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Deep Learning-Driven Digital Twin for Remote Control of Power Systems

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ABSTRACT

At present, digital twin technology has been developed in many fields and plays a very important role. In this study, digital twin technology is applied to remote control of power system to build a set of remote control system of power system, which contains perception layer, data layer, operation layer, function layer and application layer. In order to make the power system remote control system more reliable and effective, a power system fault diagnosis method based on MRPSODE-ELM is proposed using deep learning technology. The method combines PSO algorithm and DE algorithm to construct a multiple stochastic variation particle swarm differential evolution algorithm, and it is used for the optimization seeking ability of the number of neurons in the hidden layer of the limit learning machine. The experimental results show that the MRPSODE-ELM model performs superiorly in detecting different fault types in terms of accuracy, recall and F1 score, with the results of each index above 95%, and the fault diagnosis accuracy is improved by 4.77% and 3.36% over SVM algorithm and DNN algorithm, respectively, and possesses a smaller training time consumption. The fault detection method proposed in the study can be applied to the remote control of power systems based on digital twins.

Keywords: Deep learning, PSO algorithm, DE algorithm, extreme learning machine,, digital twin, power system

1. Introduction

Power system is a whole composed of power plants, transmission grids, distribution grids, and power users, which is a unified system that converts primary energy into electrical energy and then transmits and distributes it to users [1-2]. Realizing the automation of the power system can further improve the allocation of human resources in China's electric power utility, and effectively improve the economic efficiency of the electric power utility [3-4]. The remote control technology has an extremely important

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role in the development of power system automation, which can effectively promote the transformation and upgrading of the power system, thus promoting the development of power system automation [5-6].

Such a structure can ensure that on the basis of advanced technical equipment and high economic efficiency, it can effectively realize the reasonable coordination of electric energy production and consumption [7-8]. Remote control technology is a kind of communication technology based, can carry out all-round monitoring and control of remote equipment technology, and in the process of monitoring and control of remote equipment to realize the comprehensive detection of equipment, signal transmission and remote adjustment and other operations [9-11]. The use of remote control technology can realize more accurate scheduling of power plants and substations to the energy generated [12-13].

Remote control technology in the power system is widely used in substations, distribution networks, power system scheduling and other fields, responsible for data acquisition, channel coding and decoding, communication transmission and other tasks of the secondary equipment in the power system, with the functions of monitoring and controlling, generally with the characteristics of centralization, real-time, interactivity [14-16]. The monitoring function of remote control technology is embodied in the comprehensive telemetry of the main secondary equipment in the power system, real-time monitoring of the value of the operational indexes of the equipment, to ensure that the first time to find the abnormal operating state of the secondary equipment [17-19].

The control function of remote control technology is embodied in the human-computer interaction of the power system staff, through remote control, telemetry, teleadjustment and other ways, using remote operation, realizing the human-computer real-time interaction between the power system staff and power equipment [20-22]. The value of remote control technology for the power system is mainly reflected in that it is conducive to the realization of power system intelligence, conducive to saving the maintenance cost of the power system, saving labor resources, saving the budget cost of power system operation, conducive to guaranteeing the power system self-diagnostic ability, self-operating ability and stability of operation, and conducive to improving the quality of real-time analysis and fault handling of the power system [23-26].

The article briefly discusses the digital twin technology and its application in power system remote control, combines the digital twin model of the power system with the actual physical world, and proposes a set of remote control system of power system based on digital twin. Deep learning technology is used to study the fault detection at the system functional layer, and the update strategy of particle swarm algorithm is introduced into the differential evolution algorithm to design a multiple random mutation particle swarm differential evolution algorithm (MRPSODE). Then the MRPSODE algorithm is used to automatically determine the optimal number of hidden layer nodes of ELM and complete the construction of the fault diagnosis model. After a fault occurs, fault diagnosis is realized by running the ELM model. The power system fault dataset is selected, the constructed MRPSODE-ELM model is trained and tested for fault diagnosis, and compared and analyzed with SVM algorithm and DNN algorithm to explore the diagnostic effect of the MRPSODE-ELM model on power system faults.

2. Remote control system for power systems based on digital twins

With the growing demand for energy and the increasing complexity of power systems, traditional power systems are facing a series of problems, including low energy utilization, inconsistent power supply quality, and inefficiencies in system operation. In order to solve these problems, digital twin power systems have emerged. Digital twin power systems use advanced information technology, data analysis and simulation modeling techniques to combine the actual power system with a virtual digital model.

2.1. Digital twin technology and applications

Digital twin technology is a technology that connects digital systems with actual physical systems, which is based on the mutual coordination and connection between the physical, digital and human worlds. The principle of digital twin technology is shown in Figure 1. Digital twin technology can transform the phenomena in the physical world into the data in the digital world through deep learning and other technologies, and simulate the real operating state of the physical world based on these data, so as to realize the enhancement of auxiliary decision-making, optimization of operation and other capabilities of the actual system.

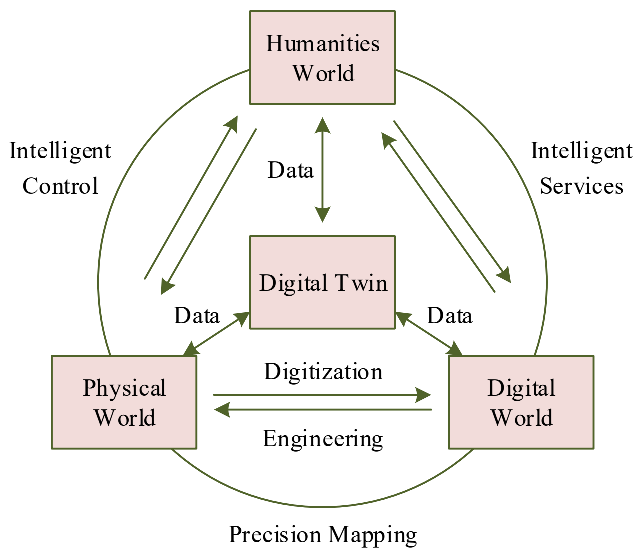


Fig. 1. The principle of digital twin technology

In the remote control of the power system, the application of digital twin technology is mainly reflected in three aspects. Firstly, digital twin technology can quickly and accurately monitor the operating status of the power system, such as load changes, current and voltage fluctuations, etc., so as to predict the occurrence of abnormalities in the power system in advance. Secondly, digital twin technology can be based on real-time power system operation, intelligent management and optimization of the system, such as controlling the switch of power equipment, adjusting the power of generator sets, etc., so as to realize the efficient operation of the power system. Finally, digital twin technology can also provide decision makers with comprehensive and accurate data and analysis results, thus helping them to quickly develop effective response programs.

2.2. Power system remote control system

With the rise of digital twin technology, its application in remote control of power systems has gradually been emphasized by researchers. Digital twin technology can not only monitor and analyze the operation status of the power system in real time, but also carry out intelligent management and optimization of the power system through the modeling method of digital twin technology, so as to improve the reliability, safety and economy of the power system. Based on this, this paper builds a set of remote control system of power system based on digital twin, which realizes the comprehensive management of power system through the implementation of five-layer system architecture of perception layer, data layer, operation layer, function layer and application layer. The architecture of the power system remote control system is shown in Figure 2.

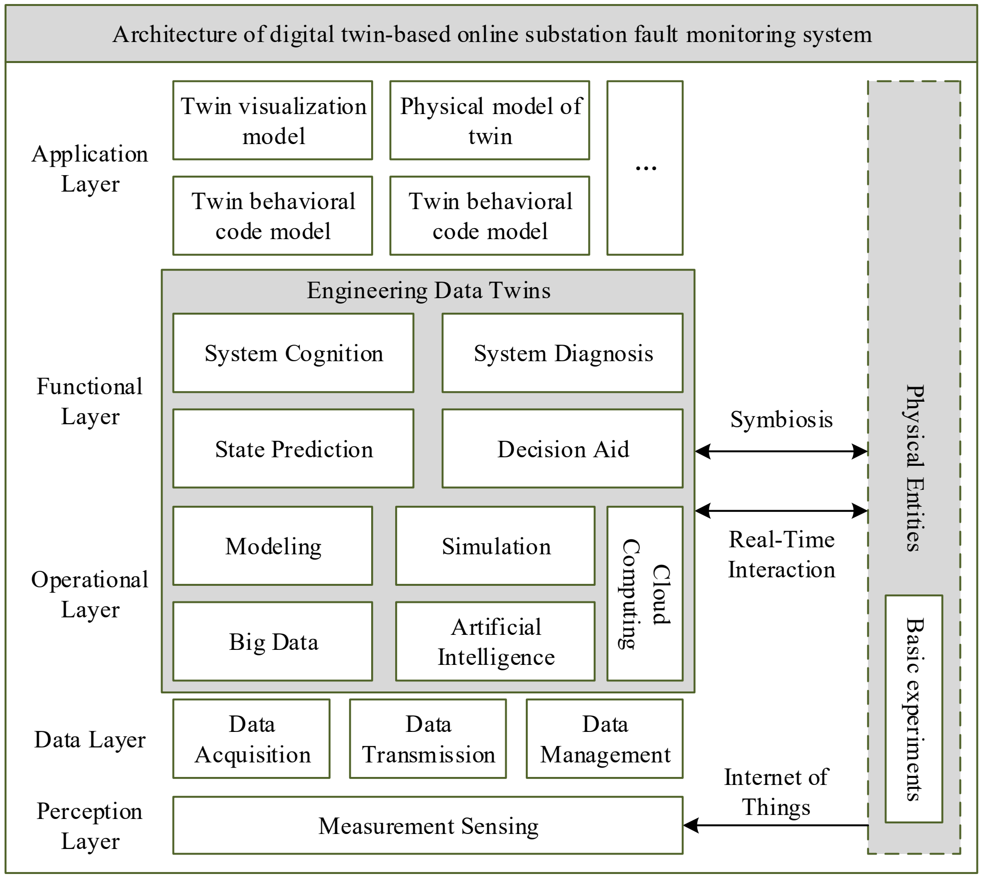


Fig. 2. Architecture of remote control system of power system

In the perception layer, the infrastructure of the power system is measured and perceived through the Internet of Things, so that the parameters of the power system can be collected in real time, which improves the perception accuracy and efficiency. The data layer transforms the physical data collected in the perception layer into the digital twin data of the power system through digital twin technology, realizing the digitization and standardization of the data, eliminating the error of manual data input, and at the same time meeting the requirements of digital twin technology for data quality and real-time.

The operation layer and the function layer form the engineering digital twin, which realizes the establishment of the power system digital twin model, and provides real-time data support for the power system digital twin model, at the same time, it can carry out intelligent management and optimization of the power system. Among them, the engineering digital twin is not only a digital clone of the power system, but also an important bridge that exists between the digital twin model, the digital twin entity and the actual physical world. In this system, the core is the digital twin model, which is a digital mapping of the actual operation of the power system, which can provide real and complete information of the power system and realize the intelligent simulation and optimization management of the power system. The computing layer of the engineering digital twin allows data management and remote control of hundreds of digital twin partitions, avoiding inconsistencies between the digital twin theory and the actual physical system.

The application layer enables the twin visualization model, the twin physical model, and the twin security criterion model, etc., with the aim of providing a comprehensive, visualized, and operable power system management. It also supports intelligent management and optimization of the power system, such as intelligent control of power equipment switching and adjustment of power of generator sets. The goal of the application layer is to transform the digital twin model into business applications and operations with practical significance, so that the digital twin model of the power system and the actual operation can be seamlessly connected through visualization and interactive operation, and to provide a smarter, more flexible, and more efficient management for the power system.

This paper mainly investigates the work related to the model function layer, and in order to improve the efficiency of the digital twin-based power system remote control system in abnormal fault disposal, a power system fault diagnosis model is proposed using deep learning algorithms.

3. Deep learning based fault diagnosis model for power system

Extreme Learning Machine (ELM), as a simple but effective machine learning algorithm, has been widely used in the era of big data. In this paper, Extreme Learning Machine is selected as a fault diagnosis algorithm for power systems, and a Multiple Randomly Variable Particle Swarm Differential Evolutionary Algorithm (MRPSODE) is used to optimize it, and an ELM model based on MRPSODE is proposed.

3.1. Extreme Learning Machines

Extreme Learning Machine (ELM) is a fast and efficient single-layer feed-forward neural network model.The training process of ELM is very fast because it only needs to randomly initialize the weights between the hidden layer and the output layer and does not require iterative tuning. This makes ELM suitable for processing large-scale data. Also, ELM has strong generalization capabilities.

Let the training set be $X=\left[x_1,x_2,\ldots,x_n\right]\in R^{n\times m}$, where n is the number of samples in the training set and m is the number of dimensions. $T=\left[t_1,t_2,\ldots,t_n\right]\in R^{n\times d}$ is the training output sample set, i.e., sample label information, where d represents the number of categories. Let the number of neurons be L, and $g(\cdot)$ represents the activation functions, such as radial basis function, sine function and sigmond function. Then the nonlinear mapping of the hidden layer can be expressed as equation (1):

$$h_i(x)=g\left(\omega_i^T x+b_i^T\right),\omega_i\in R^L,b_i\in R,i=1,2,\ldots,n \tag{1}$$

where input weights ω and bias b are randomly generated.

Let $\beta\in R^{L/d}$ be the output weights between the implicit and output layers, then for inputs X, ELM the output of the network can be expressed as:

$$\mathrm{F(x)=h(x)\beta} \tag{2}$$

β can be determined by minimizing the sum-of-squares loss of the prediction error. This is a least squares optimization problem with the following formula:

$$\begin{aligned}&\min_\beta \frac{1}{2}\|\beta\|^2+\frac{C}{2}\sum_{i=1}^{n}\|\xi_i\|^2\\&s.t.h\left(x_i\right)\beta=t_i^T-\xi_i^T\end{aligned} \tag{3}$$

where the first term acts as a regulator to prevent overfitting, $\xi_i\in R^d$ denotes the training error for x_i, and C is the penalty parameter.

Substituting the constraint terms in Eq. (3) into the objective function yields an equivalent unconstrained optimization problem:

$$\min_\beta \frac{1}{2}\|\beta\|^2+\frac{C}{2}\|T-H\beta\|^2 \tag{4}$$

$H=\left[h\left(x_1\right);h\left(x_2\right);\ldots;h\left(x_n\right)\right]\in R^{n\times L}$ is the implicit layer output matrix.

Equation (4) is a regularized least squares problem. The optimal solution β can be obtained by setting the gradient of the objective function with respect to β to zero, which leads to Equation (5):

$$\beta^* = \begin{cases} H^T \left(HH^T + \frac{I_n}{C} \right)^{-1} T & (n < L) \\ \left(HH^T + \frac{I_L}{C} \right)^{-1} H^T T & (n \geq L) \end{cases} \tag{5}$$

where I_L denotes a unit matrix of size L and I_n denotes a unit matrix of size n. Since the output weights can be determined directly by Eq. (5) without gradient descent, the ELM is computationally efficient. It is worth mentioning that when setting the expected output $T = X$, the output of ELM will be close to the input data.

3.2. *Construction of MRPSODE*

3.2.1. Particle Swarm Algorithm.Particle Swarm Algorithm (PSO) is an optimization algorithm based on swarm intelligence, inspired by the observation of the behavior of groups such as flocks of birds or schools of fish.PSO searches for an optimal solution by simulating the collaboration and information sharing of individuals (particles) in a group. Particles have only two attributes: velocity and position, where velocity represents how fast or slow they move and position represents the direction of movement. In PSO, the solution space of the problem is viewed as a particle's moving process in a multidimensional space. Each particle has its own speed and position, as well as an individual optimal solution related to it and the global optimal solution of the whole particle swarm, and all particles in the particle swarm adjust their speed and position according to the current individual extreme value they find and the current global optimal solution shared by the whole particle swarm.

The particle swarm algorithm is initialized as a group of random particles (random solutions) and then iterates to find the optimal solution. In each iteration, the particles update themselves by tracking two "extremes" (the current individual optimum and the global optimum). After finding these two optimal values, the particle updates its velocity and position using the following formula:

$$v_i = v_i + c_1 \times rand(\ ) \times (p_{best} - x_i) + c_2 \times rand(g_{best} - x_i) \tag{6}$$

$$x_i = x_i + v_t \tag{7}$$

Where in Eqs. (6), (7), $i = 1, 2, \ldots, N$, N is the total number of particles in the population, v_i is the velocity of the particles, $rand(\ )$ a random number between $(0,1)$, x_i: the current position of the particles, c_1 and c_2 are the learning factors, usually the maximum value of $c_1 = c_2 = 2$, v_i is $v_{\max}$ (greater than 0), and $v_i = v_{\max}$ if v_i is greater than $v_{\max}$. p_{best} is the current optimal value, and g_{best} is the global optimal value.

Equations (6) and (7) are the standard form of PSO. The first part of Eq. (6) is called the "memory term" and represents the effect of the magnitude and direction of the last velocity. The second part of Eq. (7) is called the "self-cognition term", which is a vector pointing from the current point to the particle's own best point, and represents the part of the particle's action that originates from its own experience. The third part of Eq. (6), called the "population cognition term", is a vector pointing from the current point to the best point of the population, reflecting inter-particle cooperation and knowledge sharing. It is through their own experience and the best of their peers that the particle determines its next movement. Based on the two formulas above, the standard form of PSO is formed.

The basic steps for solving using particle swarm algorithm are as follows:

1) Initialize the population. A certain number of particles are randomly generated, each with a random initial position and velocity. These initial positions and velocities are usually randomly distributed in the solution space of the problem.

2) Fitness evaluation. For each particle, calculate the fitness value corresponding to its current position, i.e., the value of the objective function. The fitness value indicates the degree of superiority or inferiority of the particle at its current position.
3) Update individual optimal solution. For each particle, record the optimal position encountered in its history, called the individual optimal solution. If the fitness value of the current position is better than the individual optimal solution, the individual optimal solution is updated to the current position.
4) Update the global optimal solution. In the whole particle swarm, record the optimal position encountered in history, called the global optimal solution. If the individual optimal solution of a particle is better than the global optimal solution, the global optimal solution is updated as the individual optimal solution of the particle.
5) Update speed and position. According to the core formulas (6) and (7) of the particle swarm algorithm, update the velocity and position of each particle. The velocity update takes into account the influence of the particle's own historical optimal position and global optimal position, as well as parameters such as the inertia factor. The position update, on the other hand, is adjusted according to the new velocities so that the particles move in the direction of a more optimal solution.
6) Iterative optimization. The above steps are repeated until the termination conditions are met (e.g., the maximum number of iterations is reached or a satisfactory solution is reached). In each iteration, the particle continuously adjusts its position and velocity according to its own experience and the collaborative information of the group, gradually approaching the optimal solution.

3.2.2. Differential Evolutionary Algorithm. The DE algorithm completes population evolution through a process of mutation, crossover and selection.

(a) Mutation. The DE algorithm employs a mutation operation to generate mutation vectors $k_{i,t+1}$ for each target vector $x_{i,t}$. One common mutation strategy DE/current-to-rand/1 is:

$$k_{i,t+1} = x_{i,t} + F \cdot \left(x_{r_1,t} - x_{i,t}\right) + F \cdot \left(x_{r_2,t} - x_{r_3,t}\right) \tag{8}$$

Where: r_1, r_2, r_3 are mutually exclusive integers and F is the scaling factor.

(b) Crossover. Mix the target vector $x_{i,t}$ with the mutation vector $k_{i,t+1}$ to get the test vector $u_{i,t+1}$ by crossover, i.e:

$$u_{i,z+1}^{j} = \begin{cases} k_{i,t+1}^{j} & rand_j \le C_R \ Or \ j = j_{rand} \\ x_{i,t}^{j} & Other \end{cases} \tag{9}$$

where: $j = 1, 2, \cdots, D$, C_R is the crossover probability.

(c) Selection. By calculating the fitness values of the target vector $x_{i,t}$ and the mutation vector $k_{i,t+1}$, the smaller one is saved into the next generation, i.e:

$$x_{i,t+1} = \begin{cases} u_{i,t+1} & f\left(u_{i,t+1}\right) \le f\left(x_{i,t}\right) \\ x_{i,t} & Other \end{cases} \tag{10}$$

3.2.3. MRPSODE algorithm.MRPSODE is an improved algorithm based on the DE algorithm, which effectively solves the problem of slow convergence of the basic DE algorithm, resulting in low convergence accuracy.MRPSODE introduces the PSO update strategy into the DE algorithm, thus realizing the improvement of global convergence ability, and at the same time, it chooses the mutation strategy of DE/current to rand/1 to increase the diversity of the population to avoid falling into the local optimization. In order to balance the exploration and open ability of the algorithm, MRPSODE combines three mutation strategies, which can effectively play their respective advantages and make up for the shortcomings of the other strategies, so as to have good stability and convergence while ensuring population diversity. For each individual, MRPSODE uses the parameters P_r (taking the value of 0.9) and R_M (a random number between 0 and 1) to determine the mutation strategy adopted by the individual:

(a) If some random number rand is less than the probability parameter P_r and R_M is less than 0.5, then:

$$\begin{aligned} k_{i,t+1} &= \rho \cdot v_{i,t} + c_1 \cdot rand_1 \cdot \left(\frac{p_{best,t} + g_{best,t}}{2} - x_{i,t} \right) \\ &+ c_2 \cdot rand_2 \cdot \left(\frac{f_{best,t} - g_{best,t}}{2} - x_{i,t} \right) \end{aligned} \tag{11}$$

(b) If some random number rand is less than the probability parameter P_r and R_M is not less than 0.5:

$$k_{i,t+1} = x_{i,t} + F \cdot \left(x_{r_1,t} - x_{i,t} \right) + F \cdot \left(x_{r_2,t} - x_{r_3,t} \right) \tag{12}$$

(c) Otherwise, there:

$$k_{i,t+1} = x_{\min} + rand \cdot \left(x_{\max} - x_{\min} \right) \tag{13}$$

where $x_{\min}$ and $x_{\max}$ are the lower and upper individual position limits, respectively.

It is worth noting that the rest of MRPSODE is consistent with the basic DE except for the mutation strategy selection mechanism.

3.3. *The MRPSODE-ELM model*

The inputs and outputs of the ELM depend on the specific simulation case, and the weights and thresholds are given randomly during the initialization phase, so there is another important parameter of the ELM that needs to be given, which is the number of nodes in the implicit layer. In order to determine the optimal number of nodes in the hidden layer, a trial and error approach over a range of values is often used. When the range of values is very large trial and error method needs to be calculated for each possible value, and the whole calculation process takes a lot of time and effort. While using evolutionary algorithms can be more convenient and fast to determine the optimal number of hidden layer nodes in different models. In this paper, MRPSODE is utilized to determine the number of ELM implied layer nodes, and the root mean square error (RMSE) is chosen as the fitness function, i.e.:

$$f = \sqrt{\frac{\sum_{i=1}^{N} \left| \vec{O}_i - \vec{O}'_i \right|^2}{N}} \tag{14}$$

Where: N is the number of samples, $\vec{O}_i$ and $\vec{O}'_i$ are the actual and desired outputs of the ELM, respectively.

Considering that the training samples may contain noisy data, which will affect the accuracy of the ELM network, in order to improve the accuracy of the system and reduce the impact of noisy data on the final experimental results, this paper chooses to use the 5-fold cross-validation method to process the training samples. Divide the training data into 5 equal parts that do not intersect each other. Divide the data into 5 parts, and the proportion of the total data accounted for by each part is 20%. Through cross-validation, the influence of noisy data can be minimized and the fault tolerance of ELM can be improved.

4. Experimental results and analysis

In order to test the effectiveness of MRPSODE-ELM deep learning algorithm in power system fault diagnosis, this study carried out experimental simulation tests to examine the practical effectiveness of the model in fault diagnosis.

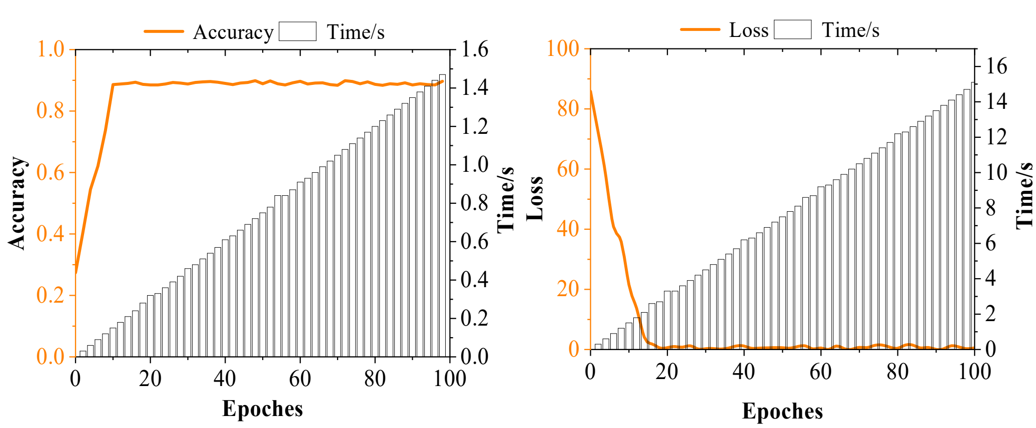
4.1. Experimental data

The power system fault dataset was chosen for the experiment, which contains about 50,000 data records from 50 different power devices, each containing sensor readings such as current, voltage, temperature, vibration frequency, timestamps, and device identifiers. The maintenance team labeled the data fault types based on power system maintenance records and fault logs, categorizing them as mechanical, electrical, environmental and operational faults. Prior to testing, all sensor data was standardized to eliminate the effects of different magnitudes and ranges to ensure consistency of data inputs, and time-series data was converted into a format suitable for processing by the MRPSODE-ELM network, which integrates consecutive time-point data into a sequence. 80% of the data in the dataset was designated as the training set for model training and optimization. The remaining 20% of the data was used as a test set to evaluate the diagnostic accuracy of the model.

4.2. Model training results

The computer CPU for the simulation experiments is Inter(R) Core(TH) i5-12440, and the experimental data processing platform is MATLAB.The study firstly analyzes the training results of the MRPSODE-ELM model, and the model training results are shown in Fig. 3.Fig. (a) shows the relationship between the model's accuracy, the training time, and the number of iterations, and Fig. (b) shows the relationship between the model training relationship between loss, training time and number of iterations.

The performance of the system improves significantly as the number of iterations increases from 0 to 18, and the accuracy gradually increases in this phase while the loss value continues to decrease. The training process in this phase has a fast convergence rate and the algorithm is able to quickly adapt and learn the fault diagnosis characteristics of the transformer. The system tends to stabilize when the number of iterations increases to more than 18, at which time the diagnostic effect on power system faults is already at a high level, and the accuracy rate stabilizes at about 0.90. At this stage, the fluctuations of both the accuracy rate and the loss value are within a reasonable range. Under the premise of ensuring the high accuracy rate and low loss value of the system, the study sets the number of iterations of the algorithm to 50 times.



(a) Accuracy and time consuming (b) loss and time consuming

Fig. 3. Model training results

4.3. *Model diagnostic results*

After the model training, the test set of MRPSODE-ELM model power system was applied, and the results of the fault diagnosis test are shown in Table 1.The accuracy of MRPSODE-ELM model is generally higher than 95%, and some of the data are close to 98%, whereas most of the accuracy of the traditional methods is between 80% and 90%, which indicates that the MRPSODE-ELM model can more accurately identify the normal and faulty states of the power system.The diagnostic accuracies of the MRPSODE-ELM algorithm on mechanical faults, electrical faults, environmental faults, and operational faults are 97.45%, 96.76%, 95.32%, and 96.32%, respectively, and its excellent performance on the recall and the F1 score indicates that the model effectively identifies most of the real faults and has a low probability of missing diagnosis.

Table 1. Fault diagnosis test results

Fault type	Method	Training set size	Test set size	Accuracy/%	Recall/%	F1 score/%
Mechanical failure	Our	32000	8000	97.45	97.53	95.46
	Traditional	32000	8000	84.46	87.70	88.97
Electrical failure	Our	32000	8000	96.76	95.96	96.02
	Traditional	32000	8000	86.01	85.75	85.07
Environmental failure	Our	32000	8000	95.32	96.62	97.44
	Traditional	32000	8000	89.28	84.15	83.97
Operating fault	Our	32000	8000	96.32	97.89	96.17
	Traditional	32000	8000	85.19	84.62	86.74

4.4. *Model comparison results*

Support Vector Machine (SVM) and Deep Neural Network (DNN) are two common data classification algorithms, in order to verify the feasibility and reliability of the model in practical applications, the study compares and analyzes the accuracy and training time of the above two algorithms and the proposed MRPSODE-ELM algorithm of the study. Figure 4 shows the accuracy comparison results of the three algorithms, and it can be seen that the average accuracy of the three algorithms is above 91%, while the average accuracy of SVM is the lowest, only 91.07%, and the average accuracy of the proposed MRPSODE-ELM algorithm is the highest, reaching 95.84%. Figure 5 shows a comparison of the training time consumed by the three algorithms, and it can be seen that the training time consumed by all three algorithms is more than 54s.

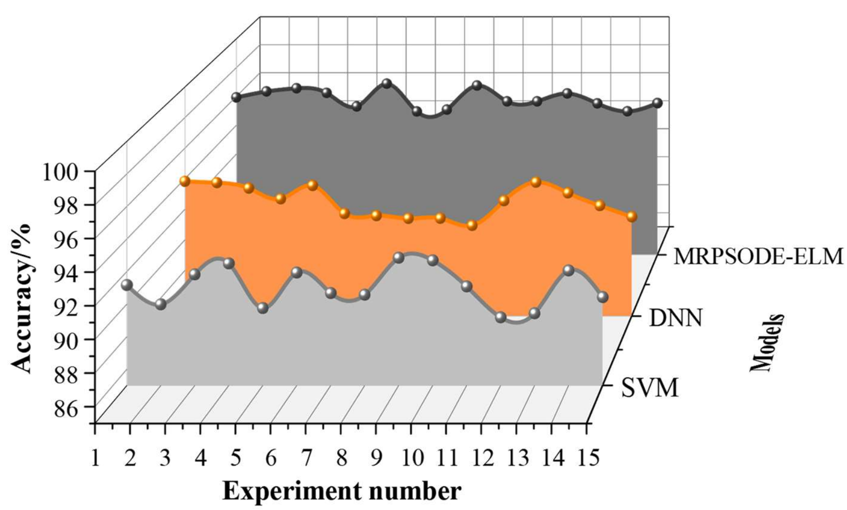


Fig. 4. The accuracy comparison result of three models

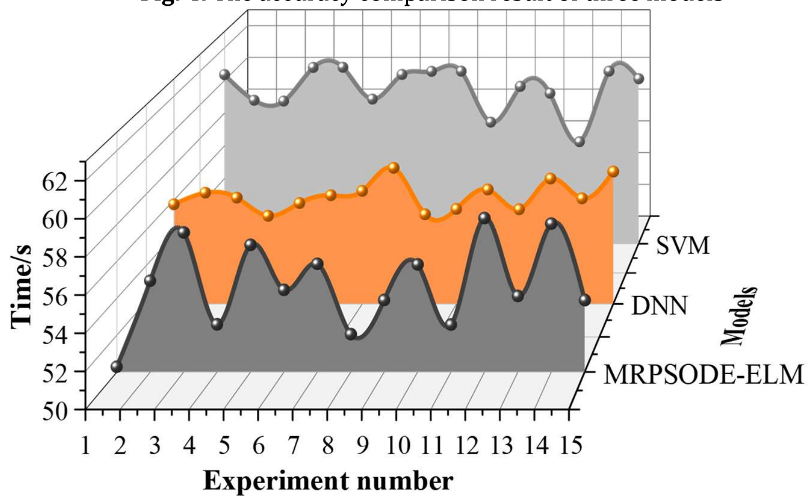


Fig. 5. The time-consuming comparison result of three models

4.5. Results of ablation experiments

In order to test the effect of model improvement on the detection performance, the improved YOLOv4 algorithm is compared with the original model in ablation experiments, and the results of the ablation experiment comparison are shown in Table 2. When only ELM algorithm is used for the power system, the mAP value decreases by 10.04% compared with the original model, but the detection speed is improved by 3.5 s. When only DE algorithm and only PSO algorithm are used to optimize the ELM model, the mAP value is 85.59% and 90.17%, respectively, in which the DE-ELM model has the shortest time for the detection of the faults in the power system. While the mAP value of fault diagnosis of ELM model optimized with MRPSODE is 95.42% and the time taken is 54.61 s. Although the time taken is slightly increased, the average accuracy of fault diagnosis obtains a significant improvement.

Table 2. Ablation experiment

PSO	DE	MRPSODE	mAP/%	Time/s
—	—	—	85.38	51.11
√	—	—	85.59	50.83
—	√	—	90.17	53.18
—	—	√	95.42	54.61

5. Conclusion

With the emergence of digital twin technology, it is an important opportunity for innovation in the power industry. In this paper, digital twin technology is utilized to establish a remote control system for electric power system, and the fault detection application in it is explored based on deep learning algorithm. The particle swarm differential evolution algorithm with multiple stochastic variants is used to optimize the extreme learning machine model, and the power system fault diagnosis method based on MRPSODE-ELM is proposed. Experiments are carried out to test the fault detection effect of the model, and the results show that as the number of iterations increases from 0 to 18, the accuracy of the model training gradually improves and stabilizes at about 90%, while the loss value continues to decrease.The MRPSODE-ELM model exhibits high accuracy, recall, and F1 scores in fault diagnosis of power systems, with detection accuracies of more than 95%. And in the comparison experiments with SVM and DNN algorithms, the MRPSODE-ELM model has higher accuracy and less time-consuming, with the accuracy improved by 4.77% and 3.36%, respectively, showing superior power system fault detection performance. The fault diagnosis model based on digital twin technology constructed in the study can effectively improve the fault diagnosis accuracy of power system remote control. With the continuous optimization of algorithms and the expansion of application scenarios, the deep learning-driven digital twin technology will play a more important role in the power system and help the power system to develop in the direction of more efficient, smarter and more reliable.

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