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EXTREME LEARNING MACHINE'S THEORY & APPLICATION

Extreme learning machine-based predictor for real-time frequency stability assessment of electric power systems

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Abstract As a novel and promising learning technology, extreme learning machine (ELM) is featured by its much faster training speed and better generalization performance over traditional learning techniques. ELM has found applications in solving many real-world engineering problems, including those in electric power systems. Maintaining frequency stability is one of the essential requirements for secure and reliable operations of a power system. Conventionally, its assessment involves solving a large set of nonlinear differential–algebraic equations, which is very time-consuming and can be only carried out off-line. This paper firstly reviews the ELM's applications in power engineering and then develops an ELM-based predictor for real-time frequency stability assessment (FSA) of power systems. The inputs of the predictor are power system operational parameters, and the output is the frequency stability margin that measures the stability degree of the power system subject to a contingency. By off-line training with a frequency stability database, the predictor can be online applied for real-time FSA. Benefiting from the very fast speed of ELM, the predictor can be online updated for enhanced robustness and reliability. The developed predictor is examined on the New England 10-generator 39-bus test system, and the simulation results show that it can exactly (within acceptable errors) and rapidly (within very small computing time) predict the frequency stability.

Keywords Extreme learning machine (ELM) · Power system · Frequency stability

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1 Introduction

Modern electric power system is regarded as the largest artificial system in the world. Its essential responsibility is to maintain a secure and economic process of electricity generation, transmission, and distribution. However, the operation of a power system is usually exposed to various disturbances (contingencies), such as short circuits and un-anticipated generator outages. When the contingency is sufficiently severe, it can trigger dynamic insecurity problems, which could result in cascading failures and/or widespread blackouts [1]. Dynamic security assessment (DSA) is needed to examine the security conditions under the imminent contingencies and determine appropriate controls where needed.

According to different physical natures of the resulting mode of the dynamic insecurity, the dynamic security of a power system can be divided into three categories [2], known as rotor angle stability, voltage stability, and frequency stability. Since power system is a highly nonlinear system, its stability is modeled as a large set of differential–algebraic equations (DAEs), normally up to thousands of order. Conventionally, the DSA involves solving the DAE set step-by-step in a time frame (typically up to 10s or even several min), known as time-domain simulation. Historically, it can only be carried out off-line since the process is very time-consuming. However, the off-line approach becomes inadequate due to the increased uncertainties in modern power systems such as power market and increased penetration of wind power. Consequently, there is a pressing need for real-time DSA tools that can determine power system dynamic security conditions as soon as the current system operating parameters are obtained [3].

In recent years, artificial intelligence (AI) techniques have show strong potential for real-time DSA applications [3–9], and by off-line training and online application, the AI-based DSA models can provide many attractive advantages, especially the high DSA speed that is one of the most important factors in real-time DSA activities. As an emergent AI technology, extreme learning machine (ELM) has been utilized for solving several power engineering problems such as:

1. Load demand forecasting

Load demand forecasting is a traditional yet important task for daily operations of power system. It aims to forecast the power demand of the next period, based on which the generation of generators can be scheduled. According to the different lead time requirement, it can be divided into quarter-hourly, half-hourly, hourly, daily, weekly, monthly, and even yearly load forecasting. In [10], an ensemble model of ELM was designed and then applied for short-term load forecasting of Australian National Electricity Market, and satisfactory testing performance is observed.

2. Electricity price forecasting

Electricity price forecasting is to predict the electricity price of next trading interval in power market, which provides benefits for the participants during decision-making. Similar to load forecasting, the electricity price forecasting can also be divided into different time frames. In [11], ELM has been employed for electricity price forecasting, and the speed and accuracy have been shown better than other learning algorithms.

3. Wind power generation forecasting

Wind power is the most important and promising renewable energy. However, due to the intermittent nature of the wind source, the output of wind generators is always intermittent, making a very bottleneck of its large utilization. In order to better integrate wind power into traditional power systems, it is very important to forecast the generation output of wind power in specified lead time. In [12], ELM was employed for short-term wind speed forecasting and it is shown that the proposed ELM-based approach can not only effectively captures the nonlinear characteristics from wind speed data, but also requires less computation time than most of the conventional approaches as compared.

4. Power utility non-technical loss analysis

Power utility non-technical loss accounts for a noticeable portion of electricity loss of a utility company. It usually relates to the theft of electricity and occurs not only in developing countries but also developed countries, so it is very important to identify the non-technical loss for the utilities. In [13], ELM and OS-ELM were used for analyzing non-technical loss and satisfactory results have been obtained.

5. Extreme weather damage to power grid forecasting

Extreme weather can make a catastrophic impact on power system, such as the ice storm disaster on 2008 in China, which damaged a large part of the China southern power grid and caused tremendous economic and society loss. In order to prevent the power grid from the extreme weather, it is important to forecast the possible damage on the power grid, in [14], the ELM is employed to predict the possibility of the ice storm damages to electricity transmission facilities.

6. Power system dynamic security assessment

As is the topic of this paper, power system DSA is another essential task of the secure and reliable operations of the power system. In [8, 9], ELM was employed for rotor angle stability assessment and was compared with Artificial Neural Network (ANN), Support Vector Machine (SVM), and Decision Tree (DT), and the simulation results have shown that ELM can provide better performance over the other 3 state-of-the-art techniques.

This paper focuses on frequency stability, which is increasingly faced by today's power systems due to the large penetration of wind power. Motivated by ELM's initial successful applications in power engineering, this paper develops an ELM-based predictor for real-time frequency stability assessment (FSA) to enhance the power system dynamic security.

In the rest of this paper, Sect. 2 describes the problem including the ELM theory and power system frequency stability and its assessment problems, Sect. 3 proposes the ELM-based predictor for FSA, Sect. 4 describes a case study on the New England 10-machine 39-bus system to verify the predictor, and Sect. 5 concludes the whole paper.

2 Problem description

2.1 Extreme learning machine

ELM was proposed by Huang [15] as a new learning scheme working for single-hidden layer feed-forward networks (SLFNs). The structure of a SLFN is shown in Fig. 1.

Given a training set with N samples, the output function of the SLFN with L hidden nodes and activation function ϑ is:

$$f_L(\mathrm{x}_j) = \sum_{i=1}^{L} \beta_i \cdot \vartheta(\mathrm{w}_i \cdot \mathrm{x}_j + b_i) = \mathrm{t}_j, \quad j = 1, 2, \ldots, N \qquad (1)$$

ELM is completely different from traditional iterative learning algorithms as it randomly selects the input weights and biases for hidden nodes, that is, $\mathbf{w}$ and b, and analytically calculates the output weights, that is, β by finding least square solution [15]. In doing so, it is proven that the training error can still be minimized with even better generalization performance [15].

Equation 1 can be rewritten in a compact format as:

$$\mathbf{H}\beta = \mathbf{T} \qquad (2)$$

For a training set, given the activation function and hidden node number, the ELM algorithm can be summarized as three steps:

Step 1. Randomly generate the input weights $\mathbf{w}_i$ and b_i, $1 \leq i \leq N$;

Step 2. Calculate the hidden layer output matrix $\mathbf{H}$; and

Step 3. Calculate output weights matrix $\beta = \mathbf{H}^{\dagger}\mathbf{T}$.

where $\mathbf{H}^{\dagger}$ is called the *Moor-Penrose (MP) generalized inverse* of $\mathbf{H}$ [15].

There are several methods to calculate the *MP generalized inverse* matrix $\mathbf{H}^{\dagger}$. It is suggested that *singular value decomposition* is most appropriate due to its universality [15].

In marked contrast to traditional learning algorithms, ELM requires no iteratively adjusting of network parameters during the training; therefore, its training speed can be thousands times faster. Besides, it can avoid difficulties like stopping criteria, learning rate, learning epochs, and local minima, which are commonly encountered by traditional algorithms. A further attractive advantage of ELM is its fast tuning mechanism: to train an ELM involves almost no user input, except for the number of hidden nodes. To obtain an optimal ELM structure, a tuning procedure can be performed by examining the error over a validation set for a varying number of hidden nodes, and the architecture yielding the lowest error is selected as the optimal structure.

It has been widely demonstrated that ELM provides a much faster learning speed and other attractive properties compared with the alternatives. In [16], the performance of the ELM was compared with other algorithms, including SVM and conventional back-propagation, on a number of benchmark problems, and the results showed that ELM has an outstanding performance in relative terms. In [17], ELM has been extended for online sequential learning, and OS-ELM was proposed. Also in [17], OS-ELM was compared with other online sequential learning algorithms, and it is shown that OS-ELM has much better performance in relative terms. In [18], ELM is combined with evolutionary algorithm (EA) to select tuned input weights for higher forecasting accuracy. In [19], fuzzy techniques are used with ELM for online sequential learning. In [20], ELM was modified with optimization method for classification, and it was compared with its similarity, SVM. It has been shown in [20] that (1) under the ELM learning framework, SVM's maximal margin property and the minimal norm of weights theory of feedforward neural networks are actually consistent; (2) from the standard optimization method point of view, ELM for classification and SVM are equivalent, but ELM has less optimization constraints due to its special separability feature; and (3) as analyzed in theory and further verified by the simulation results in [20], ELM for classification tends to achieve better generalization performance than traditional SVM. More recently, a comprehensive survey of ELM has been reported in [21]. More detailed analysis of ELM's learning and storage capabilities are given in [22].

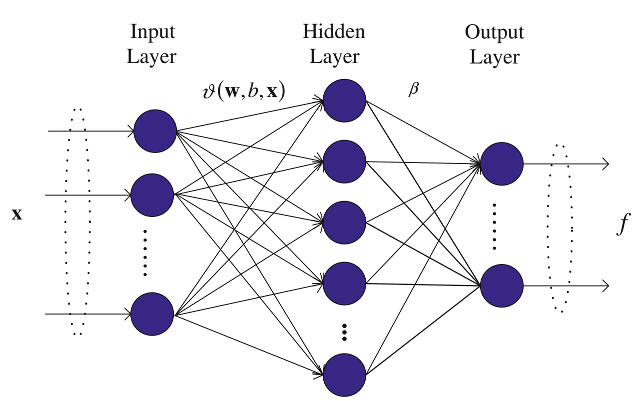

Fig. 1 Structure of a SLFN

2.2 Power system frequency stability and its assessment

Power systems are required to operate within a normal frequency level, such as 50 Hz ± 0.2 Hz in Chinese power systems. When subjected to a disturbance, the frequency will fluctuate, and when the disturbance is sufficiently severe, the frequency may continuously decline or rise, to an extent that may harm power plants and load-side equipments and even the system integrity. According to [2], frequency stability refers to the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generation and load. It depends on the ability to maintain/restore equilibrium between system generation and load, with minimum unintentional loss of load. Instability that may result occurs in the form of sustained frequency swings leading to tripping of generating units and/or loads.

For illustration, two cases are shown in Figs. 2 and 3, where the frequency responses of the New England 10-machine 39-bus system [23] after two faults are plotted (the simulation is carried out using FASTEST software [24]). Note that the normal operating frequency is 50 Hz and the simulation time is 30 s. In Fig. 2, the fault is tripping generator 1, and it can be seen that the frequency finally drop to around 49.4 Hz, which is acceptable; in Fig. 3, the fault is the tripping generator 7, and it can be observed that the frequency decay reach around 48.2 Hz, which is much lower than the normal value.

In recent years, because of the low-carbon commitment, there is an unprecedented utilization of wind power in today's power systems. Due to the intermittent and stochastic nature of the wind resource, wind power generation is highly variable and uncertain, which can result in various generation loss patterns leading to frequency stability problems. Consequently, there is a pressing need for tools that can rapidly evaluate the power system frequency stability.

Traditionally, the frequency stability assessment (FSA) is conducted by time-domain simulation, which is to numerically simulate the frequency response after a contingency (this involves solving a large set of DAEs that represent the system and the fault) and observe whether there is any violation of frequency requirement.

In order to quantify the frequency stability, the frequency stability margin (FSM) was proposed in [25]. Let a set of two-element tables $[(F_{cr,1},\ T_{cr,1}),\ldots,\ (F_{cr,i},\ T_{cr,i})]$ describe the frequency dip acceptability for each bus, the frequency stability can be determined according to if the maximum duration time that the bus frequency below $F_{cr,i}$ is smaller than the corresponding $T_{cr,i}$. The FSM can be calculated by:

$$\eta = \begin{cases} T_{cr,i} - T_i, & F_{\min,i} \leq F_{cr,i} \\ F_{\min,i} - F_{cr,i} + T_{cr,i}, & F_{\min,i} > F_{cr,i} \end{cases} \tag{3}$$

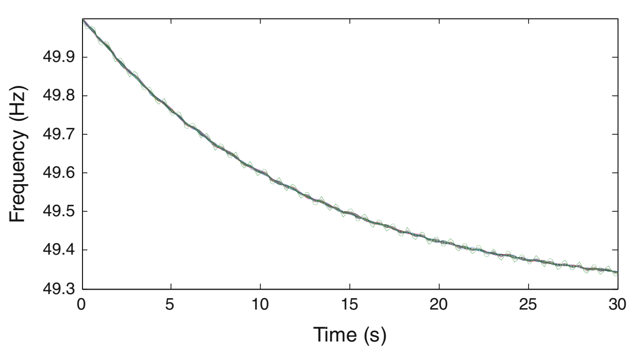

Fig. 2 Frequency response after tripping generator 1 of the New England test system

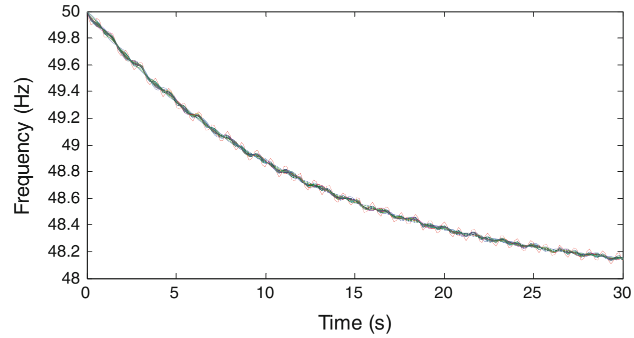

Fig. 3 Frequency response after tripping generator 8 of the New England test system

where $F_{\min,i}$ is the minimum frequency of the bus i during the transient period.

In order to reduce the two-dimension frequency stability requirement $(F_{cr,i},\ T_{cr,i})$ into one-dimension so as to decrease the computation burden of the FSM, a converting factor k is employed, and $(F_{cr,i},\ T_{cr,i})$becomes $\left(F'_{cr,i}, 0\right)$, where $F'_{cr,i} = F_{cr,i} - k \cdot T_{cr,i}$. And the FSM becomes:

$$\eta = \left(F_{\min,i} - F'_{cr,i}\right) \times 100\% \tag{4}$$

The FSM ranges from -100 to $+100$, and when the FSM is larger than zero, it means that the system is secure, otherwise, the system is insecure. The concept of FSM is very valuable since it can numerically measure the stability degree, even more important, it opens avenues to sensitivity approach, based on which, the frequency stability control can be systematically designed on an optimization basis [25].

For the two illustrated cases, the FSM of Figs. 1 and 2 is 41.35 and -47.21, respectively (the two-element table is [(49.00 Hz, 10.00 s)]). In this paper, we adopt the concept of FSM and use it to evaluate the degree of the frequency stability with respect to a contingency, this can be beneficial for the further decision-making of FSA, and the reasons behind this will be presented in later section.

It is evident that time-domain simulation is very time-consuming for real-world large-scale power systems since there can be a large set of DAEs to solve. For real-time FSA, this calculation time may be insufficiently short for quick decision-making.

3 ELM-based predictor for real-time frequency stability assessment

In this paper, an ELM-based predictor is proposed for very fast FSA. The general principle is to train the predictor by off-line database and apply it in online to predict the frequency stability with respect to possible contingencies.

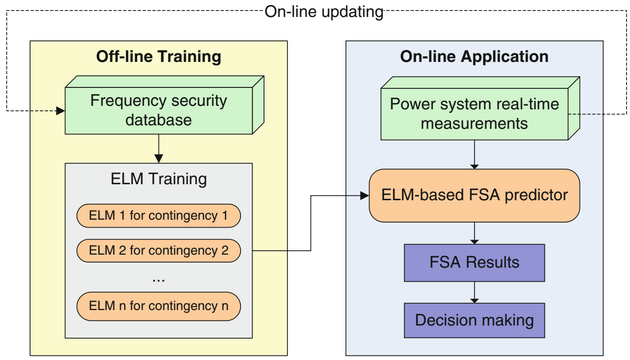

Fig. 4 Structure of the proposed ELM-based FSA predictor

The structure of the predictor is given in Fig. 4, and the critical parts are introduced subsequently.

3.1 Frequency stability database

The frequency stability database is for training and it consists of features and the objects. The features are the power system operating variables; in this paper, they are generation output of each generator, load demand of each load bus, system total power generation, and system total load, all of them can be obtained by measuring units in the power system. The objects are the frequency stability indices; in this paper, the FSM is adopted. The generation of the database consists of operation conditions (OCs) production and contingency simulation. The former is to produce prospective OCs for practical frequency stability prediction, it is important to produce sufficient similar OCs to the practical situation, and this can be achieved by load/generation forecasting that is associated with operational planning jobs. Besides, the historical OCs can also be included in the database. For contingency simulation, it can be performed by time-domain simulation using practical analysis tools. To directly obtain the FSM, software such as FASTEST [24] can be employed.

3.2 ELM tuning

The tuning of ELMs is quite efficient since there are only two user-defined parameters, known as the number of hidden neuron nodes and the activation function. For tuning, the training data are divided into two non-overlapped sets, one is for training and the other is for validation, and the optimal parameters can be determined when the parameters reach the lowest error during the validation.

3.3 Real-time FSA and decision-making scheme

Once the predictor is well trained, it can be online applied for real-time FSA. During the practical application phase, as soon as the input (provided by power system measurement units) is fed, the predictor can immediately give the FSM of the current system state with respect to postulated contingencies. It is worth mentioning that in previous research, the DSA can only give the binary or discrete indications of the security, such as “secure” or “insecure” [5–9], and the prediction error can lead to complete different decision-making results. However, it can be seen that the FSM-based output employed in this paper is continuous which measures different degrees of the frequency stability, and the impact of prediction errors can be much less than that of discrete ones. For more reliable FSA, a flexible decision-making scheme can be employed: when the predicted FSM (absolute value) by the predictor is very large (exceed a pre-defined threshold), it can be determined that the current OC is secure or in secure, while if the FSM is near zero, for more reliable FSA result, operators can employ time-domain simulations to exactly obtain the FSM. Although this can require added computation time, the accuracy can be guaranteed and the computation speed can still be very fast due to the very computationally efficient predictor (the required computing time is still compatible with online computing requirements). Consequently, the ELM-based predictor tends to be more reliable and accurate than those crisp DSA mechanisms.

3.4 Online updating

Since the frequency stability database is generated in off-line environment based on forecasting at a given lead time, it is possible that the database can not always catch the practical operating conditions (due to the unpredicted factors). In order to keep the accuracy and the robustness of the predictor, it is necessary to update the predictor with the practical operating information. As already shown in [8], owing to the very fast learning speed of ELM, this can be achieved within very small time delay and thus make the updating meaningful.

4 Simulation results

In order to verify the proposed ELM-based FSA predictor, a case study is conducted on the New England 10-machine 39-bus system [23]; this system represents the simplified network of the New England region of the US, it has been usually employed as the testing system in power system research [8, 9], and its one-line diagram is given in Fig. 5.

4.1 Database generation

Starting from the basic operating point of the testing system, we proportionally increase/decrease the total load

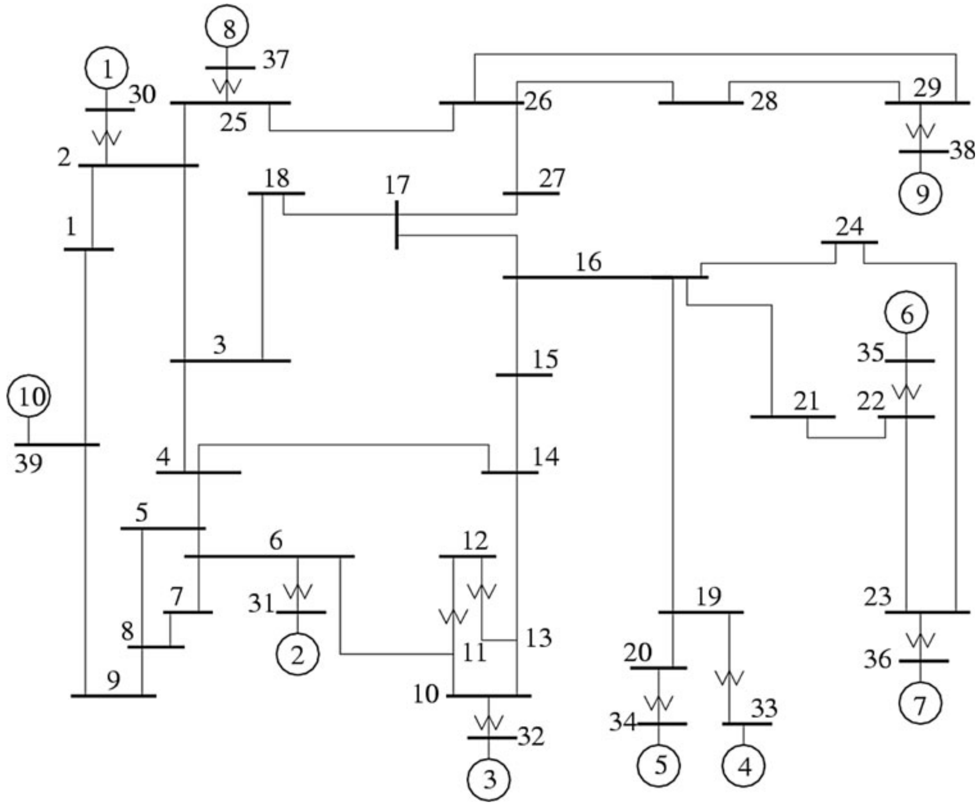

Fig. 5 New England 10-generator 39-bus system

demand while randomly distribute the increment/decrement of the power demand among the load buses, and the output of generators is allocated according to their size and generation costs. In such a way, aggregately 400 load/generation patterns are produced, the 400 cases are then put into power flow program, and 360 OCs are obtained (the other 40 cases are non-convergence in power flow solution). For the testing system, there are aggregately 33 features. The total load of the 360 OCs is shown in Fig. 6, and it can be seen that the database has covered a wide range of operating conditions.

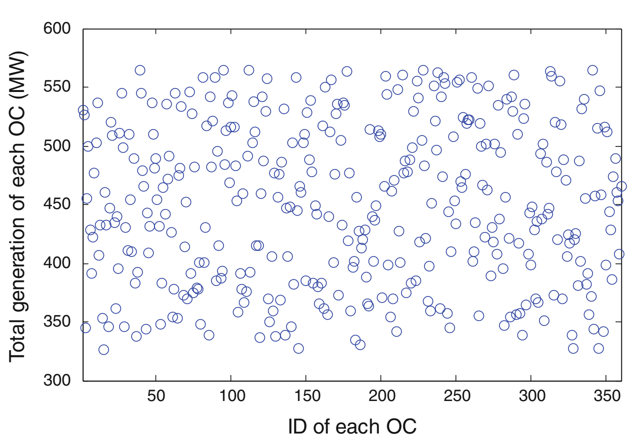

Fig. 6 Total generation of each OC in the database

A very severe fault, tripping generator 8 is assumed as the contingency, and under this contingency, the FSMs of the OCs are obtained through time-domain simulation using FASTEST software [24] (simulation time is 30 s, and the two-element table is [(49.00 Hz, 10.00 s)]), and all of the FSMs are plotted in Fig. 7. It can be seen that, generally, the heavier of the system total generation, the smaller FSM it has, this is because when the system load is heavy, the resulting power imbalance of the system is large, which leads to the deeper decline of the frequency.

4.2 Optimal ELM structure determination

The tuning of ELM consists of selecting the optimal activation function and the corresponding hidden nodes. To this end, the database is divided into two non-overlapped sets, one consists of 240 and the other comprises 120 samples, respectively, for training and validation. The optimal ELM structure can be determined as the one which results in the lowest validation error.

To measure the accuracy, the mean average percentage error (MAPE) and the mean average error (MAE) are used, which are calculated as follows:

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{d} y_i - y_i'}{|y_i| \cdot d}, \ \mathrm{MAE} = \frac{\sum_{i=1}^{d} y_i - y_i'}{d} \tag{5}$$

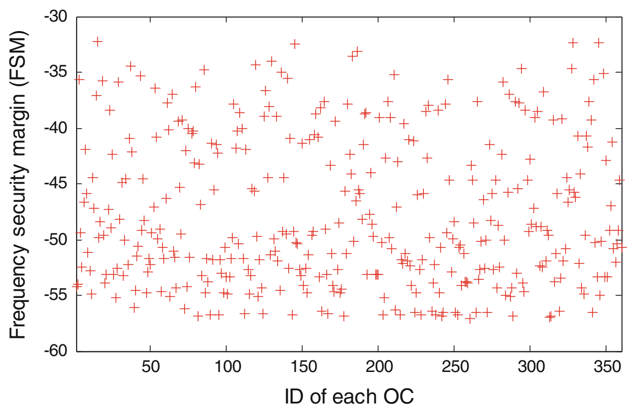

Fig. 7 FSM of each OC in the database

where y_i and y_i' are the real and predicted FSM, respectively, and d is the total number of the testing samples.

The validation result is given in Fig. 8, note that the MAPE is the average value of a 10-round simulation of ELM. It can be seen that the MAPE declines sharply as the hidden nodes increase from 0 to 40, then the MAPE swings steadily as the hidden nodes still add, finally, the MAPE reaches to a steady level. The lowest MAPE is 0.49%, which is achieved by 61 hidden nodes using *sigmoidal* function. Consequently, the optimal structure of ELM can be determined as *sigmoidal* function with 61 hidden nodes. On the other hand, one can also choose a range of hidden nodes in practice, take Fig. 7, for example, the optimal range of hidden nodes can be [50, 80] as it corresponds to the lowest MAPE range.

4.3 Testing results

To comprehensive test the proposed method without loss of generality, the k-folder cross-validation criterion [26] is employed in the case study. For this, the initial database is randomly partitioned into k mutually exclusive subsets or "folds," D_1, D_2, …, D_k each of approximately equal size.

Table 1 10-fold testing results

Training time	Testing time	MAPE	MAE
0.156 s	0.001 s	0.63%	0.3052

Training and testing are performed k times. In iteration i, partition D_i is reserved as the test set, and the remaining partitions are collectively used to train the model. The accuracy can be computed as the total loss from the k iterations, divided by the total number of initial instances. In this case study, a 10-folder test is conducted.

The overall 10-folder testing results are given in Table 1, and the testing error in each folder is shown in Fig. 9.

It can be seen from the testing results that the training speed of the predictor is very fast, it only requires 0.156 s to learn the database (360 OCs), and the prediction on the database needs negligible computation time, which is just 0.001 s. By contrast, the time-domain simulation for 30 s on only one OC may, however, need as long as 5.2 s. As for the accuracy, the 10-folder MAPE and MAE are only 0.63% and 0.3052 (FSM value), which are sufficiently high for practical application.

4.4 On the sensitivity of the ELM outputs

Since ELM randomly chooses the input weight vector during its training, its outputs can be varied subject to different input weight vectors. This section investigates the impact of the randomly selected input weight vectors on the sensitivity of the FSM prediction results of the predictor. For this, 100 independent simulations are run, and the standard deviations of the MAPE and MAE are calculated. As shown in Table 2, the standard deviations of both MAPE and MAE are relatively small, and since the accuracy of the predictor is very high, such impact of

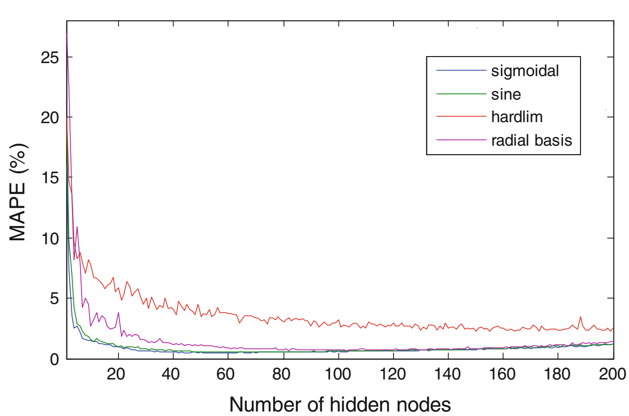

Fig. 8 Validation result

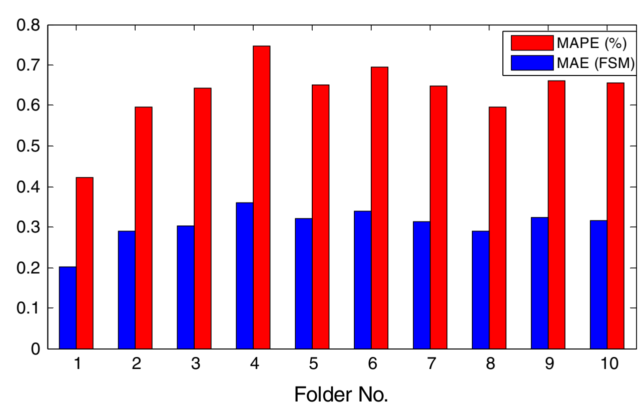

Fig. 9 MAPE and MAE of each folder test

Table 2 Standard deviations of 100 rounds of simulation

MAPE	MAE
0.036%	0.0571

output variations due to the random selection of input weights is limited and is acceptable for practical use.

5 Conclusions

As a novel and promising artificial intelligence technology, ELM has been widely applied to solve many real-world problems, including those in power engineering. A review of the ELM applications in power engineering is firstly given in this paper. An ELM-based predictor is then developed for power system FSA. By off-line training and online application, the predictor can be used for real-time FSA to enhance the dynamic security of the power systems. The developed predictor is demonstrated on the New England 10-generator 39-bus test system, and the simulation results show that its speed is very fast and the accuracy is acceptably high, which is promising for practical use.

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