application of fuzzy neural networks in photovoltaic systems and proposed an optimal control method of the photovoltaic system based on fuzzy neural network. Their research results showed that fuzzy neural networks combined the advantages of the fuzzy control algorithm and the neural network control algorithm, which can effectively improve the power generation efficiency and stability of photovoltaic system. Miraftabzadeh et al. [37] found that the power output of photovoltaic system can be effectively predicted and real-time control can be realized by using properly designed neural network model. Their research results showed that the neural network control algorithm had high accuracy and stability, and the prediction error is smaller than the actual power. This is consistent with the conclusion of this study, which further proves the superiority and reliability of neural network control algorithm in photovoltaic system. However, compared with previous studies, this paper has a certain level of innovation and superiority in research methods and result analysis. Firstly, this study adopts a comprehensive evaluation method, which not only considers the power prediction effects of fuzzy control algorithm and neural network control algorithm in different environmental conditions but also analyzes the response time, stability score, and other indicators of the system and evaluates the performance of the control algorithm from multiple angles. Secondly, this study discusses the applicability and stability of fuzzy control algorithm and neural network control algorithm under different conditions, which provides a more comprehensive and reliable research basis for the practical application of photovoltaic system. Therefore, the research in this study has certain scientific novelty and practicability in the field of photovoltaic system control and optimization and provides an important reference for promoting the progress and application of clean energy technology.

In this study, the fuzzy control algorithm and the neural network control algorithm are used to discuss the control and optimization of the photovoltaic system. The experimental results show that these algorithms have a positive effect on improving the power generation efficiency and stability of photovoltaic system. In particular, the fuzzy control algorithm shows some advantages in dealing with the nonlinearity and uncertainty of photovoltaic system, especially in low light and moderate temperature conditions, which can improve the power generation efficiency of the system. The neural network control algorithm shows good adaptability and prediction accuracy because of its excellent ability in time series data modeling and real-time control. Compared with the research in the existing literature, this study shows innovation and advantages in method and result analysis. Firstly, this study adopts a comprehensive evaluation method. It not only considers the power prediction effects of fuzzy control and neural network control algorithms in different environmental conditions but also comprehensively analyzes the response time, stability score and other indicators of the system and evaluates the performance of the control algorithms from multiple angles. Secondly, this study also discusses the applicability and stability of fuzzy control algorithm and neural network control algorithm under different conditions. This study provides a more comprehensive and reliable research foundation for the practical application of photovoltaic systems.

5. Conclusions

Through the detailed trend analysis of experimental results from fuzzy control, neural network control, and combined fuzzy neural network control, we observed distinct variations in power generation efficiency across different lighting and temperature conditions. Notably, the combined approach of fuzzy neural network control demonstrated significant improvements in efficiency, underscoring its potential to optimize photovoltaic systems for sustainable energy production. The experimental evaluation revealed that while the fuzzy control algorithm effectively addresses the non-linearity and uncertainty of photovoltaic systems—and is particularly beneficial under low illumination and moderate temperatures—neural network control excels in modeling time series data and managing real-time system dynamics. These capabilities contribute directly to the sustainable operation of photovoltaic systems by enhancing energy output and system reliability under diverse environmental conditions. The superior performance of the fuzzy neural network control, compared to single-strategy controls, not only boosts efficiency but also ensures stability, making it a pivotal development in sustainable photovoltaic technology. This study sets the groundwork for future research to explore the application of fuzzy neural network control in more complex photovoltaic systems and across a broader range of environmental scenarios. Furthermore, optimizing the parameters and structure of the algorithm to improve the performance of across diverse conditions represents a worthwhile direction for further investigation. This not only advances the technical field but also contributes to the broader agenda of reducing dependency on fossil fuels and lowering carbon emissions through more efficient renewable energy systems.

Author Contributions: Conceptualization, F.X. and X.P.; methodology, X.G. and Y.Z.; software, Z.W.; validation, X.G.; formal analysis, Y.Z. and T.Q.; investigation, Z.W.; resources, F.X.; data curation, X.P.; writing—original draft preparation, X.G., Y.Z. and T.Q.; writing—review and editing, F.X., Z.W. and X.P.; visualization, T.Q.; supervision, Z.W.; project administration, X.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Yancheng Social Science Fund Project (grant no. 24skA186), and the Guangzhou Basic and Applied Basic Research Topic (Young Doctor's "Sailing" Program) of Guangzhou Science and Technology Bureau (grant no. 2024A04J4239).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author, upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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