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Evaluation of Power Grid Social Risk Early Warning System Based on Deep Learning

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ABSTRACT

In the context of the continuous development of the power grid, the tasks of regulation, operation, and management are becoming increasingly complex, and the operation risks are also increasing dramatically. Sensor technology can deal with the impact of uncertain risk factors, such as extremely disastrous weather, equipment failure, and load fluctuation, on the power grid. Therefore, this article proposes a real-time risk analysis and early warning system for the power grid based on machine learning and combined with sensing technology—a stack self-coding (SSC) neural network prediction model—and introduces the functional composition of the system, clarifying the research content. The experiment compared the accuracy of power grid load forecasting between the SSC forecasting model and the fuzzy neural network (FNN) forecasting model and obtained the forecasting curves of a holiday, a workday, and a Sunday, as well as a comprehensive forecasting accuracy comparison. The experimental results showed that the SSC prediction model based on machine learning designed in this paper improved the prediction accuracy by 12.94% compared with the FNN model. The power grid risk can be assessed through load forecasting, and it is also of great significance for load dispatching and reducing generation costs.

KEYWORDS

Deep Learning, Grid Risk Warning, Monitoring Systems, Sensing Technology

INTRODUCTION

The regional power grid plays various roles, such as allocating distributed power for users and allocating wind, solar, and other renewable energy for the regional power grid. The failure of the regional power grid would directly affect the reliable power supply of various users, so it is necessary to analyze the power grid's social risk early warning system. There is already some research on power grid risk early warning systems. Tian et al. (2020) studied the early warning and suppression of subsequent commutation faults during the restoration process under a power grid fault. Gu et al.

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(2019) studied the lightning risk assessment and early warning of the UHVDC transmission channel. Y. Liu et al. (2021) developed the risk early warning technology for the overhead transmission line tripping process caused by wildfire. Zhang et al. (2017) conducted intelligent early warning on power system dynamic insecurity risks to achieve the best balance between accuracy and precision. Chen et al. (2019) designed a statistical risk assessment framework for distribution network resilience to address grid risks. Stone et al. (2021) combined the weather forecast regional climate model with the advanced building energy model to simulate the interior building temperature of more than 2.8 million residents in Atlanta, Detroit, Michigan, and Phoenix, Arizona, in heat wave and power failure conditions. The research results showed that 68% to 100% of the urban population was exposed to a high risk of heat exhaustion or heatstroke due to the simulated recent intensity and duration of the composite heat wave and power grid failure events. P. Liu et al. (2017) designed wind turbines' dynamic tripping risk alarm mechanism in large-scale wind farms. The above research has analyzed the power grid risk early warning.

Many scholars have studied the application of deep learning power grids. He et al. (2017) designed an intelligent mechanism based on deep learning for real-time detection of false data injection attacks in smart grids. Jeyaraj and Nadar (2021) argued that the computer-aided demand-side energy management in the residential smart residential grid could adopt a new set-depth learning algorithm. Ibrahim et al. (2021) designed an intelligent grid power theft detection method based on deep learning to deal with grid risk. Alam et al. (2022) designed the best energy management scheme for photovoltaic and battery energy storage integrated home microgrid systems based on deep learning. Kishor et al. (2021) designed the intelligent grid operation on deep learning and data analysis to support renewable energy. The research of the above scholars has made fruitful progress in the in-depth study of grid applications. Compared with traditional load forecasting methods, the random forest algorithm, and the LSTM model, the load forecasting model based on the fuzzy neural network has higher forecasting accuracy in tasks related to time series data and can be applied to short-term load forecasting research of power systems.

At present, there is an urgent need to analyze and control the risks of regional power grids comprehensively. Currently, research on short-term load forecasting mainly focuses on deep learning. Still, the training cost of deep learning models is often high, especially when combined with other time series decomposition methods. The most intuitive manifestation is that the model requires a longer training time. The existing research has fully considered the impact of meteorological information and transmission line fault characteristics on power grid risks and has achieved some results. It is essential to formulate production operation plans and other risk checks to achieve planning optimization and safety control to eliminate and prevent known risks.

The innovations of this article include the following points:

1. This article proposes security analysis standards for transmission networks and successfully applies them to energy management systems in transmission networks.
2. This article studies the safety evaluation indicators of power system operation under the influence of sudden faults.
3. This article proposes a real-time risk analysis and warning system for power grids based on machine learning combined with sensing technology, which has higher accuracy than traditional methods.

GRID RISK

Control Strategy of Switching a Regional Power Grid On and Off

Bus automatic transfer switch (BATS) refers to an automatic device that can quickly and automatically input the backup power supply, backup equipment, and other normal operating power supply to avoid using power failure when the working power supply is cut off due to a power system failure and other reasons. In recent years, with the increasing scale of the power grid, the topology of the power system network has become more and more complex. To ensure the reliability of the power supply of the power system, the automatic input device of the standby power supply is increasingly used in the regional power grid. Although the application of the mechanical input device of the standby power supply has improved the reliability of the power supply of the power grid, some problems need to be solved urgently. In case of power grid failure, multiple buses may stop running, and multiple BATS may meet the action requirements. If the action coordination problem is not considered among these BATS, it may trigger various BATS actions. In fact, not all BATS actions are required. The more devices that move, the more likely further failures would occur. At the same time, the capacity load ratio of the main transformer at the remote standby power supply side and the thermal stability limit of the line are fully considered to ensure the safe and reliable operation of the power grid better.

Static Security Evaluation Index of Distribution Network

For a long time, power workers have mainly focused on the static security analysis of the transmission network, proposed the security analysis standard, and successfully applied it to the energy management system of the transmission network. The static safety analysis function of the transmission network energy management system is to observe the steady-state performance of the system after opening one or several network elements when there is no fault. The selected network elements are opened separately. After calculation, various operating state parameters of each node voltage, branch, and other network elements are obtained, and the given security indicators are calculated. Finally, the separate network elements are sorted according to the size of the security indicators. In recent years, the urban distribution network has made rapid progress due to accelerating urbanization. However, the security analysis of the distribution network has not been paid as much attention as the transmission network. In addition, because the topology of the distribution network and transmission network is quite different, that is to say, it is generally closed loop design and open loop operation. Therefore, it has become an important research topic to propose a more practical and efficient static security evaluation index for urban distribution networks.

Grid Sensor Warning

Some scholars pointed out that advanced sensors and the Internet of Things would play a massive role in the future power grid (Morello et al., 2017). The sensing technology of smart cities and power grids has made some progress (Morello et al., 2017). There are also cases where scholars use machine learning technology to sense loads in ultra-low voltage DC microgrids intelligently (Quek et al., 2017). Threat analysis and security protection platforms constitute a sensor-based power grid security risk early warning device. The threat analysis platform collects real-time data from the power grid, analyzes and processes them to determine the security level of the power grid, and then generates appropriate early warning information according to the security level, which is sent to the security protection platform. Then, the security platform uses early warning signals to find appropriate protection measures in the security strategy database. The power grid sensor early warning device can evaluate the security status of the power grid and can also improve the safe and stable operation of the power grid. Figure 1 shows the module structure.

DISTRIBUTION NETWORK STATIC SECURITY EVALUATION INDEX

Security of power system operation refers to ensuring to avoid serious power supply interruption when sudden faults cause interference. Power system security analysis can be divided into two parts according to its performance after the failure. One is static security analysis, and the other is dynamic security analysis. Figure 2 shows the power system security diagram.

Figure 1. Module construction

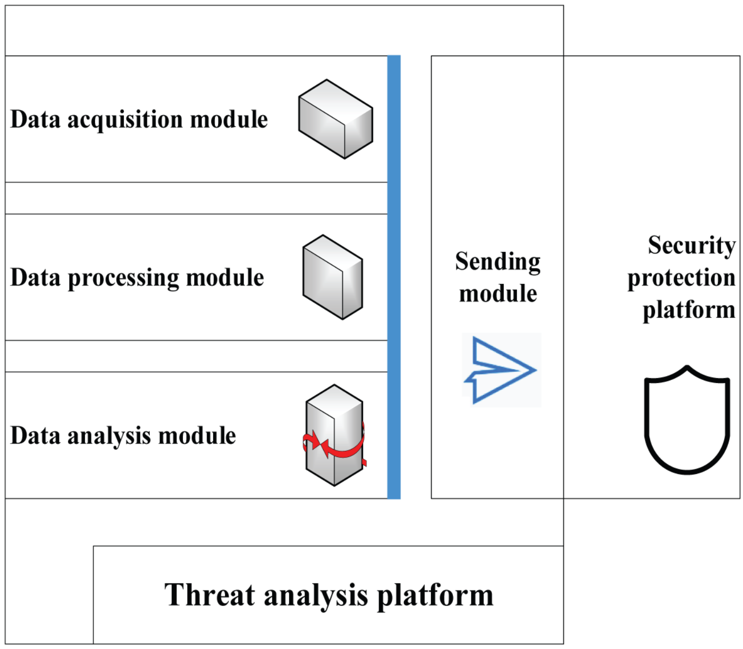
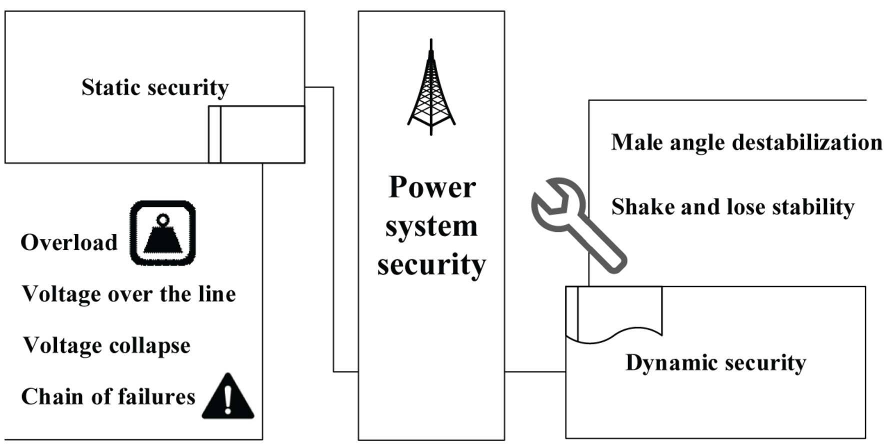
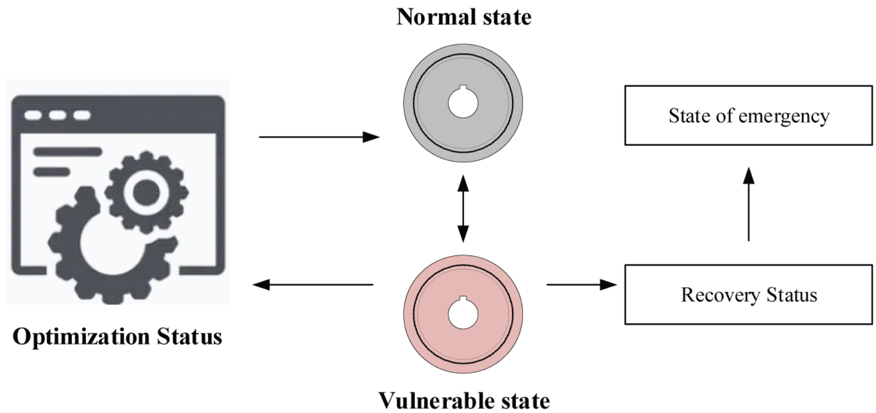


Figure 2. Power system security



The key problem in dynamic security analysis is whether the system is stable and whether the power system can operate smoothly after various disturbances. The most important work in the static security analysis of a power system is to study the situation when the system's main components withdraw from operation under a given operation mode. Static safety analysis is usually mainly used for overload analysis and voltage out-of-limit system analysis, usually only considering the distribution of system power flow when a single substation or line is out of operation. The power system must meet two kinds of constraints under normal working conditions. One is the *equality constraint*: the balance of active power generated and absorbed by the system. The other is the *inequality constraint*, which means that the system's transmission power, voltage amplitude, and generator active power output of node lines are within the specified safe range. Figure 3 shows the grid operation status.

Figure 3. Power system operation status



When the system is in a fragile state, the transmission power of some lines or transformers is too large, and when it exceeds the power limit under a normal working state without preventive control or preventive control measures are not in place, the system enters an emergency state. The optimization state generally refers to the optimal operation state, such as the maximization of the system security domain and the minimization of system operation cost, under a specific target. In the *normal* state, the power system is changing the load all the time, and the generator output is adjusted to meet the load demand, to ensure the power frequency quality. It is also necessary to ensure the safe operation of the power system on the premise of the economic process. In the *vulnerable* state, the power system is not likely to suffer catastrophic interference. In most cases, the security level of the power system gradually decreases due to accumulating a series of small interferences under normal conditions, which leads to a fragile state. In the *fragile* state, although the voltage and frequency are within the allowable range, the system safety reserve and the ability to resist external interference have also reduced. The operating parameters of a single component or area are close to the edge of the safe range, and the interference would cause the operation to be in an *emergency* state, in which some unpredictable interference occurs or the load increases to a certain extent, the voltage and frequency deviation would exceed the allowable range, and some devices would be overloaded, thus endangering the safe operation of the system. In an *alert* state, after detecting that the system has entered the alert state, it is necessary to report to the dispatcher in time to adjust the generator so that the system can recover to the normal state as soon as possible. In a *fault* state, the power balance between the power supply and load is broken, resulting in the system frequency and node voltage exceeding the allowable deviation value, and the system is in crisis. Various corrective control and stability control measures shall be taken for the power system at fault to restore it to normal as far as possible. In a *recovery* state, after the emergency, the power system is stabilized through relay protection, automatic device, or manual intervention.

Power Flow Calculation

The power flow calculation is the most basic calculation in power system analysis. It calculation can be done under the given power system network topology, component parameters, generation, and load parameters. The phenomenon that the operation state approaches the operation limit value is increasingly common, and the typical power flow calculation methods often have non-convergence. In order to solve this problem, some enhanced power flow algorithms have emerged, such as nonlinear programming and optimal multiplier methods. However, due to the different characteristics between the distribution and high-voltage transmission networks, the convergence performance of various effective power flow calculation methods originally applicable to high-voltage transmission networks is significantly reduced. Therefore, the forward-backward power flow calculation method is generated. This algorithm has high convergence speed and numerical stability for power flow calculation of distribution networks and does not occupy significant computer resources. However, in the case of a large distribution network scale, the number of iterations of such algorithms also increases linearly.

Anticipated Fault Set

Static voltage stability control aims to enable the system to achieve sufficient load margin requirements under normal operating mode and various fault conditions. Therefore, it is necessary to comprehensively consider multiple faults in the system, which is the expected fault set. The desired fault set size is usually large, and the control model is also complex, prone to over-control or under-control. Dispatchers can define various complex faults in fault set at will to reduce the calculation amount of static security analysis and facilitate the simulation of the working conditions in case of power grid failure. The essence of automatic screening of predicted accidents is to automatically screen out the predicted accidents that may lead to similar voltage out-of-limit and branch power flow overload according to the current operation of the power grid. These indicated accidents need attention, and specific evaluation indicators are used to quantitatively describe the damage that the accident may cause to the system.

Evaluation Indicators

As a quantitative means, evaluation indicators can specify the severity of expected accident consequences. This article follows the practice of most literature. It selects the average absolute percentage error, root mean square error, and root mean square error as the evaluation indicators of the model for the following experiments. The evaluation indicators have no fixed form of expression. According to the actual needs of the project, their expressions are various. Most evaluation indexes of high-voltage transmission networks are defined according to the deviation of the ideal value of system state variables. In the static security analysis of transmission networks, the evaluation index of fault consequence is relatively mature. However, the research on this aspect of distribution networks is still insufficient.

DEEP LEARNING AND POWER GRID RISK PREDICTION

Power System Load Problem

Power system load forecasting is an integral part of the energy management system, and its forecasting error is directly related to the effect of subsequent power grid security checks and analyses. *Load forecasting* is a quantitative prediction that utilizes past power load data and other relevant influencing factors to predict future load values. Before conducting load forecasting, it is necessary to know its characteristics to construct a more reasonable forecasting model. Affected by the uncertainty and complexity of the load itself, accurate load characteristic analysis and prediction model construction are the key points to improve prediction accuracy. The existing prediction models mainly focus on shallow learning. It is difficult to extract the deep features of load series due to the limited approximation ability of complex functions in limited samples and computing units. The model generalization performance is limited, hindering the further improvement of prediction accuracy. Moreover, the depth learning model emerging in recent years has an excellent information expression ability, robustness, and generalization. It has been successfully applied to image recognition, computer vision, and many other fields and has begun to stand out in the field of prediction. Traditional load forecasting methods include time series model forecasting, grey forecasting, and regression analysis. The prediction model established by this method is simple in calculation and has a wide range of applications. However, the demand for the stability of load series is relatively high. Most of them only use historical loads for prediction, and sometimes the prediction accuracy is affected. To overcome these shortcomings, artificial neural networks and support vector machines, as the representatives of shallow machine learning algorithms, have become hot issues due to their excellent nonlinear function fitting ability. The improvement and combination of these methods have partially improved load forecasting accuracy.

Deep Self-Coding Neural Network

Assuming that the network input and output data are isomorphic, the historical load, weather elements, and daily types are reconstructed to form a learning sample set. In the coding stage, the feature vectors are input into the hidden layer to obtain the coding results, and feature extraction is completed. The first-order feature representation is reconstructed to obtain the decoding output. Equations 1 and 2 show the first-order feature representation and decoding production, respectively:

$$h = f\left(w_1 x_i + b_1\right) \tag{1}$$

$$y\left(x_i\right) = g\left(w_2 h + b_2\right) \tag{2}$$

where w_1 and w_2 represent the connection weight value and b_1 and b_2 represent the offset value matrix.

The transformation kernel function is:

$$g(x) = f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

The error cost function of the self-encoder is:

$$C_{sparse}(w,b) = \frac{1}{2N}\sum_{i=1}^{N}\sum_{j=1}^{d}\left(y\left(x_{i,j}\right) - x_{i,j}\right)^2 + \frac{\lambda}{2}\sum_{l}\sum_{i}\sum_{j}\left(w_{i,j}(l)\right)^2 + \gamma\sum_{k=1}^{n} KL\left(\rho \middle\| \hat{\rho}_k\right) \tag{4}$$

Prediction Model Design of Stack Self-Coding Neural Network

In this paper, the designed prediction model is named stack self-coding (SSC) neural network prediction model. The self-coded hidden layer is:

$$x\left(l+1\right) = h(l), l = 12,\ldots,n-1 \tag{5}$$

where n is the number of self-encoders in the model.

The changing trend of power load depends on its characteristics and is directly affected by many random factors, especially meteorological factors. For example, the influence of temperature on load is the most essential meteorological factor, while high temperatures in the summer, air conditioning, and other refrigeration equipment cause a significant increase in power load; in the winter, the temperature is high, but the power load would be increased due to the use of heating equipment:

$$J\left(w,b\right) = \frac{1}{2N}\sum_{i=1}^{N}\left(y_i - f_i\right)^2 + \frac{\lambda}{2}\sum_{l}\sum_{i}\sum_{j}\left(w_{i,j}(l)\right)^2 \tag{6}$$

where y_i and f_i are target output values and predicted values.

The model is trained using the layer-by-layer learning algorithm. The core idea is that the network contains only one hidden layer each training time. After the self-encoder is optimized, the visual reconstruction layer is removed. With the output of the hidden layer as the input, the next self-encoder is retrained until the last self-encoder reaches the optimal state and the unsupervised pre-training is completed. The rules for updating the weights are:

$$w_{k+1}(l) = w_k(l) - a\nabla_{w(l)} C_{sparse}(w,b) \tag{7}$$

$$b_{k+1}(l) = b_k(l) - a\nabla_{b(l)} C_{sparse}(w,b) \tag{8}$$

EXPERIMENTAL EVALUATION OF LOAD FORECASTING ACCURACY

Experimental Data

The experimental data comes from the actual load data collected in the power grid of a specific region, as well as the hourly weather and other influencing factors. Since there are often some outliers and missing values in the historical load data, these abnormal values must be corrected and filled to make them consistent and stable. The commonly used model for power load forecasting is to model the daily load with a lead of days, which uses the daily load data from the previous days to predict the load for the next day, then slide along the data timeline and expect the load data for the next day in sequence. At the same time, non-load data should also be preprocessed. Table 1 shows sample data.

Forecast Result Analysis

To comprehensively analyze the prediction effect of the SSC depth model, this paper uses a fuzzy neural network as the comparison algorithm and a multivariable sliding window mechanism to obtain three periods of load curve comparison and training time comparison of the prediction model. This article uses a fuzzy neural network as a comparison algorithm. It adopts a multivariable sliding window mechanism to obtain the comparison of load curves and training time for three cycles of the prediction model. The load has specific characteristics on various time scales, and generally speaking, for short-term load forecasting, the primary considerations are date factors and meteorological factors.

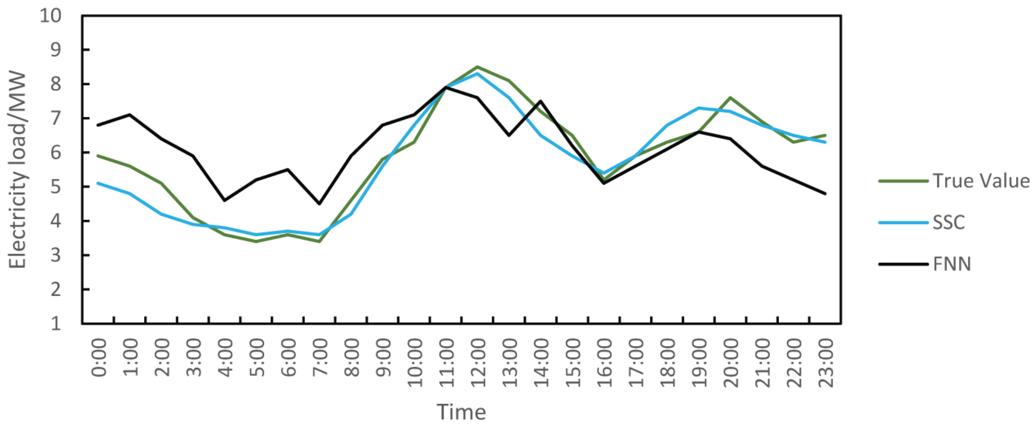
Holiday: January 2

Figure 4 compares the predicted value of the SSC model and the predicted value of the FNN model designed in this paper and the actual value. The daily load curve of electricity has two essential characteristics that are very obvious: *similarity* and *smoothness*, also known as *horizontal similarity* and *vertical similarity*. By collecting a large amount of historical data and classifying the collected data, several distinct load curves can be extracted. It is not difficult to see that the trend line of the predicted value of the SSC model is closer to the trend line of the real value than the trend line of the

Table1. Sample data

Parameter setting	Variable
Input	Historical load values for the 8 hours before the test
	Historical load values for the previous 6 days to be measured
	Historical load values to be measured three weeks ago
Output	Forecasted daily momentary load value

Figure 4. Load forecast curve for January 1



predicted value of the FNN model, and the prediction accuracy is higher. All of the predicted values were the highest in the midday interval.

Working Day: January 8

Figure 5 compares the predicted value of the SSC model, the predicted value of the FNN model designed in this paper, and the actual value. It can be seen from the figure that the trend line of the SSC model prediction value is better than that of the FNN model prediction value. The predicted value is the highest in the interval afternoon.

Sunday: July 3

Figure 6 shows that for the load forecast on July 3 (Sunday), the FNN's model prediction effect is inferior, while the SSC's model prediction effect is good, which is close to the real value. Its load value is higher at noon, but there is no special difference compared with other periods.

Figure 5. Load forecast curve for January 8

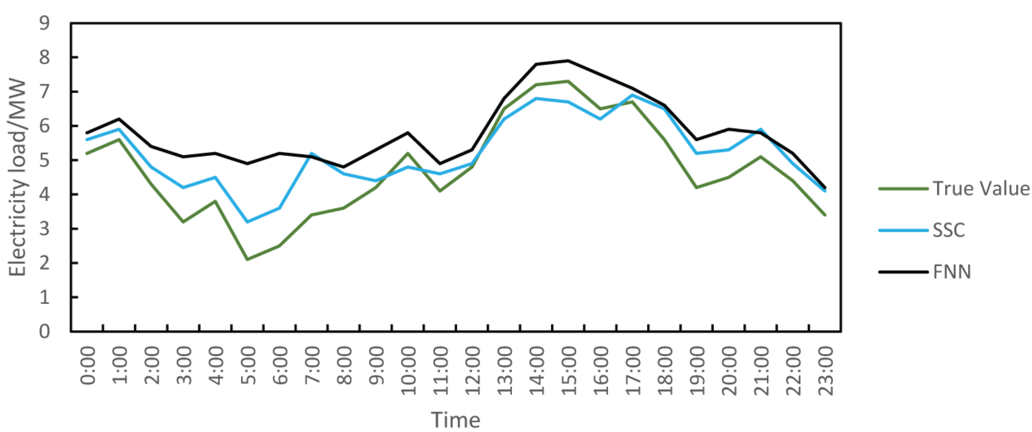
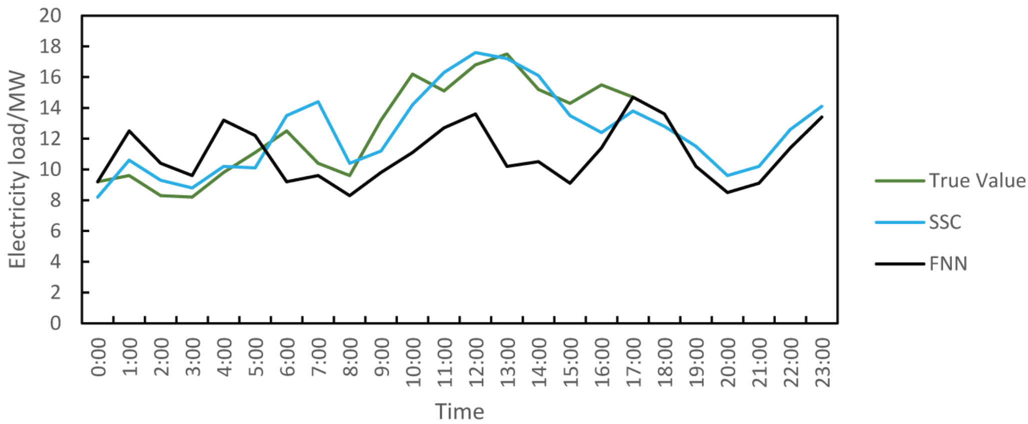


Figure 6. Load forecast curve for July 3



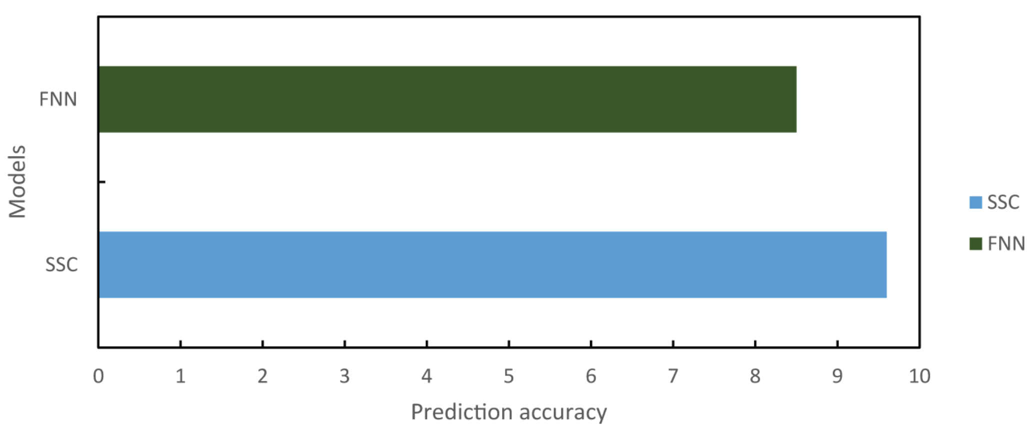
Comprehensive Prediction Accuracy

Figure 7 shows the comprehensive prediction accuracy comparison of the two prediction models; the prediction accuracy is 0–10 from small to large. Compared with the FNN model, the SSC model designed in this paper can improve the prediction accuracy by 12.94% and obtain higher prediction accuracy for summer load forecasting, which can be fully applied to forecasting loads in different seasons and different day types.

CONCLUSION

The trend of power system data magnanimity is the basis of load characteristic analysis and high-quality prediction model construction. Still, the overfitting problem on large sample sets would reduce the prediction accuracy. Therefore, the deep learning method was introduced into the field of power grid risk early warning. According to the nonlinear characteristics of power load, a stack self-coding power grid risk depth prediction model was constructed. This model effectively overcomes the shortcomings of falling into local optima caused by gradient dispersion, thus achieving future load forecasting and power grid risk warning. The experimental results show that compared with the

Figure 7. Comprehensive prediction accuracy comparison



FNN model, the SSC model designed in this paper can improve the prediction accuracy by 12.94%. This has great reference value for developing power grid risk early warning.

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REFERENCES

Alam, M. M., Rahman, M. H., Ahmed, M. F., Chowdhury, M. Z., & Jang, Y. M. (2022). Deep learning based optimal energy management for photovoltaic and battery energy storage integrated home micro-grid system. *Scientific Reports*, *12*(1), 1–19. doi:10.1038/s41598-022-19147-y PMID:36071070

Chen, X., Qiu, J., Reedman, L., & Dong, Z. Y. (2019). A statistical risk assessment framework for distribution network resilience. *IEEE Transactions on Power Systems*, *34*(6), 4773–4783. doi:10.1109/TPWRS.2019.2923454

Gu, S., Wang, J., Wu, M., Guo, J., Zhao, C., & Li, J. (2019). Study on lightning risk assessment and early warning for UHV DC transmission channel. *High Voltage*, *4*(2), 144–150. doi:10.1049/hve.2018.5081

He, Y., Mendis, G. J., & Wei, J. (2017). Real-time detection of false data injection attacks in smart grid: A deep learning-based intelligent mechanism. *IEEE Transactions on Smart Grid*, *8*(5), 2505–2516. doi:10.1109/TSG.2017.2703842

Ibrahim, N., Al-Janabi, S., & Al-Khateeb, B. (2021). Electricity-theft detection in smart grid based on deep learning. *Bulletin of Electrical Engineering and Informatics*, *10*(4), 2285–2292. doi:10.11591/eei.v10i4.2875

Jeyaraj, P. R., & Nadar, E. R. S. (2021). Computer-assisted demand-side energy management in residential smart grid employing novel pooling deep learning algorithm. *International Journal of Energy Research*, *45*(5), 7961–7973. doi:10.1002/er.6449

Kishor, N., Srivastava, A. K., & Pota, H. R. (2021). Guest editorial: Special section on "Deep Learning and Data Analytics to Support the Smart Grid Operation With Renewable Energy.". *IEEE Transactions on Industrial Informatics*, *17*(10), 6935–6938. doi:10.1109/TII.2021.3072770

Liu, P., Li, Z., Zhuo, Y., Lin, X., Ding, S., Khalid, M. S., & Adio, O. S. (2017). Design of wind turbine dynamic trip-off risk alarming mechanism for large-scale wind farms. *IEEE Transactions on Sustainable Energy*, *8*(4), 1668–1678. doi:10.1109/TSTE.2017.2701348

Liu, Y., Li, B., Wu, C., Chen, B., & Zhou, T. (2021). Risk warning technology for the whole process of overhead transmission line trip caused by wildfire. *Natural Hazards*, *107*(1), 195–212. doi:10.1007/s11069-021-04579-y

Morello, R., De Capua, C., Fulco, G., & Mukhopadhyay, S. C. (2017). A smart power meter to monitor energy flow in smart grids: The role of advanced sensing and IoT in the electric grid of the future. *IEEE Sensors Journal*, *17*(23), 7828–7837. doi:10.1109/JSEN.2017.2760014

Morello, R., Mukhopadhyay, S. C., Liu, Z., Slomovitz, D., & Samantaray, S. R. (2017). Advances on sensing technologies for smart cities and power grids: A review. *IEEE Sensors Journal*, *17*(23), 7596–7610. doi:10.1109/JSEN.2017.2735539

Quek, Y. T., Woo, W. L., & Logenthiran, T. (2017). Smart sensing of loads in an extra low voltage DC pico-grid using machine learning techniques. *IEEE Sensors Journal*, *17*(23), 7775–7783. doi:10.1109/JSEN.2017.2723925

Stone, B. Jr, Mallen, E., Rajput, M., Gronlund, C. J., Broadbent, A. M., Krayenhoff, E. S., Augenbroe, G., O'Neill, M. S., & Georgescu, M. (2021). Compound climate and infrastructure events: How electrical grid failure alters heat wave risk. *Environmental Science & Technology*, *55*(10), 6957–6964. doi:10.1021/acs.est.1c00024 PMID:33930272

Tian, D., Xiong, X., & Xiao, C. (2020). Early Warning and Inhibition of HVDC subsequent commutation failure during recovery process under grid fault. *IEEE Transactions on Power Delivery*, *36*(2), 1051–1062. doi:10.1109/TPWRD.2020.3001123

Zhang, Y., Xu, Y., Dong, Z. Y., Xu, Z., & Wong, K. P. (2017). Intelligent early warning of power system dynamic insecurity risk: Toward optimal accuracy-earliness tradeoff. *IEEE Transactions on Industrial Informatics*, *13*(5), 2544–2554. doi:10.1109/TII.2017.2676879