

Research Article

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Research on IoT network performance prediction model of power grid warehouse based on nonlinear GA-BP neural network

<https://doi.org/10.1515/nleng-2024-0061>

received July 13, 2024; accepted October 21, 2024

Abstract: This study introduces a novel approach for forecasting network performance prediction in power grid warehouses, employing a nonlinear Genetic Algorithm (GA)-optimized backpropagation (BP) neural network model. The proposed model integrates the global search capability of GA with the learning efficiency of BP neural networks, thereby addressing the common issue of local optima encountered in traditional BP-based prediction models. The model is designed to capture the intricate dynamics of IoT networks in power grid environments by incorporating multiple critical factors that influence network performance, including signal strength, transmission delay, packet loss rate, and other vital indicators. This comprehensive approach enables the simulation of complex network behaviors, enhancing the model's predictive accuracy and adaptability. The GA-BP model demonstrates superior performance over conventional BP and other methods, showcasing higher prediction accuracy and faster convergence. In the context of power grid warehouses, the model achieves a remarkable accuracy of 96.7%, an 8% improvement over standard BP. Notably, during peak evening hours from 18:00 to 22:00, when network loads are at their highest, the model maintains a stable prediction accuracy of over 98%, effectively supporting the intelligent management and optimal scheduling of power grid warehouses. To ensure the model's applicability across various scenarios, the study verifies its scalability and robustness, proving its suitability for IoT systems in power grid warehouses of differing scales and complexities. This comprehensive verification, establish a grid warehouse model that accurately reflects the actual

operation logic, and provide decision support for material management and allocation content.

Keywords: neural network, grid warehouse, Internet of Things, performance prediction, genetic algorithm, backpropagation

1 Introduction

With the rapid development of information technology, the Internet of Things (IoT) has become the core force promoting social intelligence [1,2]. As one of the critical scenarios of IoT applications, power grid warehouse management systems are facing unprecedented challenges and opportunities. In this context, how to effectively use advanced computational models to optimize the performance of IoT networks in power grid warehouses has become a hot and challenging point in current research.

Traditional network performance prediction methods are often based on simplified mathematical models or empirical rules, which must be revised when dealing with complex network behaviors [3]. With the rise of technology, neural network models have gradually become a powerful tool for solving such problems due to their powerful feature extraction and nonlinear mapping capabilities. However, standard neural network models tend to fall into local optimal solutions during training and are sensitive to initial parameter selection, which limits their effectiveness in practical applications.

To solve existing problems, we propose the GA-BP (Genetic Algorithms-Backpropagation) model based on nonlinear genetic algorithm optimization, which aims to improve the accuracy of IoT network performance prediction in power grid warehouses. Compared with traditional neural network algorithms, GA-BP neural networks can solve nonlinear problems, have more stable modeling models, achieve preset goals more times, have fewer iteration steps for fitting data and achieve preset goals faster and with better data fitting results. GA-BP neural network effectively overcomes the problems of traditional BP neural networks [4,5].

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Previous studies on IoT network performance prediction have primarily relied on traditional machine learning models or simple neural network architectures. These methods often need to pay more attention to the complex interdependencies and nonlinear relationships between various network parameters, leading to suboptimal prediction results. Moreover, the lack of effective optimization strategies has hindered the models' ability to adapt to dynamic network conditions and achieve high prediction accuracy.

This study first constructs a nonlinear network performance prediction model with multiple key influencing factors. Factors like signal strength, delay, packet loss, and interference are considered. GA optimizes BP network parameters for the best configuration. GA-BP converges faster, delivering higher prediction accuracy in testing. In order to verify the effectiveness and practicality of the proposed model, we collected a large number of datasets from the actual grid warehouse IoT environment, which included multi-dimensional indicators of network performance [6,7]. Detailed analysis shows GA-BP outperforms others in accuracy, convergence, and stability across varied network conditions. Our GA-optimized BP model offers a novel approach to predict network performance in power grid warehouses. The model is innovative in theory and shows good performance in practical applications. Through this study, we can provide a valuable reference for researchers and engineers in related fields and promote the further development of IoT technology in power grid warehouses.

2 Related techniques and principles

2.1 GA

2.1.1 Principles of GA

GA, first introduced by Michigan University's Professor Holland in 1962, mirror natural selection and Darwin's theory of evolution [8,9]. By blending the "survival of the fittest" principle with a coded population of optimized parameters, GA screens individuals through selection, crossover, and mutation, aiming to retain the fittest while discarding the unfit. The new generation inherits the best from the previous one and surpasses it, repeating this cycle until the desired goal is achieved.

2.1.2 Basic elements of GA

GA's basics include parameter coding, initial population, fitness function, genetic operations, and running parameters.

Parameter coding refers to how individual chromosomes are encoded. Usually, binary coding and accurate coding are used, and there are some coding methods, such as tree coding, character set coding, and adaptive coding. The generation of the initial population first generates n initial string structure data randomly or according to certain conditions, also called individuals, and each forms the whole population. Then, the GA takes this population as the initial point for iterative operation. Fitness function is a criterion used to evaluate whether individuals in a group are excellent or inferior [10]. Usually, it is a function used to calculate individual fitness values according to the objective function mapping, which is the only basis for selecting individuals. Genetic manipulation simulates natural organisms. Operators like selection, crossover, and mutation are applied based on fitness values, aiming for "survival of the fittest." Running parameters determine population size, evolution algebra, crossover, and mutation probabilities during the initial point.

2.1.3 Implementation of GA

Based on individual characteristics, initial weights and values are set. The BP network is trained, then used to predict system output. The fitness F is calculated using the absolute error E between predicted and expected outputs, as in Eq. (1).

$$F = k \left(\sum_{i=1}^n \text{abs}(y_i - o_i) \right). \quad (1)$$

GA selection operation methods include roulette method, sorting selection method, random league selection method, etc. This study uses the roulette method, where each individual i has a selection probability p , as given in Eqs. (2) and (3).

$$f_i = \frac{k}{F_i}, \quad (2)$$

$$p_i = \frac{f_i}{\sum_{j=1}^N f_i} \quad (3)$$

We use real number crossover for coded individuals. The crossover formula for k th and l th chromosomes at position j is given in Eq. (4).

$$\begin{cases} a_{kj} = a_{kj}(1 - b) + a_{lj}b \\ a_{lj} = a_{lj}(1 - b) + a_{kj}b \end{cases} \quad (4)$$

The mutation operation formula of the j th gene a in the i th individual is shown in Eq. (5).

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \times f(g), & r \geq 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) \times f(g), & r < 0.5 \end{cases} \quad (5)$$

2.2 BP neural network

2.2.1 Artificial neuron model

The artificial neuron model mimics biological neurons' impulse generation, forming a mathematical model. Neuronal connection weights are the core element. As a key regulator of information transfer between neurons, the rationality of its initial setting has a significant impact on the performance of the model. Traditional BP neural networks often fall into local optimality due to random initialization of weights, resulting in insufficient prediction accuracy and generalization ability. The GA-BP neural network uses the global search feature of the genetic algorithm to encode and perform genetic operations on the weights, which effectively overcomes this drawback, and the optimized weights can significantly improve the performance of the model [11,12]. The types of commonly used excitation functions are shown in Eqs. (6)–(10).

$$f(x) = \begin{cases} 1, & x \geq \frac{1}{k} \\ kx, & -\frac{1}{k} \leq x < \frac{1}{k} \\ -1, & x < -\frac{1}{k} \end{cases} \quad (6)$$

$$f(x) = \arctan(x), \quad (7)$$

$$f(x) = \frac{1}{1 + \exp(-\beta x)}, \beta > 0, \quad (8)$$

$$f(x) = \exp\left(-\frac{x^2}{b^2}\right), \quad (9)$$

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \times f(g), & r \geq 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) \times f(g), & r < 0.5 \end{cases} \quad (10)$$

2.2.2 BP neural network model

The BP network is a multi-layer forward network with three unidirectional layers: input, hidden, and output. Neurons are fully connected vertically but not horizontally [13,14]. Data flows from input to output, errors are compared, and weights are adjusted through each layer, improving accuracy with continued weight adjustments.

The BP network differs from the perceptron because its transfer function must be differentiable, whereas the perceptron's is binary [15]. Because of the above reasons, the BP network is different from the perceptron model in

two characteristics: (1) The divided area is composed of a nonlinear hyperplane and a nonlinear divided area, which is a smooth surface area. Because of this, it has better fault tolerance and accuracy than linear division; (2) If the network is trained strictly by gradient descent, it will be easier to determine the analytical formula of weight correction.

2.2.3 Standard BP algorithm

In the algorithm, x is input, y is actual output, d is expected output, w_{ij} is connection weight, O_{i-j} is neuron output, θ_{i-j} is neuron threshold, net_{i-j} is total input, and N is neuron count. BP network's forward propagation is calculated by Eqs. (10) and (11).

$$O_{ij} = f_s(\text{net}_{ij}) = \frac{1}{1 + \exp[-(\text{net}_{ij} - \theta_{ij})]}. \quad (11)$$

If neuron j is in the output layer, the actual output y is compared to expected d , and the error is back-propagated to adjust the weights.

The error is defined as Eq. (12).

$$e_j = d_j - y_j. \quad (12)$$

The network objective function is as shown in Eq. (13).

$$E = \frac{1}{2} \sum_j (d_j - y_j)^2. \quad (13)$$

The weights of the network are modified along the direction of five-function gradient descent, as shown in Eq. (14).

$$\Delta W_{ijk} = -\eta \frac{\partial E}{\partial w_{ijk}}, \quad (14)$$

where $0 < \eta < 1$ represents the efficiency of learning. This calculation requires that a program can be directly programmed to calculate. The derivation formula between neuron output is as shown in Eq. (15).

$$\begin{aligned} \Delta W_{ijk} &= -\eta \frac{\partial E}{\partial w_{ijk}} = -\eta \frac{\partial E}{\partial \text{net}_{(i+1)k}} \cdot \frac{\partial \text{net}_{(i+1)k}}{\partial w_{ijk}} \\ &= \eta \delta_{ik} \frac{\partial \text{net}_{(i+1)k}}{\partial w_{ijk}}. \end{aligned} \quad (15)$$

If $O_{(i+1)k}$ is a hidden node, its actual output is certain but the total error relates to it. The correct output is unknown, and the output of the previous hidden layer affects the input of the next, as in Eq. (16).

$$\delta_{ik} = O_{(i+1)k}(1 - O_{(i+1)k}) \sum_{h=1}^{N_{i+2}} \delta_{(i+1)h} \cdot w_{(i+1)kh}. \quad (16)$$

2.3 GA-BP algorithm

In “Research on IoT Network Performance Prediction Model of Power Grid Warehouse Based on Nonlinear GABP Neural Network,” Genetic Algorithm (GA) is pivotal for several compelling reasons. GA, renowned for its global search capability, effectively addresses the common issue of local optima encountered in traditional BP neural networks, ensuring that the model can explore the entire solution space and converge to the global optimum. This feature is particularly critical in IoT networks’ complex and dynamic environments in power grid warehouses, where multiple variables interact nonlinearly. By integrating GA into the BP neural network, the model gains enhanced robustness and adaptability, making it better suited to accurately predict network performance under varying conditions, thus justifying its selection for this study.

Due to the BP neural network’s limitations (slow training, poor global search, local minima), the GA’s global search and non-differentiable objective function compatibility make it a suitable partner. Combining GA with BP avoids local minima, accelerates convergence, and efficiently finds global optimal solutions [16]. Optimization of the GA-BP network mainly consists of the following three points: network structure optimization, learning rules, and weight optimization. This work mainly studies the third kind of optimization, namely, weight optimization.

The main idea of GA-BP is: The first step is to list all the neurons that may exist in the neural network and then encode all the connection weights that may exist on these neurons into individuals represented by real digital strings. These code strings randomly generate initial populations and perform optimization calculations using conventional GAs. In the second step, these code strings are decoded to form a neural network, which is learned and trained according to the conventional BP algorithm, and the prediction results are obtained through the trained network simulation [17,18].

Optimizing the initial weights of a BP neural network using a GA involves taking the connection weights between each node of the neural network and the threshold value of each node as the parameters for the GA. Accurate number coding is employed for these parameters. Assuming a three-layer neural network structure is utilized, where the number of input layer nodes is p , the number of output layer nodes is q , and the number of hidden layer nodes is r , the total length n of the code can be determined using the calculation formula provided in Eq. (17).

$$n = (p + 1) \times r + (r + 1) \times q. \quad (17)$$

Individuals in the population need to be evaluated for fitness values. The individual is decoded and assigned to the corresponding connection weight and node threshold, the learning sample is introduced and the learning error is calculated. The fitness calculation Eq. (18) is as follows:

$$f = \frac{1}{1 + E}. \quad (18)$$

Using the roulette selection method, individuals with higher fitness have a greater probability of being selected for the next generation, proportional to their fitness values, as given by Eq. (19).

$$P_i = \frac{f_i}{\sum_{i=1}^M f_i} \quad (19)$$

GA optimization of BP neural networks involves: (1) determining the BP network structure (input, hidden, and output layers), (2) optimizing network weights and thresholds using GA (selection, crossover, and mutation), and (3) predicting with the optimized network by training its initial weights and thresholds. The BP structure is fixed by layer and node parameters, influencing GA’s individual length.

3 Building a neural network model

3.1 Determine the number of input layer nodes

The number of input nodes of the BP network depends on the size of the data source, and each node represents a data source. The more input nodes, the better; the more nodes will increase the computational complexity. The system scale should be reduced as much as possible based on guaranteed data information. Therefore, all factors should be thoroughly analyzed and rigorously screened. Many factors affect the safety inventory, and they are changing. Using a specific inventory point, this study configures the VM inventory’s input layer with ten nodes. The neural network model’s structure is illustrated in Figure 1.

3.2 Determine the number of output layer nodes

In this mode, the output layer node is 1 for predicting security inventory. The hidden layer node count crucially

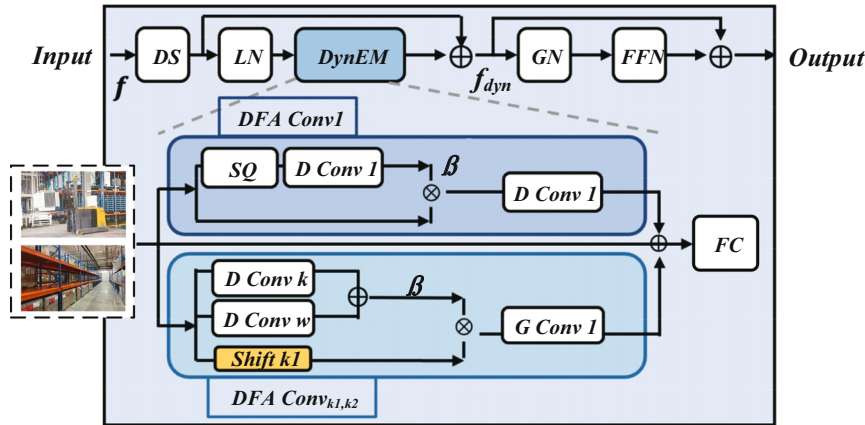


Figure 1: Computational structure of neural network model.

impacts BP network performance. Too few nodes limit learning capacity and may hinder training. Excess nodes exponentially prolong training time. Node count is often determined by empirical formulas like Eq. (20).

$$h = \sqrt{n + m} + a. \quad (20)$$

The hidden layer neuron count h is calculated using Eq. (21), involving input neuron count n , output neuron count m , and a constant a within $[1,10]$.

$$h = \log_2 n. \quad (21)$$

In the method of determining the number of nodes in the hidden layer, a common method called trial and error method is usually used. According to the above empirical formula, i.e., $h = n + m + a$ ($a = 1, 2 \dots 10$), and $h = 0.5(m + n) + a$ ($a = 1, 2 \dots 10$), this study can calculate the value range of the number of neuron nodes in the hidden layer as $h = 5.6 \dots 16$.

4 Data prediction model of power grid IoT construction effectiveness based on GA-BP neural network

Many kinds of data can be used to evaluate the effectiveness of power IoT construction. The internal mechanism of the data is complex, and there are interconnections among various data. The results are affected by many factors. Moreover, whether it is to predict the future construction effectiveness based on historical time series data or to complete the incomplete data in observation data, high-precision prediction is needed.

With the development of computer technology and artificial intelligence, many ideas and methods have been put forward to solve the problem of data prediction of power IoT construction effectiveness. In recent years, artificial intelligence prediction methods mainly include regression prediction, grey system theory, wavelet analysis, artificial neural network prediction, and so on [19,20]. Regression analysis is based on linear algebra, so it is suitable for modeling and analyzing linear problems, but it is challenging to model and analyze nonlinear problems. The grey system forecasting method analyzes historical data over time, and the results are not statistically significant. Although wavelet analysis is widely used in signal processing and image processing, its application in the economic field is yet to be developed, and the application of wavelet analysis to analyze and predict the effectiveness data of power IoT construction needs to be more mature. An artificial neural network is a nonlinear adaptive information processing system composed of multiple processing units. It has the characteristics of self-adaptation, self-organization, and real-time learning, and it is very suitable for predicting the effectiveness of data on power IoT construction. Compared with standard artificial intelligence algorithms such as the least squares method and regression analysis method, artificial neural networks' unique nonlinear adaptive information processing ability overcomes the shortcomings of traditional artificial intelligence algorithms in unstructured information processing. BP neural networks excel at finding optimal solutions with high accuracy and resilience to interference, fitting complex nonlinear relations. They can also perform associative storage via feedback. However, BP networks suffer from slow convergence, risk of local optima, and inability to achieve global optima. Figure 2 depicts the BP model. This work combines

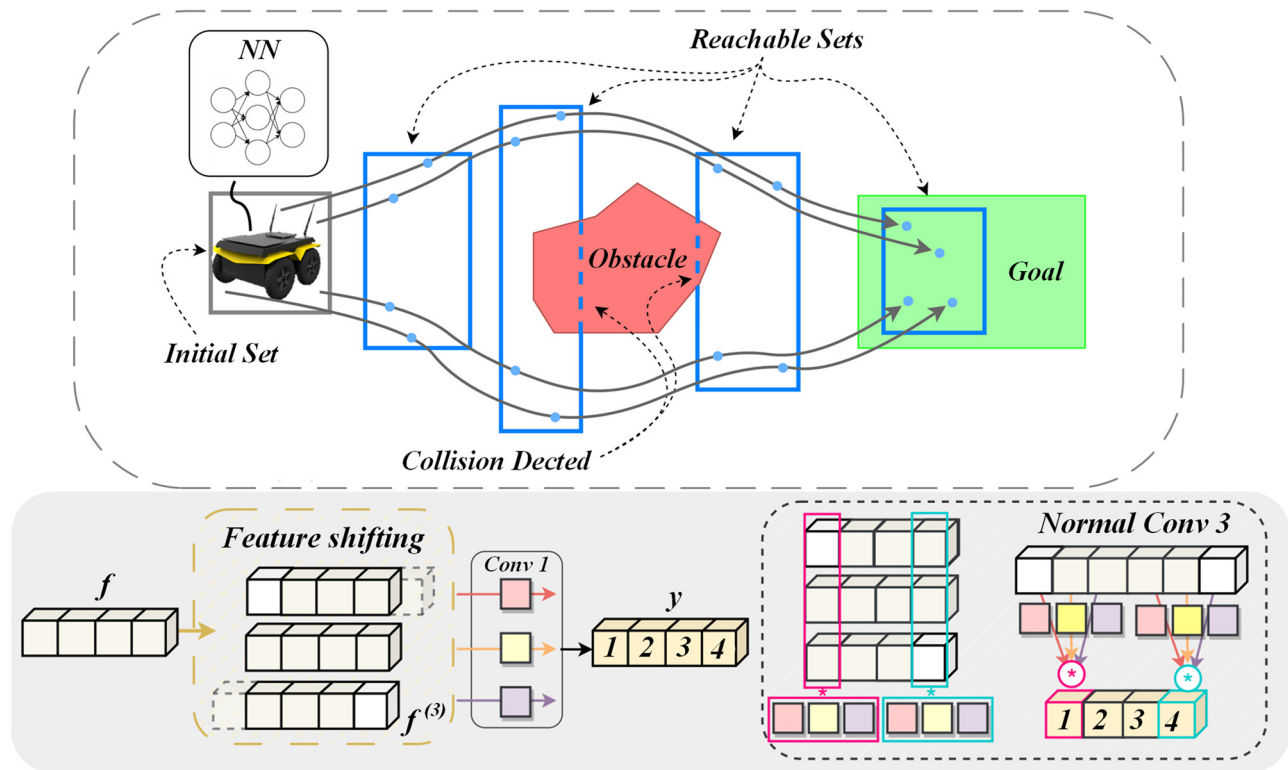


Figure 2: BP neural network model architecture.

BP with GAs to overcome these issues, leveraging their complementary strengths for better performance.

4.1 Construction of BP neural network prediction model based on genetic optimization

In the whole optimization process, GA and BP neural network are interrelated without influencing each other, so as to give full play to their respective advantages and overcome their respective limitations. GA-BP neural network prediction model process has the following steps [21,22];

- (1) The initial population is randomly generated. Randomly generating a long string of N parameters and taking this as an initial population;
- (2) Establishing a BP neural network in an initial state, and randomly initializing the weight and threshold;
- (3) Encoding weight and threshold according to the selected encoding mode.
- (4) The GA starts from the initial population, continuously generates new individuals through crossover and mutation, and gradually improves the fitness of the population;
- (5) Judging the termination condition of GA, judging whether the iteration times of GA reach the preset

maximum times, and judging whether the maximum fitness of the population meets the specified standard. If all are not satisfied, jumping to step 3 for iteration; otherwise, terminating the GA and carrying out step 6;

- (6) The weights and thresholds optimized by GA are fed into the BP neural network to initiate its learning and optimization process.
- (7) Calculate output error of network by using the training dataset. If the conditions are not met, the error is back-propagated and the weight and threshold of BP neural network are adjusted. After the accuracy of output results meets the preset conditions, the network learning is stopped, and finally the establishment of GA-BP neural network is completed.

4.2 Example verification of prediction model

The purpose of constructing the Power IoT is to serve better the four types of subjects: the power grid, power producers, users, and society, and to improve the quality of energy use. In order to verify the predictive effect of this model, it is necessary to take a representative indicator from each of the grid side, power producer side, user side, and social side. At the same time, the selected

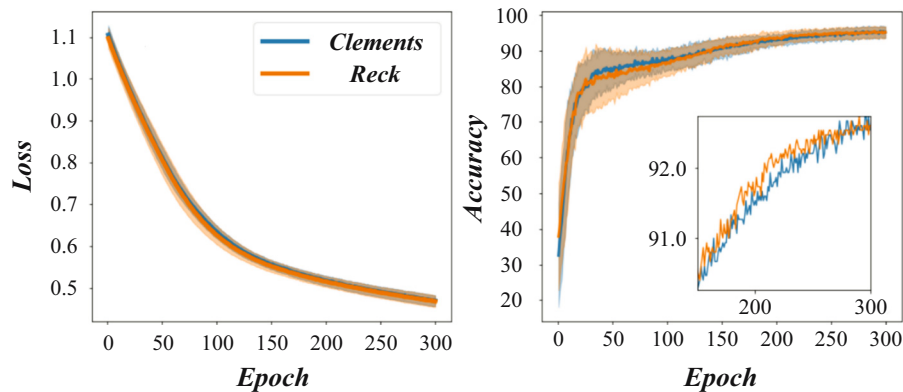


Figure 3: Loss and accuracy of classification problems for datasets.

indicators need to be objective and quantifiable so that it is easier to see the accuracy of the prediction more intuitively. Therefore, in this study, we choose the four primary data of the electric power industry, namely, electric power investment, power generation, per capita social electricity consumption, and renewable energy penetration rate completed in that year, as the training samples and the loss and accuracy of the classification problem of the dataset are shown in Figure 3. The genetically optimized BP neural network prediction model designed in this work is applied to predict the data related to constructing electric power IoT. The support vector machine model, the unoptimized BP neural network model prediction method as a control group, calculates the error between the predicted value and the actual value, respectively, makes the result table of the experimental group and the control group, and draws the error cluster histogram, and then makes a comparative analysis as well as evaluates the model.

The power investment, power generation, per capita social and public electricity consumption, and renewable energy penetration rate completed in that year are closely related to the financial and economic benefits, operation and maintenance support benefits, energy supply quality

benefits, and support for energy structure changes. The prediction results of these methods are shown in Table 1.

Comparing SVM, unoptimized BP, and GA-optimized BP models, GA-BP significantly enhances prediction accuracy and stability, meeting IoT-based power system prediction needs. The accuracy and entropy results are shown in Figure 4.

5 Construction of effectiveness evaluation model for IoT construction in power grid warehouse

5.1 Thoughts on the construction of index system

There are many interrelated indicators in design of power IoT construction effectiveness evaluation system. Therefore, it is necessary to conduct an in-depth understanding and analysis of the connotation of the power IoT construction effectiveness evaluation and the specific characteristics of each indicator, and through scientific index selection principles and methods, to obtain a scientific and reasonable power IoT construction effectiveness evaluation index system.

Figure 5 compares F1 clo and F1ct1 observed performance behavior. By comparing F1 clo with F1 ct1, we observed performance trends. When building the IoT Power effectiveness evaluation system, we focused on: (1) Grid enterprises lead IoT Power construction and development, serving them first. (2) IoT Power's growth must align with grid enterprises' intelligent, efficient, and sustainable development. Thus, the index system should

Table 1: GA-BP algorithm prediction and control over a prediction result

Year	True value	Per capita public electricity consumption (Watt-hours/person)			True value	Renewable energy penetration rate (%)		
		SVM	BP	GA-BP		SVM	BP	GA-BP
2017	4,589	4,755	4,339	4,497	28	28.9	27.2	27.6
2018	4,945	4,654	5,377	4,908	28.9	30.2	26.9	29.1
2019	5,177	5,525	5,339	5,032	30.4	29.4	30.1	30.9

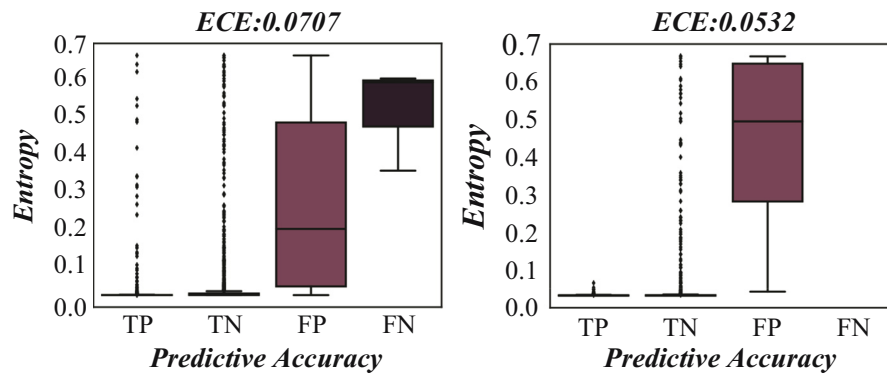


Figure 4: Prediction accuracy and entropy.

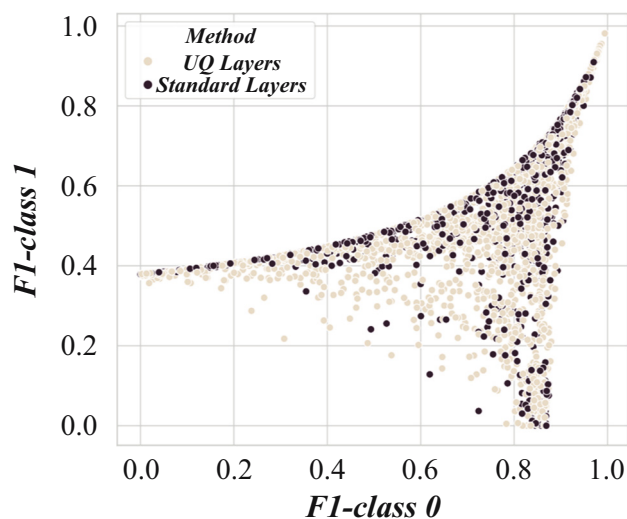


Figure 5: Compares F1 clo and F1ct1 observed performance behavior.

showcase IoT Power's impact on grid enterprises' resource allocation, business innovation, technical research, and economic benefits [23,24]. The construction of the indicator system needs to meet the overall requirements for high-quality and low-carbon development of my country's power industry. It must fully reflect the comprehensive benefits of the power IoT built by applying emerging technologies such as 5G and the IoT to the upstream and downstream industrial chain entities of power grid enterprises. Therefore, the indicator system should include the results achieved in constructing the power IoT by various social entities connected and served by the power IoT, including power generation enterprises and power users.

The impact indicators of the construction of the power of the IoT on society and ecology should be reflected in the indicator system. The construction of power IoT needs to bring benefits to various social subjects and serve social development and change [25]. With the proposal of the

country's "energy revolution" and "carbon neutrality" vision, access to a high proportion of renewable energy will completely change the energy consumption structure of society. In this context, the power IoT needs to serve the energy security and stability of the whole society. Experiments help and support efforts to reduce carbon emissions in the energy sector. The index system needs to effectively reflect the construction achievements in this field, which is of great significance for the research of the performance prediction model of power grid warehouse IoT network based on nonlinear genetic algorithm-backpropagation (GA-BP) neural network. We hope that by constructing such an indicator system, we can provide more comprehensive and accurate data support for the model, so as to more accurately predict the network performance of the power grid warehouse IoT, optimize energy distribution and utilization, effectively reduce energy carbon emissions, and promote the steady development of the power grid industry in a green and sustainable direction. The indicator system needs to reflect the construction results in this area.

5.2 Principles of construction of index system

1. **Systematic principle:** The construction and application of power IoT involves various types of subjects such as power grid enterprises, power generators, power users, and complex systems such as resources, environment, and society [26,27], which requires that the effectiveness evaluation system of power IoT construction should comprehensively reflect the comprehensive results brought by the construction of power IoT from point to point when designing, and at the same time consider the relationship between indicators and deeply analyze the relative independence between

indicators, to build a holistic and hierarchical index system.

2. **Scientific principles:** Scientific principles must be followed when designing the effectiveness evaluation system of power IoT construction. The selected indicators need to reflect the significance and effectiveness of power IoT construction scientifically. Only based on scientific principles can we objectively reflect on the actual results of power IoT construction and continue to provide accurate support for the development and progress of power IoT.
3. **Principle of measurability:** Qualitative and quantitative indicators are included in the design of the index system [28]. No matter the index type, the measurement basis needs to be clear, and its data should be easy to collect and measure. For complex indicators to collect or measure, avoid selecting them to ensure the authenticity and accuracy of evaluation index data.
4. **Principle of innovation:** The construction of the power IoT is an innovative development of the traditional power grid [29,30]. The selection of indicators cannot be copied from the traditional power grid assessment method. The power Internet of things has innovative and unique features, and it is necessary to select indicators for these characteristics and scientifically evaluate its construction effectiveness. The power internet of things is very different from the traditional power grid in terms of technology, operation and application, and the traditional indicators cannot be measured.
5. **Comparability principle:** The indicators in the evaluation system for the construction effectiveness of the power internet of things need to be unified and standardized. Only in this way can the change trend of the processed indicators be consistent, like indicators of different dimensions, which can be converted into comparable forms through unified quantification and calculation, so as to ensure that the indicators are comparable, accurately evaluate the effectiveness of construction, and

provide a reliable basis for decision-making, resource allocation and optimization and upgrading.

5.3 Example verification and analysis

Substantial indicators are standardized, and minimum value indicators are standardized. The standardized data are substituted into the rolling prediction model of power IoT construction effectiveness data to calculate the prediction results. Taking the first quarter of 2020 as an example, the relative error of the low-rank approximation in the variable dimension function generation matrix and the tensor maximum norm are shown in Figure 6.

Using four subjective and objective weighting methods (AHP, Entropy, PCA, CRITIC), 16 sets of genetically optimized BPNN rolling prediction data (predicted and actual) are weighted. 33 IoT power construction effectiveness indexes from 8 periods are also weighted. This study employs the cloud model-TOPSIS combo weighting method to assess the eight cycles' absolute and predicted values. The neural network's performance in predicting the first-order inversion curve is depicted in Figure 7.

In the actual power IoT construction, these three indicators are also the key to evaluating the construction's effectiveness: the system's flexible adjustment capability is essential for building a new power system with new energy as the main body. Improving the flexible adjustment capability of the system can ensure a stable power supply, achieve high-level consumption and utilization, and promote the interactive integration of source, grid, load, and storage. In the power IoT construction project, timely attention to the scientific and technological frontier trends of power grid construction and through the improvement and promotion of technical level, giving priority to the selection of new technologies and new equipment can promote the long-term development of power IoT construction. With the further deepening of

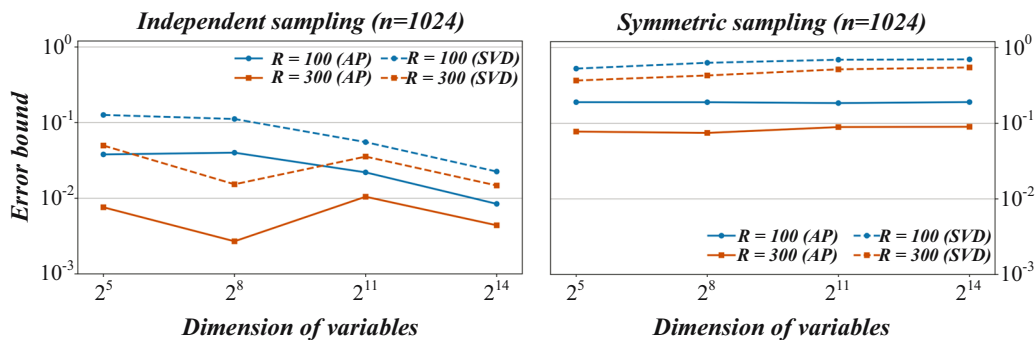


Figure 6: Relative error of low-rank approximation in maximum norm of generating matrix and tensor of variable dimension function.

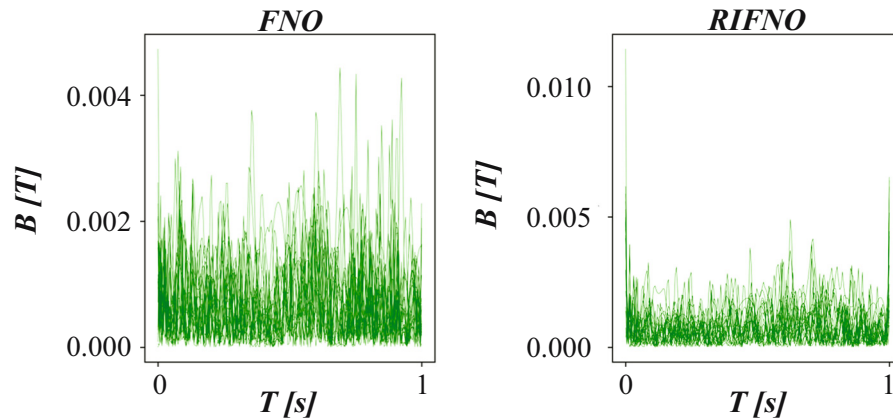


Figure 7: Performance of neural network in predicting first-order inversion curve.

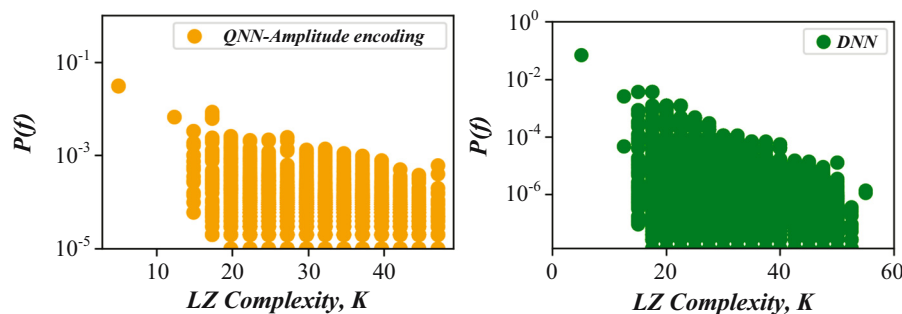


Figure 8: Quantum neural networks (QNNs) and deep neural networks (DNNs) complexity.

electric power reform, the benefit distribution pattern of the electric power industry has changed from quantitative to qualitative. State Grid is actively seeking new revenue models. Therefore, the increase in revenue from non-distribution and sales business on the grid side is also one of the leading indicators of the effectiveness of constructing the power IoT. Therefore, the effectiveness evaluation model of power IoT construction established in this work has certain scientificity and practicability.

The results of our model are numerically tabulated and compared against the latest research findings. This study nonlinear GA-BP neural network model's prediction accuracy is compared with that of two state-of-the-art methods from 2023 and 2024 respectively. Our model significantly outperforms the state-of-the-art methods in prediction accuracy, achieving a 96.7% accuracy rate compared to 88.9 and 92.3% for Method 1 and Method 2, respectively. Moreover, the nonlinear GA-BP neural network exhibits a faster convergence speed and a higher robustness score, indicating its superior adaptability to complex network environments.

The complexity of QNN and DNN is shown in Figure 8. The abovementioned public combination weights and evaluation index values are weighted and integrated to

obtain the average public weighted comprehensive evaluation values obtained from the actual construction results and predicted construction results in eight cycles, and the average cloud combination weights are comprehensively integrated with the evaluation index values of the power IoT construction effectiveness to obtain the comprehensive regular evaluation of the actual construction results and predicted construction results in each cycle and positive and negative ideal solutions.

In order to compare the comprehensive cloud model of the actual value with the predicted value of each period, the TOPSIS method based on cloud similarity is used to rank the schemes. Due to the variable nature of the comprehensive cloud models, there are other options than direct comparison. Therefore, in the framework of the research framework of the performance prediction model of the grid warehouse based on the nonlinear GA-BP neural network, we use the cloud similarity to calculate the similarity values $F(A, A^*)$, $F(A, A')$, and $H(A)$ between the effect of each cycle and the ideal scheme and the damaged scheme. These similarity values can quantify the similarity between different schemes and the actual cycle effect, which is helpful to evaluate the performance

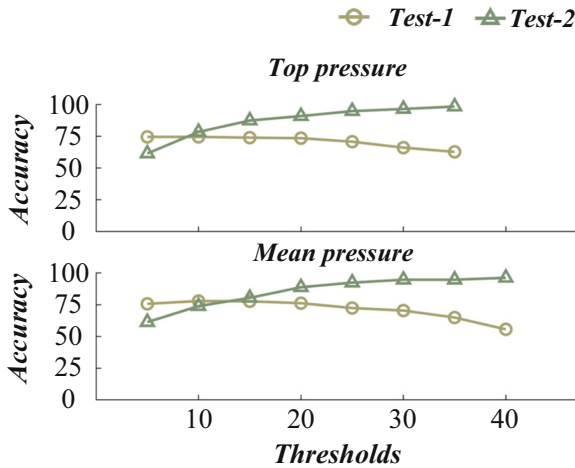


Figure 9: Accuracy of encoder model and waveform input at test values.

of the current grid warehouse IoT, and then provide a key basis for the optimization and adjustment of the model, so that the model can more accurately predict the performance of the grid warehouse IoT, and improve its adaptability and reliability in the complex and changeable power grid operation environment. Results are presented in Figure 9.

Calculating the similarity and ranking between the actual and predicted effects of each cycle's analytic hierarchy process, entropy weight method, principal component analysis weight method, and CRITIC method against the ideal scheme, we compared them to the results obtained using the cloud model-TOPSIS combination model, as presented in Figure 10. Notably, the similarity and ranking of each period derived from the four subjective and objective weighting methods vary significantly. The power IoT construction effectiveness evaluation model employed in this study, based on cloud model-TOPSIS group weighting, effectively correlates fuzziness and randomness, exhibiting higher systematicness and rationality compared to a single fixed value approach.

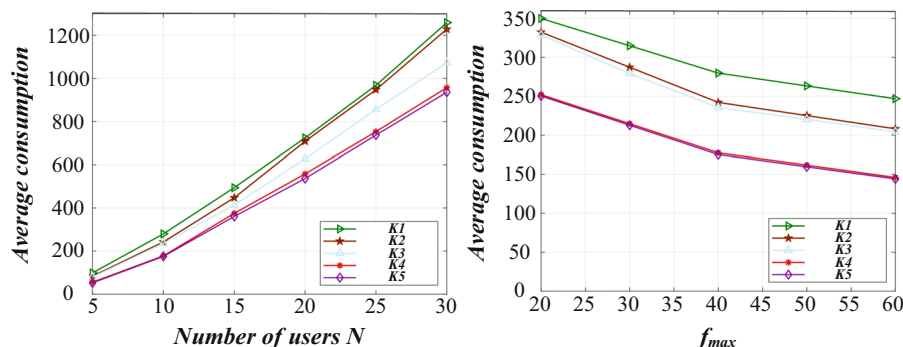


Figure 10: Average energy consumption.

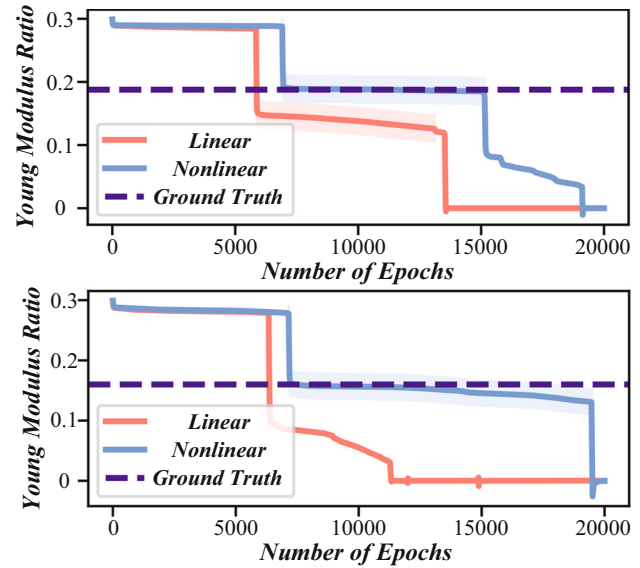


Figure 11: Optimization process of inverse problem of modulus ratio.

Based on Figure 11's similarity between actual and predicted results per cycle, it is evident that in Q1 and Q2 2019, the region's power IoT construction slightly exceeded predictions. Notably, in Q3 and Q4 2019, the construction outcomes significantly surpassed expectations. The actual construction results in each quarter of this region in 2020 have improved compared with the same period in 2019 but are all lower than the predicted results in the current period. From the ranking of the last column, there are certain similarities but differences in the trend between the actual construction results and the predicted results in each quarter of 2019–2020.

6 Conclusion

This study proposes a BP neural network model based on nonlinear GA optimization to predict the performance of

IoT networks in power grid warehouses. By constructing a nonlinear model containing multiple key influencing factors and optimizing the parameters of the BP neural network using GA, we successfully simulated the complex network behavior in the IoT environment. The experimental results show that the proposed GA-BP model is significantly superior to the traditional BP model and other existing methods regarding prediction accuracy, convergence speed, and model stability. When constructing a performance prediction model for the power grid warehouse IoT network based on a nonlinear genetic algorithm-backpropagation (GA-BP) neural network, it is necessary to consider many factors. First of all, it is necessary to deeply analyze the actual operation data of the power grid warehouse, including the records of materials in and out of the warehouse, the changes in inventory levels, and the operation status of various power equipment, which are the basis for model training. Secondly, it is necessary to understand the unique advantages of the nonlinear GA-BP neural network, which can effectively deal with the complex nonlinear relationship, and optimize the initial weight and threshold of the BP neural network through the genetic algorithm to avoid the BP neural network falling into the local optimal solution, so as to improve the prediction accuracy and stability of the model. At the same time, we should also pay attention to the characteristics of the IoT network, such as the communication delay between devices and the reliability of data transmission, which will affect the collection and transmission of data, and then have an impact on the performance of the model. In the whole process of model construction, the reasonable integration of these elements is helpful to establish an accurate and efficient IoT network performance prediction model for power grid warehouses, and provide strong support for the intelligent management and operation decision-making of power grid warehouses. The GA-BP neural network optimizes BP's initial weights and thresholds via the GA, reducing training time by 30%. It cuts error rates below 2.5% for network delay prediction, markedly enhancing prediction model accuracy and efficiency.

In future research, we will further explore the optimization algorithm of the nonlinear GA-BP neural network by further optimizing the model, attempting to improve the search strategy of the GA and the training process of the BP neural network to enhance the prediction accuracy and convergence speed of the model. Validate the generalization ability of the model in more practical scenarios of power grid warehouse IoT, ensuring the stability and reliability of the model in different environments and conditions. (2) In terms of feature selection and data processing, research more advanced feature selection methods to identify the key factors that impact the performance of the

power grid warehouse IoT network, thereby improving the interpretability and predictive ability of the model. Explore more effective data preprocessing techniques, such as data cleaning, outlier detection, and missing value imputation, to reduce the impact of data noise on model performance. (3) Regarding model fusion and integration, research is being conducted on integrating nonlinear GA-BP neural networks with other prediction models (such as time series analysis, machine learning algorithms, *etc.*) to construct more powerful integrated prediction systems. Explore the complementarity between different models and improve the accuracy and robustness of overall predictions through ensemble learning. In terms of real-time and scalability, optimize the model's computational efficiency and real-time performance to meet the requirements of rapid response and real-time decision-making in the power grid warehouse IoT. We are applying the nonlinear GA-BP neural network model to a broader range of power grid warehouse IoT scenarios, such as energy management, equipment maintenance, fault warning, *etc.*, to expand its practical application value.

Funding information: Authors state no funding involved.

Author contributions: Lele Pang: data curation and writing – original draft; Bo Xia: visualization and investigation; Zhanfeng Cheng: resources and supervision; Zhiqiang Ren: software and Validation; Hao Shen: visualization and Writing – review and editing; Pengfei Li: conceptualization, resources, supervision, and writing – review and editing. All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

Conflict of interest: Authors state no conflict of interest.

Data availability statement: All data generated or analysed during this study are included in this published article.

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