21th International Conference on Renewable Energies and Power Quality (ICREPQ'23)
Madrid (Spain), 21th to 25th July 2023 Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.21, July 2023

Construction and Optimization of Power Quality Risk Spillover Trend Prediction Model Based on Deep Learning

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Abstract.

This study aims to establish and refine a deep learning-based predictive model for power quality risk spillover trends, thereby addressing the challenges posed by the escalating diversity and adaptability of power systems in the evolution of the renewable energy industry. Initially, the study introduces the concept of power quality risk spillover, referring to the influence exerted by power quality issues in one region on other regions. This influence initiates a chain reaction, ultimately leading to a more widespread deterioration in power quality. Then, the advantages and applications of the deep learning model in power quality risk spillover trend prediction are expounded. During the model development process, we employed deep learning algorithms such as the multilayer perceptron and extended short-term memory network, tailored specifically to the unique characteristics of power quality data. To enhance the model's predictive accuracy and stability, we implemented optimization strategies encompassing data preprocessing, feature engineering, and model integration. Our experimental findings demonstrate that the optimized model exhibits remarkable precision and stability in anticipating power quality risk spillover trends, thereby offering robust support for risk management and ensuring the stable operation of power systems. This study provides a valuable exploration and practice for the application and development of a power quality risk spillover trend prediction model based on deep learning.

Key words. Piezoelectricity, electro-magnetic induction, renewable, harvesting.

1. Introduction

Energy supply restricts economic development. With continuous development of the energy system with fossil energy as the core, climate change, energy, and resource constraints are increasingly severe around the world, and energy transition is imperative [1]. Clean replacement and the importance of electricity in energy services are increasing; therefore, the power industry in the energy " double Carbon " takes important responsibility [2]. Natural factors at the PV site mainly include damage from storms and lightning strikes, ice, snow and hail, dust, landslides, earthquakes, floods and animal bites. As photovoltaic power stations are generally located in complex remote areas such as barren hills, abandoned fish ponds, deserts and beaches, safety accidents caused by the above natural factors are unavoidable. Therefore, in order to prevent the occurrence of fire and other accidents, need through an intelligent security system for the whole wind turbines and photovoltaic power fields, automated real-time monitoring and early warning, timely finding the fault in the system, the arranged diagnosis and maintenance, to ensure timely eliminate these faults, ensure the stable operation of wind power and photovoltaic power station, for more stable and reliable power resources [3]. To sum up, According to the fan intelligent security system and photovoltaic power stations the importance and urgency of intelligent security system construction, this paper is based on modern sensing technology and signal processing technology from the hardware configuration and algorithm, design two angles, through the physical sensor collection critical information of the scene, and use advanced signal processing, data analysis and diagnosis, realize the goal of data mining and real-time monitoring, timely discover the possible harm, and Inform the maintenance personnel to ensure the healthy and safe operation of the wind farm and photovoltaic power station [4].
The fundamental premise underlying the utilization of historical power demand data for forecasting purposes is trend extrapolation, which relies on inherent patterns within the data. This approach involves the establishment of a model that captures the evolving trends or correlations within the historical dataset [5]. It assumes that these patterns and relationships will persist into the future, enabling the accurate projection of future power demand. Prevalent forecasting methodologies include the exponential smoothing method, trend extrapolation method, grey forecasting, and random time series analysis [6]. Grey forecasting has the advantages of requiring fewer load data, not considering the distribution law and change trend of data and convenient operation, so it has become a standard method of load forecasting. Literature analyzes and compares different grey forecasting models (GM) and summarizes the advantages and disadvantages of various GM models and their applicable scope according to the characteristics of annual electricity consumption growth in a city. In order to avoid the theoretical error caused by the grey prediction method [7], Zhu et al [8] improved the traditional grey model, mainly including smoothing the historical data, modifying the model parameters, and processing the equal dimension new information data. This article will analyze the construction and influencing factors of human resource management systems based on previous research.

2. Literature Review

2.1 Analysis of Periodic Fluctuation Characteristics of Power Demand

Quantitative Prediction of Power Quality Fluctuation

Currently, the quantitative examination of power demand fluctuations in China is primarily concentrated on medium- to long-term forecasting horizons. This theoretical pursuit gained significant traction in the 1980s, spawning diverse forecasting methodologies such as time series analysis and grey theory. These advancements have been instrumental in shaping the current understanding and prediction of power demand patterns in China. These methods have been widely adopted in power demand projections. Today, numerous approaches are employed for medium- to long-term power demand forecasting. Depending on the data utilized in the forecasting process, these methods can be categorized into three distinct groups. The first is the extrapolation method, which leverages historical data to predict future power demand trends. The second is the factor analysis method, which incorporates both historical power demand data and its influencing factors. Lastly, there is the combination forecasting method, which integrates multiple models to generate a more comprehensive prediction.

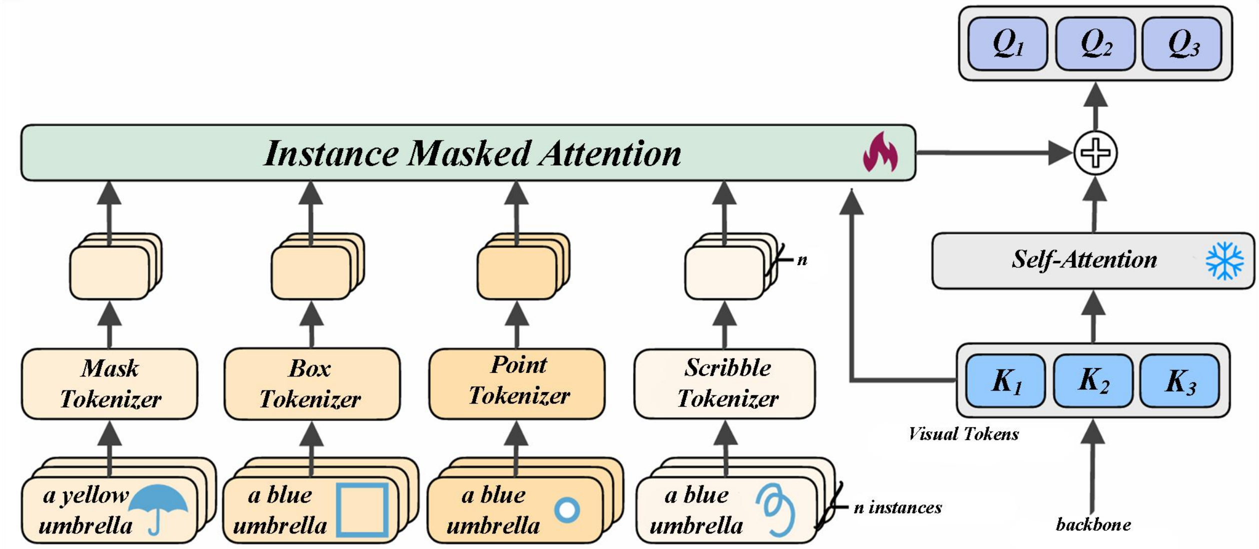

Figure 1. Flow Chart of the Prediction Model of Deep Learning

Figure 1 shows a flow chart of the prediction model of deep learning. On one hand, it is manifested as the up-and-down deviation around a specific growth trend line in the process of power demand growth. However, the data accumulation, smoothing and differential processing in grey forecasting and time series methods make this periodic fluctuation obvious or even submerge it. Therefore, grey forecasting needs to take into account the data distribution law and change trend, which has the advantages of a wide application range. However, it becomes a disadvantage in forecasting power demand with periodic fluctuation characteristics. Because of exponential smoothing, the power consumption predicted by the grey model increases according to a specific constant growth rate (which can be proved theoretically), and the prediction results can not reflect the fluctuation characteristics of the growth rate of power demand, so it is impossible to predict the fluctuation trend and turning point of power demand. Grassi [9] first fits the exponential trend of China's electricity consumption over the years, then establishes an ARMA model for the residual sequence after eliminating the growth trend, and finally synthesizes the two to obtain an "exponential-ARMA" model. Zhang [10] has the same idea as the above, except that the grey model replaces the exponential trend model.

Another method idea is to establish a model that can characterize the relationship between influencing factors and power demand through historical data. Then, it uses this model and the predicted values of future influencing factors to predict power demand [11]. Among them, the influencing factors involved in the model mainly include economy, industrial structure, population and electricity price. In contrast, factors such as policy and power demand side management are usually not reflected in the model because they are difficult to quantify [12]. According to the different number of influencing factors, these methods can be divided into single-factor analysis and multi-factor analysis.

This kind of method is relatively simple [13]. Taking the elastic coefficient method as an example, as long as the value of the electric power elastic coefficient and the development speed of the national economy in the forecast period are determined, the development speed of electric power demand can be calculated. However, the elasticity coefficient, unit consumption of output value and per capita electricity consumption are constantly changing with the influence of economic development level, industrial structure change, energy efficiency improvement national policies, etc. Only using a single factor method to analyze demand has limitations, especially when economic transformation and industrial structure change greatly; it is not suitable to use the above methods.

Aiming at the problems of single-factor analysis, multi-factor analysis quantifies many factors affecting power demand. It takes them into the forecasting model as independent variables, among which the least square method is the standard method to solve the model parameters. In view of the severe multi-correlation among the influencing factors of power demand, the accuracy and reliability of the regression model fitted from this can not be guaranteed. Song et al. used the Sichuan partial least square regression method to eliminate its collinearity and avoid the abnormal country return coefficient when using ordinary least square regression. However, the neural network method usually needs a large number of training samples, and it is difficult to obtain a large number of annual data with similar laws due to the influence of China's macroeconomic environment and relevant national policy changes, so the neural network method is more used in the research of short-term load forecasting. The leading factors affecting the fluctuation of power demand (such as GDP) must also present a specific periodic fluctuation law. If there is no good grasp of the changing trend of various influencing factors in the long-term range, there will be a significant deviation in the medium and long-term power demand predicted by the regression model.

Construction Idea of Index System

Chinese oil and gas foreign dependence is high, and economic growth is closely related to fossil energy consumption demand; considering the security of the long-term development of energy, our energy development to non-fossil energy transformation, energy, structure, through the power supply side clean alternative and electricity consumption side power alternative, gradually promote the development of clean energy. Further, the green and low-carbon energy transformation has a particular impact on the safe and reliable operation of the power system. The growth of source and load scale with intense uncertainty further increases the difficulty of coordinated operation of the power system. The power structure and the integrated construction of "source network, load and storage" can improve the flexibility of the system and alleviate the problem of declining system regulation capacity caused by access to clean energy. Among them, the "source network load storage" integration construction needs to drive the power generation enterprise, energy storage system, users, sell electricity, and so many other central bodies to participate in. Therefore, the power system is a market trading mechanism for the guarantee, with a virtual power plant, a comprehensive energy business model for the pilot, and a trading price mechanism to guide each subject to participate in the power city, field trading, to achieve from the source, lotus, store all-round joint security energy structure optimization, better support the development of electric power system, promote the energy transformation.

To sum up, the power structure is the supporting framework for the development of the power system. With the transformation of the power system to the new power system with new energy as the main body, the power structure will be safe, reliable, flexible and controllable, economical and efficient. In this process, the energy policy will play an important guiding, safeguarding, and controlling role and is an indispensable factor in the power system transformation. Therefore, this paper, from the safe and reliable, green carbon, flexible and controllable, economic and efficient evaluation index, and based on the "source network load storage" interactive mechanism, selects the corresponding policy perfect index and builds regional power structure quality index evaluation target system.

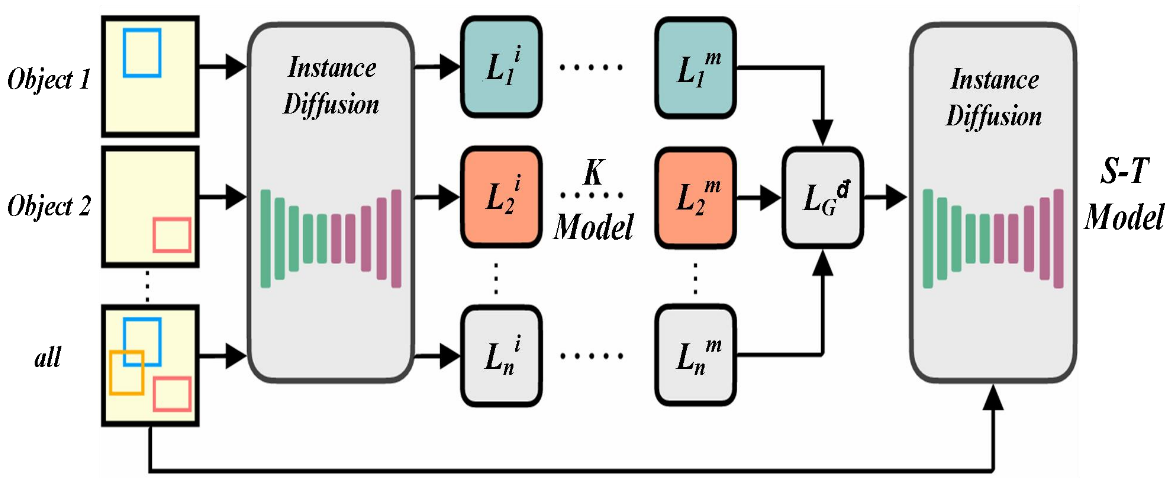

Figure 2. Optimization Flow Chart of the Power Quality Risk Spillover Trend Prediction Model Based on Deep Learning

Figure 2 shows an optimization flow chart of the power quality risk spillover trend prediction model based on deep learning. Power structure quality evaluation involves the power system "source load storage" each link, sending variable distribution in various fields, to build a power structure, should follow the corresponding principles on the basis of reading much literature, combined with the development trend of power energy structure and "source load storage" interactive mechanism, put forward the power structure quality evaluation index selection principle is as follows:

Evaluation Index System of Safety And Reliability Index

Safety and reliability refer to the ability of the power system to continuously power supply under the premise of ensuring power quality. The power system is the infrastructure supporting industry, transportation, communication and other vital fields of the country. Therefore, safety and reliability are the primary premises of power system operation. Under the construction of a new power system, due to the randomness and intermittent influence of clean energy generation, the large-scale clean energy grid connection on the supply side will lead to the fluctuation of the voltage level of the grid, the increase of the system short circuit capacity [14]. Due to the energy consumption revolution and electric energy substitution, the demand side load surges, and meanwhile, the weak adjustable ability of clean energy increases the problem of insufficient system abundance.

Power Supply Safety and Reliability Index

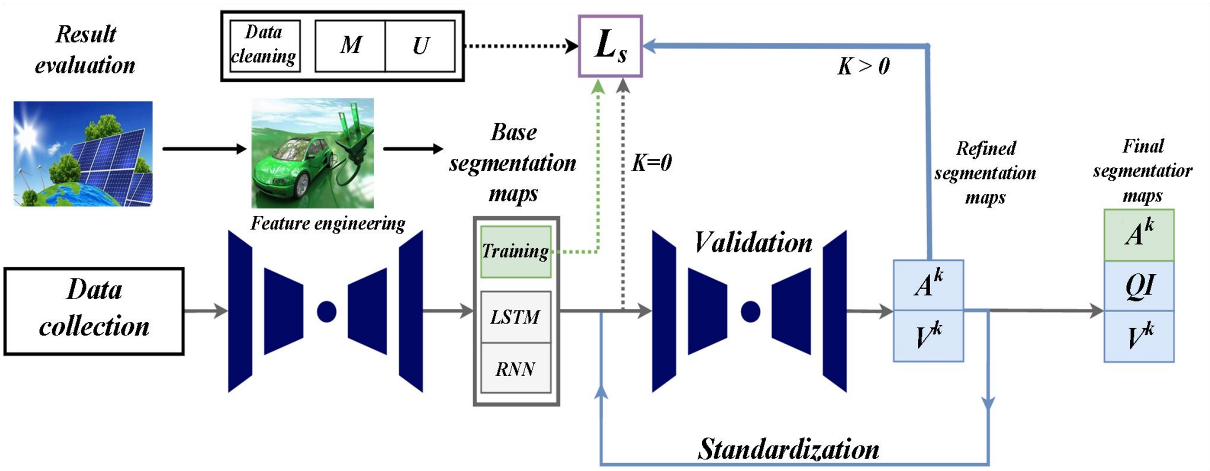

Figure 3. Flowchart of Deep Learning Model Training and Performance Evaluation

Figure 3 shows a flowchart of deep learning model training and performance evaluation. All power equipment shall operate in a safe and orderly manner within the rated voltage, rated current and limited range and time so as to avoid power grid equipment or power grid accidents. The safety and reliability assessment index is mainly based on the qualified rate of power grid voltage, reliability rate of power supply and the difference rate of power grid frequency such factors constitute.

1) Qualified rate of voltage

The voltage qualification rate represents the operation of distribution networks at all levels in a certain period. Where γ is the qualified rate of voltage, T and Tr are the voltage super upper limit time and voltage super lower limit during the detection period, respectively. Time length,T, is the total time of the detection period.

2) Power supply reliability rate

The energy supply adequacy index of the system comprehensively represents the power supply guarantee capacity of the power system under the access of new energy [15]. Under the development trend of "complementary source and source" conversion to the power supply side, the energy supply adequacy index is based on the proportion of the reserve capacity. The degree of system complementary and the proportion of energy storage installed capacity are considered.

The degree of system complementary represents the sum of the power supply capacity of various "source complementary" power supply modes of the access system, which is reflected in the ratio of the sum of the power generation of the complementary mode to the sum of the system generation [16]. The greater the degree of system complementary, the stronger the power supply capacity of the system stability under the transformation of the power structure. The data collection is shown in Table 1.

Table 1. Data Collection

Data source	Data type	Data size (GB)
New Energy Power Station	Power production data	200
Market Analysis Company	Market price data	50
Weather Bureau	Weather data	100
Other	Related policies, news, etc	50

3. Methodology

3.1 Power Quality Fluctuation Prediction Model

Data Pre-processing

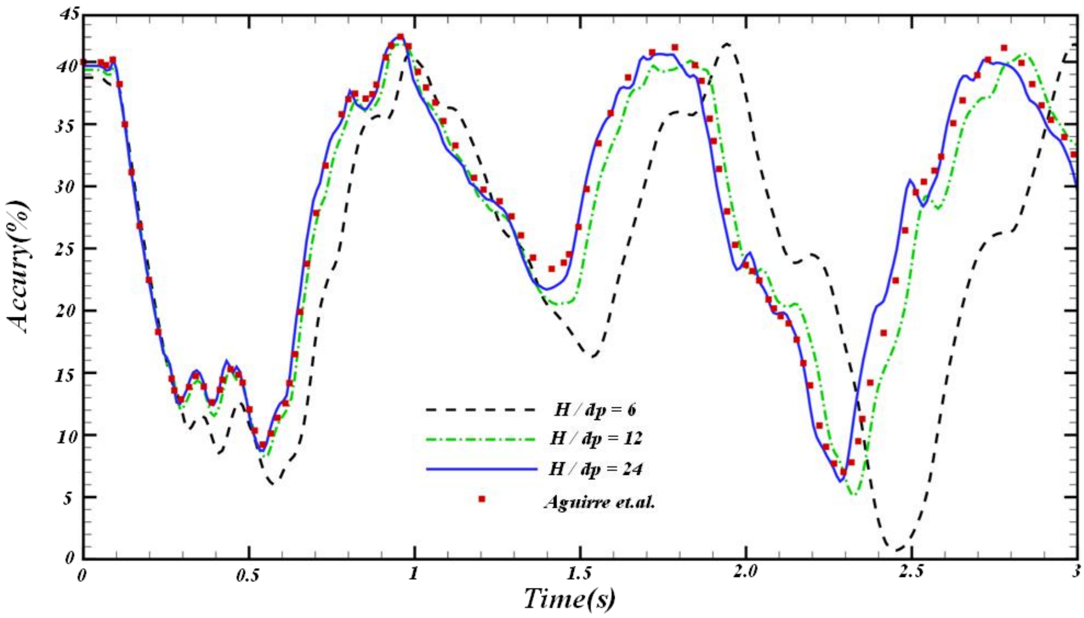

Figure 4. White Correlation Function Graph of Power Demand Growth Rate Series

As can be seen from Figure 4 above, the autocorrelation coefficient of this sequence is always controlled within the standard deviation range of 2 times after K=2, and the autocorrelation coefficient gradually decays to zero with the increase of delay order K. Therefore, it can be preliminarily judged that this sequence is stationary. Although the method of judging order stationarity by observing sequence diagrams and autocorrelation diagrams is simple and convenient, it has some subjective colour. Next, the unit root test (ADF) is further adapted for the test, and the test principle is shown in reference [19]. Using Eviews 6.0, the ADF test is made on the growth rate series of electricity consumption in China. According to the timing diagram, select the intercept item and automatically select the lag period. The ADF value of this time series is 3.4125, which is less than the critical value of a 5% significant level of 2.972. Therefore, this time series is considered to be stationary at a 95% confidence level. In order to evaluate the effectiveness of the model optimization strategy, we have conducted a large number of experiments and comparative analyses. Through the experimental results, we find that the optimized model has a significant improvement in prediction accuracy, stability and operation efficiency. Prediction accuracy improvement: By comparing the prediction results of the model before and after optimization, we find that the prediction accuracy of the optimized model has been significantly improved. This is due to the practical application of optimization strategies such as data enhancement and ensemble learning. Stability enhancement: By comparing performance, we find that the optimized model has better stability. Even in the face of new and unseen data, the model can maintain good prediction performance. Raw dataset samples are shown in Table 2.

Table 2. Raw Dataset Samples

Number	Time stamp	New energy types	Generating capacity (MWh)	Power quality index	Weather regime	Market price (RMB / MWh)
1	2022-01-01 00:00	solar energy	500	0.95	overcast sky	500
2	2022-01-01 01:00	wind energy source	800	0.92	windiness	480
3	2022-01-01 02:00	hydro energy	450	0.97	clear day	510

Operational efficiency improvement: Through optimization strategies such as model pruning, we successfully reduced the complexity of the model and improved its operational efficiency. This makes the model can give the prediction results faster in practical application and meet the real-time requirements.

4. Results and Discussion

4.1 Key Technologies of New Energy Power Quality Prediction

Electric Energy Conversion

The fundamental problems to be solved by using new energy for power generation are power conversion, power storage, power management and power quality control. Its core is to adopt power electronics technology, automatic control technology, computer technology and artificial intelligence technology, especially the integration and fusion of the above technologies. However, the long-established discipline system and the fragmentation of industries have formed one of the main bottlenecks restricting the wide application and development of new energy power systems [20]. Therefore, it is indispensable to research and develop power electronic power converters matched with new energy power generation equipment through interdisciplinary research and form products through system integration to facilitate users.

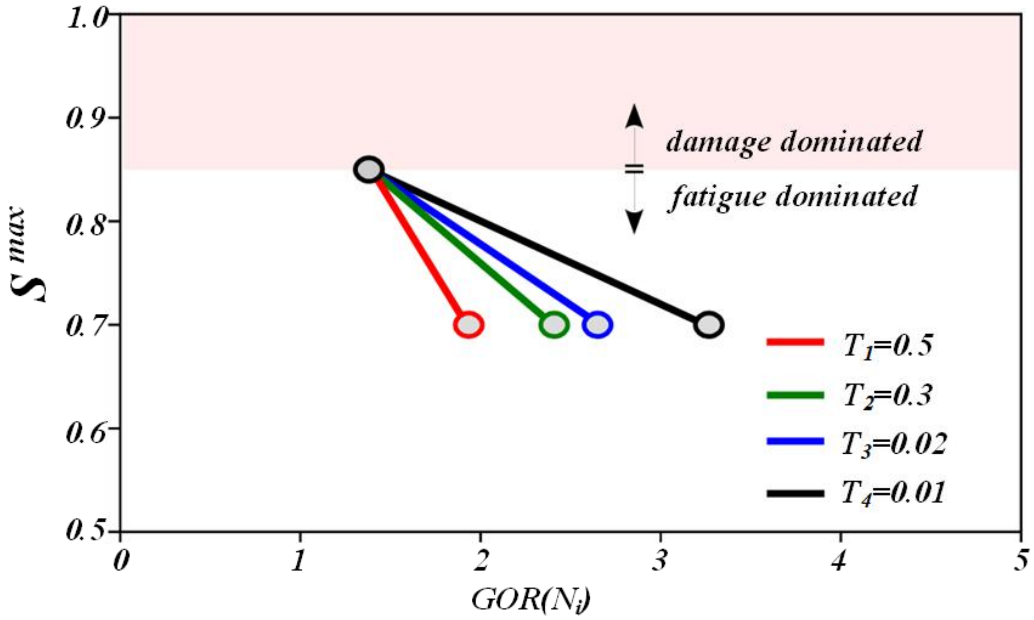

Figure 5. Comparison Diagram of the Performance Optimization of the Deep Learning Model

Figure 5 shows a Comparison diagram of the performance. Power generation equipment matches the requirements of existing power equipment in form and meets the needs of users in quality. Because the power conversion in new energy power systems is mainly DC/DC conversion and AC/DC conversion, it is imperative to improve the conversion efficiency and power density [21]. Soft-switching technology is an effective means to reduce switching loss and improve current density and conversion efficiency, so it is necessary to develop converters based on soft-switching. In addition to the traditional storage battery and inductance, modern energy storage devices include supercapacitors and flywheels.

Electric Energy Storage

Compared with electrolytic capacitors, supercapacitors use double-layer electrodes generated on the surface of carbon electrodes to store energy, which has a very high power density and substantial energy density. Nowadays, the power density of supercapacitors can be as high as 20kW/kg, and the charging and discharging time is 0.1 ~ 100 minutes, respectively. In the past few years, these devices have been used in many fields such as consumer electronics, T industry and automobile. At present, reducing the friction loss of a flywheel is the key to improving energy storage efficiency, and it is an effective solution to make the flywheel shaft stably suspended in space by using magnetic levitation technology [22]. It is predicted that flywheel energy storage devices will have application prospects in national defense, electric power, transportation and other fields. The main research contents of power quality control are:

(1) Power harmonic detection and analysis technology. Harmonic measurement and analysis is the precondition of harmonic control. Accurate harmonic measurement and analysis can provide a reasonable basis for harmonic control. However, spectrum leakage and fence effect will occur. Therefore, how to reduce the measurement error caused by synchronization deviation has become the focus of many scholars. Data preprocessing statistics are shown in Table 3.

Table 3. Data Preprocessing Statistics

Data type	Data volume (article)	Proportion of missing values	Number of outliers
Power data	1,000,000	0.5%	500
Market data	500,000	1.0%	800
Weather data	750,000	0.7%	600

(2) Power quality control and management, including power factor correction and filter design. Now, it has developed from circuit topology and control strategy to integrated module and first achieved results in a single-phase PFC circuit. Such as Buck, Boost, Buck-boost, Cuk DC/DC primary conversion circuit dedicated or general PFC controller [23]. Recently, the research has focused on three-phase PFC control technology, such as the development of single-switch, multi-switch and soft-switch three-phase PFC circuits. Significantly, the integration of soft switching technology and PFC technology is a new development trend. Although PFC products have been limited by power recently, it is a significant opportunity to apply them to distributed new energy power generation systems.

Source Network Coordination

"Source network coordination" refers to the interactive mode that solves the uncertainty problem of new energy grid connection and enhances the flexible dispatching ability by improving power regulation technology.

The "source network coordination" complex now has the perception ability of the new energy, the prediction ability, the new energy end to withstand the power grid voltage, the disturbance ability of the frequency fluctuation and so on. With the new energy scale development process, there is a need to achieve "source network coordination" through technical means to improve the grid control ability of new energy access, enhance new energy by uncertainty power to flexible, controllable power supply, to ensure the proportion of new energy power in the power supply structure, enhance the power energy structure of clean low carbon and safe reliability. The typical scheme, "Source network coordination", is a necessary means to realize the large-scale development of clean energy [24]. At present, "source network coordination". The typical pattern is as follows:

(1) Improve the power grid perception ability with the high-precision monitoring device

The operation process of new energy units is dynamic and complex. It is difficult to upload the critical operation information of various types of units in real-time, which leads to the weak information coordination ability of traditional power grid for the operation status of new energy and the inability to realize flexible and accurate control and evaluation of controllable resources [25]. Through the new energy power station with the high precision monitoring device, can realize the wind, light, water, and fire, including new energy units and the whole process of station state perception, combined with DC, flexible AC transmission system (FACTS) control resources, the power grid can realize the number of controllable resources and distribution of information real-time perception, master and call as a whole. Table 4 shows the power structure quality index grade classification.

Table 4. Power Structure Quality Index Grade Classification

Type	Scope	Subgroup
Harmonious Development	0.9<D≤1	Senior Coordination
Transformation	0.6<D≤0.9	Basic Coordination
Uncoordinated Development	0.3<D≤0.6	Basically Incongruous
	0<D≤0.3	Serious Incongruity

Improve the prediction capability of the power grid with multi-scale and hierarchical rolling prediction.

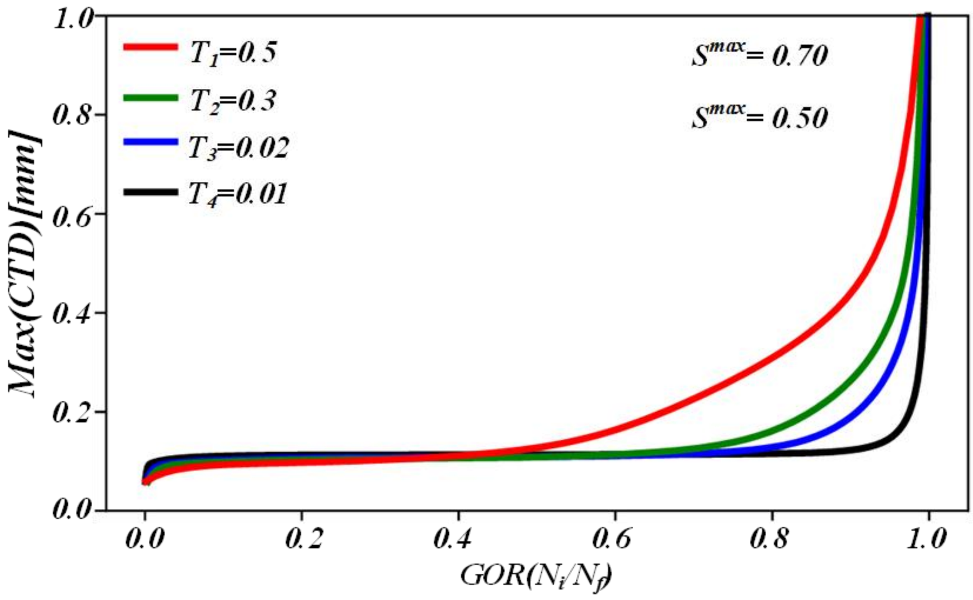

Figure 6. Power Quality Risk Data Distribution and Characteristic Analysis Diagram

Figure 6 shows the Power quality risk data distribution and characteristic analysis diagram. The new energy generation is highly random and difficult to predict, which will have an impact on the steady-state regulation level of power system [26]. Reactive power regulation capacity of new energy is not entirely played, and the significant change of power easily causes the voltage fluctuation of the power grid; on the other hand, the fluctuation of the output of new energy is problematic. Through multi-scale hierarchical rolling prediction, the scientific control of the new energy power supply can be realized. The assessment is presented in Table 5.

Table 5. Assessment of Prediction Results are Presented

Evaluation Indicators	LSTM Model	CNN Model
Mean Absolute Error (MAE)	0.05	0.06
Root Mean Square Error (RMSE)	0.07	0.08
Mean Percentage Error (MAPE)	2.5%	3.0%
Accuracy Rate	90%	88%

Improve the disturbance resistance of the power grid by transforming the voltage/frequency resistance of the primary and secondary equipment of new energy. The voltage wave of the new energy machine at the end of the power grid [27]. The movement is generally more violent, and the pressure resistance and frequency resistance of new energy units are insufficient, which will further cause chain off-grid accidents and seriously affect the safe and stable operation of the power system. Through the implementation of the voltage and frequency resistance capacity of the new energy units, the acceptance range of voltage and frequency of the new energy units can be increased so as to effectively improve the disturbance ability of the new energy machine terminal to the abnormal voltage and frequency. Data set of quality risk in new energy industry is shown in Table 6.

Table 6. Power Quality Risk Data Set of the New Energy Industry

New Energy Types	Time Stamp	Power Quality Index: 1	Power Quality Index: 2	Risk Grade
Solar Energy	2022-01-01 08:00	0.95	0.88	Low Risk
Wind Energy Source	2022-01-01 09:00	0.85	0.92	Medium Risk
Fire Can	2022-01-01 10:00	0.70	0.80	High-Risk

Construction guarantee of "source network coordination". With continuous development of new energy, coverage area of power electronic equipment in the power system will gradually increase, and the form of the power grid will also undergo profound changes. Therefore, "source network coordination" should always take innovative technology as the guarantee for development. For example, as proportion of power generation gradually increases, power grid volatility may still be more serious [28]. At this stage, with new energy primary and secondary equipment, voltage/frequency resistance upgrade power grid disturbance ability may not be enough to support the safe operation of new energy units; therefore, there is also a need to expand through technological innovation power system allows frequency fluctuation bandwidth, further optimize the new energy disturbance ability [29],[30],[31].

5. Conclusion

In this paper, aiming to predict the power quality risk spillover trend, a prediction model based on deep learning is proposed, and it is constructed and optimized in detail. By deeply analyzing the characteristics of power quality data and the mechanism of risk spillover, we designed a deep learning network structure suitable for this field. We realized the effective prediction of the power quality risk spillover trend.

In the aspect of model construction, we fully consider the time series, nonlinearity and uncertainty of power quality data, adopt cyclic neural network as the basic model, and introduce long and short time memory network and gated cyclic unit to optimize the performance of the model. In addition, in order to improve the prediction accuracy and generalization ability of the model, we also introduce attention mechanism, residual connection and batch normalization to improve the model further.

In order to avoid over-fitting and improve the stability of the model, we adopt a variety of optimization strategies, including parameter initialization, learning rate adjustment, regularization, early stop and so on. At the same time, we also carefully adjust and verify the super parameters of the model and determine the optimal model configuration.

Through experimental verification, we prove that the power quality risk spillover trend prediction model based on deep learning has high prediction accuracy and robustness and can provide adequate support for power quality monitoring and early warning. At the same time, the research methods and achievements of this paper also provide a valuable reference for risk prediction and decision support in other fields.

To sum up, this paper has made remarkable progress and achievements in power quality risk spillover trend prediction, which not only provides a new solution for power quality monitoring and early warning but also provides a new idea and direction for the application of deep learning in the field of risk prediction. In the future, we will continue to deeply study the related problems of power quality risk prediction, explore more advanced prediction methods and models, and make more significant contributions to the sustainable development of the power industry.

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