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RESEARCH ARTICLE

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Application of AI techniques in monitoring and operation of power systems

Abstract In recent years, the artificial intelligence (AI) technology is becoming more and more popular in many areas due to its amazing performance. However, the application of AI techniques in power systems is still in its infancy. Therefore, in this paper, the application potentials of AI technologies in power systems will be discussed by mainly focusing on the power system operation and monitoring. For the power system operation, the problems, the demands, and the possible applications of AI techniques in control, optimization, and decision making problems are discussed. Subsequently, the fault detection and stability analysis problems in power system monitoring are studied. At the end of the paper, a case study to use the neural network (NN) for power flow analysis is provided as a simple example to demonstrate the viability of AI techniques in solving power system problems.

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1 Introduction

In recent years, due to the emerging of new methods and concepts of artificial intelligence (AI), the new AI techniques such as deep learning [1] are widely implemented in various fields [2–4]. Great progress has been made in areas such as image recognition, speech recognition, predictive analysis, and decision making thanks to the application of AI techniques. One of the most famous examples is the AlphaGo [5], a deep learning-based Go game software. Winning two best professional human Go game players in 2015 and 2016, respectively, AlphaGo shows great potential of AI techniques in solving complex problems, such as Go game, which are not possible at all by using the traditional methods. The reason for this is that these problems usually require human experience and abstract thinking, which cannot be easily transferred into the deterministic rules or codes in the traditional methods. But, deep learning is a method to mimic the neuron activities in human brain. The human experience and the thinking ability can be learnt by deep learning based on data resources. AlphaGo is developed based on the reinforcement learning method and the Monte Carlo tree search (MCTS) algorithm [5], in which the software includes two neural networks (NNs): a value network and a policy network. The value network can identify the current status and possible moves in the Go game, while the policy network is used to determine the best move in the next step. Inspired by AlphaGo, the deep learning-based operation and monitoring method for power systems can be developed. By replacing the Go game board with the power system model, the movement in the Go game is made similar to the actions in the operation in the power system. Therefore, a value network can be developed to monitor the status of power systems, and a policy network can be created to operate power systems.

In power systems, the traditional operation and monitoring methods have gained great achievement in making the power systems stable, efficient, and safe. However, there are still some problems, for example the operation ticket compiling, in power systems that require human experience and abstract thinking. For these problems, the traditional methods cannot provide a good solution. Therefore, a lot of work in these problems are still completed manually, which is not efficient and reliable. Therefore, to solve such problems, AI techniques may be a good choice as demonstrated by the AlphaGO. Some research on the application of AI techniques in power systems has been conducted [6]. For example, fault detection and fault diagnosis with AI techniques have been studied in Refs. [7–9]. The power consumption prediction problem with AI techniques such as convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM) and deep belief network (DBN) has been addressed in Refs. [10–16]. Besides, a genetic algorithm (GA)-based method has been proposed to find the optimal topology, size, location, and the number of distributed generators of the power system network in Ref. [17]. Therefore, the performance of the distribution power system can be improved and the power losses in the system can be reduced. In some research, the expert system has been used to design and analyze the power system. For example, in Ref. [18], a power system planning method has been developed based on the expert knowledge, the quality judgement method, and mathematical optimization techniques. The proposed system can be applied in power system planning in which the number of units, the types and ratings of generating plants, are determined to be installed at future stages of system growth. In Ref. [19], in order to better design and analyze power supply products, an AI system based on the power electronics expert system (PEES) has been developed, which can be implemented to develop and analyze power electronics, such as buck-boost power factor correction (PFC), bridgeless PFC, fly-back, single switch forward, or dual switches forward, in power supply equipment. Moreover, in order to obtain a better expert system for the diagnosis of nuclear power plants, a supporting system for knowledge acquisition and refinement has been proposed in Ref. [20]. In Ref. [21], the unsupervised learning network has been employed to identify the anomalies of transformers in power systems by monitoring several states simultaneously, and detecting whether one or several states vary incoherently. Furthermore, Ref. [21] also has used the GA method to optimize the allocation and parameters of flexible alternating current transmission system (FACTS) devices in a power transmission system.

According to the review of existing literatures related to applications of AI in power systems, previous works on the AI technologies in power systems are found to be very limited. The potentials of AI methods in power systems are not widely studied, and the newly emerged technologies, such as deep learning, are rarely applied. At the same time, as the modern power system becomes more and more complex, the traditional methods, such as the techniques based on the control theory or the optimization theory, may not be the best choice to solve all the problems in the power system. So, the application of AI techniques in power systems becomes emergent. Therefore, in order to study the potential applications of AI techniques in power systems, a field study is conducted in Tianjin Power System Control Center in China. The result of this field research will be discussed in this paper.

2 Potential applications of AI in power system operation and monitoring

In this section, several potential applications of AI in power systems will be discussed including the control, the optimization, and the decision making problems in power system operation, as well as the fault detection and stability analysis problems in power system monitoring. For the control, the basic neural network (NN) method is suggested to be used for the simple control problems, such as frequency control, due to its simplicity. But for the more complex control problems, the advanced NNs, such as the CNN, the RNN, and the LSTM, can be used. For the optimization, the concept of AlphaGo is suggested to solve the optimization problems in power systems. Besides, the similar concept of AlphaGo can be used for decision making in power systems. In addition, for fault detection and stability analysis problems, the advanced method such as CNN and other deep learning methods can be employed due to their strong pattern preconization ability.

2.1 Power system operation

2.1.1 Control

Control is ubiquitous in power system operation. Many important problems in the power system, such as the primary control and secondary control, are control problems. For these problems, the traditional control methods, such as the PID control, the optimal control, and the adaptive control, can provide good solutions. However, as power systems become more and more complex, the traditional methods may not be the best choices any more. The reason for this is that the majority of traditional control methods are model-based methods, in which the model of the system is needed for the design of the control schemes and the determination of the parameters of the controller. However, for complex systems like interconnected power networks, it is difficult to develop their detailed state space model. So, in typical controller design, the approximation or equivalence for some parts of the power system are often adopted. As a result, the designed controller may not be able to reach the desired performance because of the difference between the model and the actual system. Therefore, model-free methods seem to be a better choice for these complex power systems. The most famous model-free control method is the PID control, which has already been widely used in power systems. However, the PID control method is not a perfect solution for many problems in the power system. Due to the lack of good PID tuning method in practice, the tuning of the PID controller parameters heavily relies on human experience, and thus is not very reliable. In some cases, in order to achieve good parameters for PID controllers, the model of the system is developed and then the parameters of PID controller is optimized with the model, which makes the PID method not model-free any more. Also, some advanced control methods, such as the adaptive control and optimal control, cannot be realized by only using the PID method. Therefore, the AI technique can be introduced in power systems to deal with the control problems, since many AI methods are not model-based methods. Another advantage of the AI-based control method is the learning ability of the AI, which is sometimes called the data assimilation ability. This is important for power systems since the power system is a long-running system built in vast areas, so the characteristics of the power system may shift with time due to its interactions with nature environment and humans. Therefore, with the data assimilation ability, the AI-based control system can learn the new characteristics of the power system and perform the control scheme adaptively.

In recent years, some AI-based control methods have been applied in power systems to solve different problems. For example, in Ref. [22], a NN based estimator has been adopted for the active power control of a photovoltaic system. Reference [23] has employed the adaptive non-linear NN for the control of wide-area power systems. Besides, the adaptive NN has been used in Ref. [24] for the control of a multi-area interconnected power system with hybrid energy storage. In addition, the NN has been used in Refs. [25–27] to solve the control problems in power systems. However, in the existing works, only the basic NN method has been adopted to solve the simple problems such as frequency control and active power control in power systems. In the future, the advanced methods, such as CNN, RNN and LSTM, should be employed to solve the more complex problems in power systems. For example, the optimal control strategy may be distinct when the power system is in different operation status. Thus, the advanced NN methods can be used to determine the operation status of the system and decide which control strategy is the best. Since it is good at classification, CNN can classify the status of the current power system into a suitable control strategy, thus the optimal control strategy is chosen. On the other hand, since RNN and LSTM are the NN models with memory, they can be applied to determine the operation status of the power system with the memory of the previous status.

2.1.2 Optimization

Optimization is another very important problem in power systems. The efficiency and economy of the power system are usually the most important characteristics of power systems besides stability. To achieve a better efficiency and economy in power systems, many techniques have been proposed. For example, the gradient method and the Lagrange multiplier method have been used in economic dispatch to reduce the operational cost of the power system; unit commitment has been solved by dynamic programming to achieve the long-term optimization [28]. However, as power systems become larger, the number of variables in the objective functions in optimization problems is increasing. Consequently, the search space for the optimization problem is exponentially increased. It becomes a challenge to optimize some complex problems with the consideration of all the important factors. This is more obvious in problems such as unit commitment, since the optimization should be performed along a long time horizon. This is similar to the Go game. In the Go game, different stone placement in each step will lead to a distinct result. Therefore, the search space of the Go game becomes gigantic, making it impossible to use the traditional method to optimize each step within an acceptable time. In addition, the development of renewable energy poses another difficulty in the optimization of the power system. With the increasing penetration of renewable energy, the intermittent nature of the renewable energy sources, such as solar and wind, introduces uncertainties into the optimization problem. The traditional method to solve this problem is the stochastic programming method [29,30]. In this technique, the expectation of the objective function is calculated based on the possibilities of different scenarios and is maximized to achieve the final result. But, owing to the large search space caused by the uncertainties in renewable resources, the scenario set is usually very big. Therefore, the technique to reduce the size of the scenario set has been employed to reduce the size of the search space and accelerate the optimization [31,32]. In the scenario reduction methods, the typical approach is to merge the “similar” (having small distance between each other in some norms) scenarios into one representative scenario. The problem is that it is difficult to balance the size of the scenario set and the speed of the optimization. Since, with a small scenario set, the optimization can be less time consuming, the actual optimal solution may not be obtained because the real optimal scenario may be deleted during the scenario reduction. But with less reduction on the scenario set, the time for optimization could be very long so that it is not viable for many problems, especially for some real-time optimization problems. However, with the AI techniques like deep learning, the optimization of such problems becomes possible. This has been proven in the Go game by the AlphaGo. It is commonly believed that the number of possible scenarios on the board is larger than the number of atoms in the universe. Therefore, it is impossible to calculate the optimal solution of the Go game by using the traditional methods. But, with the deep learning technique, the AlphaGo has beaten the best players in the world. Similarly, in power systems, the AI methods can be used to learn the relation between the current status of the power system and the optimization object. Since the deep learning technique is not a recursive method, and not all scenarios should be considered in the calculation, the optimization can be very quick. Therefore, the AI methods have a great potential in the optimization problems in power systems.

2.1.3 Decision making

In the power system control center, the operators need to frequently make a lot of decisions to operate the power system and deal with the incidents. Operation ticket compiling is one of the most important parts in the decision making process of operators. Typically, in a power system, if any incident or damage is spotted by the maintenance staff or the sensors, a repair ticket will be submitted to the power system control center to request an outage or other appropriate operations at the faulted area, so that the repair workers can repair the equipment safely. Thus the operators in the power system control center should provide an operation ticket to take the corresponding actions, e.g., turn on or off certain switches and breakers, based on the repair ticket. Since the operation ticket is the guideline for many critical operations in the power system, the stability of the power system relies on the correctness of the operation ticket. Therefore, it is very important to keep the operation ticket error-free. Currently, the operation tickets are compiled manually by the operators, thus human errors may occur. However, the compiling of the operation ticket usually relies on human experience. As a result, for the same incident, the operation tickets compiled by different operators may be distinct. This makes it very difficult to judge the correctness of the operation ticket by any deterministic rule. Also, since the power system control center is an important facility in power systems, it is required to be operated in 24/7. Therefore, it is very hard to keep the operators alert and energetic for such a long time. Especially at night, the possibility for the operators to make mistakes may increase greatly due to tiredness. Therefore, in order to prevent mistakes on the operation ticket, the compiling of the operation tickets in current power systems are accomplished by at least two operators, in which one operator compiles the operation ticket and the chief-operator check the operation ticket. As the operation ticket is compiled and checked by two operators, the possibility of mistake on the operation ticket can be reduced. In addition, to avoid the errors caused by the operators because of tiredness, in a typical power system control center, the compiling of operation tickets must be completed before 10 p.m. every day.

As discussed above, the manual compiling of operation tickets is not very efficient. It is also very time-consuming since operators need to collect a lot of information from the power system and the historical data to create an operation ticket, and sometimes a lot of trial-and-errors are needed to obtain a good operation ticket. Therefore, the manual compiling of operation ticket by the operator is not the best choice. However, since human experience and abstract thinking are usually needed in the compiling of operation ticket, it is very difficult to develop an automatic operation ticket generation system by using the traditional methods. However, the AI methods, such as deep learning, may be a better choice to develop such an automatic operation ticket generation system or decision making system. As shown by AlphaGo [5], the deep learning techniques can be utilized in decision making problems. In the Go game, the AlphaGo decides the next step by evaluating the win rate of each possible move. The evaluation is done by using the MCTS method and reinforcement learning-based value network, in which the most possible movement sequences are randomly checked by the value network to find out the optimal movements. Similarly, an AI-based decision making system can be developed for power systems. The MCTS method can be used to check the most possible actions for operation tickets. Meanwhile, a value network can be employed to evaluate the performance of the actions. The value network for power systems can be developed by learning the historical operation tickets compiled by human and the data generated by the operator training simulator (OTS) which is used to train the operators. It is very likely that the AI-based decision making system can generate better operation tickets than the operation tickets manually compiled by human, and with a much higher efficiency.

2.2 Power system monitoring

2.2.1 Fault detection

Since power systems are very large systems, fault is usually unavoidable. Especially, since power systems are built in a natural environment, natural factors like weather can cause faults in power systems. Therefore, fault detection and analysis is very important. In many areas, such as on airplanes, satellites, and high speed trains, fault detection techniques are widely applied. For example, two major types of fault detection methods, the data-driven methods and model-based methods, are implemented for fault detection in different areas. Besides, the advanced fault detection and analysis method, called prognostics and health management (PHM) [33,34], is utilized in many areas to not only detect the existing fault on the equipment, but also predict the potential faults. In recent years, in order to improve the accuracy of fault detection and deal with complex faults, AI techniques have been introduced into related areas. For example, the convolutional sparse autoencoder (CSAE) method has been employed in Ref. [35] for the fault detection of transmission lines. CNN has been adopted for the earth fault detection in distribution systems in Ref. [36]. Self-encoding neural network has been used in Ref. [37] for fault detection in the distribution system.

The current fault detection methods in power system are usually simple and straightforward. They usually solve the problems caused by a single factor, for example, the grounding fault and phase unbalance caused by tree touching or line touching. These faults can be solved once the fault location is identified. However, in power systems, some faults are more complex since they are caused by multiple reasons or unobvious reasons. For these faults, human experience is usually required. For example, for some incidents in power systems, the fault is not caused by the power system itself but by the environment. As a result, the correct cause cannot be identified simply by using the data collected from the sensors in the power system. However, the operators in the power system control center can figure out the cause of the fault based on their knowledge about the environment and their experience. According to some examples such as the AlphaGo and image recognition, the AI techniques can solve some abstract problems by learning from human experiences. So, it is possible to improve the fault detection methods by using the AI technique. Typical fault detection problems can be treated as the classification problem in the AI methods, since the power system can be classified into two different conditions, faulted or normal. Furthermore, for fault analysis, the faulted power system can be categorized into different types of faults. In general, since the image recognition problem is a typical classification problem, the fault detection and analysis are similar to the image recognition problem, in which the states of the power system are similar to the pixels on the image and then the deep NN can tell what the fault is (or, what is in the image). As one of the most popular image recognition methods, the CNN method has a great potential to be applied in fault detection and fault analysis in power systems.

2.2.2 Stability analysis

In the traditional power systems, the dynamic security assessment (DSA) system is employed for the stability analysis of the power system. However, the DSA system is not time efficient. For example, in the Power System Control Center in Tianjin, the power system analysis and the information collection are performed every 15 min. In each 15-min time interval, it usually takes 3 to 5 min to calculate the states of the power system in SCADA. Then the states of the power system are input into the DSA system for analysis which usually takes another 5 min. So the traditional DSA system is not fast enough to deal with the emergent incidents in power systems. Most of the methods in the traditional power system analysis are recursive approaches. For example, in the AC power flow analysis, the Newton-Raphson (NR) method is usually used to calculate the power flow in the power system [28]. The NR method is a typical recursive method which recursively updates the solutions to approach the actual solution. Also, in the $N-1$ contingency analysis, the analysis is usually accomplished by calculating the states of the system for the outage on every transmission line. Apparently, the performance of these methods decreases greatly as the size of the power system increases. With the AI techniques, a better power system analysis system can be developed. Since the AI methods, like deep learning, are not recursive method, the speed of analysis can be greatly improved. For example, the NN can be used for the input-output fitting, in which the relation between the input data and the output data can be discovered. This feature is very useful for the problems such as power flow calculation. The initial load and generation data of the power system can be input into the NN whose output is compared with the result of the actual power flow to learn the relationship between the input and the output. With this method, the problems such as power flow calculation and $N-1$ contingency analysis can be solved without using the recursive method. In addition, the output of the NN can be the stability indices, such as the frequency compliance rate, the voltage compliance rate, the area control error (ACE), the spinning reserve rate, the $N-1$ contingency stability, the power supply margin, stability margin, the short circuit current, the voltage instability, the small perturbation alarm, and the transient instability. An example to use the NN for power flow analysis is provided in the case study.

3 Power flow analysis using NN

A NN is used in this paper to calculate the power flow in power systems without using the recursive calculation as in the traditional NR method. As a result, the power flow analysis can be completed faster than the traditional methods.

The model of neuron in NNs is shown in Fig. 1, whose mathematical model is presented as

$$y = f\left(\sum_i w_i u_i + b\right), \tag{1}$$

where y is the output of the neuron; $f(z)$ is called activation

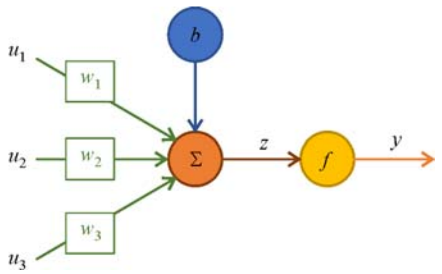

Fig. 1 Model of a neuron

function, in which the sigmoid function $f(z)$ = sig(z) = 1 = $(1 + e^{-z})$ is usually employed; u_i is the ith input of the neuron; w_i is the weight for the ith input; and b is a constant bias. Typically, each layer of a NN is formed by several unconnected neurons. In the NN, the inputs of the first layer are the inputs of the entire network, while the inputs of the second layer are the outputs of the first layer, and so on.

To calculate the power flow of the power system by using the NN, the initial states of the power system should be input into the NN. According to the AC power flow analysis, the required states for the calculation are the voltage, the phase angle, the real power injection, and the reactive power injection on each bus. In addition, the real power injection and reactive power injection on a bus can be divided into the real power and reactive power produced by the generator on the bus, and the real power and reactive power absorbed by the load on the bus. Therefore, the initial values of the 6 different states of each bus should be input into the NN as shown in Fig. 2. As an example, the number of the inputs of the power flow analysis NN for the IEEE 39 bus power system in Fig. 3 is 39 × 6 = 234. On the other hand, the output of the NN should be the states of the power system in the steady-state, in which the output has the same number of variables as the input.

The Levenberg-Marquardt method, a least square method which can be used to optimize the parameters of the NN model $\boldsymbol{f}(\boldsymbol{W}; \boldsymbol{b})$, is adopted to train the NN. The objective function is

$$\text{Minimize } F(\boldsymbol{W},\boldsymbol{b}) = \sum_{i=1}^{m} [y_i - f_i(\boldsymbol{W},\boldsymbol{b})]^2, \tag{2}$$

where $\boldsymbol{W}$ is the vector of weights on the links between neurons in the NN; $\boldsymbol{b}$ is the vector of biases of the NN; m is the total number of output of NN; $f_i(\boldsymbol{W}, \boldsymbol{b})$ is the ith output of the NN; and y_i is the actual value of the ith state of the power flow, which can be calculated by using the NR method in the training process. The Levenberg-Marquardt algorithm updates the parameters $\boldsymbol{p} = [\boldsymbol{W}, \boldsymbol{b}]$ with $\boldsymbol{p} + \boldsymbol{\delta} = [\boldsymbol{W} + \boldsymbol{\delta}_1, \boldsymbol{b} + \boldsymbol{\delta}_2]$, where $\boldsymbol{\delta}$ can be determined by

$$[\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J} + \lambda(\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J})]\boldsymbol{\delta} = \boldsymbol{J}^{\mathrm{T}}[y - f(\boldsymbol{W},\boldsymbol{b})] \tag{3}$$

where $\boldsymbol{J}$ is the Jacobian matrix of the NN model $\boldsymbol{f}(\boldsymbol{W}, \boldsymbol{b})$, in which its ith row

$$\boldsymbol{J}_i = \partial \boldsymbol{f}_i(\boldsymbol{W},\boldsymbol{b}) / \partial[\boldsymbol{W},\boldsymbol{b}]. \tag{4}$$

During the training process, in order to evaluate the performance of the trained NN, the original training data can be separated into the training data and the validation data. The training data is used to train the NN, and the validation data is employed to assess the training result. The reason to use validation data to evaluate the training result is that the NN may be over-fitted with the training data, and consequently, the new data (validation data) can provide a more accurate assessment for the training result. Finally, after the training process, the NN can be tested in the testing data.

To learn as much information as possible from the training data, the NN should be re-trained by the same training data for several times. Meanwhile, in order to avoid over-fitting, the number of re-training should be set reasonably. In this paper, the NN parameters obtained in the training iteration with the lowest MSE (mean squared error) is chosen as the final training results. An example to re-train the NN and to choose the final NN parameters is demonstrated in Fig. 4. In this example, the NN has been re-trained for three more times after the first training. In the third training iteration, the MSEs in the training, validation, and testing are the lowest compared to other training iterations. Then, in the fourth training iteration, the MSEs begin to increase, which indicates that the training result is over-fitted. Therefore, the result of the third iteration is chosen as the final NN parameter and the training is stopped after the fourth training iteration.

4 Case study

In this case study, NN is used to calculate the power flow of the IEEE 39-bus power system [38]. The parameters of the buses in the IEEE 39-bus power system are listed in Tables 1 and 2.

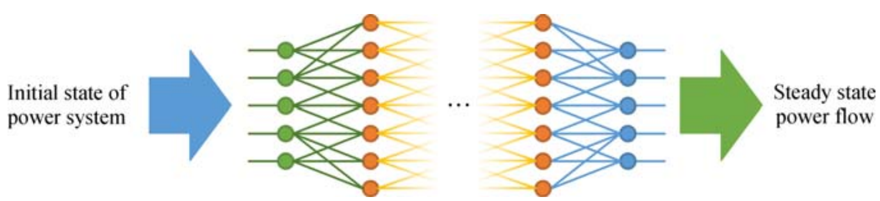

Fig. 2 Diagram of NN for power flow calculation

Table 1 Parameters of buses in IEEE 39-bus power system [38]

Bus #	V/(p.u.)	θ/rad	P_L/MW	Q_L/Mvar	P_G/MW	Q_G/Mvar
1	1	0	0	0	0	0
2	1	0	0	0	0	0
3	1	0	322	2.4	0	0
4	1	0	500	184	0	0
5	1	0	0	0	0	0
6	1	0	0	0	0	0
7	1	0	233.8	84	0	0
8	1	0	522	176	0	0
9	1	0	0	0	0	0
10	1	0	0	0	0	0
11	1	0	0	0	0	0
12	1	0	7.5	88	0	0
13	1	0	0	0	0	0
14	1	0	0	0	0	0
15	1	0	320	153	0	0
16	1	0	329	32.3	0	0
17	1	0	0	0	0	0
18	1	0	158	30	0	0
19	1	0	0	0	0	0
20	1	0	628	103	0	0
21	1	0	274	115	0	0
22	1	0	0	0	0	0
23	1	0	247.5	84.6	0	0
24	1	0	308.6	192	0	0
25	1	0	224	47.2	0	0
26	1	0	139	17	0	0
27	1	0	281	75.5	0	0
28	1	0	206	27.6	0	0
29	1	0	283.5	26.9	0	0
30	1.0475	0	0	0	250	0
31	0.982	0	9.2	4.6	0	0
32	0.9831	0	0	0	650	0
33	0.9972	0	0	0	632	0
34	1.0123	0	0	0	508	0
35	1.0493	0	0	0	650	0
36	1.0635	0	0	0	560	0
37	1.0278	0	0	0	540	0
38	1.0265	0	0	0	830	0
39	1.03	0	1104	250	1000	0

Table 2 Parameters of lines in IEEE 39-bus power system [38]

Bus in	Bus out	R/(p.u.)	X/(p.u.)	B/(p.u.)	Tr. tap
1	2	0.0035	0.0411	0.6987	1
1	39	0.0010	0.0250	0.7500	1
2	3	0.0013	0.0151	0.2572	1

(*Continued*)

Bus in	Bus out	*R*/(p.u.)	*X*/(p.u.)	*B*/(p.u.)	Tr. tap
2	25	0.0070	0.0086	0.1460	1
3	4	0.0013	0.0213	0.2214	1
3	18	0.0011	0.0133	0.2138	1
4	5	0.0008	0.0128	0.1342	1
4	14	0.0008	0.0129	0.1382	1
5	6	0.0002	0.0026	0.0434	1
5	8	0.0008	0.0112	0.1476	1
6	7	0.0006	0.0092	0.1130	1
6	11	0.0007	0.0082	0.1389	1
7	8	0.0004	0.0046	0.0780	1
8	9	0.0023	0.0363	0.3804	1
9	39	0.0010	0.0250	1.2000	1
10	11	0.0004	0.0043	0.0729	1
10	13	0.0004	0.0043	0.0729	1
13	14	0.0009	0.0101	0.1723	1
14	15	0.0018	0.0217	0.3660	1
15	16	0.0009	0.0094	0.1710	1
16	17	0.0007	0.0089	0.1342	1
16	19	0.0016	0.0195	0.3040	1
16	21	0.0008	0.0135	0.2548	1
16	24	0.0003	0.0059	0.0680	1
17	18	0.0007	0.0082	0.1319	1
17	27	0.0013	0.0173	0.3216	1
21	22	0.0008	0.0140	0.2565	1
22	23	0.0006	0.0096	0.1846	1
23	24	0.0022	0.0350	0.3610	1
25	26	0.0032	0.0323	0.5130	1
26	27	0.0014	0.0147	0.2396	1
26	28	0.0043	0.0474	0.7802	1
26	29	0.0057	0.0625	1.0290	1
28	29	0.0014	0.0151	0.2490	1
12	11	0.0016	0.0435	0.0000	1.006
12	13	0.0016	0.0435	0.0000	1.006
6	31	0.0000	0.0250	0.0000	1.070
10	32	0.0000	0.0200	0.0000	1.070
19	33	0.0007	0.0142	0.0000	1.070
20	34	0.0009	0.0180	0.0000	1.009
22	35	0.0000	0.0143	0.0000	1.025
23	36	0.0005	0.0272	0.0000	1.000
25	37	0.0006	0.0232	0.0000	1.025
2	30	0.0000	0.0181	0.0000	1.025
29	38	0.0008	0.0156	0.0000	1.025
19	20	0.0007	0.0138	0.0000	1.060

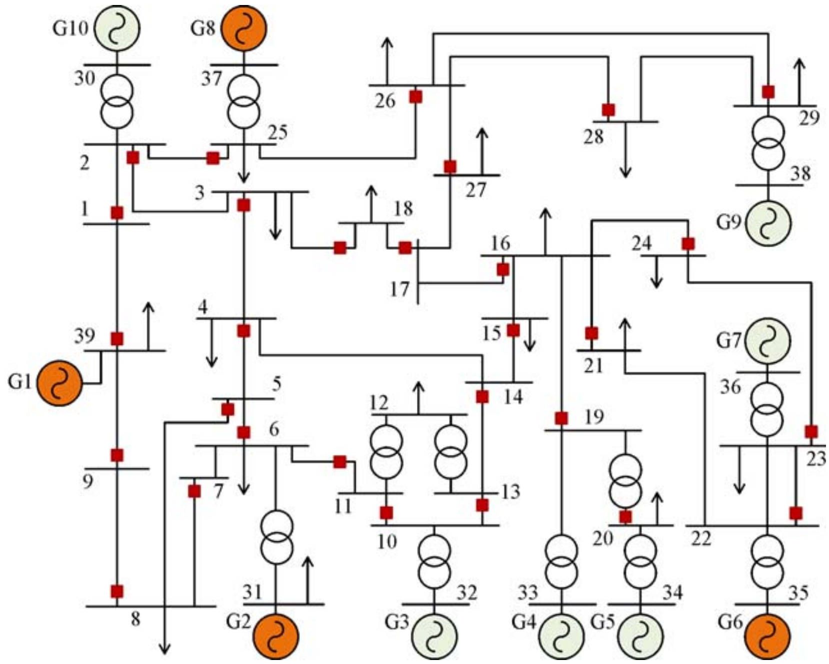

Fig. 3 IEEE 39 bus power system

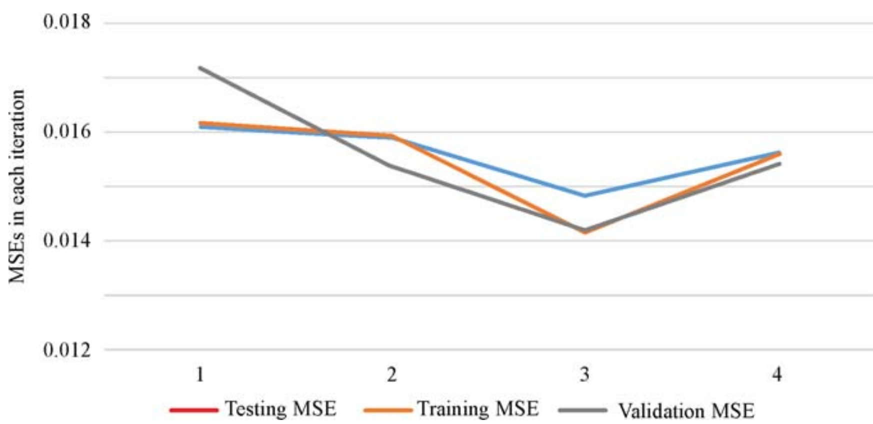

Fig. 4 MSEs at each training iteration

4.1 NN-based power flow calculation comparing with NR method

The training data set in this case study is generated by performing the NR method on the model of the IEEE 39-bus power system. The input data are obtained by randomly changing the parameters listed in Table 1 to the values which are between 85% and 125% of the original values to simulate the different initial values for the power flow problem. The output data are obtained by calculating the power flow by using the NR method. A two-layer NN is employed in this case for the power flow analysis. The first layer (hidden layer) of the NN has 100 neurons and the second layer (output layer) has 234 neurons. The Levenberg-Marquardt method is adopted to train the NN. The results are depicted in Fig. 5 to Fig. 16. The results indicate that similar results are obtained from the NN and the NR method, which demonstrate that the NN technique is viable to be applied in the power system analysis problem.

4.2 Comparison of different neural network structures

In addition, several NNs with different structures are tested. For these NNs, the number of layers and number of neurons are distinct, so that the effect of the structure of the NN can be studied. Different from the previous NN, the NNs in this part are trained by using the scaled conjugate

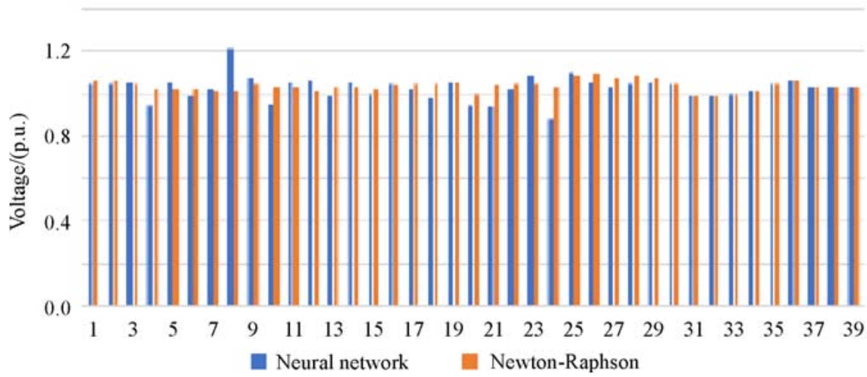

Fig. 5 Voltage on each bus calculated by using the NN and the NR method

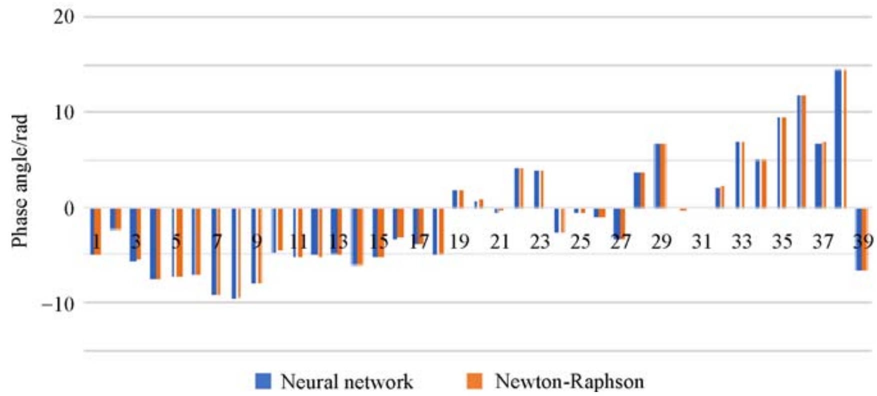

Fig. 6 Phase angle on each bus calculated by using the NN and the NR method

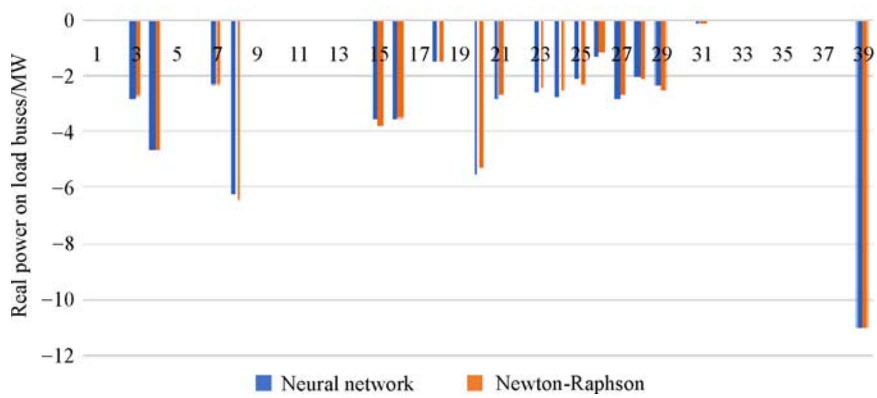

Fig. 7 Real power of the load on each bus calculated by using the NN and the NR method

gradient (SCG) backpropagation method [39] due to its high speed. The training data for these NNs is the same as the data set used in Subsection 4.1. During the power flow calculation, the input data for each NN is randomly generated in the same way as in Subsection 4.1. The results are presented in Table 3.

In Table 3, the serial numbers in the first column indicates the structures of the NNs. The numbers separated by "-" represent the numbers of neurons in different layers, i.e., the last number in the series is always the number of neurons in the output layer, and the numbers before it are the numbers of neurons in the hidden layers. For example, "20-20-121" means that there are two hidden layers and one output layer in the NN, in which each of the two hidden layers has 20 neurons and the output layer has 121 neurons. The second column in Table 3 stands for the accuracy of each NN according to MSE. The last column indicates the time consumed in calculation by NN and NR

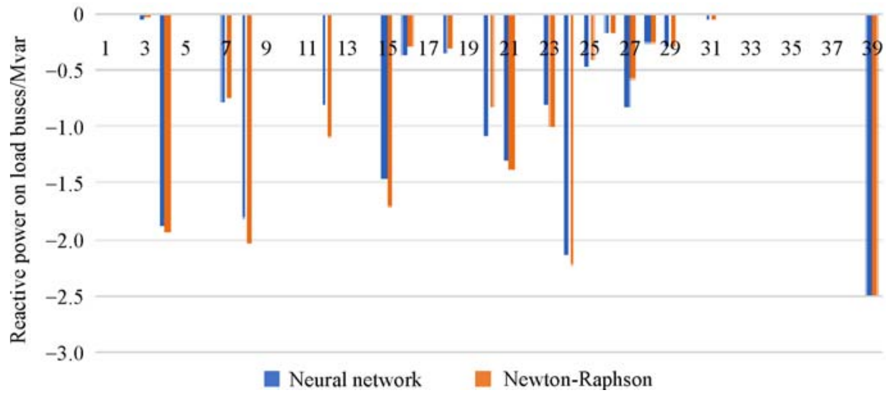

Fig. 8 Reactive power of the load on each bus calculated by using the NN and the NR method

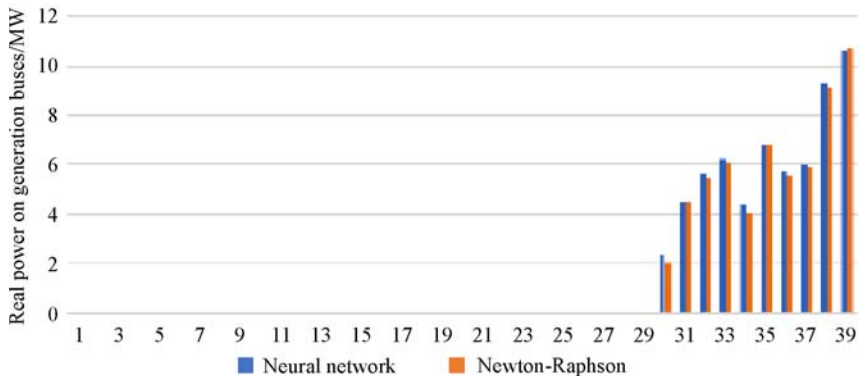

Fig. 9 Real power of the generator on each bus calculated by using the NN and the NR method

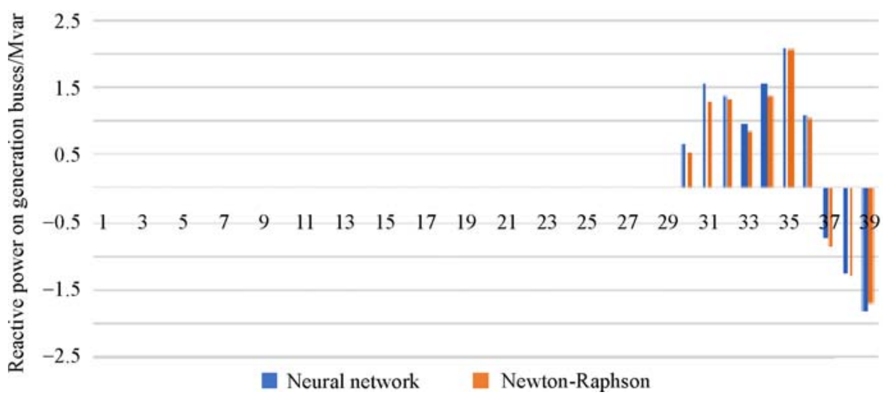

Fig. 10 Reactive power of the generator on each bus calculated by using the NN and the NR method

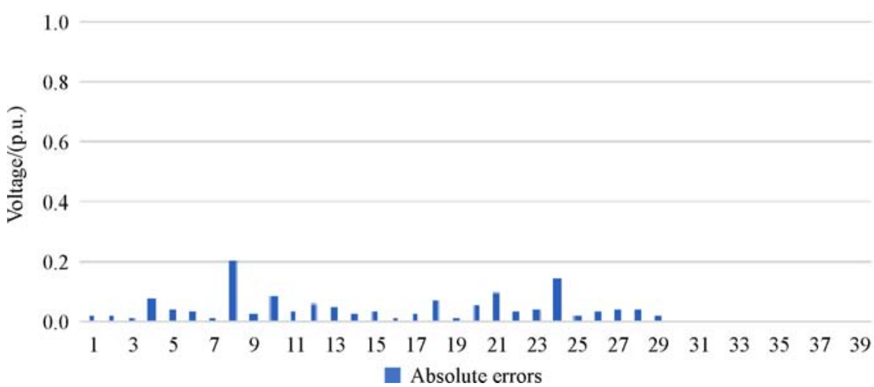

Fig. 11 Absolute errors of the voltage calculated by using the NN

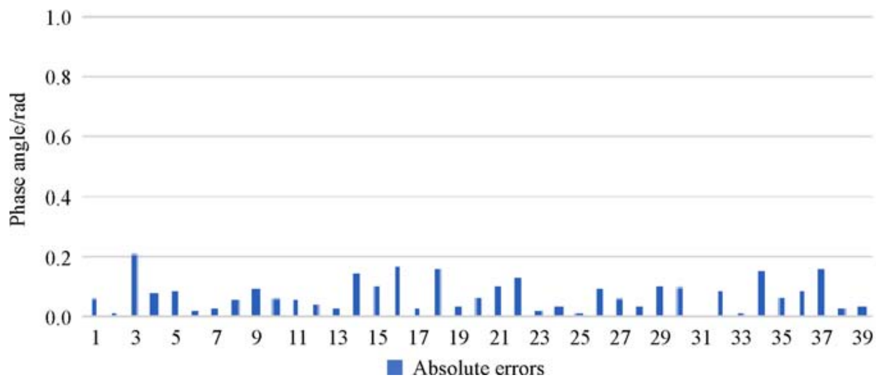

Fig. 12 Absolute errors of the phase angles calculated by using the NN

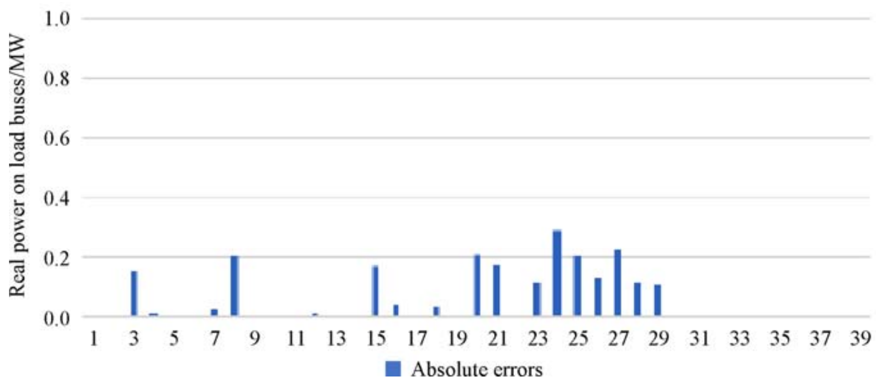

Fig. 13 Absolute errors of the real power of the loads calculated by using the NN

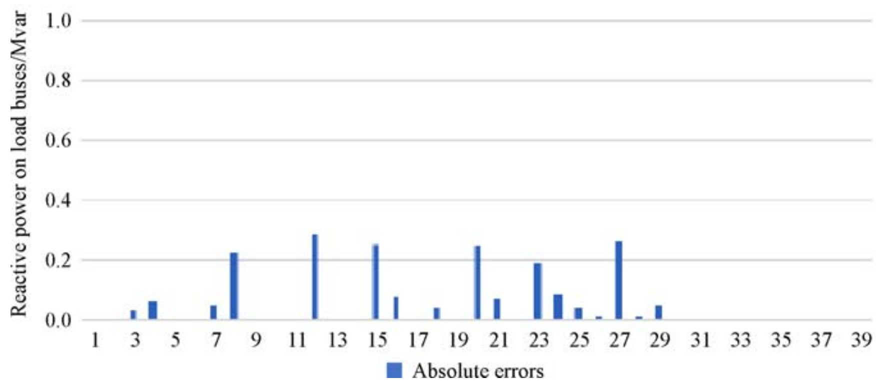

Fig. 14 Absolute errors of the reactive power of the loads calculated by using the NN

method. According to the results, the most accurate NN model is "300-121," in which there is only one hidden layer. With the increasing of layers, the accuracy of the calculation decreases. This may be caused by the vanishing gradient problem [40] in gradient-based learning methods and backpropagation methods. On the other hand, if there is only one hidden layer, 300 neurons in the hidden layer is the optimal configuration. However, if the hidden layer has more than 300 neurons, the accuracy of the NN will decrease. Finally, by comparing the time consumptions of the two different power flow calculation methods, the NN method is about 3–10 times faster than the NR method. Therefore, the NN-based power flow calculation method can be used in the fast power system analysis system as discussed in Sections 2 and 3.

5 Conclusions

This paper discusses the potential applications of AI

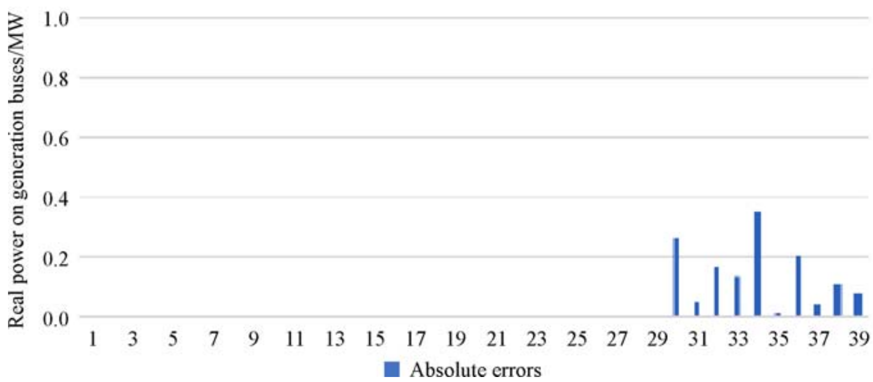

Fig. 15 Absolute errors of the real power of the generators calculated by using the NN

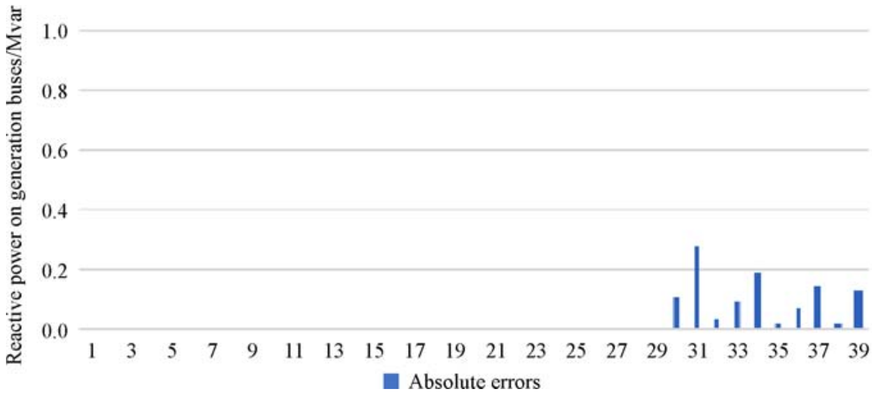

Fig. 16 Absolute errors of the reactive power of the generators calculated by using the NN

Table 3 Comparison of different NN structures

NN structure	Accuracy (MSE)	Time by NN/s	Time by NR/s
20-121	0.0441	0.0103	0.0855
20-20-121	0.0802	0.0135	0.0859
20-20-20-121	0.1583	0.0139	0.1336
100-121	0.0143	0.0139	0.0982
100-100-121	0.1357	0.0196	0.0925
100-100-100-121	0.2149	0.0186	0.1010
300-121	0.0051	0.0147	0.0841
300-300-121	0.1897	0.0234	0.0900
300-300-300-121	0.1677	0.0242	0.0960
500-121	0.0084	0.0184	0.0883
1000-121	0.3315	0.0323	0.1495

techniques in power systems by mainly focusing on the problems in power system operation and monitoring. These problems include control, optimization, and decision making problems in power system operation, and fault detection and stability analysis problems in power system monitoring. Besides, it provides several cases to demonstrate the application of the NN in the power flow analysis problem so that the viability of AI techniques in power system problems is verified.

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