ADVANCES in NATURAL and APPLIED SCIENCES

ISSN: 1995-0772
EISSN: 1998-1090
2016 September 10(13): pages 93-100

Published BY **AENSI Publication**
http://www.aensiweb.com/ANAS
Open Access Journal

Transient Security Classification of Power System Using Extreme Learning Machine

[1]K. Jothinathan and [2]S. Ganapathy

[1]Assistant Professor, Department of Electrical Engineering, Annamalai University, Tamil nadu -608002, India.
[2]Professor, Department of Electrical Engineering, Annamalai University, Tamil nadu - 608002, India.

Received 7 June 2016; Accepted 12 September 2016; Available 20 September 2016

Address For Correspondence:
K.Jothinathan. Assistant Professor, Department of Electrical Engineering, Annamalai University, Tamil nadu -608002, India.
E-mail: jothi.eeau@yahoo.com, phone: 9942444417

Copyright © 2016 by authors and American-Eurasian Network for Scientific Information (AENSI Publication).
This work is licensed under the Creative Commons Attribution International License (CC BY).
http://creativecommons.org/licenses/by/4.0/

Open Access

ABSTRACT

This paper presents a novel design procedure for Transient security assessment of power systems using Extreme Learning Machine classification technique. The objective of this research work is to design and implement a transient security classifier using ELM and to enhance the performance of classifier using suitable feature extraction technique. Transient security investigation estimates the operation of the power system as it takes place after an unexpected disturbance. The main intention of Power system security is to make certain suitable system operation within agreeable limits. On the contrary, power system failure to operate securely may guide to outages which can have extensive consequences on power system equipments and users. Technical and economic results can be maintained by ensuring power system security. In this research paper, an Extreme Learning Machine (ELM) technique has been applied for power system transient security categorization purpose. An extreme learning machine is a single-hidden layer feed forward neural network (SLFN) based learning algorithm which has been utilized to achieve good generalization performance at exceedingly fast learning speed. The input weights are chosen randomly by ELM which analytically determines the output weights of SLFNs. The large dimensionality of the input data or variables for complex problems is reduced by patronizing the problem into small size by using the well suited feature selection methods. This paper investigates the use of F-value criterion for feature selection process. The effectiveness of the proposed ELM classifier is demonstrated by comparing with Artificial Neural Networks (ANN) such as deep neural network (DNN) and back propagation neural network (BPNN). The proposed strategy is tested on a standard IEEE 14 bus system. In the proposed power system model, three phase faults have been applied to examine the proposed ELM based classifier and the test results are validated. The classifier has shown high efficiency in classification. The simulation results prove that the proposed method could be assessed in a rapid manner and accurately predict the security status of the power system using ELM.

KEYWORDS: Artificial Neural Network,Extreme Learning Machine, F-value feature selection, Transient security assessment

INTRODUCTION

In present environment, power system operation is highly unpredictable and multifaceted; especially the intensive loading of existing generation and transmission facilities makes more burdens on system operators as it tremendously increases doubtfulness for all customers. Consequently, the difficulties in generation, load variations and drawing power from remotely located generation could result in inadequate security of power systems. Therefore, maintaining sufficient security is a major problem for the utilities and it is essential to monitor the system status with load changes and contingencies. It is not practical to run time domain simulations or full AC load flow for all credible contingencies of a large power system, due to the computational time required, so utility engineers need to ensure a fast and accurate security condition [1].

The power system security evaluation is based on the measurements of some of its variables from load flow studies, in general, these measurements are not truthful and have varying degree of accuracy. The measurement

To Cite This Article: K. Jothinathan and S. Ganapathy., Transient Security Classification of Power System Using Extreme Learning Machine. **Advances in Natural and Applied Sciences**. 10(13); Pages: 93-100

errors may result in misclassification of an insecure state into a secure state causing insecure operation of the power system and leading to deterioration or interruption of the power supply [2]. So, there is a need in design and implementation of a security classifier that might predict the stable position of power system and also scale the abnormality [3].

On-line security evaluation allows the operator not only to know the security status, but also helps to determine the remedial actions. Power system security assessment is a significant study that has to be carried out in real-time operation to determine the security and stability of a system. Power system security may be divided into three modes: (a) Steady state security characterizes the steady state performance of the system, (b) Transient security concerns with the stability of the system when it is subjected to a large and sudden disturbance (c) Dynamic security pertains to the system responses of the order of a few minutes [4,5]. The steady state security is based on the mathematical model of a set of algebraic equations where as the transient and dynamic securities are based on the description of the system by a set of differential equations. Studies on Transient security are presented in this section.

Transient Security Assessment (TSA) is part of dynamic security assessment of power systems which involves the evaluation of the ability of a power system to maintain synchronism under severe but credible contingencies. In most situations, the assessments of TSA are done in traditional way by means of time domain simulations and direct simulation methods. These conventional approach results are considered as most accurate but do not provide the detailed modeling of the power system components required for security assessment [6,7].

In literature, many Artificial Intelligence (AI) techniques have been proposed to overcome the drawbacks of the conventional methods of evaluation. Use of AI techniques like Self organizing feature map [8]. Multi layer feed forward neural networks, Genetic based NN [9], Fuzzy logic based NN [10], Query based learning approach with NN [11], improves accuracy of classification but still pertains to some of the inconvenience stated in traditional methods. Some of the researchers have shown their interest to figure out the transient condition of power system with aid of Artificial Neural Networks, due to its improved ability, high accuracy and fast response. Although successfully applied for online monitoring schemes, it requires extensive training process [12]. For large power systems, the size of data set is too large and hence the training becomes complex and time consuming. In general, ANN, for applications in large sized power systems, requires a large number of input features for training the neural network. Hence, to overcome this drawback, this paper targets to design a new or unique transient security classifier that classifies the state of the security of a selected model with reduction in larger memory space, lesser computational time and superior accuracy using Extreme learning Machine(ELM) [13].

Extreme learning Machine(ELM), is a class of Single-Hidden Layer Feed Forward Neural Networks (SLFNs) used for various applications such as automatic pattern recognition,signal processing, human action recognition, feature selection ,time-series, real-time learning and prediction ,security and data privacy [14,15]. ELM was originally proposed with standard single hidden layer feed forward neural networks having random hidden nodes and has recently been extended to kernel learning as well. The significance of the ELM is that random computational nodes can be applied with the hidden layer, which is independent of the training data. ELM not only provides least training error but also least normalised weights. When normalised weights are smaller better performance is achieved and there is no need for tuning the hidden layer. So,ELM provides a unified learning platform with widespread type of feature mappings and can be applied in regression and multi-class classification applications directly.

The feature selection is one of the important steps in the classification problem to enhance the assessment accuracy. In this paper, F-value Feature Selection algorithm based on correlation between features has been presented to reduce the data size and improve classification efficiency.

Transient Security Assessment:

The transient security assessment is a problem of classification of power system operating states into secure and insecure states from security point of view [16,17]. The intended approach entails possible system configurations which can be attained from scheduled outages of system components and a separate transient security classifier function is appraised offline and stored [18,19]. The projected Extreme learning Machine approach for transient security assessment entails defining of all significant variables of power system. The vector along with the power system transient security state are evaluated for many different operating situations to generate a set of variables or patterns known as training set.

The transient security is evaluated by performing load flow analysis and transient stability studies. If the relative rotor angle remains less than 180° with respect to slack generator, the position of power system is said to be Transient Secure (Binary 1) after fault clearing for a specific transient fault condition. Otherwise, the power system position is considered as Transient Insecure (Binary 0).The security classifier does not require all the components of the pattern vector for classification purpose as some components of the pattern vector may be strongly correlated with one another. Hence, the process of dimensionality reduction is performed to identify the

set of significant and uncorrelated set of variables. This set of significant and uncorrelated variables is called the feature set. The process of obtaining feature set is known as feature selection. In this paper, F-value Feature Selection [20], has been implemented for obtaining feature set. The F-value Feature Selection method is simple, fast and suitable for large data classification problems in power system. After obtaining the security classifier, any operating state of the power system can be classified resourcefully.

Variables For Transient Security Evaluation:

All the steady state variables obtained from load flow studies along with transient state variables are used as features for Transient Security Evaluation. Some of the important steady state variables are voltage, real and reactive power output of generators, real and reactive loads on each bus, voltage magnitude and angle of each load bus [21]. The transient state variables are mechanical input power, electrical output power and relative rotor angle of all generators at fault application time and fault clearing time .

Generation Of Data Set For Training And Testing:

The input data for the proposed work are generated by varying load and generation levels within permissible limits. Usually, the response of the system for various disturbances and possible contingencies are simulated and a set of features are collected. The load flow is performed for incremented and decremented values of generation and load between 70% and 130% of base value and corresponding steady state security analysis is performed. The steady state data is classified as secure and insecure based on the voltage and MVA limits. The secure steady state variables are then subjected to Transient analysis. For transient analysis, the data is generated by applying the three phase fault at each transmission line. The training practice is an off-line process. This is done to avoid the computational burden during on-line application. From the total data set generated, randomly about 80% of generated data are used for training and the remaining 20% of the generated data from the total data set is used for testing purpose.

Extreme Learning Machine:

Extreme learning machine is a tuning free unified learning technique for regression and multiclass classification. ELM as projected by Huang is a latest learning format for Single Hidden Layer Feed-Forward Neural Networks (SLF-NNs) which can prevail over the insufficient learning speed of the traditional learning algorithms. The input weights and biases for additive hidden nodes of ELM do not require to be tuned by conventional algorithms. Relatively, we can arbitrarily allocate hidden nodes parameters when the activation functions in the hidden layer are infinitely differentiable .Analytically, the output weights between the hidden layers to the output layer can be computed by using inverse operation of hidden layer output matrices [21].

For N arbitrary distinct samples, $\aleph_N = \{(x_i, t_i) | x_i \in R^n, t_i \in R^m\}_{i=1}^N$, (1)

Where x_i is the n x 1 input feature vector and t_i is a m x 1 target vector. A standard SLN-NN which has $\tilde{N}$ hidden nodes and activation function: $\partial(x)$ can be mathematically modeled as

$$\sum_{i=1}^{\tilde{N}} \beta_i \vartheta_i (w_i, b_i, x_j) = o_j, \quad j = 1,\ldots..,\ N \tag{2}$$

where $w_i = [w_{i1}, w_{i2},\ldots. w_{in}]^T$ is the weight vector connecting the *i*th hidden node and the input nodes, is the weight vector connecting the *i*th hidden nod and the output nodes a b_i is $\beta_i = [\beta_{i1}, \beta_{i2},\ldots\beta_{in}]^T$ the threshold of the *i*th hidden node. Here w_i and x_j denote the inner products of w_i and x_j. Fig.1 shows the general structure of an SLF-NN.

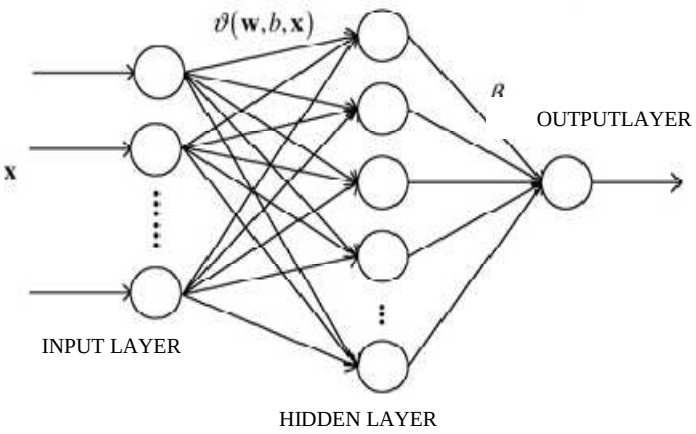

Fig. 1: Single Hidden Layer Feed-Forward Neural Network

Approximating these N samples with zero error using SLF-NNs,

Weget $\sum_{j=1}^{N} \left\| o_j - t_j \right\| = 0$ (3)

That is, there exist β_i, b_i, $w_i$such that $\sum_{i=1}^{\tilde{N}} \beta_i \ \vartheta_i \left(w_i,\ b_i,\ x_j\right) = t_j,\ j = 1, \ldots..,\ N.$ (4)

The above N equations can be written as

$H\,\beta = T$ (5)

Where $H\left(w_1,\ldots..,\ w_{\tilde{N}},\ b_1,\ldots..,\ b_{\tilde{N}},\ x_1,\ldots..,\ x_N\right)$

$$= \begin{bmatrix} \vartheta\left(w_i,\ b_i,\ x_1\right) & \cdots & \vartheta\left(w_{\tilde{N}},\ b_{\tilde{N}},\ x_1\right) \\ \vdots & & \vdots \\ \vartheta\left(w_i,\ b_i,\ x_N\right) & \cdots & \vartheta\left(w_{\tilde{N}},\ b_{\tilde{N}},\ x_N\right) \end{bmatrix}_{N \times \tilde{N}} \quad (6)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m} \quad and \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\tilde{N}}^T \end{bmatrix}_{N \times m} \quad (7)$$

H is the hidden layer output matrix of the NN and the ith column of H is the ith hidden node output with respect to inputs x_1, x_2, …and x_N. The input weight vectors $w_i$and the hidden biases b_i are not tuned and the matrix H can be assigned random values.

1. If the activation function ∂ is infinitely differentiable, when the number of hidden neurons is equal to the number of distinct training samples, that is, $\tilde{N} = N$, one can randomly assign the parameters of hidden nodes (w_i and b_i or kernel parameters) and based on this one can analytically calculate the output weights β by simply inverting H, and therefore SLFNs can approximate $\aleph_N$ with zero error.

2. For $\tilde{N} << N$, which is the common case in the real world, H will be a non square matrix and there may not exist β_i, b_i, w_i. However, one specific set of $\tilde{\beta}_i,\ \tilde{b}_i,\ \tilde{w}_i$ could be found such that

$$\left\| H\left(\tilde{w}_1,\ ....,\ \tilde{w}_N,.....,\ \tilde{b}_{\tilde{N}}\right)\tilde{\beta} - T \right\| = \min_{\beta_i,\ b_i,\ w_i} \left\| H\left(w_1,....,\ w_{\tilde{N}},\ b_1,.....,\ b_{\tilde{N}}\right)\beta - T \right\| \quad (8)$$

Which is equivalent to minimizing the cost function-

$$E = \sum_{j=1}^{N} \left(\sum_{i=1}^{\tilde{N}} \beta_i \ \vartheta_i \left(w_i,\ b_i,\ x_j\right) - t_j \right)^2 \quad (9)$$

For fixed w_i and b_i, (5) becomes a linear system, and the output weights β can be estimated as

$$\hat{\beta} = H^T T \quad (10)$$

Where H^T is the Moore–Penrose generalized inverse of matrix H. Therefore, one can still randomly assign the parameters w_i and b_i of the hidden nodes and calculate the output weights $\hat{\beta}$ by (10) to give a small non-zero training error $\varepsilon<0$.

Algorithm for ELM:

Given a training set $\aleph = \{(x_i,t_i)|\ x_i \epsilon\ R^d, t_i \epsilon R^m,\ i = 1, \ldots, N\}$, hidden node output function $G(a_i,b_i, x)$, and hidden node number L,

Step 1: Randomly generate hidden node parameters $(a_i; b_i)$; i =1, . . .L.

Step 2 Calculate the hidden layer output matrix H:

Step 3 Calculate the output weight vector β:

$\hat{\beta} = H^*T$

ELM can be used to train threshold networks directly. Different methods can be used to calculate generalized inverse of a matrix

Extreme Learning Machine Based Tsa Classifier:

Modern power systems are often huge, complex and highly unpredictable in the context of restructuring and increasing penetration of renewable energy; this makes the off-line generated knowledge base insufficient for accurate real-time complex classification problems. ELM technique [23] can carry out learning at a very high rate, Based on it, an ELM based TSA classifier model has been presented in this paper.

An initial data set is generated off-line from the past TSA records and off-line illustration simulations, and then significant features as input for training are selected using suitable feature selection process. The selected important feature data set not only enhances the accuracy of ELM classifier but also provides sufficient information regarding the critical system parameters.

During training stage, ELMs are trained by means of selected features with possible contingencies and this process is completed swiftly. For real-time TSA, ELM-based model utilizes the system dataset as input and predicts the TSA results within a very short duration of time. From the TSA status, if insecure status is predicted, preventive control measures are initiated to preserve system stability. The initial data base should be continuously updated, which concurrently updates the ELM's performance.

Feature Selection:

The number of input features describing the power system depends on the size of the power system. The larger the size of power system, the greater will be the number of features. Analysis of large power system requires large computational memory space for data storage and computational time. For a power system, all the features which are selected initially as input features may not be necessary because some features may be redundant and do not contribute to the biasing of the features. Consequently, for dimensionality reduction of data set and to optimize the input features, feature selection process has to be implemented. The resultant features vectors may be utilized for transient security analysis. In this paper, F-value Feature Selection has been implemented for obtaining feature set.

In the F-value Feature Selection method, the F-value is computed using the expression given by (Pang et al., 1973).

$$F = \frac{|m_s - m_i|}{\sigma_s + \sigma_i} \quad (11)$$

Where,

m_s – mean of the variable in the secure class

m_i – mean of the variable in the insecure class

σ_s^2– variance of the variable in the secure class

σ_i^2- variance of the variable in the insecure class

The F-value gives a count of the classification error that could occur when the variable is used only as feature. Greater the value of 'F', the smaller will be the classification error. Therefore, features with high value of 'F' are used as feature variables.

For feature selection, the F value is computed for all the variables in the data set. The variable having largest value of F is chosen as the first feature. Then, the correlation coefficient between the first feature and the rest of the variables are evaluated. All the variables which are highly correlated to the first feature are discarded thus eliminating most of the least significant variables. Among the rest of the features, a feature with highest F value is selected and it is chosen as the second feature variable. This procedure is repeated until the F values of all the remaining variables are small.

Performance Evaluation Of Classifier:

The performance of a classifier is judged by evaluating the subsequent parameters for test data, training data and overall data set [22].

1. Classification Accuracy (CA):

$$CA\ (\%) = \frac{\text{No of samples classified correctly}}{\text{Total number of samples in data set}} \times 100 \quad (12)$$

2. False Dismissal (FD):

$$FD\ (\%) = \frac{\text{No of insecure classes classified as secure}}{\text{Total no of insecure classes}} \times 100 \quad (13)$$

3. False Alarm (FA):

$$FA\ (\%) = \frac{\text{No of secure clases classified as insecure}}{\text{Total number of secure classes}} \times 100 \quad (14)$$

In power system security evaluation, the false alarms are not much harmful. In case of false dismissals, failure of control events may lead to a rigorous blackout. It is, for that reason, essential to make certain that false dismissals are kept at minimum. The classifier must be professionally planned to satisfy this condition.

RESULTS AND DISCUSSION

Initially, load flow analysis is performed for incremented and decremented values of generation and load between130% to 70% of base value. From the load flow data, steady state security analysis is conducted and the system is classified as steady state secure or steady state insecure. The steady state secure states are subjected to transient security analysis.

An IEEE 14 bus system is used to test the proposed ELM based classifier for transient security assessment (Pai, 2000). The load flow is performed for incremented and decremented values of generation and load and it has been found that from a total of 310 states, 181 states are secure and 129 states are insecure. For transient security analysis, the 129 insecure states are left out and the remaining 181 static secure states are considered for further analysis.Table1 shows the results of Steady state operating scenario.

Table 1: Steady state operating scenario

Number of Operating Scenarios	310
Static secure	181
Static insecure	129

Three phase fault has been simulated in each line and fault is cleared by opening that fault line. The three phase fault is simulated at time t=0 seconds and cleared at time t=0.25 seconds. Table2 shows the results of data generation obtained by off-line simulation and feature selection of the pattern recognition system for the proposed test case.

For transient security assessment, a total of 1062 operating scenarios have been considered. From this, 80% of the 1062 operating scenarios (i.e.) 850 operating scenarios have been used as training data and remaining 212 operating scenarios have been used as test data. The number of features chosen by the F-Value feature selection method, as shown in Table2, is quite less and is obvious from the figure of Dimensionality Reduction. The list of optimal features selected serves as an input database for the design of classifier function.

Table 2: Generation of data set and features for transient security assessment

Total number of Operating Scenarios	1062
Total numbers of training data (80%)	850
Total numbers of testing data (20%)	212
Transient Secure	666
Transient insecure	396
Total number of input variables	249
Features selected after feature selection process	13

Table 3 shows the reduced set of features before and after implementation of F-value feature selection method. The ELM based classifier is trained and tested with features obtained before and after feature extraction and the performance of the classifier is evaluated. It shows that there were 249 features before feature extraction and the number of features has been reduced to 13 after feature selection. The selected features were voltage

angle of bus - 6, reactive power of load at bus-11,realpower demand of bus-2, real power demand of bus-11, real power demand of bus-12, real power demand of bus-10, real power flow in transmission line-16, real power flow in transmission line-12, real power flow in transmission line-15,reactive power flow of transmission line-15 , real power flow of transmission line -2, relative rotor angle of generator-3 and electrical power output of generator-4. It has also been observed that the overall performance increases with implementation of feature extraction process. The computational time has decreased with increased efficiency. Table 3 shows the performance evaluation of proposed ELM classifier.

Table 3: Transient security classification results for IEEE 14 bus system

	Without feature selection		With feature selection	
Performance Evaluation	Training	Testing	Training	Testing
Classification accuracy (CA)%	99.88	92.92	100	98
False Dismissal (FD)%	0	0	0	0
False Alarm (FA)%	0.22	7.08	0	2

Table 4: Comparison of transient security classifications for IEEE 14 bus system

Performance	ELM classifier	DNN	BPNN
Classification accuracy (%)	98	92	84
False dismissal (%)	00	00	00
False alarm (%)	02	08	16

Table 4 shows the effectiveness of ELM classifier for transient security classification purpose. To evaluate the performance level of ELM classifier, its performance has been compared with other NN based classifiers such as DNN and BPNN. It has been observed that the ELM classifier provides better results in terms of classification accuracy and false alarm. The false dismissals are treacherous and will lead to a rigorous blackout. Hence, the classifier should make certain that false dismissals are kept at minimum. In Table 3, it has been observed that the false dismissals are zero with the proposed technique and false alarms are also minimum which proves the robustness of the ELM classifier.

Conclusion:

In this paper, an accurate and swift classifier to appraise the transient security of power system based on extreme learning machine has been described. The security classifier designed based on the proposed extreme learning machine confirms to meet all the requirements of a security assessment system. For a superior performance of ELMs, a fast feature selection method based on F-value is used to identify significant features as the input to ELM. The extreme learning machine classifier model is tested on an IEEE 14 bus standard test case. The misclassified occurrences in the test system are investigated and the proposed scheme is also discussed to reduce the risk of misclassification during the practical implementations. Simulation results clearly show that high accuracy of classification is realizable with extreme learning machine based classifier. The misclassification rate have been confined using ELM. The time taken for training and testing is very less, making it practicable for on-line execution. The false dismissals are zero and false alarms are minimum. The extreme learning machine based classifier gives less misclassification rate reducing the chances of failure of control actions. Thus, the proposed method is appropriate for real time transient security assessment of large scale power systems.

REFERENCES

1. Wood, A.J., B.F. Wollenberg and P. Generation, 1984. Operation and Control John Wiley & Sons. New York.
2. Niazi, K.R., C.M. Arora and S.L. Surana, 2004. Power system security evaluation using ANN: feature selection using divergence. Electric Power Systems Research, 69(2): 161-167.
3. Thamizhselvan, R., and S. Ganapathy, 2016. A New Approach for Static Security Assessment of Power Systems using Core Vector Machine, International Journal Of Advanced Engineering Technology, 7(1): 362-366.
4. Hakim, H., 1992. Application of pattern recognition in transient security assessment. Electric machines and power systems, 20(1): 1-15.
5. Mitra, P., V. Vital, B. Keel, J. Mistry, 2016. A systematic approach to N-1-1 analysis for power system security assessment. IEEE power and energy technology systems Transactions on Power Apparatus and Systems, 3(2): 71-80.
6. Saeh, I., W. Mustafa and N. Al-Geelani, 2016. New Classifier Design for Static Security Evaluation Using Artificial In-telligence Techniques. International Journal of Electrical and Computer Engineering, 6(2): 870-876.

7. Jothinathan, K. and S. Ganapathy, 2016. Transient security assessment in power systems using deep neural network. International Journal of Applied Engineering Research, 10(15): 35787-35790.
8. Silveira, M.C.G., A.D.P. Lotufo and C.R. Minussi, 2003. June. Transient stability analysis of electrical power systems using a neural network based on fuzzy ARTMAP. In IEEE Power Tech Conference Proceedings, Bologna. 3(7): 7-20.
9. Sun, J., H. Zheng, Y. Chai, Y. Hu, K. Zhang and Z. Zhu, 2016. A direct method for power system corrective control to relieve current violation in transient with UPFCs by barrier functions. International Journal of Electrical Power And Energy Systems, 78: 626-636.
10. Yijia, L.I.U.X.J.Q.C.A. and C.H.E.N. Weihua, 2009. Transient security risk assessment of power system based on risk theory and fuzzy reasoning. Electric Power Automation Equipment, 29(2): 15-20.
11. Ukil, A., 2007. Intelligent systems and signal processing in power engineering. Springer Science & Business Media.
12. Boudour, M. and A. Hellal, 2006. Combined use of unsupervised and supervised learning for large-scale power system static security assessment. International journal of power & energy systems, 26(2): 157-163.
13. Huang, G.B., Q.Y. Zhu and C.K. Siew, 2004. July. Extreme learning machine: a new learning scheme of feed forward neural networks. In Neural Networks. Proceedings. IEEE International Joint Conference, 2(4): 985-990.
14. Li, M.B., G.B. Huang, P. Saratchandran and N. Sundararajan, 2005. Fully complex extreme learning machine. Neurocomputing, 68(3): 306-314.
15. Huang, G.B., Q.Y. Zhu and C.K. Siew, 2006. Extreme learning machine: theory and applications. Neurocomputing, 70(1): 489-501.
16. Arora, C.M. and S.L. Surana, 1996. Transient security evaluation and preventive control of power systems using PR techniques. Journal-institution of engineers India part el electrical engineering division,76: 199-203.
17. Tso, S.K., X.P. Gu, Q.Y. Zeng and K.L. Lo, 1998. Deriving a transient stability index by neural networks for power-system security assessment. Engineering Applications of Artificial Intelligence, 11(6): 771-779.
18. Warwick, K., 1997. Artificial intelligence techniques in power systems. Iet.
19. Karami, A. and S.Z. Esmaili, 2013. Transient stability assessment of power systems described with detailed models using neural networks. International Journal of Electrical Power & Energy Systems, 45(1): 279-292.
20. Abdelaziz, A.Y., 2012. Transient Security Classification Using Gene Expression Programming Algorithm. In Proceedings of the Fifteenth International Middle East Power Systems Conference, Alexandria, Egypt.
21. Abdelaziz, A.Y., S.F. Mekhamer, M.A.L. Badr and H.M. Khattab, 2011. Probabilistic Neural Network classifier for static voltage security assessment of power systems. Electric Power Components and Systems, 40(2): 147-160.
22. Lajimi, Ardeshiri, R., and T. Amraee, 2016. A two stage model for rotor angle transient stability constrained optimal power flow. International Journal of Electrical Power & Energy Systems, 76(6): 82-89.
23. Huang, G.B., Q.Y. Zhu and C.K. Siew, 2006. Extreme learning machine: theory and applications. Neurocomputing, 70(1): 489-501.
24. Pai, M.A., 1984. Survey of practical direct methods of stability analysis in power systems. Electric machines and power systems, 9(2-3): 131-143.