Implementation of Artificial Intelligence Techniques for Steady State Security Assessment in Pool Market

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Abstract

Various techniques have been implemented to include steady state security assessment in the analysis of trading in deregulated power system, however most of these techniques lack requirements of fast computational time with acceptable accuracy. The problem is compounded further by the requirements to consider bus voltages and thermal line limits. This work addresses the problem by presenting the analysis and management of power transaction between power producers and customers in the deregulated system using the application of Artificial Intelligence (AI) techniques such as Neural Network (ANN), Decision Tree (DT) techniques and Adaptive Network based Fuzzy Inference System (ANFIS). Data obtained from Newton Raphson load flow analysis method are used for the training and testing purposes of the proposed techniques and also as comparison in term of accuracy against the proposed techniques. The input variables to the AI systems are loadings of the lines and the voltage magnitudes of the load buses. The algorithms are initially tested on the 5 bus system and further verified on the IEEE 30 57 and 118 bus test system configured as pool trading models. By comparing the results, it can be concluded that ANN technique is more accurate and better in term of computational time taken compared to the other two techniques. However, ANFIS and DT's can be more easily implemented for practical applications. The newly developed techniques can further improve security aspects related to the planning and operation of pool-type deregulated system.

Keywords: Artificial intelligence, deregulated system.

1. INTRODUCTION

Power industry in the world is undergoing a profound restructuring process [1]. The main goal is to introduce competition so as to realize better social welfares, higher quality services and improved investment efficiency. Security is defined as the capability of guaranteeing the continuous operation of a power system under normal operation even following some significant perturbations [2].

The new environment raises questions concerning all sectors of electric power industry. Nevertheless, transmission system is the key point in market development of a deregulated market since it puts constraints to the market operation due to technical requirements. Especially, in systems having weak connections among areas, congestion problems arise due to line overloading or to voltage security requirements especially during summer [3].

The deregulation of the electric energy market has recently brought to a number of issues regarding the security of large electrical systems. The occurrence of contingencies may cause dramatic interruptions of the power supply and so considerable economic damages. Such difficulties motivate the research efforts that aim to identify whether a power system is insecure and to promptly intervene. In this paper, we shall focus on Artificial Intelligence for the purpose of steady state security assessment and rapid contingency evaluation [4]. For reliability analysis of fault-tolerant multistage interconnection networks an irregular augmented baseline network (IABN) is designed from regular augmented baseline network (ABN) [5].

In the past, the electric power industry around the world operated in a vertically integrated environment. The introduction of competition is expected to improve efficiency and operation of power systems. Security assessment, which is defined as the ability of the power system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system load, is one of the important issues especially in the deregulated environment [6]. When a contingency causes the violation of operating limits, the system is unsafe. One of the conventional methods in security assessment is a deterministic criterion, which considers contingency cases, such as sudden removals of a power generator or the loss of a transmission line. Such an approach is time consuming for operating decisions due to a large number of contingency cases to be studied. Moreover, when a local phenomenon, such as voltage stability is considered for contingency analysis, computation burden is even further increased. This paper tries to address this situation by treating power system security assessment as a pattern classification problem.

A survey of several power flow methods are available to compute line flows in a power system like Gauss Seidel iterative method, Newton-Raphson method, and fast decoupled power flow method and dc power flow method but these are either approximate or too slow for on-line implementation in [7,8].With the development of artificial intelligence based techniques such as artificial neural network, fuzzy logic etc. in recent years, there is growing trend in applying these approaches for the operation and control of power system [8,9]. Artificial neural network systems gained popularity over the conventional methods as they are efficient in discovering similarities among large bodies of data and synthesizing fault tolerant model for nonlinear, partly unknown and noisy/ corrupted system. Artificial neural network (ANN) methods when applied to Power Systems Security Assessment overcome these disadvantages of the conventional methods. ANN methods have the advantage that once the security functions have been designed by an off-line training procedure, they can be directly used for on-line security assessment of Power Systems. The computational effort for on-line security assessment using real-time systems data and for security function is very small. The previous work (10,11,12,13) have not addressed the issue of large number of possible contingencies in power system operation. Current work has developed static security assessment using ANN with minimum number of cases from the available large number of classified contingencies. The proposed methodology has led to reduction of computational time with acceptable accuracy for potential application in on line security assessment. Most of the work in ANN has not concentrated on developing algorithms for ranking contingencies in terms of their impact on the network performance.

Such an approach is described in Ref. [14], where DTs are coupled with ANNs. The leading idea is to preserve the advantages of both DTs and ANNs while evading their weaknesses [15].A review of existing methods and techniques are presented in [16].

A wide variety of ML techniques for solving timely problems in the areas of Generation, Transmission and Distribution of modern Electric Energy Systems have been proposed, Decision

Trees, Fuzzy Systems and Genetic Algorithms have been proposed or applied to security assessment[17] such as Online Dynamic Security Assessment Scheme[18].

3 Existing Models of Deregulation

The worldwide current developments towards deregulation of power sector can be broadly classified in following three types of models [19].

3.1 Pool model

In this model the entire electricity industry is separated into generation (gencos), transmission (transcos) and distribution (discos) companies. The independent system operator (ISO) and Power exchanger (PX) operates the electricity pool to perform price-based dispatch of power plants and provide a form for setting the system prices and handling electricity trades. In some cases transmission owners (TOs) are separated from the ISO to own and provide the transmission network. The England & Wales model is typical of this category. The deregulation model of Chile, Argentina and East Australia also fall in this category with some modifications.

3.2 Pool and bilateral trades model

In this model participant may not only bid into the pool through power exchanger (PX), but also make bilateral contracts with others through scheduling coordinators (SCs).
Therefore, this model provides more flexible options for transmission access. The California model is of this category. The Nordic model and the New Zeeland model almost fall into this category with some modifications.

3.3 Multilateral trades model

This model envisages that multiple separate energy markets, dominated by multilateral and bilateral transactions, which coexist in the system and the concept of pool and PX disappear into this multi-market structure. Other models such as the New York Power Pool (NYPP) model fall somewhere in between these three models.

4 ARTIFICIAL INTELLIGENCE (AI) METHODS

Artificial Neural Networks (ANNs), Decision Trees (DTs) and Adaptive Network based Fuzzy Inference System (ANFIS) belong to the Machine Learning (ML) or Artificial Intelligence (AI) methods. Together with the group of statistical pattern recognition, they form the general class of supervised learning systems. And while their models are quite different, their objective of classification and prediction remains the same; to reach this objective, learning systems examine sample solved cases and propose general decision rules to classify new ones; in other words, they use a general “pattern recognition” (PR) type of approach.
For the Static Security Analysis the phenomenon is the secure or insecure state of the system characterized by violation of voltage and loading limits, and the driving variables, called attributes, are the control variables of the system. In the problem examined the objects are pre fault operating states or points (OPs) defined by the control variables of the System and are partitioned in two classes, i.e. SAFE or UNSAFE.
AI's when used for static security assessment, operate in two modes: training and recall (test). In the training mode, the AI learns from data such as real measurements of off-line simulation. In the recall mode, the AI can provide an assessment of system security even when the operating conditions are not contained in the training data.

4.1 Artificial Neural Networks (ANNs)

ANN is an intelligent technique, which mimics the functioning of a human brain. It simulates human intuition in making decision and drawing conclusions even when presented with complex, noisy, irrelevant and partial information.
ANN's systems gained popularity over the conventional methods as they are efficient in discovering similarities among large bodies of data and synthesizing fault tolerant model for nonlinear, partly unknown and noisy/ corrupted system. An artificial neural network as defined by Hect-Nielsen [20] is a parallel, distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connections or weights. There are different types of ANN where each type is suitable for a specific application. ANN techniques have been applied extensively in the domain of power system.
Basically an ANN maps one function into another and they can be applied to perform pattern recognition, pattern matching, pattern classification, pattern completion, prediction, clustering or decision making. Back propagation (BP) training paradigm also successfully describe by [21]. The compromise for achieving on-line speed is the large amounts of processing required off-line [22].
ANN have shown great promise as means of predicting the security of large electric power systems [23].Several NN's techniques have been proposed to assess static security like Kohonen self-organizing map (SOM) [24]. Artificial Neural Network Architecture is shown in figure 1.

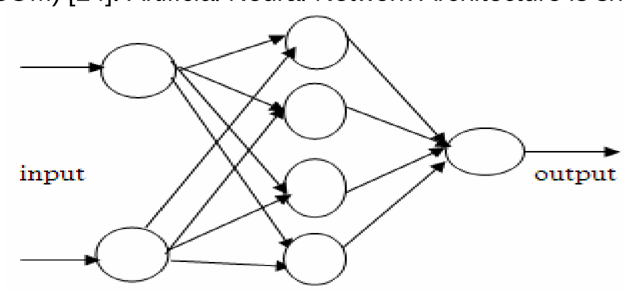

Figure1 Artificial Neural Network Architecture

4.2 Adaptive Network Fuzzy Inference System

Adaptive Network based Fuzzy Inference System (ANFIS) [25] represents a neural network approach to the design of fuzzy inference system.
A fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This fuzzy modeling, first explored systematically by Takagi and Sugeno [26], has found numerous practical applications in control, prediction and inference.
By employing the adaptive network as a common framework, other adaptive fuzzy models tailored for data classification is proposed [27].
We shall reconsider an ANFIS originally suggested by R. Jang that has two inputs, one output and its rule base contains two fuzzy if-then rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$, (1)

Rule2: If x is A_2 and y is B_2, then $f_2 = p_2 + q_2 y + r_2$, (2)

The five-layered structure of this ANFIS is depicted in Figure 2 and brief description of each layer function is discussed in [28].

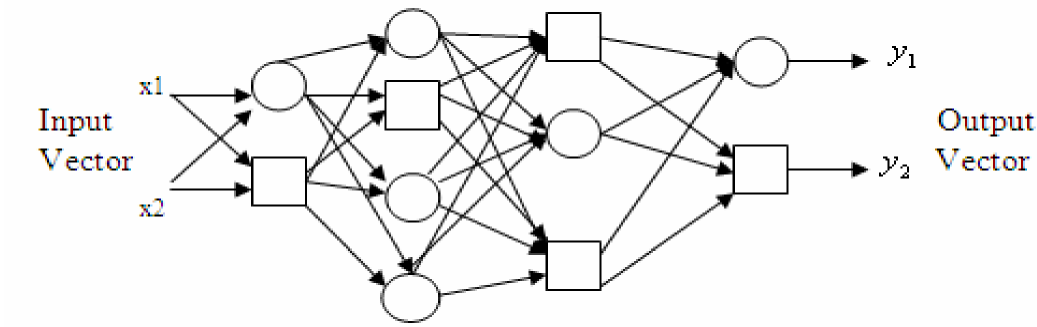

Figure2 An Adaptive Network Architectures

4.3 Decision Tree's

Decision Tree is a method for approximating discrete-valued target functions, in which the learned function is presented by a decision tree. Learned trees can also be re-represented as sets of if-then roles to improve human readability. These learning methods are among the most popular of inductive inference algorithms.
The DT is composed of nodes and arcs [29]. Each node refers to a set of objects, i.e. a collection of records corresponding to various OPs. The root node refers to the whole LS. The decision to expand a node n and the way to perform this expansion rely on the information contained in the corresponding subset En of the LS.Thus, a node might be a terminal (leaf) or a nonterminal node (split). If it is a non-terminal node, then it involves a test which partitions its set into two disjoint subsets. If the node is a terminal one, then it carries a class label, i.e. system in SAFE or UNSAFE operating state. Figure (2) illustrates the system status and view tree.
The main advantage of the DTSA approach is that it will enable one to exploit easily the very fast growing of computing powers. While the manual approach is “bottle-necked” by the number. General DT's methodology [30] and [31] .The procedure for building the Decision Tree is presented in [30]. The application of decision trees to on-line steady state security assessment of a power system has also been proposed by Hatziargyriou et al [32]. (Albuyeth et al.1982, Ejebe &Wellenberrg, 1979, etc)[33-34] respectively, these involve overloaded lines, or bus voltages that deviate from the normal operation limits.

5 RESULTS AND DISSCUSION

For the purpose of illustrating the functionality and applicability of the proposed techniques, the methodology of each technique has been programmed and tested on several test systems such as 5, 30, 57 and 118 IEEE test system. The results obtained from all techniques are compared in order to determine the advantages of any technique compared to others in terms of accuracy against the benchmark technique and computational time taken, as well as to study the feasilibility to improve the techniques further.
For the same data (train, test data) and the same system ANN, ANFIS and DT techniques are used to examine whether the power system is secured under steady-state operating conditions. The AI techniques gauge the bus voltages and the line flow conditions. For training, data obtained from Newton Raphson load flow analysis are used. The test has been performed on 5-IEEE bus system.

Figure 3 shows the topology of the system

The IEEE-5 bus is the test system which contains 2 generators, 5 buses and 7 lines. The topology of this system is shown in Figure 3.

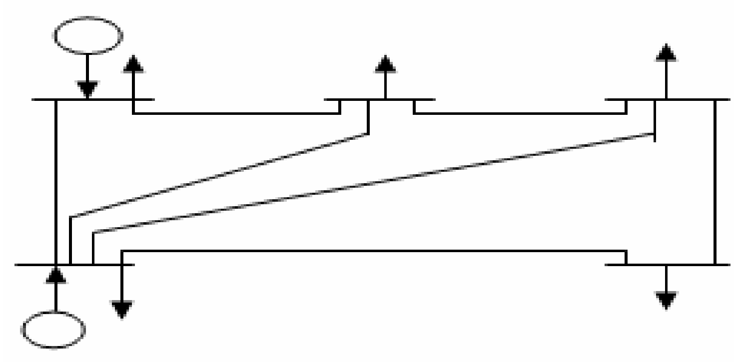

Figure 3: The Topology of IEEE 5bus System

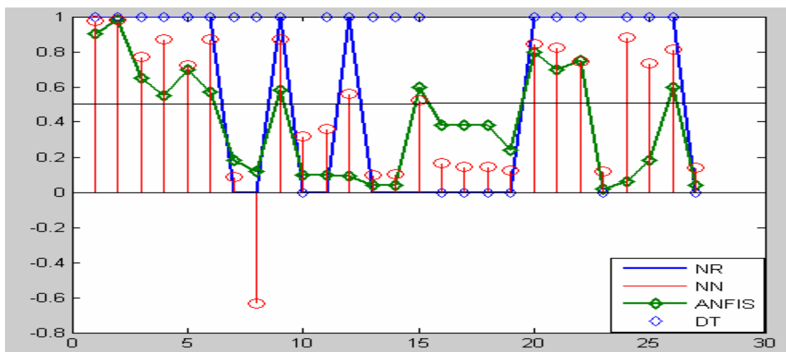

Figure 4: NR, **ANN, ANFIS and DT** performance comparison

Using the same input data, comparing ANFIS , ANN and DT against NR results, it is observed that NN has got acceptable results (classification).In figure(4) we consider the result over 0.5 is in security region while pointes below it is in insecurity region, in this case, 0.5 is then as cut-off point for security level. NN results have got one misclassification, it was found in pattern 8. For ANFIS the misclassification was12, 15, 23, 24 and 25 5 neurons, while for DT results have got one misclassification, it was found in pattern 7,8,11,13,14,15,21,22,23and 24 ,and as result the ANN is better than ANFIS in term of static security assessment.
Table 1 compares ANN, ANFIS and DT against the load flow results using Newton Raphson method for static security assessment classification in term of accuracy. It can be seen that ANN got better results in term of accuracy (96.29), and ANFIS was (81.48) while DT was (74.07).

Methods	Load Flow	ANN	ANFIS	DT
Accuracy (100%)	100	96.29	81.48	74.07

Table1: LOAD FLOW, ANN, ANFIS, and DT COMPARISON

Table 2 shows the number of neurons in the training and the testing mode for each test system.

Bus System	Train	Test
5	240	138
30	2700	1035
57	3400	1088
118	7500	3000

Table 2: Number of Neurons in the Train and the Test Mode

5.1 Decision Tree's Comparison

The five types of decision trees are compared in term of accuracy, computational time and root mean square error (RMSE) and then we will use the better for the artificial intelligence techniques comparison. The following Tables 3-a and 3-b illustrate this comparison in the train and test mood.

Tree's	Accuracy	Time	RMSE
AT Tree	100	0.020	0.1933
NB Tree	100	0.230	0.1474
J48 Tree	100	0.001	0.1507
Random Tree	100	0.001	0.2834
Forest Tree	100	0.020	0.0100

Table 3-a: Training Decision Trees comparison

Tree's	Accuracy	Time	RMSE
AT Tree	93.56	0.02	0.4404
NB Tree	93.45	0.03	0.5481
J48 graft	95.66	0.02	0.5409
Random Tree	96.55	0.001	0.5409
Forest Tree	94.66	0.001	0.473

Table 3-b: Testing Decision Trees comparison

From these tables, it can be seen that in the training mode all types of DT technique achieve acceptable accuracy (100%) while in term of the computational time, the J48 type has the best result (0.001 sec.).In the testing mode, we can say that both J48 and Random Tree got better accuracy(95.66,96.55 %) respectively, while in the aspect of the computational time we found that Random Tree is better(0.001 sec.). As a result, we select Random Tree for the comparison of DT against ANN and ANFIS.

5.2 AI Techniques Comparison

A comparison in term of accuracy between ANN, ANFIS and Random Tree for 5, 30, 57 and 118 IEEE bus test system is presented in next two tables. In table (4), the result shows that in the train mood Random Tree got better results 100%) and the overall results are acceptable.

AI / Bus no.	ANN	ANFIS	RANDOM TREE
5	98.76	100	100
30	97.98	97.05	100
57	97.88	95.65	100
118	97.50	96.00	100

Table4: Train AI comparison

In the table (5) we illustrate the comparison in the test mood for the 5, 30,57and 118 test system and it can be seen clearly that ANN got better accuracy in the all system used. And as result we recommend ANN.

5.3 ANN IMPLEMENTATION FOR THE DEREGULATED SYSTEM

In the current work, we attempt to implement static security assessment methodology for pool trading type of deregulated environment. The implementation is to be tested on several test systems, i.e. 5- bus.

AI / BUS NO.	ANN	ANFIS	RANDOM TREE
5	95.65	91.30	95.55
30	97.77	90.44	94.44
57	96.87	85.79	92.56
118	98.88	80.45	92

Table5: Test AI comparison

It is to be noted here, that the trading in this paper is from the view of security so that the pricing is not taken into account.
In the tables below A, B, C and D are generation companies (GenCo.) while A1, B1, C1and D1 are customers companies (DesCo.) which put their bids in the spot market with their amounts and prices.

GenCo.	Amount(MW)	Price($/KWh)
A	25	55
B	15	17
C	10	12
D	5	22

Table6-a: GenCo. Names, Amounts and Prices

DesCo.	Amount(MW)	Price($/KWh)
A1	15	20
B1	10	17
C1	25	15
D1	5	10

Table6-b: GenCo. Names, Amounts and Prices

As to be mentioned later, we take only security in the account, the procedure in this type of trading is:

- A1 ask from the market 15 MW, the lowest price in the generation companies which is here C can gives the 10 MW and test for the security.
- A1 needs 5 MW, so B can give this amount because B is the lowest price after C and check for the security.
- B1 ask for 10 MW, the rest of the amount of B can be given to B1, and check for the security also.
- C1 ask for 25 MW it can be given as folow:5 MW from D and the rest from A
- Finally, D1 ask only 5 MW it will be given from the rest of the amount of D1, table (7) shows all of these trading process.

Transaction No.	GenCo.	DesCo.	Transaction Amount(MW)
1	A1	C	10
2	A1	B	5
3	B1	B	10
4	C1	D	5
5	C1	A	20
6	D1	A	5

Table7: Market Transactions scheduled between GenCo. and DesCo.

the power flow for this market transactions illustrated in table (8).from this table it can be seen that all bus voltages and power lines are in the limit.

Bus Voltage (p.u)	V1	1.06	1.06	1.06	1.06	1.06	1.06
	V2	1.045	1.045	1.045	1.045	1.035	1.035
	V3	1.03	1.03	1.03	1.03	1.01	1.01
	V4	1.019	1.019	1.019	1.02	1.002	1
	V5	0.99	0.99	0.99	0.991	0.997	0.997
Line Flow (MW)	L12	54.067	50.301	50.301	50.064	66.274	69.032
	L13	57.807	57.904	57.904	57.494	60.569	61.383
	L23	20.989	20.421	20.421	20.563	29.594	30.762
	L24	11.297	11..464	11.464	11.637	18.188	18.838
	L25	19.547	19.714	19.714	18.97	24.233	25.679
	L34	52.449	52.146	52.146	46.475	38.544	42.989
	L45	15.827	15.756	15.756	16.147	13.541	12.878
Status	secure	secure	secure	secure	secure	secure	secure

Table8: Market Transactions Power Flow

6 CONSLUSION & FUTURE WORK

Artificial Intelligence promises alternative and successful method of assessment for the large power system as compared to the conventional method. All these methods can successfully be applied to on-line evaluation for large systems. By considering the computational time and accuracy of the networks, it can be safely concluded that ANN is well suited for online static security assessment of power systems and can be used to examine whether the power system is secured under steady-state operating conditions. Like Neural Networks in general, this classification technique holds promise as a fast online classifier of static security of large-scale power systems. The limitations of the work are static security, so that, pricing, dynamic security and stability are not taken into the account. Further work is needed to develop ANFIS and DT's to enhance the accuracy to handle the concept of static security assessment. The results from the application of Decision tree techniques show the accuracy, computation time and RMSE of the methods. It shows that decision tree Random Tree and Random Forest was the best in the train while J 48 graft was better in the test.

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