Machine Learning Classifiers for Steady State Security Evaluation in Power System

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Abstract

Deregulation of power system in recent years has turned static security assessment (SSA) into a challenging task for which acceptably fast and accurate assessment methodology is essential. The objective of this paper is to investigate the reliability of the SSA in determining the security level of power system from serious interference during operation. Artificial Intelligence Classifiers are implemented to classify the security status in the test power system, comparison are made in terms of computation time and accuracy of the networks. Data obtained from Newton Raphson Load Flow (NRLF) analysis method are used for the training and testing purposes of the proposed AI techniques. The data are used also as a benchmark to validate the results from AI techniques to achieve high speed of execution and good classification accuracy. A new methodology of feature selection technique based on extracting variables has also been applied. The proposed techniques have been extended and tested on 5, 30, 57 and 118 IEEE test systems. Generally, the proposed AI techniques have successfully been applied to evaluate SSA for various IEEE test system.

Keywords:*Steady State Security Assessment, Artificial Intelligence Classifiers, Power System.*

1. Introduction

Power systems of today are highly complex system network, sometimes made of thousands of buses and hundreds of generators [1]. The three main components of power system are generation, transmission and distribution systems in interconnected networks. This shift in electric energy sector from vertically integrated to deregulation, with the intention to improve operation and efficiency, has brought along a number of issues regarding the security of large systems [2]. The primary role of a power system is to provide reliable and continuous electrical energy to satisfy system load. Power system reliability, in a broad sense, can be defined as the ability of the system to provide an adequate supply of electric power with satisfactory quality.

Among the various power system functions, security remains a source of major concern. Power system deregulation and the increasing need to operate systems closer to their operating limits imply the use of more systematic approaches to security in order to maintain reliability at an acceptable level.

Security assessment is analysis performed to determine whether, and to what extent, a power system is "reasonably" safe from serious interference to its operation. Thus, security assessment involves the evaluation of available data to estimate the relative robustness (security level) of the system in its present state or some near-term future state. The SSA problem is considered as an important aspect in power system operation. The main difficulty lies in the fact that electric power systems are highly nonlinear. The solution of a nonlinear system of equations (named the load flow equations) is necessary in order to determine the power flow pattern and the voltage profile of the system. Time constrained is the main problem to solve systems of several thousand buses within a few seconds on a desktop computer. Difficulties do arise in solving the power flow equations for unusual or highly stressed operating conditions resulting in either slow, or no, convergence to a solution. The problem is further complicated when power system is deregulated. In recent years, this deregulation of power system has turned SSA into a challenging task for which acceptably fast and accurate assessment methodology is essential. Therefore, a crucial need for faster and more accurate methods is required for SSA.

2. Machine Learning Techniques

Machine Learning (ML) are well-suited to deal with pattern recognition in an efficient way, as they can be trained off line and used on line to classify outages thanks due their generalization capabilities. Research started with Pattern recognition in the late sixties by DyLiacco[3], and in seventies by Pang et al [4]. ANN promises successful assessment for the large power system compared to the conventional method like DC load flow, AC load flow method. 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 [5].
ANN using pattern recognition methodology for security assessment of electric power systems is presented [6].
Among these works, El-Sharkawi[7-10] 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. Back propagation (BP) training paradigm also successfully described by [11].
A counter propagation neural network (CPNN) is a hybrid learning network. 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 Backpropagation Algorithm (EBA) for steady state security assessment [6]. Its advantage is, the time required is very small compared to the time taken even by fast decoupled load flow.
Radial Basic Function (RBF) was used for contingency evaluation of power system, which is to exploit the non-linear mapping capabilities of RBF in estimating line thermal and bus voltage [12].Piglione[13] proposed a fast on line method based for SSA on an original progressive learning ANN. Firstly, the influence zone of each outages is located and then a dedicated ANN is trained to forecast the post-fault value of critical line flows and bus voltages. Recently, Support Vector Machines (SVM), based on statistical learning theory, have been used in the different areas of machine learning, computer vision and pattern recognition, because of their high accuracy and good generalization capability. The SVM has some advantages [5].
ANN and SVM need large training time and space and are not suitable for security assessment of a large-scale power systems [14].
A frame work and the application to use DT and other automatic – learning methods to on-line steady state security assessment of a power system has also been proposed by Hatziargyriou et al [15].
Among variations of approaches available, the decision tree approach has by now reached maturity enough to crystallize its salient features. The procedure for building the DT with general methodology was presented with a review of existing methods and techniques in [16]. DT techniques were found suitable for classification and identification of operating state. Among the salient features of the decision tree are addressed. Albuyeth et al. [17], involve overloaded lines, or bus voltages that deviate from the normal operation limits.

3. Implementation of Feature Selection Methodology on IEEE 5-bus test system

For the system used (5 bus) the input data for both training and testing are 12 (5 buses and 7 lines) while in this work only 6 of input data are used. Table 3.1 shows how the input data for both training and testing are minimized.

Table 3.1 Minimizing training and testing IEEE 5-bus test system input data

No. of input	load scenario		No. of neurons
12 to6	training	40	480 to 240
	Testing	23	276 to 138
	total	63	756 to 378

From this table it can be seen that the total load scenario is 63 patterns. For training, 40 patterns are used while in testing only 23 patterns are used.

4. AI Techniques for Static Security Assessment

The general framework of the AI Techniques used in this work is elaborated in Figure 4.1.

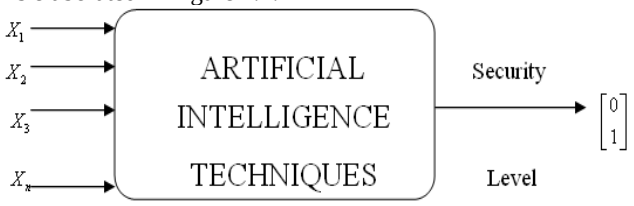

Fig. 4.1: General framework of the AI techniques

From this figure it can be seen the input and the output variables for the AI techniques. X_1, X_2, X_3 and X_n are SSA variables which are bus voltages and line thermal power. The output is the security level in the range between 0 and 1.

4.1 ANN Technique Procedures for Static Security Assessment

ANN simulates human intuition in making decision and drawing conclusions even when presented with complex, noisy, irrelevant and partial information.

4.1.1 Architecture of ANN

ANN has shown great promise as means of predicting the security of large electric power systems. Structure of multilayered feed forwards neural network shown in Figure 4.2 [18].

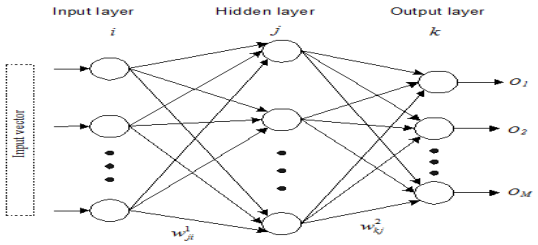

Fig. 4.2: Structure of multilayered feed forwards neural network

As illustrated in Figure 4.2, the input vector for the ANN is bus voltage and the line thermal while the output layer is the security level of the network.The major steps in the training algorithm are: Feed forward calculations, propagating error from output layer to input layer and weight updating in hidden and output layers.Forward pass phase calculations are shown by the following equations:

Between input (*i*) and hidden (*j*) [19]

$$O_j = f(net_j) = \frac{1}{1+e^{-net_j}} \quad (3.1)$$

$$net_j = \sum_j w_{ij} O_i + \theta_j \quad (3.2)$$

Between hidden (j) and output (k)

$$O_k = f(net_k) = \frac{1}{1+e^{-net_k}} \quad (3.3)$$

$$net_k = \sum_k w_{jk} O_j + \theta_k \quad (3.4)$$

where:

O_j is the output of node j, O_i is the output of node i, O_k is the output of node *k*

w_{ij} is the weight connected between node i and j, w_{jk} is the weight connected between node j and k and θ_j is the bias of node j, θ_k is the bias of node k.

In backward pass phase, error propagated backward through the network from output layer to input layer as represented in equation (3.5) [19]. The weights are modified to minimize mean squared error (MSE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m}(d_{ij} - y_{ij})^2 \quad (3.5)$$

where d_{ij} is the j^{th} desired output for the i^{th} training pattern, and y_{ij} is the corresponding actual output. More details of the mathematical procedure are available in [19].

4.2 ANFIS Technique Procedures for Static Security Assessment

Fuzzy inference is the process of formulating the mapping from a given input to an output using the theory of fuzzy sets. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the previous sections: membership functions, fuzzy logic operators, and if-then rules.

The Sugeno fuzzy model was proposed for generating fuzzy rules from a given input-output data set. A typical Sugeno fuzzy rule is expressed in the following form:

IF x_1 is A_1 AND x_2 is A_2 …AND x_m is A_m

THEN y = f (x_1 , x_2 ,…, x_m)

where x_1 , x_2 , . . . , x_m are input variables; A_1, A_2 , . . . , A_m are fuzzy sets; and y is either a constant or a linear function of the input variables.

When *y* is a constant, we obtain a zero-order Sugeno fuzzy model in which the consequent of a rule is specified by a singleton. When *y* is a first-order polynomial as in equation 4, we obtain a first-order Sugeno fuzzy model.

$$y = k_0 + k_1 x_1 + k_2 x_2 + ... + k_m x_m \quad (3.6)$$

4.2.1 Architecture of ANFIS

Jang's ANFIS [19] is normally represented by six-layer feed forward neural network. Figure 4.3 shows ANFIS Architecture that corresponds to the first-order Sugeno fuzzy model. For simplicity, we assume that ANFIS has two inputs; X_1 and X_2 ; and one output y. Each input is represented by two fuzzy sets and the output by a first-order polynomial. The ANFIS implements four rules:

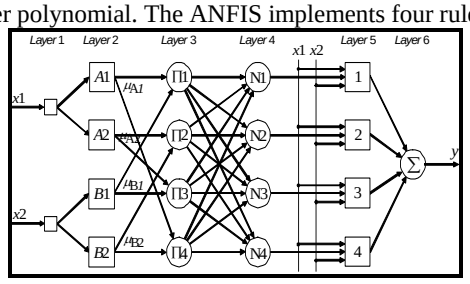

Fig. 4.3: ANFIS architecture

Layer 1 is the input layer.

Layer 2 is the fuzzification layer. Neurons in this layer perform fuzzification. In Jang's model, fuzzification neurons have a bell activation function. A bell activation function, which has a regular bell shape, is specified as follow:

$$y_i^{(2)} = \frac{1}{1+\left(\frac{x_i^{(2)} - a_i}{c_i}\right)^{2bi}} \quad (3.7)$$

where $x_i^{(2)}$ is the input and $y_i^{(2)}$ is the output of neuron *i* in Layer2; and a_i, b_i and c_i are parameters that control, respectively, the centre, width and slope of the bell activation function of neuron *i*.

***Layer* 3** is the rule layer. In ANFIS, the conjunction of the rule antecedents is evaluated by the operator product. Thus, the output of neuron *i* in *Layer* 3 is obtained as follow:

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \quad (3.8)$$

where,

$x_{ji}^{(3)}$ are the inputs and $y_i^{(3)}$ is the output of rule neuron *i* in layer 3.

***Layer* 4** is the normalisation layer. It represents the contribution of a given rule to the final result. Thus, the output of neuron *i* in *Layer* 4 is determined as follow:

$$y_i^{(4)} = \frac{x_{ii}^{(4)}}{\sum_{j=1}^{n} x_{ji}^{(4)}} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j} = \bar{\mu}_i \quad (3.9)$$

where,

$x_{ii}^{(4)}$ is the input from neuron *j* located in layer 3 to neuron *i* in layer 4, and *n* is the total number of rule neurons.

***Layer* 5** is the defuzzification layer. A defuzzification neuron calculates the weighted consequent value of a given rule as follow:

$$y_i^{(5)} = x_i^{(5)}\left[k_{i0} + k_{i1}x1 + k_{i2}x2\right] = \bar{\mu}_i\left[k_{i0} + k_{i1}x1 + k_{i2}x2\right] \quad (3.10)$$

where, $x_i^{(5)}$ is the input and $y_i^{(5)}$ is the output of defuzzification neuron *i* in layer 5, and k_{i0}, k_{i1} and k_{i2} is a set of consequent parameters of rule *i*.

***Layer* 6** is represented by a single summationneuron. This neuron calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIS output *y*

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} \bar{\mu}_i\left[k_{i0} + k_{i1}x1 + k_{i2}x2\right] \quad (3.11)$$

It is not necessary to have any prior knowledge of rule consequent parameters since ANFIS learns these parameters and tunes membership functions accordingly.

4.3 Decision Tree Technique Procedures for Static Security Assessment

DT is a tree, structured upside down, built on the basis of a Knowledge Base (KB) consisting of a large number of operating points (OPs), covering all possible states of the under study power system in order to ensure its representatives. The knowledge base is defined as [21] these attributes are the predisturbance steady-state variables and characterize each operating point.

The KB is divided in a learning set (LS) used for deriving the classifier structures and a test set (TS) used to evaluate the performance of these structures on new, unobserved OPs. The construction of a DT starts at the root node with the whole LS of preclassified OPs. At each step, a tip-node of the growing tree is considered and the algorithm decides whether it will be a terminal node or should be further developed. To develop a node, an appropriate attribute is first identified, together with a dichotomy test on its values. The selected test is applied to the LS of the node splitting into two exclusive subsets, corresponding to the two successor nodes.

The construction of a DT starts at the root node with the whole LS of preclassified OPs. These OPs are analyzed in order to select the test T which splits them "optimally" into a number of most "purified subsets.

Figure 4.4 illustrates the SSA construction using decision tree. As illustrated in this Figure, for SSA tree only one secure case which is the voltage magnitude (V_m) of each bus and the thermal power (S) of all the lines, are in the limitations. Those limitations are:
$1.06 > V_m > 0.94$ and $S < S_{max}$

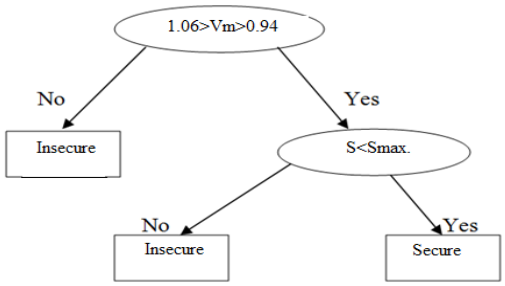

Fig. 4.4: DT construction for SSA

From Figure 4.4, it is clear that only one case can be considered as secure that is all voltages within their range ($1.06 > V_m > 0.94$) p.u. and all lines power are not exceeding ($S < S_{max}$).

5. Implementation of AI Techniques on Test Systems

For the same data (training, testing data) and the same system (IEEE test systems), ANN, ANFIS and types of DT techniques are used to examine whether the power

system is secured under steady-state operating conditions. Data obtained from NRLF analysis are used for both training and testing. It is to be noted here that the testing data are not part of the training data, the test result accuracy is measured in terms of root mean square error (RMSE).

5.1 Implementation of ANN on IEEE 5-bus test system

By changing the BPNN parameters depending on trial and error base, it is found that the following setting produces the following results: Learning rate is 0.7; Momentum rate is 0.9; and the minimum error for the network is 0.005. Figure 5.1 elaborates the implementation of ANN on 5 bus test system with training, validation, MSE and number of epochs.

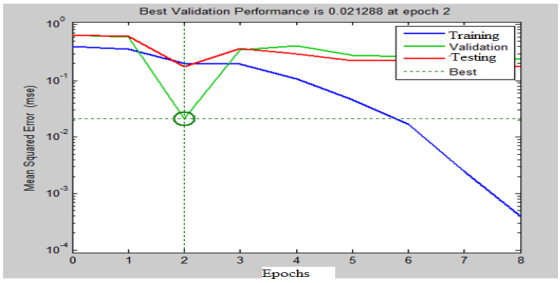

Fig. 5.1: ANN 5-bus training system

From the Figure 5.1, it can be seen that the training mean square error is decreasing as the number of epochs increases. The best validation point of the performance is at epoch two and the MSE value is 0.021188, after that point the validation performance increases to reach 0.16 at epoch number 3.

5.2 Implementation of ANFIS

By heuristic approach, it is found that the network converges faster and produces small MSE in both training and testing. Depending on the dataset, ANFIS is trained to adjust the membership function parameters using hybrid learning algorithm that combines the least-squares method and the back-propagation algorithm. ANFIS training is performed using the parameters mentioned in the above table. Error convergence of ANFIS with training dataset of the system used shown in Figure 5.2.

Fig. 5.2: ANFIS 5-bus training system

5.3 Implementation of DT

For the same training and testing data and system used, a comparison of many types of trees is attempted. Learning algorithms of the trees is presented in [76]. It is to be noted that next table 5.1 shows decision tree methods in X axis of the Figures.

Table 5.1 DT methods in X axis

No	DT Types
1	AD Type
2	BF Tree
3	Decision Stump
4	J48
5	J48 graft
6	LMT
7	NB Tree
8	Random Forest
9	Random Tree
10	REP Tree

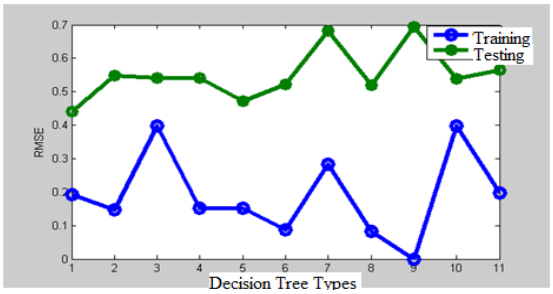

Fig. 5.3 Illustratesa comparison of 11 types of decision tree

From figure 5.3, comparison the methods in term of computation time. From that figure, it is shown that in the training data the Random Tree and decision Stump obtained 0.01 second, while in recall mode J48 graft computed 0.0001sec and Random Tree is 0.005.

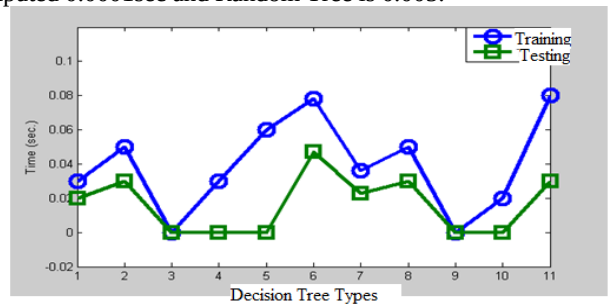

Fig. 5.4: Computation time training and testing data comparison

Figure 5.5 illustrates the training and testing data comparison in term of accuracy. It can be seen clearly that Tree and Random Forest obtained acceptable

accuracy (100 %) and J 48 graft tree obtained acceptable results in the recall mode (74.07%).

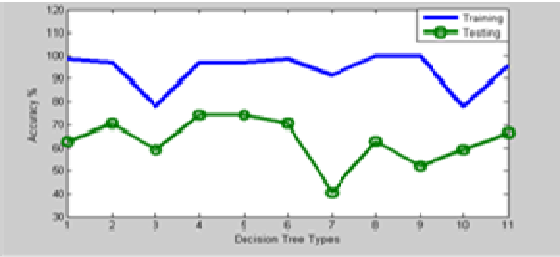

Fig. 5.5: Comparison between accuracy of training and testing data

For root mean square error (RMSE) Figure 4.6 shows that in the training mode the Random Tree and Random Forest is 0.001 and 0.0816 respectively. In the recall mode the J48 graft and Random Forest produced 0.473 and 0.5185 respectively.

Figure 5.5: Root Mean Square Error for Training and Testing Data

The results from the application of Decision tree techniques comparison show the accuracy, computation time and RMSE of the methods. It shows that decision tree can be used to examine whether the power system is secured under steady-state operating conditions. In term of accuracy, Random Tree and Random Forest are the best in the training while J 48 graft is better in the recall mode. In term of computation time Random Tree and decision Stump and Random Tree obtained acceptable training computation time and were Random Tree and REP Tree obtained acceptable testing computation time.

6. AI General Comparison

6.1 AI General Comparison in Term of Accuracy

Using the same input data, comparing ANN, ANFIS and DT against NR results on IEEE 5-bus test system, it is observed that NN has obtained acceptable results (classification). In figure 6.1 it is considered that the result over 0.5 is in secure region while points below are in insecure region. In this case, there is no hard and fixed rule regarding the cut-off point for security level. However, in general 0.5 is considered acceptable to be adopted as cut-off point for security level. NN results have obtained one misclassification, it found in pattern 8. For ANFIS the misclassification have 5 neurons (12, 15, 23, 24 and 25), while for DT results have obtained one misclassification, it is appeared in pattern 7, 8, 11, 13, 14, 15, 23 and as result the ANN is better than ANFIS in term of SSA accuracy.

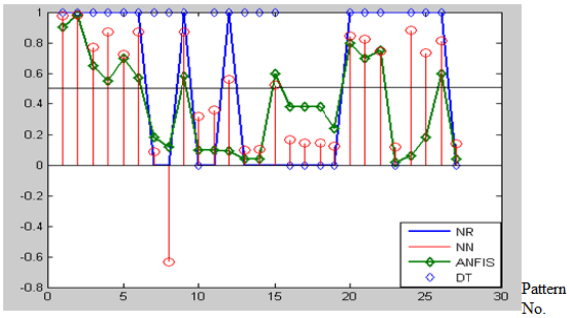

Fig. 6.1: NR, ANN, ANFIS and DT performance comparison

Figure 6.2 compares ANN, ANFIS and DT against the load flow results using N-R method for SSA classification in term of accuracy. It can be seen that ANN obtained better results in term of accuracy 96.29%, and ANFIS is 81.48% while DT is 74.074%.
Figure 6.2 shows the comparison of ANN, ANFIS and DT against NRLF in term of accuracy.

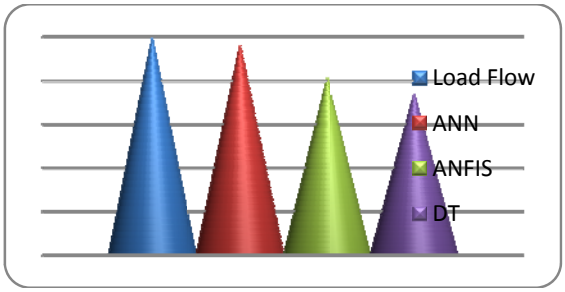

Fig. 6.2: Load flow, ANN, ANFIS, and DT accuracy comparison

6.2 AI General Comparison in Term of Computation Time

As mentioned earlier, 70 patterns and 27 patterns are used for training and testing respectively. Table 6.1 shows the computation time comparison in the training and testing phases for the AI techniques against NRLF method.

Table 6.1 Comparison for computation time using training and testing

Elapse Time(Sec.) / Techniques	Training computation time (Sec.)	Testing computation time (Sec.)
NRLF	1.925	0.54
ANN	0.01	0.01
ANFIS	0.28	0.1
DT	0.02	0.01

From the ANN, ANFIS and DT comparison it can be concluded that all these techniques have been found to be very suitable for SSA classification of the operating state. From the accuracy point of view, based on the good performance of the ANN structure, the results show that the ANN in the recall mode performs more accurate than using ANFIS and DT for SSA classification. From the computation time point of view, the ANN with DT is the fastest among the three techniques.

6.3 Comparison of AI Techniques for Various Sizes of Power System

Table 6.2 tabulates AI techniques comparison on various system sizes in term of accuracy and computation time. Input data with training and testing patterns are also shown.

Table 6.2 Testing AI comparison on different system size

	Data			*ANN*		*ANFIS*		*DT*	
System size	***Input***	***Training***	***Testing***	***Accuracy%***	***Time***	***Accuracy%***	***Time***	***Accuracy%***	***Time***
5-bus	6	40	23	97.45	0	90.80	0.2194	95.65	0
30-bus	23	120	45	97.00	0.01	90.07	0.2467	90.00	0.015
57-bus	34	100	32	97.53	0.02	93.21	0.2841	96.00	0.02
118-bus	50	150	60	96.66	0.02	88	0.301	74.50	0.02

From this table, it can be seen that depending on the system size the computation time slightly increase for "ANN" from 0 second and in 5 bus test system to 0.02 second for 118 bus test system. For ANFIS from 0.2194 second to 0.3014 second while for DT from 0 second and to 0.02 second. On the other hand it can be observed that the accuracy for ANN in slightly better 97.45% for 5 bus, and decrease slightly for largest systems.

7. Conclusion

This work has presented the results and discussions. The study of implementation AI techniques on various test system involved suitability of using ANN, ANFIS and DT for SSA classification. From the studies, it is observed that AI 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 assess SSA of deregulated power systems in real time. By considering the computation time and accuracy of the networks, it can be concluded that ANN is well suited for online SSA of deregulated power systems. In general, this classification technique holds promise as a fast online classifier.

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