IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 12, Issue 4 Ver. II (Jul. – Aug. 2017), PP 61-77
www.iosrjournals.org

Voltage Security Assessment of Online System based on Voltage Stability Indices and FDT

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Abstract: *Present-day power networks all over the world need to transfer bulk amount of power. This has resulted in vast interconnection of grids for assuring reliability, security, stability and economic operation. The challenges to ensure smooth system operation with stressed grid and averting system blackout provided the stimulus for research on voltage security. Voltage stability indices aid the security studies. Real-time voltage security assessment is based on synchronized phasor measurement obtained from phasor measurement units (PMUs). For fast accurate handling of data to synthesize information in order to estimate system security state decision tree (DT) approach of data mining is opted. Power system operating constraints are soft constraints, to implement the situation in real-time and improve decision making abilities at the overlapping and conflicting security boundaries present scheme adopts fuzzy decision tree (FDT). The decision tree is trained offline considering past representative operating conditions, identify critical attributes as security predictors and periodically updated incorporating new operating conditions for robustness improvement. The status of critical attributes are obtained from PMUs and compared with thresholds priorly defined by FDTs. The decision at the leaf nodes considers the whole path, i.e. from the root to the terminal node including membership function of security predictors. As classification and prediction by decision trees are fast, reliable, comprehensible the present scheme employs FDT and resolve conflict in decision making by prognosticating system security status with the aid of voltage stability indices (VSI) and thereby easing the operators' role and to some extent alleviating the risk of failure. The indices helps to identify security status from the solution of basic power flow equations, i.e. system real-time measurements such as voltage magnitude, phase angle, bus injected power, branch flows etc. This thesis discusses the performance of different indices based on accuracy of FDT. The present scheme validated on IEEE-30 bus system with six performance indices. From the result and based on comparisons* PI_{vmv}*, LVSI was found to have best performance from the indices studied. This has provided an important platform to implement the scheme for real-time online application of voltage security assessment using FDT based machine learning approach.*

Key terms: *Voltage security assessment(VSA), linear voltage security indicator(LVSI) Phasor measurement unit(PMU), Decision tree(DT), Fuzzy decision tree(FDT), Voltage stability indices(VSI),*

I. Introduction

In recent years the thrust for electric power demand has grown exponentially. This has resulted in vast interconnection of formerly separated grids for assuring capacity expansion, reliability and security. In the present scenario grids operating with stressed operating point due to elevated load demand has resulted in noteworthy voltage limit deviations with respect to the imposed constraints due to which the issue of voltage collapse is looming prominently. The urgency for ensuring secure system operation has heightened the need for voltage security assessment. Due to emergence of fleet of sophisticated devices more and more data become available for the system study. Tactful utilization of data available for analysis and assessment of voltage security issues is fueled by machine learning, which has provided an evolutionary breakthrough in developing efficient and reliable tool for fast, accurate decision making under critical conditions with voltage stability indices acting as a vital tool in estimating system security status i.e. proximity to voltage collapse or signifying the stress of current operating point on power network.

This chapter concerns with the research on synthesis of fuzzy rule- based DT approach of machine learning considering multi-class decision at terminal node to counter conflict in decision making at security boundaries and selection of parameters to take a time-stamp of power system operating conditions replicating different loading conditions.

II. Major Grid Blackouts

Grid blackout synonymously termed as voltage collapse. Voltage collapse majorly occurs due to sudden change in network topology, strikingly large unbalance between demand and generation. This can be explained in short as a phenomenon traced by wide spread decline in voltage profile usually initiated by lines, transformers, and generators tripping and disturbances in consumption patterns resulting in voltage drop due to scarcity of reactive power reserves in power system [Shahidehpour, 2014]. A list of major blackouts is presented in table 1.1. Out of the major grid blackouts the blackout in India on 30-31 July, 2012 considered to be the largest black out.

Table 1.1 Major in world

Sl. No.	Date	Country
1	09/11/1965	10 states in northeast US
2	5/1977	Miami, US
3	7/1977	New York city, US
4	7/1999	New York city, US
5	11/3/1999	Brazilian power system
6	2/01/2001	India
7	14/08/2003	Northeast of US and CANADA
8	28/08/2003	South London
9	7/11/2003	Most of Chile
10	25/5/2005	Moscow, Russia
11	4/11/2006	European Power System
12	30/7/2012-31/07/2012	India(Worlds' largest blackout recorded)

Mechanism of black out can be understood on a fly from the figure 1.1. Power system operating at normal operating conditions may subjected to the vagaries of system operations such as contingency conditions which may lead to instability events. These instability events results in voltage problems, power flow surges, overloads and unsymmetrical system configurations due to lines, transformers, and generators tripping. Cascading effect of outages results in frequency, voltage collapse problems which further accentuates power flow surges, overload issues. Non-reversal of power system state due to unavailable reactive power reserve, untimely action by operators lead to system divided into islands or blackout. At this stage restoration operations need to be undertaken as the last line of security to regain the system operating status which largely depends upon the blackstart capability of system.

The increase in load has pushed the operating limit of power system beyond the stability limits and close to thermal limits, the study of contributing factors and developing appropriate security measures have become a prerequisite for the safe guarding and self healing of the network. Therefore before taking up the assessment aspect of voltage security let us get a brief idea about mechanism of voltage collapse as. This can be explained in short as a phenomenon initiated by lines, transformers, and or generator tripping and disturbance in consumption pattern due to load increase, load dynamics resulting in voltage drop at the source due to insufficient reactive power reserves in the system, generators meeting reactive power generation limits, leads to cascading overload and thereby outage of line and transformer which accentuates the voltage to decline further. Voltage drop in transmission system leads to voltage drop in distribution system. Therefore ULTCs try to recover the voltage profile by modifying the turns- ratio. The apparent impedance of low voltage levels decrease and more current is drawn resulting line overloads, disconnection of network elements by overload protection scheme. When voltage drops below the threshold level of under voltage protection of generators, synchronous condensers they trip and the scarcities of reactive reserves are further victimized. In the same line overcurrent protections for lines trip the lines causing the voltage to drop even further over a wide area resulting blackout or voltage collapse.

III. Relation Between Reliability, Security, And Stability

NERC (North American Electric Reliability Council) defines reliability as: *"Reliability, in a bulk power electric system, is the degree to which the performance of the elements of that system results in power being delivered to consumers within accepted standards and in the amount desired. The degree of reliability may be measured by the frequency, duration, and magnitude of adverse effects on consumer service".* In order to be reliable power system ought to be secure most often. In short reliability means the probability of its satisfactory operation over a span of time. Security of a power system means degree of risk involved in its ability to survive critical contingencies without service interruption to consumers. It is related to the systems' robustness to viable perturbations. Power system security can also be explained as the ability of power system to operate with stability and supply the load when associated components fail or mal-operates. Stability refers to the continuation of operation following a disturbance. Operating condition and nature of disturbance affect the stability. Now security and stability shouldn't be misinterpreted.

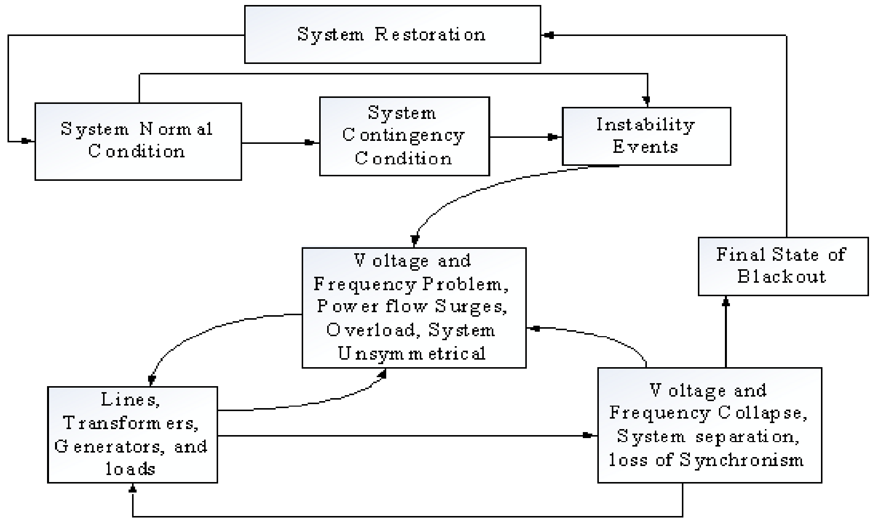


Figure-1.1

IV. Power System Stability

Power system stability can be defined as [Kundur, 2004], "*The power system stability is the ability of an electric power system for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact".* To support the demand of late the power system has been vastly interconnected. Interconnection improved the systems' stability, reliability, performance but it has also added new dimensions to stability problems. The various stability and security problems cannot be effectively understood and efficiently analyzed by considering them as a single problem. In addition to it due to high dimensionality, complexity and large number of variables it is required to make tactful assumptions and classification to allow analysis with acceptable accuracy. The classification is shown in figure 1.3.

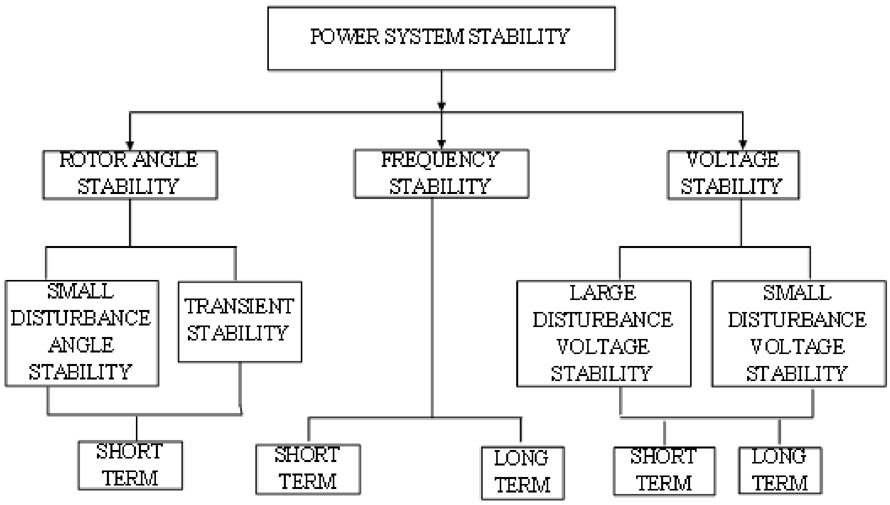


Figure 1.3 Classification of Power System

This classification is based on following consideration [Kundur, 1994]:

a) The physical nature of the resulting mode of instability as indicated by the main system variable in which instability can be observed.
b) Size of disturbance considered which influences the method of calculation and prediction of stability.
c) The devices, processes and time-span that must be taken into consideration in order to assess stability.

Power system stability in a broader prospective can be categorized as: Rotor angle stability, Frequency stability, and voltage stability. Rotor angle stability denotes the ability to maintain or restore equilibrium between electromagnetic and mechanical torque of each synchronous machine in the system. This mainly concerns with study of electromagnetic oscillations inherent in power systems. Rotor angle stability classified as, small disturbance angle stability and transient stability based on the size of disturbance considered. Frequency stability refers ability of system to maintain steady frequency following a severe system disturbance in terms of significant disturbance resulting imbalance between generation and load. Frequency stability can be short-term or long-term. Voltage stability refers to ability of system to maintain the voltages with in stipulated range at all the buses after being subjected to a disturbance. Voltage stability classified as large–disturbance, small-disturbance voltage stability.

Large disturbance voltage stability denotes ability to maintain steady voltages following large disturbance such as loss of generators, faults, circuit contingencies. This ability is quantified in terms of system, load characteristics. Assessment requires analysis of nonlinear equations of power system over a period of time. On the other hand small-disturbance denotes ability of system to maintain steady voltages when subjected to small perturbations i.e. incremental load variations. This stability is influenced by continuous, discrete controls, load characteristics. The time frame of analysis may vary from few seconds to tens of minutes. This thesis deals with the small disturbance in the power system.

The voltages may become unbalance when there is imbalance between load and supply, mainly imbalance of reactive power [Wood, 1996].

This may happen due to [Shahidehpour, 2014]:

a) Sudden change in load demand, such as loss of load or addition of load in an area.
b) Limitation in supply capacity due to tripping of a transmission line.

V. Voltage Security

Voltage security can be defined as [Kothari, 2012], "*Ability of a system, not only to operate stably, but also to remain stable following credible contingencies or load perturbations".* Hitherto has been to expand the gird capacity and accommodate the exponential increase in the load without keeping the network stability and security at stake. Probably the issue was taken up for the first in [Wehenkel**,** 1986]. An objective of security study [Wood, 1996; Wehenkel, 1989] includes:

a) Operate the system in such a way that power is delivered reliably.
b) Within constraints imposed on the system operation for reliability considerations, the system will operate most economically.
c) Appraise the systems' capability to withstand major contingencies, and
d) Suggest viable preventive or remedial corrective actions to regain the network stability.

To analyze the power system security and designing appropriate control systems, the system operating conditions classified into five states: normal, alert, emergency, in-extremis, and restorative [Wehenkel, 1998] based on physical nature of disturbance, size of disturbances, time span and the transitions between states, shown in figure 1.4. All the operating states are categorized to help the operators at the control center to study and differentiate between the network status and arm appropriate control or preventive action to abstain the network from going out step.

VI. FUZZY Decision Tree

Fuzzy decision tree employs multi-class decision by adopting probabilistic approach as compared to conventional decision tree with deterministic approach. Decision tree model primarily concerned with two aims: producing an accurate classifier and understanding the underneath inherent knowledge from the database. Supervised learning faces two types of uncertainty [Miamon, 2014]: statistical and cognitive. Statistical uncertainty implies random characteristics of nature while cognitive uncertainty deal with human perception. Cognitive uncertainty can be further divided into two categories: vagueness and ambiguity. Ambiguity arises in situations with more than two alternatives and choice to choose between is left unspecified. Vagueness arises when there is dilemma in making a precise differentiation between viable alternatives. Fuzzy set theory first put forwarded by Prof. L.A Zadeh in 1965. It deals with the degree of belongingness of a certain element to a set represented in term of membership function. Fuzzy decision tree follows the algorithm given below:

Tree induction (T.S, A, C):

a) Create a new fuzzy decision tree (FDT) with a single root node
b) **If** T.S is empty OR sum of class membership function for any of the classes $\geq \beta$ **then**
c) Mark FDT is as a leaf with probability of each class of C in T.S as a label
d) **Return** FDT
e) **End if**
f) $\forall A_i \in A$ fuzzify employing different fuzzy membership functions
g) Select an attribute A_i of A having highest information gain as per the formula

$$G(A_i, D) = I(D) - E(A_i, D)$$

where,

$G(A_i, D) = Information\ gain\ for\ an\ attribute$

$I(D)$: $Class\ entropy\ for\ the\ training\ set$

$E(A_i, D)$: $Fuzzy\ entropy\ for\ the\ attribute\ A_i\ of\ attribute\ set\ A$

h) Applying splitting criteria split the T.S into sets based on number of clusters adopted for fuzzy clustering of the attribute.

i) Connect the root node of the returned Subtree with an edge that is labeled with branch multiplication factor as given by:

$$Branch\ multication\ factor = \sum membership\ values\ for\ concerned\ cluster \Big/ \sum membership\ values\ for\ all\ the\ clusters$$

j) Recursively call procedure until stopping criteria is meet corresponding to each Subtree generated

k) **end for**

l) **return FDT**

Aforementioned algorithm has been illustrated with the help of following example [Okomoto, 1994]:

Table 3.1 Fuzzy Dataset

Membership	Height	Weight	Hair Color	Class
1	160	60	Blond	C_1
0.8	180	80	Black	C_2
0.2	170	75	Black	C_2
0.7	175	60	Red	C_1
1	160	75	Black	C_2
0.3	175	60	Red	C_2
1	165	60	Blond	C_2
0.5	180	70	Blond	C_1

Consider the fuzzy data set given in table 3.1 at the beginning of one cycle of algorithm. Attribute height fuzzified into three clusters low, middle, and high. Similarly weight fuzzified as light, middle, and heavy lastly attribute hair color fuzzified as light, dark as given below:

$$low = \left\{\frac{1}{160}, \frac{0.8}{165}, \frac{0.5}{170}, \frac{0.2}{175}\right\} \quad (3.1)$$

$$midlle = \left\{\frac{0.5}{165}, \frac{1}{170}, \frac{0.5}{175}\right\} \quad (3.2)$$

$$high = \left\{\frac{0.2}{165}, \frac{0.5}{170}, \frac{0.8}{175}, \frac{1}{180}\right\} \quad (3.3)$$

$$light = \left\{\frac{1}{60}, \frac{0.8}{65}, \frac{0.5}{70}, \frac{0.2}{75}\right\} \quad (3.4)$$

$$middle = \left\{\frac{0.5}{65}, \frac{1}{70}, \frac{0.5}{75}\right\} \quad (3.5)$$

$$heavy = \left\{\frac{0.2}{65}, \frac{0.5}{70}, \frac{0.8}{75}, \frac{1}{80}\right\} \quad (3.6)$$

$$light = \left\{\frac{1}{blond}, \frac{0.3}{red}\right\} \quad (3.7)$$

$$dark = \left\{\frac{0.6}{red}, \frac{1}{black}\right\} \quad (3.8)$$

Note that data comprises inconsistent data, fourth and sixth data. Calculate$I(D)$:

$$I(D) = -\sum_{k=1}^{n}(p_k \log_2 p_k) \quad (3.9)$$

$$I(D) = -\frac{2.2}{5.5}\log_2\frac{2.2}{5.5} - \frac{3.3}{5.5}\log_2\frac{3.3}{5.5} = 0.971 \quad (3.10)$$

Calculate: $E(A_i, D)$

$$E(A_i, D) = \sum_{j=1}^{m}\left(p_{ij} I(D_{Fij})\right) \quad (3.11)$$

$$E(height, D) = \frac{3.1}{6.7} \times 0.949 + \frac{1.2}{6.7} \times 0.871 + \frac{2.4}{6.7} \times 0.990 = 0.950$$

$$G(height, D) = I(D) - E(height, D) \quad (3.12)$$
$$= 0.971 - 0.950 = 0.021$$

Similarly,

$$G(weight, D) = 0.118$$
$$G(hair\ color, D) = 0.164$$

Select attribute with highest gain, present case hair color selected as test attribute. Since, hair color has been fuzzified into two clusters, data set divided into two parts as shown in figure 3.1. Consider the fuzzification for the attribute hair color as stated above in equation (3.7), and (3.8). Begin with the first instance from the dataset given in table 3.1. From equation (3.7), (3.8) blond has been given membership value of 1 in light and 0 in dark. Multiply this membership value with membership value given in the dataset which results in 1, 0 and drop the instance into light and dark subset. Red corresponding to fourth instance has values 0.3 in light and 0.6 in dark. Multiply these values with the original membership values which results in 0.21, 0.42 and drop into light and dark subsets. Similarly repeat until the last instance has been classified. Delete the instances with zero membership values. For the fuzzy decision sub-tree as in shown figure 3.1, repeat the procedure until the stopping criteria holds.

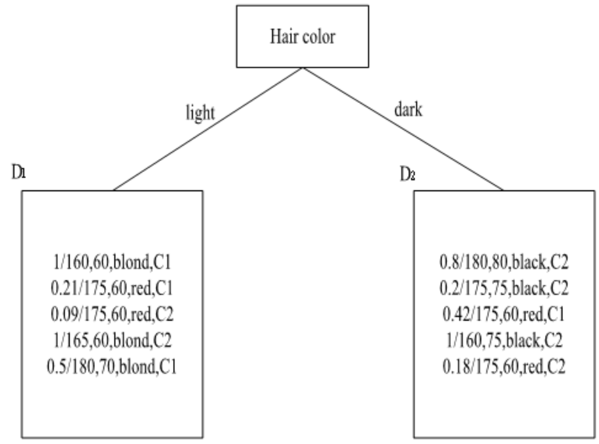


Figure 3.1 Generated

VII. Fundamental of PMU

A constant phasor implies a stationary sinusoidal waveform. It is probable that input signal may have harmonic and non-harmonic components. It is prerequisite to study frequency component and find its phasor representation. A pure sinusoidal waveform can be represented by a

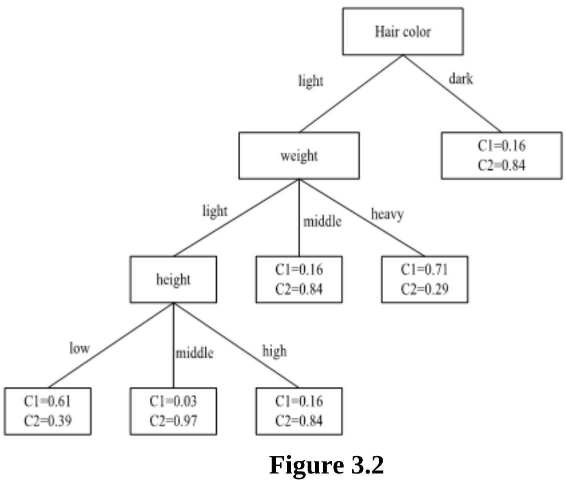


Figure 3.2

The complete fuzzy decision tree obtained by repeated partitioning is shown in figure 3.2. The contrasting feature of this approach is ease of understanding, because an attribute appears once in any path from root to leaf. In addition to that the test for an attribute is the same even when it appears at different nodes, i.e., branching by the fuzzy sets defined by user. Moreover all the decision nodes holds the probabilistic participation values for all the target attribute in contrast to conventional decision tree with single class tagged to each instance following crisp decision approach. The sum of the class participation at the decision nodes is equal to one. Number of branches for the tree at a test node depends on the number of fuzzy clusters considered corresponding to the test attribute selected.

unique complex number known as phasor [Phadke, 2010]. Consider a sinusoidal signal

$$x(t) = X_m \cos(\omega t + \emptyset) \quad (3.13)$$

The phasor representation of this sinusoidal is given by $x(t) = \frac{X_m}{\sqrt{2}} e^{j\emptyset} = \frac{X_m}{\sqrt{2}}(cos\emptyset + jsin\emptyset)$ (3.14)

Magnitude of the phasor is the r.m.s value of the sinusoid $\frac{X_m}{\sqrt{2}}$ and its phase angle is$\emptyset$, as shown in figure 3.3**.** Since frequency of the sinusoidal is implicit in the phasor definition, it is clear that all phasor which are included in a single phasor diagram must have the same frequency. Phasor representation of the sinusoidal implies that the signal remains stationary at all time.

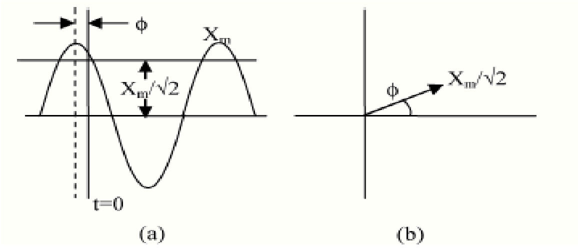


Figure 3.3 Representation of a Sinusoidal Signal a) Sinusoidal signal b) Phasor Representation

Constant phasor implies a stationary sinusoidal waveform. The PMU block diagram is shown in figure 3.4. To obtain the simultaneous measurement of phasors across a wide area of power system it is necessary to synchronize these time-tags, so that all phasors measurements belonging to the same tag are truly simultaneous. Phasors are referred to a global reference time. Synchronization is achieved by same time sampling of phasors using time signals from global positioning system satellite (GPS). In practice it is necessary to deal with phasor measurement considering the input signal over a finite data window. If the power system frequency is not equal to its nominal value, the PMU uses a frequency tacking step and thus estimate the period of fundamental frequency component before the phasor is estimated. The most common technique for determining the phasor representation of an input signal is to use data samples taken from the waveform, and applied the discrete fourier transform (DFT) to compute the phasor. The DFT eliminates the harmonic of the input signal. Anti-aliasing filter are used at the input to the signal before data samples are taken to satisfy Nyquist criterion.

If $x_k = \{k = 1,2,3 \ldots \ldots, N-1\}$ are the N-samples of the input signal taken over one period then the phasor representation is given by [Phadke, 2010]

$$X = \frac{\sqrt{2}}{N} \sum_{k=0}^{N-1} x_k e^{-jk\frac{2\pi}{N}} \quad (3.15)$$

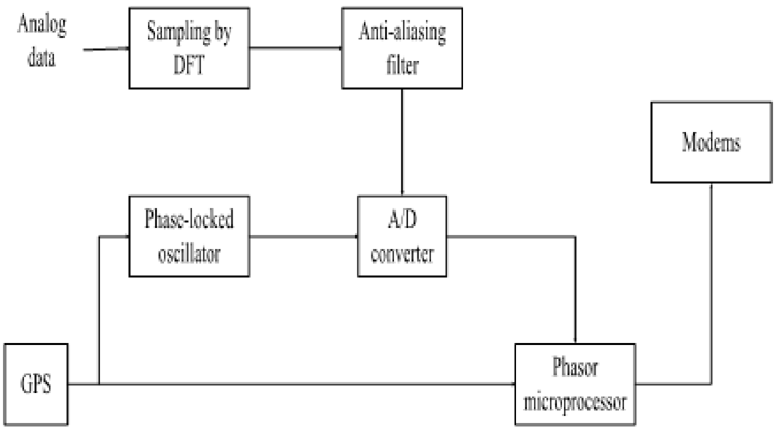


Figure 3.4 Phasor

VIII. Mathematical Modelling

The mathematical modeling adapted for synthesizing Y-bus matrix, load flow analysis for the test system have been described in the following section. Also mathematics underpinning for network reduction and FDT have been described.

IX. Power Flow Analysis

The power flow analysis deals with the detailed study of power flow in the network providing the magnitude of various bus voltage, active and reactive power through different buses and branches, line loss in addition to generation and load pattern. The flow of active and reactive power between generation and load is termed as power flow. Three phase ac power system comprises of generating stations and loads connected via network of busses and branches. In contrast to conventional circuit analysis, power flow analysis employs per unit system, and one-line diagram. In order to solve power flow problem single phase model have been adopted for the three phase system. Four parameters are associated with each bus, such as magnitude of voltage$|V|$, real power P, phase angleδ, and reactive power$Q$. For the ease of analysis and based on bus characteristics system buses are classified into four major categories [Kothari, 2012]:

TYPE OF BUS	SPECIFIED PARAMETERS	UNSPECIFIED PARAMETERS
Slack Bus	$\|V\|, \delta$	P,Q
PQ Bus/Load Bus	P,Q	$\|V\|, \delta$
PV Bus/Generator Bus	P, $\|V\|$	Q, δ
Regulated Bus	P,Q,$\|V\|$	δ

X. Classification

The test for performance of the developed FDT as mentioned above is accomplished by employing the test data set. The validation result for the FDT, 'test_reslt' in workspace, as shown in figure 6.4. It comprises of seven columns as mentioned below:

Column 1: Holds the degree of membership value for class-1
Column 2: Holds the degree of membership value for class-2
Column 3: Holds the degree of membership value for class-3
Column 4: Denotes the predicted class decision for the instance corresponding to highest degree of membership value.
Column 5: Denotes the sum of membership values for all the participating classes.
Column 6: Denotes the actual class decision from the dataset
Column 7: Denotes prediction validation for an instance
where,
1: Correct prediction
0: wrong prediction

The accuracy for the fuzzy decision tree is given by:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (6.1)$$

Accuracy obtained by taking a ratio of sum of all the 1s' in column-7 to the total number of instances in column-7.

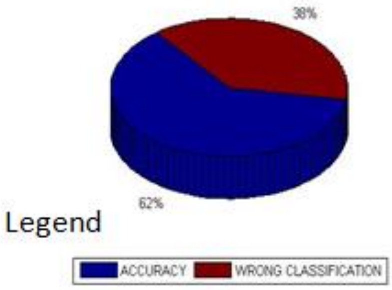
XI. Results

Voltage security assessment based on voltage stability indices and FDT as shown in figure 6.2 have been analyzed employing system parameters from figure 6.5 to figure 6.10. Synchrophasor data are used to generate the database for the FDT implementation and thereby assess the proximity to voltage collapse or degree of stress with respect to an operating condition on the adopted test system. The FDT performance for different VSI and database considered are obtained in pie charts and text files in the workspace of MATLAB 2014a. The pie charts shown in figure 6.5 to figure 6.10

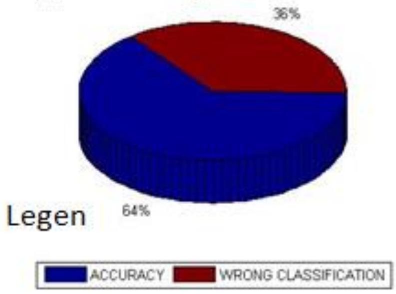
XII. L-Index

Voltage security assessment based on $L-index$ [Jasmon, 1993] carried out on three databases built by considering three sets of attributes. Different database signify the performance for the index and help to identify the system parameters which results in best performance among the attribute set considered. FDT performance on testing set accuracy given in figure 6.5. With reference to figure 6.5, it could be seen that the results for L-index have been plotted. Figure 6.5 (a) denotes the FDT performance for dataset-1. The systems total real power generation, total reactive power generation, total generation apparent power, total real power demand, total reactive power demand, total demand apparent power, total real power loss, total reactive power loss, total apparent power loss, equivalent resistance, equivalent reactance for the two bus equivalent of multi-bus system have been considered as the security predictors for the developed FDT. As shown in figure 6.5 (a) blue slice denotes accuracy percentage for FDT and red one show the misclassification accuracy. Figure 6.5 (b) denotes the accuracy for dataset-2. Bus-voltage has been employed as the attribute set for the dataset-2. Similarly 6.5 (c) Show the FDT performance for dataset-3 built by considering bus-voltage and bus-angles as the attribute set.

(a) Accuracy on Testset-1



(b) Accuracy on Testset-2



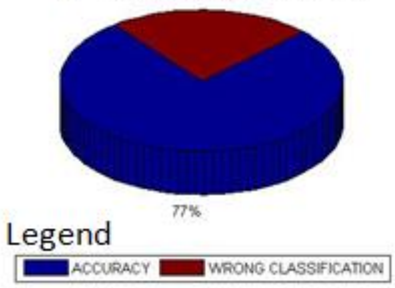
(c) Accuracy on Testset-3

Figure 6.5 L-index Implementation Results

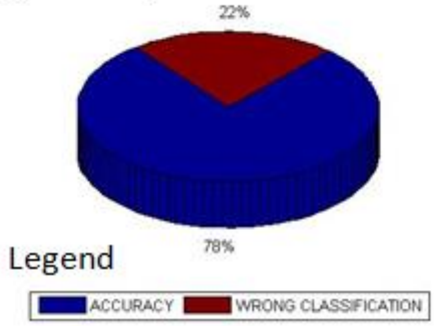
XIII. PI_{VQ}- Index

As explained in section 3.3 of chapter 3 PI_{VQ}-index [Ejebe, 1979] includes the voltage magnitude violation and generators reactive power limit for denoting the degree of stress by penalizing the violations. Dataset-1 includes the bus-voltage and generators reactive power generations as the system attributes. Dataet-2 includes the bus-voltage and bus-angles while dataset-3 employs bus-voltage and generators real power generation as system attributes to build the database. Figure 6.6 shows the FDT performance for the test set obtained by splitting the database obtained above. Figure 6.6 (a) show the FDT accuracy for dataset-1. Similarly figure 6.6 (b) and figure 6.6 (c) shows the FDT performance in predicting the voltage security status for dataset-2, and dataset-3 respectively.

(a) Accuracy on Testset-1



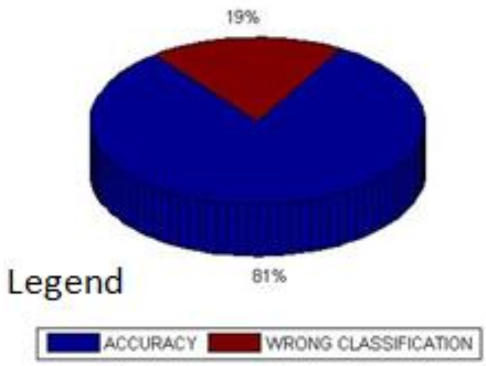
(b) Accuracy on Testset-2



(c) Accuracy on Testset-3

XIV. L_{mn}-Index

Performance for $L_{mn} - index$[Moghavvemi, 1999] is shown in figure 6.7, which shows the security prediction performance for the dataset built by considering voltage synchrophasor. This index denotes the proximity to voltage collapse. As shown in figure 6.7 blue slice denotes accuracy percentage for FDT and red one show the misclassification accuracy.



(a) Accuracy on Testset-1

Figure 6.7 L_{mn} – Index Implementation Results

XV. PI_V-Index

Results obtained for PI_V-index [Ejebe, 1979] in association with FDT performance is shown in figure 6.8. For PI_V-Index dataset-1 built by considering bus-voltage, dataset-2 by bus-angles and dataset-3 by bus-angles and bus-voltages as the attribute sets respectively. Figure 6.8 shows the FDT performance for PI_V-index for three datasets explained above. Figure 6.8 (a), Figure 6.8 (b), Figure 6.8 (c) denotes the performance for dataset-1, dataset-2, and dataset-3 respectively.

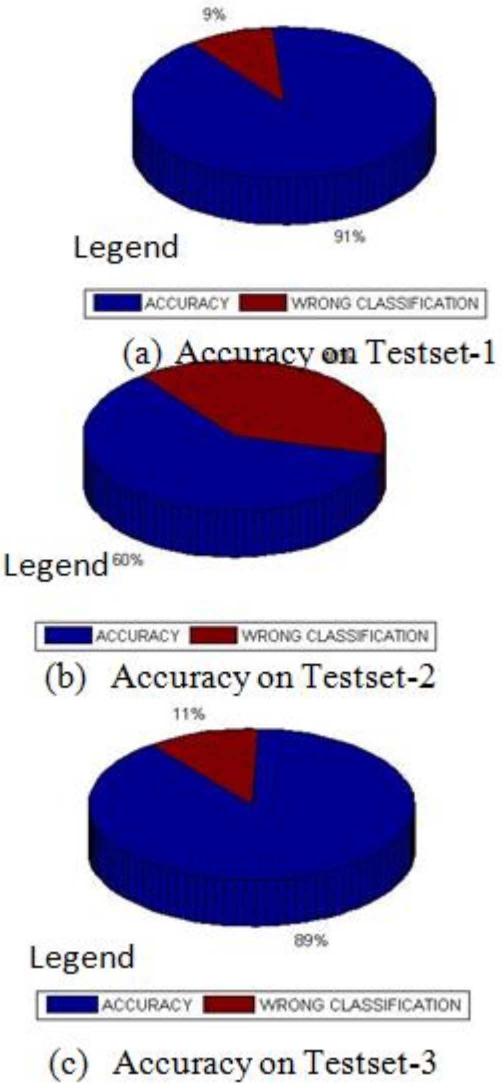
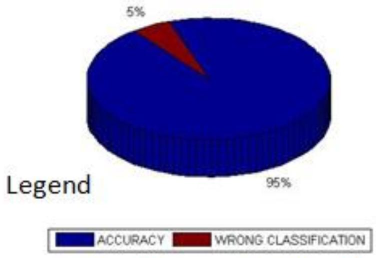


Figure 6.8 PI_V-Index Implementation Results

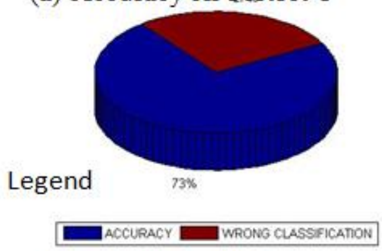
XVI.

XVII. PI_{VMV}-Index

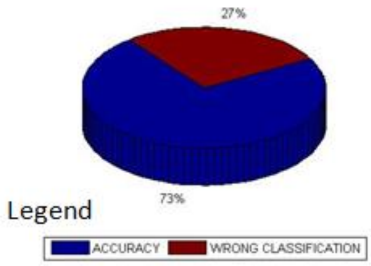
With reference to section 3.4 of chapter 3, $PI_{\_VMV}$-index [Vittal, 2010] signifies the degree of stress subjected by a disturbance on the system in terms of voltage magnitude violations. Voltage synchrophasor and real power generation by the generators have been employed to build the databases. Database-1 incorporates bus-voltage, bus-angles. Database-2 considered bus-angles and database-3 built by taking data of bus-angles and real power generation by generators. The class tagged to each instance determined by the $PI_{\_VMV}$-index, which denotes the degree of stress by penalizing the voltage limit violations. Figure 6.9 shows the FDT performance for three datasets.



(a) Accuracy on Testset-1



(b) Accuracy on Testset-2

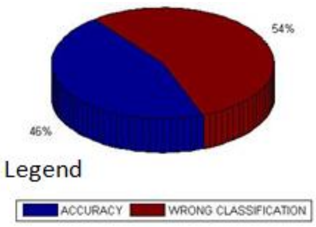


(c) Accuracy on Testset-3

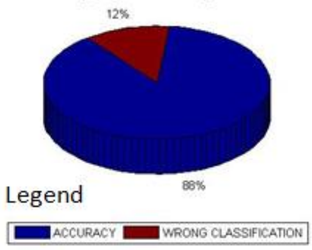
Figure 6.9 PI_{VMV}-Index Implementation Results

XVIII. LVSI-Index

LVSI [El-kateb, 1997] has been explained in section 3.4 of chapter 3. This has been implemented by adopting five datasets. Dataset-1 considers bus-voltage and bus-angles, dataset-2 includes bus-voltages, dataset-3 includes bus-angles, bus-angles and real power generation by generators employed in dataset-4, lastly bus-voltage and real power generation have been used for developing dataset-5. Figure 6.10 shows the LVSI and FDT performance on test set as obtained in workspace by MATLAB programming for the five datasets as explained above.



(a) Accuracy on Testset-1



(b) Accuracy on Testset-2

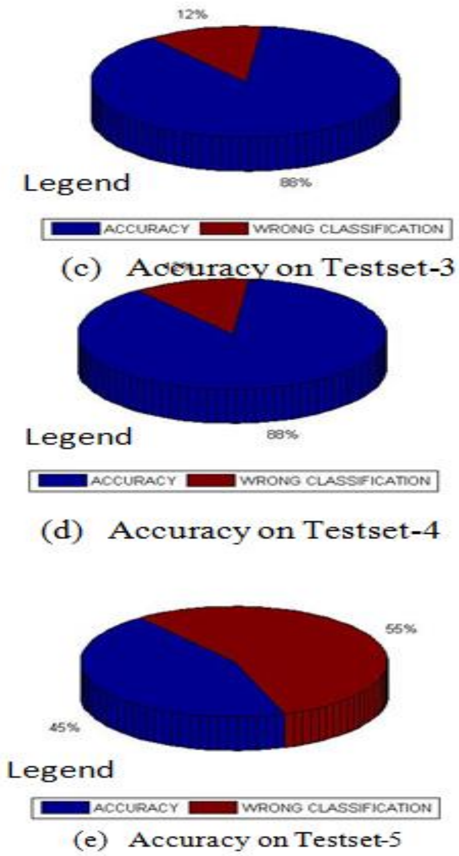


Figure 6.10 LVSI Implementation Results

XIX. Conclusion

The novel approach for research undertaken by the researcher has helped to arrive at the above mentioned conclusions, outcomes, and benefits by which the success of the research has been proved. If others can undertake the researches mentioned in the 'future scope' in section 8.5, power system security may be enhanced

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