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Artificial Neural Network for Power System Static Security Assessment: A Survey

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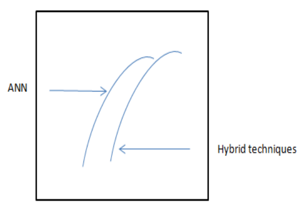
Graphical abstract



Abstract

According to the growth rate of Machine Learning (ML) application in some power system subjects, this paper introduce a comprehensive survey of Artificial Neural Network (ANN) in Static Security Assessment (SSA). Advantages and disadvantages of using ANN in above mentioned subjects and the main challenges in these fields have been explained, too. We explore the links between the fields of SSA and NN in a unified presentation and identify key areas for future research. Recent developments in the solution methods for SSA are reviewed. Hybrid techniques in SSA are also discussed and reviewed and future directions for research are suggested.

Keywords: Artificial neural network; hybrid techniques; static security assessment

Abstrak

Menurut kadar pertumbuhan penggunaan Machine Learning (ML) dalam beberapa subjek sistem kuasa, kertas kerja ini memperkenalkan satu kajian komprehensif tentang rangkaian neural tiruan (ANN) dalam penilaian keselamatan statik (SSA). Kebaikan dan keburukan menggunakan ANN dalam subjek-subjek yang disebutkan di atas serta cabaran utama dalam bidang ini juga telah dijelaskan. Kami meneroka hubungan antara bidang SSA dan NN dalam platfom yang bersepadu serta mengenal pasti bidang utama bagi penyelidikan masa hadapan. Perkembangan terkini dalam kaedah penyelesaian untuk SSA dikaji semula. Teknik-teknik hibrid di dalam SSA juga dibincangkan dan dikaji semula serta arah penyelidikan untuk masa hadapan disyorkan.

Kata kunci: Rangkaian neural tiruan; teknik hibrid; penilaian keselamatan statik

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1.0 INTRODUCTION

Nowadays, electric power system moved toward new Environment that is deregulation which has enforced its utilities to operate under stressed conditions such as closer to their security boundaries. [1]. Consequently, a persuasive needs to develop fast and more accurate real time techniques for monitoring the system security, analyzing the level security and alert network operator to take some compulsory needed actions to prevent the system in arises case needs [2].

The power system operates under two sets of constraints: The load and the operating constraints[3]. The load constraint is an equation constraint which sets the total generation equal to total load plus total power losses. The operating constraints are upper and/or lower limits of system's variables.

Security assessment (SA) and evaluation is an on-line task which is performed in real-time in an Energy Management System (EMS), to determine the current state of the power system. SSA enables us to detect, through simulation, any probable system line overloaded or\and voltage out of limits resulting a list of undesirable contingencies. Due to the large system size and deregulated power system, a steady-state security analysis based on multiple power flows for all credible outages, at frequent intervals, becomes an impossible task due to the associated computation burden.

Generally, security analysis is classified as static and transient [4-6] . after disturbances, static security assessment deals with evaluating and analyzing the system operation in the steady state mode and identifies any likely a system line overload and\or voltage out of limits[7].

On the other hand, Transient Security Analysis (TSA) gauges the system performance as after a disturbance it progresses[8]. Transient security analysis entails evaluation of power system’s ability to withstand a set of severe but credible contingencies and to continue the transition to steady-state satisfactory conditions. Any on-line TSA tool must provide a fast stability evaluation and system security analysis under perturbations.

The static security assessment (SSA) is an vital issue in electric power network when utilities design, plan, operate and control the system[9].

The contingencies severity is judged by performance index (PI) based methods which have been stated in the literatures [10-12]. A traditional methodology would include performing full AC power flow for each contingency occurrence has been stated in [13-15]. All these approaches are in feasible for real time due to its high computational necessities especially, for large scale power network [16, 17]..

1.2 Supervised Learning, General Issues

Supervised Machine Learning (SML) techniques are a set rules learning procedure from examples (instances) in the training dataset. Generally, the procedure when applying these techniques to real world problems is designated in Figure 1.

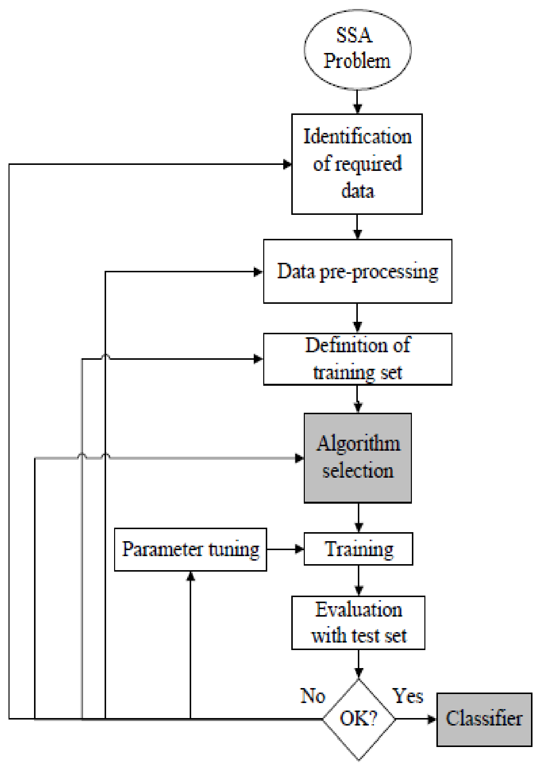

Figure 1 The procedure of supervised ML

As can be seen from this figure, the framework consists of several stages. Firstly, the data can be collected as represented in data generation stage by running the load by several configuration scenarios. Secondly, the attribute extraction and selection stage starts with attribute evaluation. In this stage several algorithms are used to make an optimum selection of the most informative attributes. Moreover, the above mentioned attribute selection approach has been done using two scenarios to insure the best attribute selection. These two scenarios are full training dataset and cross-validation. Finally, classification stage, this stage deals with the optimum selection of the best classifier that can satisfy the target goal of the security assessment. The selection is based on accuracy and computation time.

2.0 SUPERVISED MACHINE LEARNING TECHNIQUES FOR SSA

According to rules of power system operation practice, the longer the monitoring interval, the better the contingency analysis. In an efficient, way AIs are well-suited to deal with SSA as they can be trained off-line and used on-line to classify outages, thanks due to their generalization capabilities. Many researchers have suggested AI algorithms for power system security evaluation. A good security monitoring scheme must be able to assess both overloading and voltage changes. As a result, many AI's techniques have been suggested to overcome the drawbacks of the traditional techniques of security evaluation.

The application of AI algorithms for SSA in power system security has been proposed and suggested by many researchers. A good security monitoring scheme must be able to assess both overloading and voltage changes. An as result, SA has proved one of the most versatile AI techniques applications leading to a large number of publications and an advanced application stage.

An alternative approach, which has been applied successfully at all levels of the network, is state enumeration and solution of a load flow to determine the effects of each contingency upon the system. A particular advantage of this technique is the possibility to define new measures of system adequacy in terms of the overloading of components and/or violations of bus voltage limits. Significant progress has been made to reduce the complications of these techniques [18, 19].

For treatment of very complex systems, a great deal of progress has been made in Monte Carlo simulation techniques [20]. These methods are very flexible in their treatment of system conditions and operating procedures. Their main disadvantage is excessive computation times to account for events of small probability. To overcome the excessive computation times, attempts have been made to make it possible to calculate the adequacy of a power system with some approximations and still provide a satisfactory indication of adequacy performances of the system [21]. Some approximate approaches have been used to calculate the adequacy indices of large power systems [22, 23]. These approximation methods use simplified assumptions or approximate solution techniques. They do not, however, consider all credible outages and failures that might significantly affect the performances of a power system.

Moreover, an operator wants to know precisely the actual disruptions that might trigger insecurity and abnormality, instead of its amount of security [24]. Online security assessment permits the operator to understand the security position as well as assisting in determining corrective actions to be taken. The basic functional needs for these tools are [25]:

The capability to construct genuine pictures for the system state over dissimilar time casings (intraday, a day ahead, in real time and so on).

- The capability to define reliability criteria and security restrictions.
- The capability to assess the system security using running time domain simulations.

In recent years, many Artificial Intelligence (AI) techniques have been proposed to overcome the pitfalls of the traditional method of security evaluation.

Due to computational requirements, it is hard to use conventional approaches through real time, especially for large system and the deregulated power system which makes the steady-state security analysis an impossible task.

Superior algorithm to others is not the vital problem when dealing with ML techniques classifiers, but a particular technique can considerably outperform others on a given problem. So, there is essential pressing to develop as fast as possible for real time monitoring technique, which could evaluate the security level[2].

2.1 Artificial Neural Network (ANN)

Digital computers are used in the implementation of ANN's, both biological and Artificial Neural Networks are non-digital massively parallel computational devices. Reference [16] made differences between digital and neural computers: An ANN is an extremely elementary processors connected array [26] and it capable of learning from training [27].

ANN [28-31] promises successful and fast assessment for large power system compared to the conventional method like DC load flow and AC load flow methods. ANN techniques have been implemented broadly in the field of electric power system. The most popular method is ANN, because of its ability to classify patterns and its good accuracy in comparison with other machine learning methods. Its disadvantages can be listed in [32]. There are different types of ANN where each type is suitable for a specific application. Most of the published work in this area utilizes multilayer perceptron (MLP) model based on back propagation (BP) algorithm, which usually encounters to local minima and overfitting problems.

An alternative method using neural networks to address the SA problem and its effectiveness against conventional methods is discussed. Most of the method work as classifier or mapping the security level and view immediate contingency risk.

Among these works, El-Sharkawi [33-37] has focused on power system SSA. ANNs have shown great promise as means of predicting the security of large electric power systems. ANNs have been used for classifying the static security of a power system.

ANN techniques gained popularity in respect of the traditional one as they are capable to discover matches among huge datasets and accurately make mappings in complex manner. in literature. related to SSA [31, 38] and DSA [39-41] study work have been stated.

The key problems of power system monitoring and control is presented and reviewed using new studies based on various controllers ANN technique as discussed in [42]. The literature shows that the performance of the controller in terms of speed, accuracy and efficiency has improved.

2.1.1 Back Propagation Neural Network (BPNN)

Back propagation (BP) training paradigm, likewise, effectively explained by [43]. The compromise attaining the on-line speeds will be the huge amounts associated with processing needed off-line. Multilayer Feed forward uses the back propagation algorithm [44] happen to be applied to the situation connected with SSA. Fischer [45] showed how a number of BP neural networks could be conditioned to forecast power system security after a contingency.

2.1.2 Self-Organizing Map (SOM)

A number of methods have already been suggested to evaluate static security with the Kohonen Self-Organizing Map (KSOM) neural network [31, 46]. Authors [47] and [48] described the usage of KSOM to perform SA in a power system. A short description of the ANNs which compose the KSOM architecture has been presented. Better classification separation and partitioning dimensional decrease was attained with a characteristic collection plan according to Karhunen-Loe've development.

2.1.3 Kohonen's Self-Organizing Feature Map (SOFM)

Kohonen's SOFM has been proposed in the feasibility of classification of load pattern's demonstration of SSA using Kohonen and SOFM [49] and [31]. The most important feature and aspect of this network are its property of generalization. The network successfully classifies the unknown loading patterns, especially useful for power system operation.

2.1.4 Counter Propagation Neural Network (CPNN)

A Counter Propagation Neural Network (CPNN) is a hybrid learning network [50]. It combines a Kohonen layer of unsupervised learning with another layer of supervised learning, which uses the basic delta rule. It has compared the Multilayer Feed Forward Network (MFFN) with Error Back Propagation Algorithm (EBA) for SSA. Its advantage is a small time required compared to the time taken even by fast decoupled load flow.

To reduce the effective problem dimension, a feature selection technique has been adopted and to achieving high speeds of execution and good classification accuracy to improve the efficiency and effectiveness of large-scale power systems SA, a new significantly approach is proposed [48].

2.1.5 Multi-Layered Perceptron (MLP)

The most famous technique is ANN, simply because of its capability to categorize designs as well as its superior reliability when compared to different machine learning techniques. Its drawbacks could be outlined by [32]. Various kinds of ANN can be found at which each kind would work in any particular application. The majority of the written and published efforts within this field make use of a Multi-Layer Perceptron (MLP) design according to Back Propagation (BP) algorithm, which always suffers from ancient minima as well as overfitting difficulties.

Commonly, Neural Network (NN) which fulfills these kinds of circumstances is simply MLP with a back propagation training algorithms [32]. The reason behind this can be on-line learning ability. The two main issues with implementing MLP are choosing input data and the over training.

An effective technique for initial challenges utilized a few of the security indicators computed through the energy management system (EMS) which is the input to the ANN. To get rid of the most-recent challenge while using the back propagation along with a selective training algorithms proposed.

2.1.6 Radial Basic Function (RBF)

Radial Basis Function Network (RBFN) is actually broadly used in pattern classification along with a nonlinear function approximation, as a result of benefits of faster training procedure; the rate of convergence won't encounter the issue regarding neighborhood minima. A change in the input layer towards the hidden layer will be nonlinear while the actual change from the hidden layer to the output layer will be linear.

RBF is used for the contingency evaluation of a power system, which is to exploit the non-linear mapping capabilities of RBF in estimating line thermal and bus voltage [51]. Euclidean distance-based clustering method has already been used to choose the number of hidden (RBF) units and unit centers in the RBF neural network [52]. An element choice method using the type separability index and correlation coefficient continues to be used to find out the inputs to that RBF network. Piglione [53] proposed a fast online method based for SSA on an original progressive learning ANN. Firstly, the influence zone of each outage is located and then a dedicated ANN is trained to forecast the post-fault value of critical line flows and bus voltages.

RBF has been recommended to evaluate SSA and compared to other algorithms [54]. Contrasting with MLP, RBFN according to developing and trimming algorithm needs fewer calculation periods because the network includes the shorter period, which is appropriate for online SSA.

RBFN continues to be created productive power contingency screening and voltage stability assessment in [55, 56] as well as a different RBFN has been properly trained for every contingency. The amounts of neurons places and unit radius from the RBFN considerably affect the actual category reliability to get a monitored design category difficulty.

In [57], this study suggests an attribute selection and classification algorithms for static security evaluation (SSE) and its impact is proposed.

In [58], RBFN according to growing as well as pruning algorithm and Winner-Take-All have already been offered to examine static security in various IEEE test systems. Another benefit, the teaching associated with RBFN according to growing and a pruning algorithms demands a fewer calculation periods when compared with the MLP design and the evaluating precision associated with RBFN has been greater through the use of growing and the pruning algorithms.

In [59] presents a fresh classifier according to Gene-Term Programming (GEP). The algorithm is actually designed like a multi-class category challenge when using the one-against-all binarization technique. This algorithm can be in comparison to the Probabilistic Neural Network (PNN), Radial Basis Function Network (RBFN) and the Back-Propagation Neural Network (BPNN). The GEP classification algorithm demonstrates remarkable benefits in the assessment of other methods. The GEP and PNN algorithms exclusively provide the implicit attribute to attaining absolutely no mistake upon designs this has been trained to, which in turn force's category accuracy of 100%.

Sedey in [58] presents an enhanced RBF for line-flow contingency screening and fast voltage. Based on correlation coefficient and class separability index, a feature selection method has been employed.

The actual efficiency in all kinds of established methods is extremely difficult task and therefore, falls short of generalization capability. In addition, as a result of nature from the key in characteristics applied, these techniques are located to remain incompetent at promptly forecasting the long term insecure operation [60]. The main advantages of using NNs are for SSA can be listed as follows:

- Its ability of fixing stochastic differences from the planned working level having been growing data.
- Very quick as well as on-line processing and category.
- Implicit nonlinear modelling and filtering of system data.

3.0 HYBRID INTELLIGENT PROCEDURES (HIP)

HIP's means software which works a combination from artificial intelligence techniques In the past couple of years, there was a growing debate over the significance of AI systems integration. According to thoughts that there have been completely designed simple and easy particular AI programs (for example, methods regarding computer vision, speech functionality, and so forth, alternatively, even software, which uses a few of the designs stated earlier) and henceforth, onwards it was time to develop wide AI systems.

Evolutionary methods have been reviewed and presented in [61]. Electric power networks and the optimization problems using different PSO in a comprehensive coverage mode is presented. Key advantages of PSO over other optimization algorithms are highlighted with promising future applications [62].

An optimal generation scheduling model is presented [63]. Multi-objective problem was defined the gaseous pollutants' emission, the cost of the fuel and the unavailability of power generation.

Genetic based neural network emphasizes the use of genetic algorithm to identify the actual maximum ideals with the ANN variables, for example, the momentum, learning rate, and the hidden neurons. [64], The gene-based ANN strategists have been applied in the Malaysian power system. By implementing the genetic-based ANN, the selection of the ANN parameters by experimentation approach could be prevented, and the outcomes prove that the precision in the genetic-based ANN approach is actually better than_those of the actual non-genetic-based ANN [65].

Query-based learning approach in neural networks used to solve SSA problems in a power system [66]. This learning method is intrinsically different from the learning performed by randomly generated data. Query-based learning is a methodology that requires asking a partially trained neural network to respond to the questions. The response to the query is taken to the Oracle. An Oracle makes judicious decisions that improve the quality of training data, thereby guaranteeing the assessment results. Moreover, to improve the learning performance, the method is enhanced with the aid of genetic algorithms. Therefore, the neural network is intelligently guided to a near-optimal initialization. The probability of learning stagnation can be thus decreased.

The Unit Commitment (UC) problem has become gradually complex with growing electric power system sizes [67]. PSO is used to solve the key UC problem for the system security and optimal system operation by the Optimal Power Flow (OPF) subroutine running in every UC planning period interval (hour).

Author [68] suggests PSO algorithm for solving OPF problem with security restrictions. The proposed approach to attain the optimal power dispatch for a given load minimized the fuel cost with satisfaction of security constraints and all operating conditions. The results indicate the robustness and powerfulness of the proposed PSO algorithm to solve the problem of OPF.

The Bayesian Network (BN) is learnt by PSO based parameters learning algorithm for power system fault diagnosis model and proposed [69]. An experiential mathematical case study is employed to prove the efficiency of the proposed algorithm.

A comparative study of PSO in RBFN training with the advantages and weaknesses of the approach with key identification are presented [70].

PSO together with the conventional K-means algorithm, a mixed algorithm to fulfil the specifications for a classifier and to achieve high accuracy in security evaluation is proposed. [71], The way the conventional K-means clustering algorithm might be of course profitably improved to be utilized like a classifier algorithm is shown. The classifier called security function was made using the proposed PSO based K-means clustering (PSOKM) algorithm. A PSO centered category for static security assessment in power systems has been suggested [72]. A simple and fast process is utilized to choose only a few parameters just as the characteristics of the big group of elements, which might be normally in power systems. A straightforward sequence security performance was made to make use of the chosen characteristics' category. The training of weights with the classifier performs (security function) is done with PSO method. The PSO algorithm provides reduced mistake rate in the category. The process to determine the security function (classifier) is reviewed.

SVM classifier designed with parameter selection is compared to other optimization techniques [72]. The parameter selection methods use PSO [73], Differential Evolution (DE) [74] and Genetic Algorithm (GA) [75]. The results are compared with the Grid Search (GS) parameter selection technique.

SVM has been used for a multi-classification task in a security assessment model [76]. Although SVM is basically intended for binary classification, the concept of multi-class, SVM also exists.

Based on SVM, [77] proposes a network safety risk assessment method. Moreover, based upon the theory of statistical learning SVM is applied to judge the transient stability of power system networks after faults happened on transmission lines [78]. Results showed that the SVM with RBF Kernel reached the highest accuracy of classification.

Various heuristic optimization techniques used in selecting SVM variables also addressed in [79]. Simulation work performed using the possible execution of the suggested SVM classifier regarding on-line security assessment is also discussed.

In [80], the NN designs used with regard to classification, the models developed are usually examined upon different IEEE test systems. The actual efficiency of numerous NN designs is usually analyzed while in training and examining stages, and the outcomes are compared.

Literatures have also described the usage of ANN centered pattern recognition (PR) strategy [81, 82]. ANN using a pattern recognition methodology for SA of electric power systems is presented [83].

Sidhu [84] has combined ANN with Fast Fourier Transform to improve the ANN training and construct performance indices for additional input. Really good computation precision, large contingency recording rate and quicker evaluation are usually acquired through the use of BP neural network.

Neural network and wavelet transform has been suggested for assessing online voltage stability [85]. The new approach is based on feature selection of voltage profile of the network.

■4.0 CONCLUSION

This paper describes the best-known Artificial Neural Network (ANN) techniques in qualified and virtual details for SSA with their advantages and disadvantages. Of course, our list of references is not wide-ranging papers listed to discuss supervised ANN methods while the target was to give a critical survey of the key ideas, rather than a simple list of all publications and authors wish that the references listed cover the issues well. The links between the fields of SSA and NN in a unified presentation and identify key areas for future research has been explore. Although, ANN techniques for SSA discussed still lack the properties of fast computation time and acceptable accuracy. Hybrid techniques have been discussed to solve these disadvantages. Further research needed to focus on these properties and techniques to improve the accuracy and computation time in deregulated power system.

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References

[1] Niazi, K., C. Arora, and S. Surana. 2004. Power System Security Evaluation using ANN: Feature Selection Using Divergence. *Electric Power Systems Research*. 69(2): 161–167.

[2] Kirschen, D. S. 2002. Power System Security. *Power Engineering Journal*. 16(5): 241–248.

[3] Dy Liacco, T. 1967. The Adaptive Reliability Control System. Power Apparatus and Systems. *IEEE Transactions on*. 5: 517–531.

[4] Grillo, S. 2008. Static Security Assessment of Electrical Power Systems Using Neural Classification Techniques. Mathematical Problems in Engineering, Aerospace and Sciences.

[5] Fouad, A. *et al.* 1988. Dynamic Security Assessment Practices in North America. Power Systems. *IEEE Transactions on.* 3(3): 1310–1321.

[6] Balu, N. *et al*. 1992. On-line Power System Security Analysis. Proceedings of the IEEE. 80(2): 262–282.

[7] Mahadev, P. M. and R. D. Christie. 1994. Envisioning Power System Data: Vulnerability and Severity Representations for Static Security Assessment. Power Systems. *IEEE Transactions on*. 9(4): 1915–1920.

[8] Shahidehpour, M. and Y. Wang. 2003. *Communication and Control in Electric Power Systems: Applications of Parallel and Distributed Processing.* Wiley-IEEE Press.

[9] Zaborszky, J., K.W. Whang, and K. Prasad. 1980. Fast Contingency Evaluation Using Concentric Relaxation. Power Apparatus and Systems. *IEEE Transactions on*. 1: 28–36.

[10] Singh, S. and S. Srivastava. 1998. Improved Contingency Selection Algorithm for Voltage Security Analysis. *Electric Machines and Power Systems.* 26(8): 855–871.

[11] Ejebe, G. and B. Wollenberg. 1979. Automatic Contingency Selection. Power Apparatus and Systems. *IEEE Transactions on*. 1: 97–109.

[12] Verma, K. and K. Niazi. 2012. Supervised Learning Approach to Online Contingency Screening and Ranking in Power Systems. *International Journal of Electrical Power & Energy Systems*.

[13] Stott, B. and O. Alsac. 1974. Fast Decoupled Load Flow. Power Apparatus and Systems. *IEEE Transactions on*. 3: 859–869.

[14] Mori, H., H. Tanaka, and J. Kanno. 1995. A Preconditioned Fast Decoupled Power Flow Method for Contingency Screening. in Power Industry Computer Application Conference. Conference Proceedings, IEEE. 1995: IEEE.

[15] Brandwajn, V. and M. Lauby, Complete bounding method for AC contingency screening. Power Systems, IEEE Transactions on, 1989. 4(2): p. 724-729.

[16] Pang, C. K., A. J. Koivo, and A. H. El-Abiad. 1973. Application of Pattern Recognition to Steady-State Security Evaluation in a Power System. *IEEE Transactions on Systems, Man and Cybernetics.* SMC-3(6): 622–631.

[17] Pang, C. K., *et al.* 1974. Security Evaluation in Power Systems Using Pattern Recognition. *IEEE Trans Power Appar Syst.* PAS-93(3): 969–976.

[18] Ozdemir, A., J. Y. Lim, and C. Singh. 2002. Line Outage Simulation by Bounded Network Solution. IEEE.

[19] Pang, C. and A. Wood. 1975. Multi-Area Generation System Reliability Calculations. Power Apparatus and Systems. *IEEE Transactions on*. 94(2): 508–517.

[20] Billinton, R. 1969. Composite System Reliability Evaluation. Power Apparatus and Systems. *IEEE Transactions on.* 4: 276–281.

[21] Ranade, S. J. and R. Sullivan. 1981. A Reliability Analysis Technique For Bulk System Planning. Power Apparatus and Systems. *IEEE Transactions on.* (7): 3658–3665.

[22] Mikolinnas, T., W. Puntel, and R. Ringlee. 1982. Application of Adequacy Assessment Techniques for Bulk Power Systems. Power Apparatus and Systems. *IEEE Transactions on.* 5: 1219–1228.

[23] Mamandur, K. and G. Berg. 1982. Efficient Simulation of Line and Transformer Outages in Power Systems. Power Apparatus and Systems. *IEEE Transactions on.* 10: 3733–3741.

[24] Srivani, J. and K. Swarup. 2008. Power System Static Security Assessment and Evaluation Using External System Equivalents. *International Journal of Electrical Power & Energy Systems*. 30(2): 83–92.

[25] Panciatici, P., G. Bareux, and L. Wehenkel. 2012. Operating in the Fog: Security Management Under Uncertainty. Power and Energy Magazine, IEEE. 10(5): 40–49.

[26] Carpentier, J. 1993. Static Security Assessment and Control: A Short Survey. IEEE.

[27] Niebur, D. and A.J. Germond. 1992. Unsupervised Neural Net Classification of Power System Static Security States. *International Journal of Electrical Power & Energy Systems.* 14(2–3): 233–242.

[28] Swarup, K. S. 2008. Artificial Neural Network Using Pattern Recognition for Security Assessment and Analysis. *Neurocomputing*. 71(4): 983–998.

[29] Zhou, Q., J. Davidson, and A. Fouad. 1994. Application of Artificial Neural Networks in Power System Security and Vulnerability Assessment. *Power Systems, IEEE Transactions on.* 9(1): 525–532.

[30] Wehenkel, L. A. 1997. *Automatic Learning Techniques in Power Systems.* Springer.

[31] Niebur, D. and A. J. 1992. Germond, Power System Static Security Assessment Using the Kohonen Neural Network Classifier. *Power Systems, IEEE Transactions on*. 7(2): 865–872.

[32] Mohammadi, M. and G. Gharehpetian. 2008. Power System On-line Static Security Assessment by Using Multi-Class Support Vector Machines. *Journal of Applied Sciences.* 8(12): 2226–2233.

[33] Rathinam, A. and S. Padmini. 2007. Security Assessment of Power Systems Using Artificial Neural Networks-A Comparison Between Euclidean Distance Based Learning and Supervised Learning Algorithms. IEEE.

[34] Aggoune, M., *et al.* 1989. Preliminary Results on Using Artificial Neural Networks for Security Assessment [of power systems]. IEEE.

[35] Aggoune, M., *et al.* 1989. Artificial Neural Networks for Power System Static Security Assessment. IEEE.

[36] El-Sharkawi, M. and R. Atteri. 1993. Static Security Assessment of Power System Using Kohonen Neural network. IEEE.

[37] Weerasooriya, S., *et al.* 1992. Towards Static-security Assessment of a Large-Scale Power System Using Neural Networks. Generation, Transmission and Distribution [see also IEE Proceedings-Generation, Transmission and Distribution], IEE Proceedings. 139(1): 64–70.

[38] El-Keib, A. and X. Ma. 1995. Application of Artificial Neural Networks in Voltage Stability Assessment. *Power Systems, IEEE Transactions on*. 10(4): 1890–1896.

[39] Sobajic, D. J. and Y. H. Pao. 1989. Artificial Neural-net Based Dynamic Security Assessment for Electric Power Systems. *Power Systems, IEEE Transactions on*. 4(1): 220–228.

[40] Karami, A. 2011. Power System Transient Stability Margin Estimation Using Neural Networks. *International Journal of Electrical Power & Energy Systems.* 33(4): 983–991.

[41] Lin, Y. J. 2011. Prevention of Transient Instability Employing Rules Based on Back Propagation based ANN for Series Compensation. *International Journal of Electrical Power & Energy Systems.*

[42] Hassan, L. H. *et al*. 2013. Current state of Neural Networks Applications in Power System Monitoring and Control. *International Journal of Electrical Power & Energy Systems*. 51: 134–144.

[43] Bansal, R., Overview and literature survey of artificial neural networks applications to power systems (1992-2004). Journal of the Institution of Engineers (India). Part EL, 2006. 86(1): p. 282-296.

[44] Saeh, I. and A. Khairuddin. 2008. Static Security Assessment Using Artificial Neural Network. In Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International. IEEE.

[45] Fischer, D., B. Szabados, and S. Poehlman. 2003. Automatic Contingency Grouping Using Partial Least Squares and Feed Forward Neural Network Technologies Applied to the Static Security Assessment Problem. IEEE.

[46] Srinivasan, D., *et al*. 1998. Power System Security Assessment and Enhancement Using Artificial Neural Network. In Energy Management and Power Delivery, 1998. Proceedings of EMPD '98. 1998 International Conference on.

[47] Cirrincione, G., M. Cirrincione, and F. Piglione. 1996. A Neural Network Architecture for Static Security Mapping in Power Systems. IEEE.

[48] Tso, S., *et al.* 1998. A Hybrid Framework of Short-duration Simulation and ANN-based Transient Stability Assessment for Contingency Screening. IEEE.

[49] Swarup, K. and P. B. CORTHIS. 2006. Power system Static Security Assessment Using Self-Organizing Neural Network. *J. Indian Inst. Sci*. 86: 327–342.

[50] Haque, M.T. and A.M. Kashtiban. 2005. Application of Neural Networks in Power Systems; A Review. Proceedings of World Academy of Science, Engineering and Technology. 6: 53–57.

[51] Maghrabi, H., J. Refaee, and M. Mohandes. 1998. Contingency Analysis of Bulk Power System Using Neural Networks. IEEE.

[52] Jain, T., L. Srivastava, and S.N. Singh. 2003. Fast voltage Contingency Screening Using Radial Basis Function Neural Network. *IEEE Transactions on Power Systems*. 18(4): 1359–1366.

[53] Napoli, R. and F. Piglione. 1996. On-line static Security Assessment of Power Systems By A Progressive Learning Neural Network. IEEE.

[54] Javan, D., H. R. Mashhadi, and M. Rouhani. 2010. Static Security Assessment Using Radial Basis Function Neural Networks Based On Growing And Pruning Method. IEEE.

[55] Ranaweera, D. and G. Karady. 1994. Active Power Contingency Ranking Using a Radial Basis Function Network. *Int. J. Eng. Intell. Syst. for Elect. Eng. Communications*. 2(3): 201–206.

[56] Devaraj, D. and J. Preetha Roselyn. 2011. On-line Voltage Stability Assessment Using Radial Basis Function Network Model with Reduced Input Features. *International Journal of Electrical Power & Energy Systems*. 33(9): 1550–1555.

[57] Saeh, I. and M. Mustafa. 2013. Performance Evaluation of Deregulated Power System Static Security Assessment using RBF-NN Technique. *Jurnal Teknologi*. 64(1).

[58] Seyed Javan, D., H. Rajabi Mashhadi, and M. Rouhani. 2013. A Fast Static Security Assessment Method Based On Radial Basis Function Neural Networks Using Enhanced Clustering. *International Journal of Electrical Power & Energy Systems.* 44(1): 988–996.

[59] Khattab, H., *et al*. 2012. Gene Expression Programming for Static Security Assessment of Power Systems. In Power and Energy Society General Meeting, IEEE. 2012: IEEE.

[60] Kalyani, S. and K. Swarup. 2011. Particle Swarm Optimization Based K-Means Clustering Approach for Security Assessment In Power Systems. Expert Systems with Applications.

[61] Kothari, D. 2012. Power system optimization. In Computational Intelligence and Signal Processing (CISP), 2012 2nd National Conference on. IEEE.

[62] AlRashidi, M. R. and M. E. El-Hawary. 2009. A Survey of Particle Swarm Optimization Applications In Electric Power Systems. *Evolutionary Computation, IEEE Transactions on*. 13(4): 913–918.

[63] Gjorgiev, B., D. Kančev, and M. Čepin. 2013. A New Model for Optimal Generation Scheduling of Power System Considering Generation Units Availability. *International Journal of Electrical Power & Energy Systems*. 47: 129–139.

[64] Mohamed, A., S. Maniruzzaman, and A. Hussain. 2001. Static Security Assessment of a Power System Using Genetic-Based Neural Network. *Electric Power Components and Systems*. 29(12): 1111–1121.

[65] Haghifam, M. and V. Zebarjadi. 1996. Fuzzy logic and Neural Network Approach to Static Security Assessment for Electric Power Systems. In Proceedings of 4th European Congress on Intelligent Techniques and Soft Computing.

[66] Huang, S. J. 2001. Static Security Assessment of a Power System Using Query-Based Learning Approaches with Genetic Enhancement. In Generation, Transmission and Distribution, IEE Proceedings. IET.

[67] Gaddam, R. R., A. Jain, and L. Belede. 2013. A PSO Based Smart Unit Commitment Strategy for Power Systems Including Solar Energy. in Proceedings of Seventh International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA 2012). Springer.

[68] Sharma, B. and M. Pandit. 2012. Security Constrained Optimal Power Flow Employing Particle Swarm Optimization. In Electrical, Electronics and Computer Science (SCEECS), 2012 IEEE Students' Conference on. IEEE.

[69] Shi, Q., *et al*. 2013. Study on Bayesian network parameters learning of power System Component Fault Diagnosis Based on Particle Swarm Optimization. *Int. J. Smart Grid Clean Energy*. 2(1): 132–137.

[70] Mohammed, S. N .Q. 2010. Learning Enhancement of Radial Basis Function Network with Particle Swarm Optimization.

[71] Kalyani, S. and K. S. Swarup. 2011. Particle Swarm Optimization Based K-Means Clustering Approach for Security Assessment in Power Systems. *Expert Systems with Applications*. 38(9): 10839–10846.

[71] Kalyani, S. and K.S. Swarup. 2011. Classifier Design for Static Security Assessment Using Particle Swarm Optimization. *Applied Soft Computing*. 11(1): 658–666.

[73] Lin, S. W. 2008. *et al*. Particle Swarm Optimization for Parameter Determination and Feature Selection of Support Vector Machines. *Expert Systems With Applications.* 35(4): 1817–1824.

[74] Wu, S. Z. L. and X. Y. W. Tan. Parameters Selection of SVM for Function Approximation Based on Differential Evolution.

[75] Wu, C. H., *et al.* 2007. A real-valued Genetic Algorithm to Optimize the Parameters of Support Vector Machine for Predicting Bankruptcy. *Expert Systems With Applications.* 32(2): 397–408.

[76] Abe, S. 2010. *Support Vector Machines for Pattern Classification.* Springer-Verlag New York Inc.

[77] Chen, X. and Y. Li. Network Security Evaluation Based on Support Vector Machine. in Proceedings of the 2nd International Conference on Green Communications and Networks 2012 (GCN 2012): Volume 3. 2013: Springer.

[78] Ye, S., *et al*. 2012. Power System Transient Stability Assessment Based on Adaboost and Support Vector Machines. In Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific. IEEE.

[79] Kalyani, S. and K.S. Swarup. 2011. Classification and Assessment Of Power System Security Using Multiclass SVM. Systems, Man, and Cybernetics, Part C: Applications and Reviews. *IEEE Transactions on*.. 41(5): 753–758.

[80] Kalyani, S. and K. S. Swarup. 2009. Study of Neural Network Models for Security Assessment in Power Systems. *International Journal of Research and Reviews in Applied Sciences.* 1(2): 104–117.

[81] Boudour, M. and A. Hellal. 2005. Combined Use of Supervised and Unsupervised Learning for Power System Dynamic Security Mapping. Engineering Applications of Artificial Intelligence. 18(6): 673–683.

[82] Luan, W., K. Lo, and Y. Yu. 2000. ANN-based Pattern Recognition Technique for Power System Security Assessment. IEEE.

[83] Kashtiban, A. M. and M. Valizadeh. Application of Neural Networks in Power System Security Assessment.

[84] Sidhu, T.S. and L. Cui. 2000. Contingency Screening for Steady-State Security Analysis by using FFT and Artificial Neural Networks. *Power Systems, IEEE Transactions on*. 15(1): 421–426.
[85] Hashemi, S. and M. R. Aghamohammadi. 2013.Wavelet Based Feature Extraction of Voltage Profile For Online Voltage Stability Assessment Using RBF Neural Network. *International Journal of Electrical Power & Energy System*s. 49: 86–94.