Machine Learning Approach to Differentiate Excitation Failure in Synchronous Generators from Power Swing

R. Hemavathi[1] and M.Geethanjali[2]

[1]Thiagarajar College of Engineering, EEE, Madurai, Tamil Nadu, India.

[2]Thiagarajar College of Engineering, EEE, Madurai, Tamil Nadu, India.

hemavathi11@gmail.com*

ABSTRACT

Loss of Excitation (LOE) is the most considerable fault in Synchronous generators since it affects both the generators and power network. The traditional protection method for LOE is based on impedance trajectory of the machine with negative offset mho relay. Meanwhile the traditional method experiences malfunctions and speed dip in LOE detection. This paper presents machine learning approach to detect LOE fault as well as classification logic to discriminate LOE fault from power swing conditions due to Line fault. This paper utilizes Hotelling's-T^2 statistical method to calculate Hotelling's-T^2 based Fault Indices (HT^2 -FI) for fault detection and Support Vector Machine (SVM) for classification. The time series data of electrical quantities such as Terminal voltage and Reactive Power of the generator are extracted from simulated Single Machine Infinite Bus test system and used as input data. This data is involved in calculation of HT^2 –FI and in development of classification logic. The proposed method is simulated and verified for complete, partial LOE conditions and power swing conditions. Simulation outcomes depict the remarkable signs of the proposed method in LOE identification from power swing. Comparative assessment also reports that the method is capable of saving time in detecting LOE.

Keywords: Loss of Excitation, Power Swing, synchronous generator, Hotelling's T^2, Support Vector Machine.

1. Introduction

Synchronous Generators may undergo various abnormal conditions and faults. Amongst them Loss of Excitation (LOE) fault grabs foremost attention since it causes instability in synchronous machines. The excitation failure makes the synchronous machine incapable on controlling the terminal voltage. This leads the machine to act as an induction generator and starts to absorb reactive power from the power system. This leads to instability in power network [1], [2]. The causes of LOE occurrence are field breaker shutdown, failure of supply to excitation system, failure of automatic voltage regulator (AVR), field short circuit/open circuit and poor brush contact of exciter [1], [3].Since, LOE is the most significant fault, generator impedance is considered for LOE detection and a protection scheme with single mho negative offset is proposed in 1949 by Mason [4]. Because of the malfunctions of this scheme, Berdy proposed a LOE protection scheme of two negative mho zones along with time delay [5]. But providing time delay is susceptible to stable power swing (STPS) and other system disturbances since the relay may undergo on false operation [6].Moreover, in [6] a tripping criteria based on rate of change of impedance is addressed for LOE protection which excludes malfunction on STPS. But, the performance on types of LOE are unconfirmed and may require wide simulation process. An adaptive LOE relay scheme based on steady state stability limit along with mho element is suggested in [7].However, the behavior of this scheme under different generator loading conditions is unsupervised. In [8] a LOE index is derived from the generator terminal voltage and reactive power variations for LOE detection. But the index performs on limited scenarios in a predetermined manner and may involve more investigations on relay settings. The LOE protection method addressed in [9] is based on the measurement of flux linkage in the air-gap of the synchronous generator. In [10] air-gap flux linkage along with the negative sequence current of the generator is used for LOE protection. Though [9], [10] shows good outcomes on LOE protection, the sensor requirement for measuring air-gap flux is a complex process in practical. In [11] an analytical approach based on internal voltage calculation is suggested for detection of LOE event. Apart from good results, more simulation process may involve on set point calculation. The sign of generator's second order derivative of the armature current signal of synchronous generator is addressed for LOE protection in [12].The index performance needs to be enhanced for partial LOE condition. LOE protection based on measurement of rotor signals such as filed flux linkage and field current is proposed in [13], [14]. However, these approaches have a shortcoming on sense of type of Loss of Excitation. In [15] a new approach is proposed based on the calculation on DC power injection into the field circuit of the generator from the exciter. The DC power is obtained from exciter output voltage and current signal for power calculation to detect LOE. In [16], a protection method based on slip frequency is recommended to enhance the working of traditional LOE relays in order to prevent malfunctions on power swing conditions. A differential index calculation is recommended in [17], in order to observe the difference among the measured excitation current and calculated field current at the time of LOE for LOE protection. It also secures the system from other power system disturbances.

The development of AI techniques makes their implementation in fault detection, since they proved their importance in each digital platforms. In [18], fuzzy inference mechanism based LOE protection and discrimination from other situations is depicted. This method uses terminal voltage and apparent impedance of the generator as inputs to the fuzzy system, so as to develop fuzzy rules to enhance the LOE protection of conventional method. ANN based LOE protection scheme is proposed in [19] by considering the FFT of the parameters such as current, voltage, speed/angle/power deviation of the machine and admittance. The classifier is able to produce good accuracy on LOE detection but still needs enhancement. In [20] an ANN based LOE protection approach is depicted based on excitation voltage and output active power. A decision tree algorithm is proposed in [21] for LOE protection as well classification from stable power swing conditions. Due to the immense growth of AI methods, it is expected to device such AI based protection methods in practical. The motive of this research is to provide a combined statistical and classification approach for LOE fault detection and classification from power swing condition.

Though several researchers recommended numerous protection methods for LOE detection, AI based method grabs more attention in present days.

- This paper introduces Hotelling's T^2 Statistics Approach for detection of Loss of excitation fault in synchronous generators and power swing conditions too.
- Here the time series data of Terminal voltage (V_t) and Reactive Power (Q) for a specific simulation window is obtained for normal condition to calculate the threshold values.
- Then new observed data for fault condition is considered to detect LOE fault. If any deviations found with the new observed data by falling out of the threshold value then LOE fault is confirmed. In the same way the proposed approach is able to detect partial loss of excitation condition and power swing condition also.
- After fault detection, Support Vector Machine (SVM) classification is performed to classify the LOE fault from power swing and normal operating conditions. The obtained classification model is validated with k-fold cross validation and evaluated with performance indices in order to prove the performance.
- A new classification logic is recommended in this work to classify the LOE from normal and power swing condition with the Terminal voltage (V_t) and Reactive Power (Q) of the machine.

2. LOE-Background

A System that supplying DC current to the filed winding of the synchronous machine is termed as Excitation System. This system keeps the generator in synchronous with the grid. The occurrence of outages in excitation systems may induce abnormal operating consequences [22], [23].

2.2 Impacts of Loss of Excitation

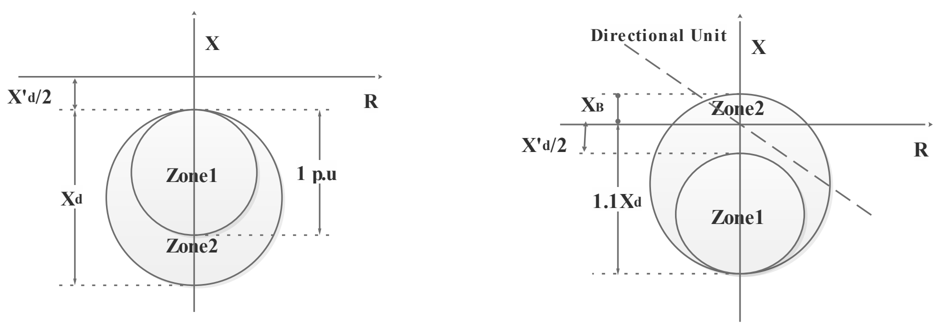
LOE fault may throw severe damages on the Generator and Power Network. On Generator – LOE makes, the rotor current decreases slowly. As well the field voltage started to decay. Correspondingly, the electromagnetic coupling between the stator and rotor decreases. Finally the generator draws reactive power from the power network. The whole LOE process leads to the development of loss of synchronism, the point at which the generator becomes incapable to supply electric power [16], [24]. In Grid connected mode, during LOE generator started to act as an induction machine which results in collapse of grid voltage in some weak system. This may also results in overloading of transmission lines/transformers and miss-operation of over current relay by considering overloading as fault [22], [24].

Hence, LOE should be treated as a critical condition that might have severe counter productivity on both synchronous generator and power grid.

2.3 Detection Schemes of LOE

Impedance (R-X) scheme plays a major role in detection of LOE. Here, the impedance calculation is done by measuring the voltage and current phasors. A typical single phase offset mho relay was introduced for LOE detection by Mason in 1949. This relay consists of single zone circle of diameter $X_d$with negative offset equal to$X'_d/2$ [25], [24].

Due to the arrival of larger reactance machines Berdy proposed Mho relay with two negative offset zones for LOE protection as shown in figure 1.a, along with d-axis transient reactance (X'_d) and synchronous reactance (X_d). The first zone with diameter equal to 1 p.u and offset of $X'_d/2$ detects LOE in heavy loaded condition. The second zone with diameter equal to X_d and offset of $X'_d/2$ detects LOE in light loaded condition of synchronous machine. Later, mho relay with combination of directional unit and two offset mho zones introduced for LOE detection and the settings are shown in figure 1.b. The positive offset mho relay has time delay of 0.1 and 0.5s for zone1 and zone 2 [25], [26]. A time delay setting is provided for both zones in both methods to avoid mal operations of the relay however this is not wise in ride through transient conditions which may cause undesirable operation [25], [26].



(a) (b)

Figure. 1. Mho Relay Characteristics: a) Negative offset Mho Relay b) Positive offset Mho Relay

3. Proposed Scheme

In this study, a power network simulation is performed with LOE fault and Power Swing Conditions. Data acquisition part is carried out in order to prepare the data. Hotelling's T^2 Statistical Approach is proposed for the detection of LOE in Synchronous Generator. This approach is also intended to detect complete LOE and Partial LOE faults as well as power swing conditions in synchronous machine. Then Support Vector Machine (SVM) is involved in LOE fault diagnosis. The proposed scheme comprises of three stages. They are

- Data Acquisition and preprocessing
- LOE detection
- LOE classification from other operating conditions

The entire structure of the proposed method is presented in figure.2

3.1 Modeling of LOE

A power system network of Single Machine Infinite Bus (SMIB) system to evaluate the proposed method is simulated in MATLAB/Simulink-2018(a) as shown in figure. 3. The sample power network consists of a Synchronous Generator with step-up transformer connected to an infinite bus through a transmission line. The data for the simulation has been given in Table 1.

Table 1. Test System Data

Generator	Transformer	Transmission Line	Loads
S=187MVA	V_H = 13.8 kV	Length = 100 km	Load1 = 13.8 kV
V= 13.8 kV	V_L = 230 kV		Load2 = 230 kV
f = 50Hz	f = 50Hz		

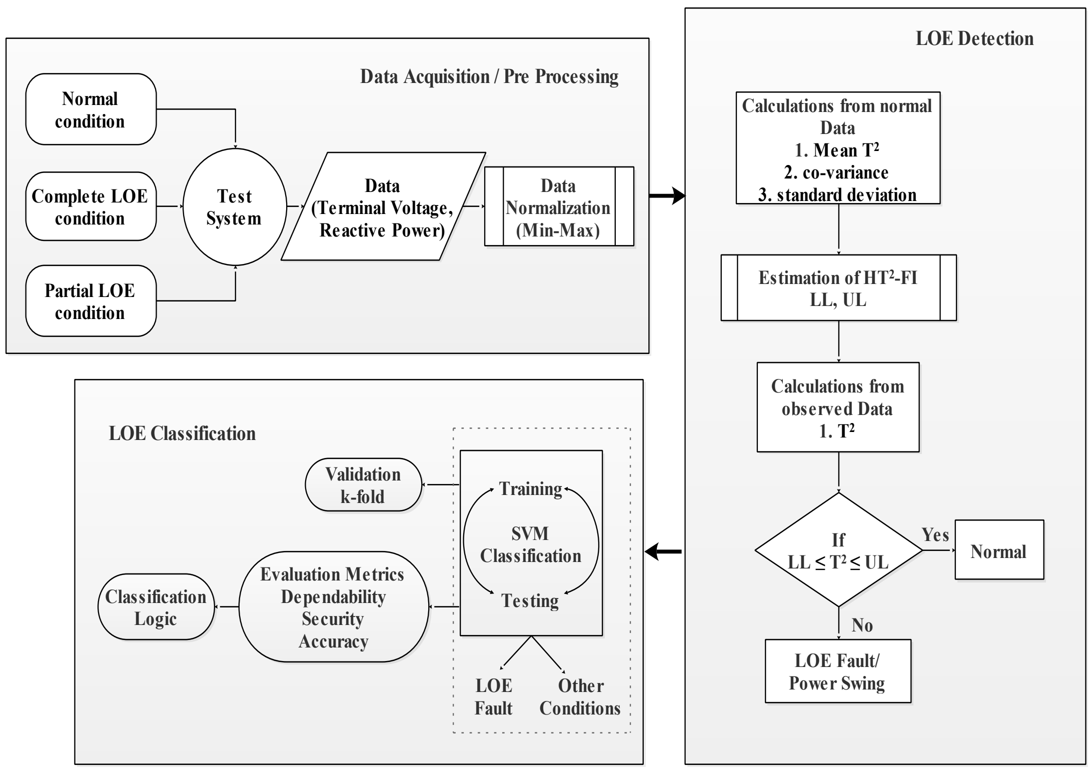


Figure. 2. Proposed Methodology

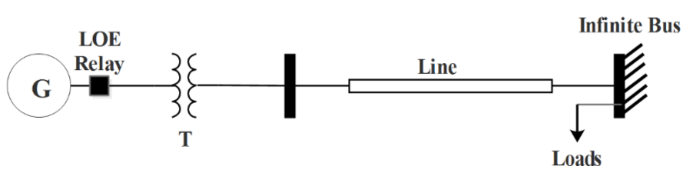


Figure. 3. Simulated Sample Power System

3.2 Data Acquisition

The sample power system is simulated and the performance of the generator is analyzed under normal operating condition. Also the performance of the generator under LOE condition is observed. During LOE condition the generator starts to act as an induction machine and changes occur in electrical and mechanical parameters. The Terminal voltage (V_t), Reactive Power (Q), are the parameters measured at the Generator terminal in this study. In the same way the parameters are measured under power swing condition.

These generator parameters are measured and collected as raw data for specific time window in the proposed method. Then preprocessing of the acquired data is achieved through data normalization to obtain a narrow data. In this work, Min-Max Normalization method is considered and the equation for normalizing data D to an arbitrary interval $[x_1 x_2]$ is given below

$$D_{scale} = x_1 + \left[\frac{D - \min_D}{\max_D - \min_D}\right](x_2 - x_1) \tag{1}$$

After normalization, the data is set for LOE fault detection through Hotelling's T-square approach [27].

3.3 Hotelling's T²Based Fault Detection

In this work, Hotelling's T^2 Statistics Approach [27] is used to determine the fault detection indices to detect LOE fault. This approach used in power system applications in finding faults [29]. This approach uses estimated mean and variance, the 1st order statistical quantities along with the 2nd order statistical quantity such as sample covariance matrix from normalized data for calculation. Moreover, T^2 calculation in this research is used to find the deviation of the LOE fault data from the normal data in order to determine the Hotelling's T^2 based fault indices (HT^2 -FI).

The data considered under normal operation is represented as D = {D_1, D_2, D_3 …DN}. After data normalization the normal data is denoted as d^{norm} = {d_1^{norm} ,d_2^{norm} ,d_3^{norm} ,……d_N^{norm} }. The mean and standard deviation are calculated and the steps involved in calculating the T^2 value [28] for normal data (T^2_{norm}) is given in the below algorithm.

T^2 calculation Algorithm for Normal Data

Input: d^{norm} = {d_1^{norm} ,d_2^{norm} ,d_3^{norm} ,……d_N^{norm}}

Step1: Calculate the sample mean $\bar{d}_N^{norm} = \frac{1}{N}\sum_{i=1}^{N} d_i$ (2)

Step2: Calculate the sample covariance matrix (C_{ij}) between the data features

$$C_{ij} = \frac{1}{N-1}\sum_{k=1}^{N}(d_{N_{i,k}}^{norm} - \bar{d}_{N_i}^{norm})(d_{N_{j,k}}^{norm} - \bar{d}_{N_j}^{norm}) \tag{3}$$

Step3: For i=1 to N; estimate$T^2_{norm_i}$

$$T^2_{norm_i} = N * \left(\bar{d}_N^{norm} - d_{N_i}^{norm}\right)^T * C_{ij}^{-1} * \left(\bar{d}_N^{norm} - d_{N_i}^{norm}\right) \tag{4}$$

Step4: Compute mean of $T^2_{norm_i}$

$$\mu_{T^2_{norm}} = \frac{1}{N}\sum_{i=1}^{N} T^2_{norm_i} \tag{5}$$

Step5: Calculate standard deviation

$$\sigma_{T^2_{norm}} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(T^2_{norm_i} - \mu_{T^2_{norm}})^2} \tag{6}$$

Output:$\bar{d}_N^{norm}$,C_{ij}, $\mu_{T^2_{norm}}$, $\sigma_{T^2_{norm}}$

By following the above mentioned algorithm mean ($\bar{d}_N^{norm}$), sample covariance (C_{ij}), T^2 value ($T^2_{norm_i}$) and standard deviation ($\sigma_{T^2_{norm}}$) for normal data can be obtained.

3.3.1Fault Detection

Using sample mean and covariance T^2 value is calculated for new observed data. This value transformed into T^2 statistic related to F-distribution with the sample mean and covariance. The T^2control limit is attained by F-distribution for significance level of α is given by the following equation.

$$T_{\alpha}^{2} = \frac{q(n-1)(n+1)}{n(n-q)} F_{\alpha(q,n-q)} \quad (7)$$

Where n denotes the number of observations in new observed data, q represents the number of variables and α represents the false alarm rate. The new observation are said to be fault when the T^2value is greater than the T^2control limit and it is given by $T^2 > T_{\alpha}^{2}$ [28], [29], [30].

But when the number of observations in the new data more than 30, the F-distribution based control limit cannot be used as threshold for fault detection. This control limit can be replaced with central limit theorem (CLT) for fault detection in new observed data. The mean and standard deviation calculated from the normal data is considered for the estimation of threshold value range for fault detection which has upper limit and lower limit. The upper limit is given by $\mu_{T_{norm}^{2}} + \lambda * \sigma_{T_{norm}^{2}}$. The lower limit is given by $\mu_{T_{norm}^{2}} - \lambda * \sigma_{T_{norm}^{2}}$. The threshold range is fixed with this two limits for fault detection. Here, λ represents the level of confidence ranging from 1-3.

The new observed data is preprocessed and given as $d^{obs} = \{d_1^{obs}, d_2^{obs}, d_3^{obs}, \ldots\ldots d_N^{obs}\}$. Then T_{obs}^{2} is calculated for the new observed data with the help of calculated mean and covariance for the data corresponding to normal operating condition. If the T_{obs}^{2}value lies within the threshold range then there is no fault. But if it lies out of the threshold limits then it is confirmed for fault. The algorithm for fault detection is given in the following steps.

Fault Detection Algorithm

Input: observed new data-d^{obs},C_{ij},$\mu_{T_{norm}^{2}}$, $\sigma_{T_{norm}^{2}}$, $\bar{d}_{N}^{norm}$, λ

Step1: Obtain preprocessed new observed data d_{N}^{obs}

Step2: Calculate $T_{obs}^{2} = N * \left(\bar{d}_{N}^{norm} - d_{N}^{obs}\right)^{T} * C_{ij}^{-1} * \left(\bar{d}_{N}^{norm} - d_{N}^{obs}\right)$ (8)

Step3: Check for threshold limits (Fault indices-HT^2 -FI). (9)

If $(\mu_{T_{norm}^{2}} - \lambda * \sigma_{T_{norm}^{2}}) \leq T_{obs}^{2} \leq (\mu_{T_{norm}^{2}} + \lambda * \sigma_{T_{norm}^{2}})$ then

Step4: Return Normal else

Step5: Return fault

Step6: End if

Here, T_{obs}^{2}indicates major deviations present in the new observed data to identify the LOE-fault with the help of threshold limits.

3.4 Support Vector Machine Classification

Support Vector Machine (SVM) - A supervised machine learning and pattern recognition technique suitable for classification problems [31]. The SVM used for classification is also termed as Support Vector Classification (SVC), which finds a decision criterion based on linear discriminant function that properly separates data with decent generalization ability with respect to the number of classes i.e., two or more. The classification (decision) criterion is a linear straight line with maximum distance from each class of data for a two class classification. This linear classifier is termed as optimal hyperplane in SVC related problems [32] and the verdict of separation is recognized by the support vectors. In this research, the input samples (d) used in training and testing stages as shown in fig.2 and the output is target/label/status of class. Here two labels of LOE fault and other conditions (Normal and Power Swing) are considered for classification. In addition, the dimensions of hyperplane that separates LOE and Other conditions status, depends on the number of features in input data. In SVC, the decision hyperplane for training data is given by the following function

$$f(x) = w^{T}x + b = \beta.x + b = 0 \quad (10)$$

Where, b is the bias term of real number, w is the n dimensional weight vector and x is the data points of training data set. SVM creates the hyperplane that should have a least possible error in separation of data and by calculating the bias and weight vector. Also the hyperplane should maximize the margin of data according to the class [32].The separation of input data (x) corresponding to the target class (y_i) can be in left (y_i=+1) or in right (y_i=-1) sides of the decision plane (where +1 and -1 denotes data belongs to LOE fault and other conditions respectively) as given in figure.4. The margins that controls the separation of data is given by as follows:

$$w^T x + b = \beta . x + b \begin{cases} \geq 1 & \text{for } y_i=+1 \\ \leq -1 & \text{for } y_i=-1 \end{cases} \qquad (11)$$

Still, there are many margins can be considered as decision boundary of each class because the hyperplane can be anywhere between +1 and -1 status. Hence, it is necessary to find out the best hyperplane that maximizes the distance between margins [32]. In order to get maximize the distance, minimizing the weight vector can be carried out which is given by $\frac{1}{2} w^T w$.

The problem of determining the optimal hyperplane is represented as follows and it is subjected to the constraint of margin of two class [32].

$$Min_{w,b} = \frac{1}{2} w^T w \text{ s.t. } y_i(\beta . x + b) \geq 1 \qquad (12)$$

However, to obtain a good hyperplane for separation, a penalty function is introduced to minimize the classification error, where the actual output (y_i) differs from the predicted output (f(x)). In this regard the optimization problem including penalty function can be represented as follows [32]:

$$Min_{w,b,\xi} = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \qquad (13)$$

$$\text{s.t.} y_i(w^T x + b) \geq 1 - \xi_i \qquad \text{for } y_i = +1 \qquad (14)$$

$$y_i(w^T x + b) \geq -1 + \xi_i \qquad \text{for } y_i = -1 \qquad (15)$$

Where, C is the flexible parameter that controls the error and the value recommended for C is 1 for many applications. The value for ξ_i lies between 0 and 1.

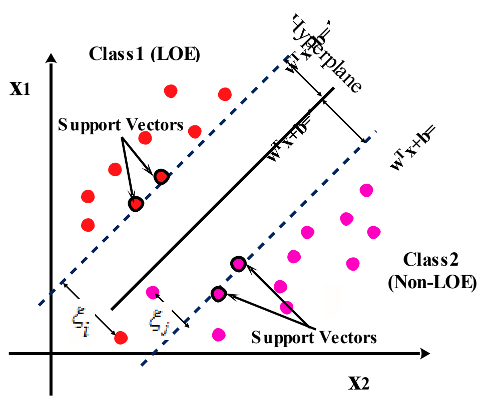


Figure. 4. SVM in Two Class Classification with Hyperplane

It is observed that the weight vector (w) and the bias value (b) are attained by resolving the optimization problems through the equations (9)-(11). Sequential Minimal Optimization (SMO) algorithm is used to resolve this optimization problem in MATLAB and this is commonly used for SVM classification training.

3.4.1 Validation

The most usual technique to evaluate the model in learning practice is k-fold cross validation (k-fold CV). The term cross validation expedites the concept of testing of each and every sample in the dataset. In k-fold CV the data is randomly separated into k-folds of same size and also for an iteration of k times over the data set to validate the obtained model. In this k-folds one fold is used for testing (validation) and the remaining k-1 folds are used as training subset to examine the model performance [33], [34]. Normally the k value will be chosen as k=1 or k=5.

In this research 10-fold cross validation is used for the evaluation of the developed algorithm. Here, the data is separated into 10 folds of same size randomly. In iteration 1, the first fold is validation fold and remaining folds are training. In iteration 2, the second fold is considered as test set and remaining are used as training sets. This process is extended till 10th iteration to evaluate the model. The process of k-fold cross validation for the value K=5 is shown in figure. 5 for understanding.

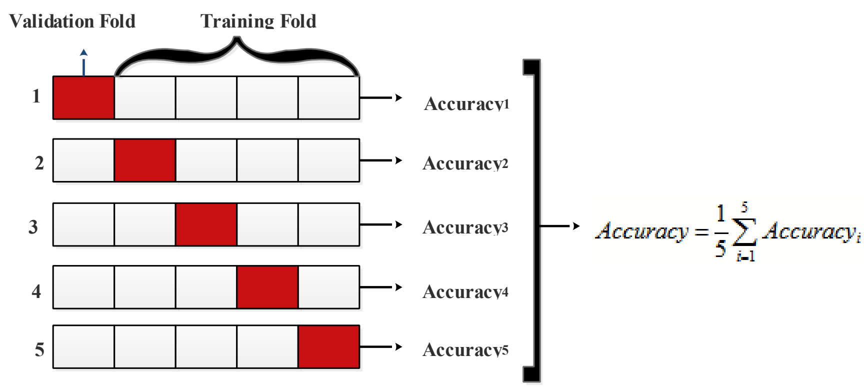


Figure. 5. K-Fold Cross Validation

3.4.2 Evaluation

The following performance indices are involved in evaluation of the performance of the developed model in classification of LOE fault.

Dependability = Predicted LOE cases/Actual LOE cases

Security = Predicted Non-LOE cases/Actual Non-LOE cases

Accuracy = correctly classified cases/All cases.

4. Simulation Environment

The modeling and simulation of the test power system under various operating conditions has carried out in MATLAB software, an important engineering tool to perform the simulation studies. The performance of the synchronous generator has monitored under the following operating conditions:

- Normal operating condition- (Non-Fault condition)
- LOE fault conditions
    1. Complete LOE (CLOE)
    2. Partial LOE (PLOE)
- Power Swing Condition (PSC)

The variation of the generator parameters such as Terminal voltage (V_t), Real power (P), Reactive power(Q), Resistance (R) and Reactance (X) at the machine terminal has measured under normal, CLOE, PLOE and PSC conditions at full load condition. From the measured parameters, terminal voltage (V_t) and reactive power (Q) alone considered for the LOE fault detection and classification. The changes of these parameters for 30 seconds of simulation period under CLOE condition is shown in figure 6.a. also the changes due to power swing because of line fault is shown in figure 6.b. The nature of change of the generator parameters V_t and Q in normal, CLOE, PLOE and PSC conditions are shown in Table 2.

Table 2. Change of Parameters under Normal, CLOE, PLOE and Power Swing conditions

Parameters	Normal Condition	CLOE	PLOE	PSC
V_t	Constant	Decreases	Decreases	Oscillates
Q	Constant	Negative	Negative	Oscillates

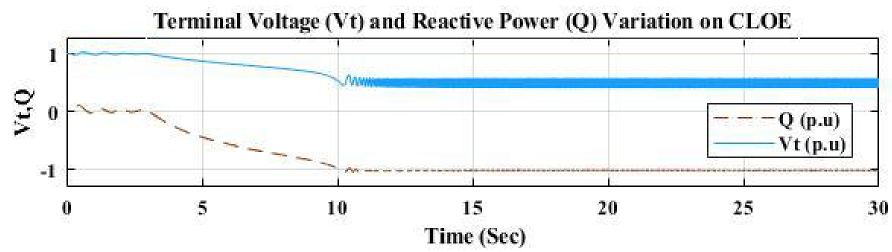


Figure. 6. a – Variation of Terminal Voltage and Reactive Power in CLOE condition at 3 sec.

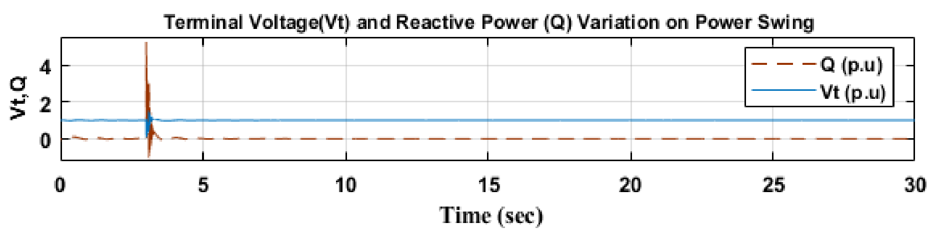


Figure. 6. b – Variation of Terminal Voltage and Reactive Power in Power Swing condition due to 3-phase Line Fault for duration of 100ms

From the simulated waveforms, the time series data has been collected for V_t and Q under normal, CLOE, PLOE and PSC conditions. Then the collected data were normalized with min-max normalization method for further analysis such as fault detection and classification.

4.1Fault Detection

The Hotelling's T^2 based fault detection has performed on the normalized data for CLOE, PLOE and PSC conditions, to detect fault in synchronous generators and this has done with the help of MATLAB software package. The steps involved in fault detection as mentioned in section 3.3 are as follows:

Step1: Acquisition of normal and observed data

Step2: Collected data has normalized.

Step3: Calculation of Mean T^2 value, co-variance and standard deviation for Normal Data

Step4: Estimation of T^2 value for observed Data

  Step4.1: Computation of HT^2 –FI as given in equation number 10

  Step4.2: Validation of step 4 with HT^2 -FI

Step5: Detection of LOE Fault

After fault detection, fault classification has carried out with Support Vector Machine (SVM) to classify LOE fault data from the other data.

4.2 Fault Classification

SVM classifier is used for the classification of LOE fault from PSC and normal operating condition. Also, here the PLOE condition is considered as LOE condition for classification. After classification, validation and evaluation of the classifier is performed to elevate the performance of the SVM classifier. The steps involved in SVM classification are as follows:

Step1: Collection of Input data from fault detection step
Step2: Training of Data with SVM classifier
Step3: Test Data classification
Step4: k-fold cross validation
Step5: Classifier evaluation with performance indices
    Step5.1: Dependability
    Step5.2: Security
    Step5.3: Accuracy

5. Simulation Results and Discussions

The procedural steps of generation of training datasets and testing datasets have been addressed in this section. The performance of the proposed method has been evaluated with the obtained features from simulated test power system. The efficiency of the proposed method has been confirmed by the simulation results.

5.1 Generation of Data sets

The data have been generated from the developed simulink model of the test power system. The simulation has been carried out for a specific time period and the time series data have been obtained for Terminal Voltage (V_t) and Reactive Power (Q) for full load condition of the power system. This dataset includes pre-fault (normal) and fault conditions. The datasets have been generated for the following conditions.

CLOE fault condition: To obtain the CLOE condition, the filed voltage has reduced to 0 at t=3s. The simulation length has been varied from 5s to 30s for CLOE at 1s. This data have been collected with samples of 51044×2. This simulation has carried out for CLOE at full load condition for the above mentioned simulation lengths to obtain variety of datasets in order to test the proposed method.

PLOE fault condition: The same process as that of CLOE condition has been followed to obtain the dataset for PLOE condition by reducing the field voltage to 0.5 p.u. The number of samples obtained are 20951×2 for PLOE at t=3s for simulation length of 5s to 30s.

Power Swing Condition: The PSC samples obtained by creating a 3-phase fault in transmission line for a duration of 50ms, 100ms and 200ms. This simulation has been carried out for different durations and the number of samples obtained are 16680×2.

Normal Condition: The normal samples have been generated by considering the system running under no fault condition. The number of samples obtained are 10193×2 for the simulation length of 5s to 30s.

5.2 Fault Detection Using Proposed HT^2 –FI

The fault detection has been performed for CLOE, PLOE and PSC data samples using the proposed method. The HT^2 –FI (Lower and Upper threshold limits) has been calculated from the normal and CLOE data to detect the CLOE fault. The same process has followed for PLOE and PSC data to detect fault condition. When the T^2 value for the observed data lies within the HT^2 –Fault Indices it is normal state. Rather if it lies outside of the Indices then the fault is confirmed. Here the lower and upper threshold limit values for 30s of simulation period for level of confidence λ=1, are-1.32e-3 and 1.32e+3. With this boundary limits the CLOE fault has been detected and the same procedure has been executed for detection of PLOE and Power Swing condition and the results are confirmed.

To assure the performance of the proposed method the simulation period has been broken into 6 stages and the data samples also obtained for the corresponding stages simulation periods. This has been carried out for the considered three conditions. For each stage of simulation the fault detection has been performed using the proposed method and the result are presented in Table3.

The CLOE fault has been applied at 3rdsec for each simulation stage and the data samples are collected for V_t and Q as mentioned in section 5.1. The HT^2 –FI for each stage has been calculated to detect the CLOE fault. The Table 1 shows that the proposed method has been detected the normal samples as No Fault condition. The CLOE condition is detected as Fault with the proposed scheme for the 6 stages of simulation period. The same procedure has been followed to detect PLOE condition for each stage and the results are shown in Table 3. Here the PLOE fault has applied at 3rd sec for each simulation stage and data samples are obtained. From the results in Table 3 it is proved that the PLOE condition is detected in a successful manner.

Table 3. LOE Fault Detection using HT^2 –FI for 6 stages of simulation period

Simulation Stages (Sec)	Normal Samples *(Nos × 2)*	Fault Detection	CLOE Samples *(Nos × 2)*	Fault Detection	PLOE Samples *(Nos × 2)*	Fault Detection
5	697	NF	699	F	706	F
10	1220	NF	1204	F	1152	F
15	1602	NF	4452	F	1432	F
20	1913	NF	9683	F	1835	F
25	2231	NF	14951	F	5307	F
30	2530	NF	20055	F	105179	F

Nos × 2*- Number of Samples for V_t and Q;NF*-Non Fault ;F*-Fault

As well this procedure executed for PSC data and the response shows as fault on PS conditions. The results for PSC is given in Table 4.

Table 4. Response of HT^2 –FI under power swing condition for 6 stages of simulation period

Simulation Stages (Sec)	Normal Samples *(Nos × 2)*	Response	Fault Duration (ms)	PSC Samples *(Nos × 2)*	Response
30	2530	NF	**50**	3692	F
15	1602	NF	**100**	1998	F
20	1913	NF	**100**	2355	F
25	2231	NF	**100**	2691	F
30	2530	NF	**100**	3034	F
30	2530	NF	**200**	2910	F

Nos × 2*- Number of Samples for V_t and Q; NF*-Non Fault; F*-Fault

From the Table 3 and Table 4 it is confirmed that the proposed HT^2 –FI method is able to detect CLOE, PLOE faults. It also detects the normal samples as Non fault condition. Meanwhile it detects power swing conditions too.

The plot indicates the HT^{2}value for the observed data of stage 6 (simulation period of 30sec) lies outside of the lower limit (LL) and upper limit (UL) which are the CLOE indices. Hence, the CLOE fault is confirmed and this shown in figure 7. Ytsdm in figure 8 represent the HT^{2}value of CLOE data.

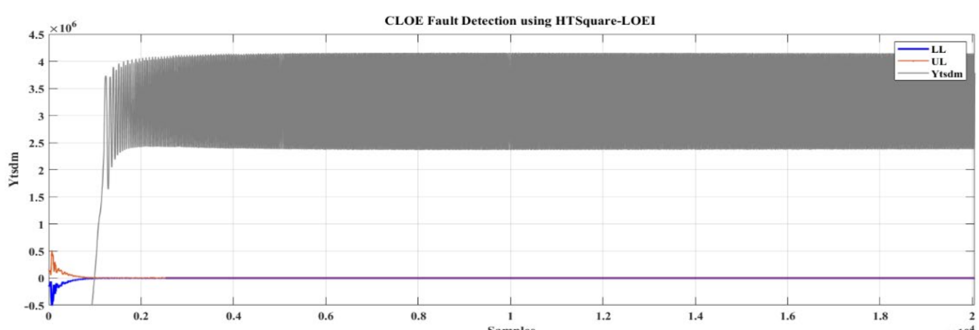


Figure. 7. HT^2 Results to detect CLOE fault

The aforementioned fault detection method has been carried out for level confidence value λ=1. This has implemented for CLOE, PLOE and power swing conditions. The results show the efficiency of the proposed fault detection method. To showcase the efficacy of the proposed method even more, the confidence region has varied and the same fault detection procedure has performed. The level of confidence (λ) value has increased from 1 to 3. However, this increment in threshold limits has no impacts on the LOE fault detection because the CLOE and PLOE faults are successfully detected using proposed scheme and the result shown in Table 5.

Table 5. Fault Detection on Various Level of Confidence Values

λ (Level of Confidence)	**Normal Condition**	**CLOE Fault Detection**	**PLOE Fault Detection**	**PSC Detection**
1	NF	F	F	F
1.5	NF	F	F	F
2	NF	F	F	F
2.5	NF	F	F	F
3	NF	F	F	F

NF*-Non Fault F*-Fault

From Table 5 it is proven that the LOE fault detection using proposed HT^2-FI method is effective even in increased threshold limits. The same method responds for power swing condition too. Hence, a classification method is proposed to classify LOE from power swing condition.

5.3 Fault Classification Using SVM

After successful detection of CLOE, PLOE fault and PSC it is required to classify the LOE fault from PSC and SVM is used for classification purpose. To provide an illustration on SVM approach the simulation stages of 15sec, 25sec and 30 sec are considered. After LOE detection the samples in each simulation stage undergone for SVM classification to portrait how many of LOE samples are classified properly from PSC and normal samples to confirm LOE fault. Through the classification model LOE is classified from PSC and normal samples successfully. The model parameter used here is Linear Kernel Function. To validate this model 10-fold cross validation is performed with k=10. In this validation the data samples in each stage is divided into 10 folds where the first fold is for testing and remaining folds are for training purpose. This process is repeated for 10 times to validate the performance of the model. This entire process is carried out for the simulation stages of 15sec, 25sec and 30 sec. Later on the performance indices such as dependability, security and accuracy are illustrated to evaluate the model for 15sec, 25sec and 30 sec of simulation stages and are shown in Table 6.

Table 6. Performance of SVM Classification Model

Performance Indices	**15sec Simulation**	**25sec Simulation**	**30sec Simulation**
Dependability (%)	80.3	94.27	96.20
Security (%)	98	98.5	98.70
Accuracy (%)	87.01	95.1	96.59

From Table 6, it is confirmed that the LOE samples are classified from PSC and normal samples in a consistent manner. For instance, the performance indices for 30sec simulation shows that the proposed model is more perfect for LOE classification since the accuracy is 96.56% and the confusion matrix for the same is given in Table 7.

Table 7: Confusion Matrix for 30sec simulation of SVM Classification

Samples of 30sec Simulation		**Predicted Class**	
		-1	**1**
True Class	**-1**	5492	72
	1	1161	29413

This SVM Classification seems to be efficient based on the Receiver Operating Characteristic (ROC) curve which shows the balance between true positive rate and false positive rate. From the figure 8, it has been incurred that the upper left triangle of the ROC plot is engaged with the results. Also the area under the curve (AUC) measure is

0.985. This depicts that the efficiency is good for the proposed classification model with ROC curve for classification of LOE from other conditions.

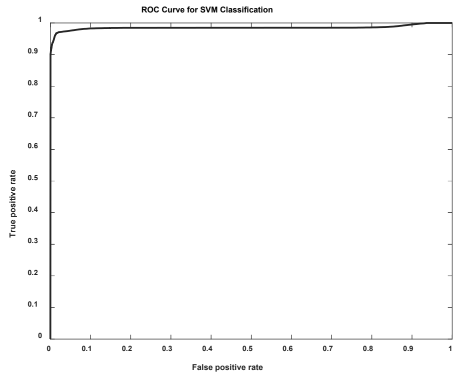


Figure. 8. ROC Plot for SVM Classification

The decision on classification is done by considering equation (8), where x in equation (8) represents the data vectors of two parameters V_t and Q. The weight vector (w^T) for classification is obtained during simulation with SVM algorithm as w^T = [-4.7542, -23.3743] and the Bias value b = -6.0207. The logic for LOE classification is shown in figure 9.

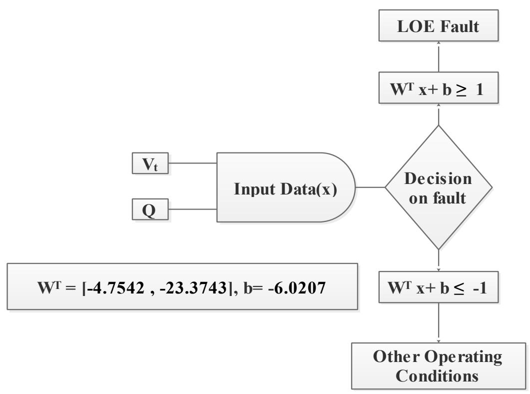


Figure .9. LOE Classification Logic

6. Performance Comparison

The performance of the proposed method is compared with other published Literatures. In this regard, performance comparison is done among the proposed method and other methods depicted in literature [16] and [18]. The time taken for LOE detection is given in Table 8. The parameters considered for LOE detection in other schemes and the LOE types taken are also mentioned in Table 8. The outcomes of Table 8 depict that the proposed method is capable of showing significant improvement in time taken to detect and classify LOE fault from other operating conditions. In addition to that, the PLOE also considered in proposed method.

Table 8. Performance Comparison of Proposed Method with other methods published in Literature

LOE Protection Scheme	Parameters Considered	Scenarios	LOE Type	Detection Time(sec)
Method [18]	V,Z	LOE/PSC	CLOE	3.4-13
Method [16]	Slip Frequency	LOE/PSC	CLOE	14.94
Proposed Method	V_t,Q	LOE/PSC	CLOE/PLOE	5.31

From the tabulated results, it is clear that the proposed method is able to detect the fault conditions and classify the LOE from Power Swing and Normal Conditions in a quick manner.

7. Conclusion

A new setting free method to detect LOE in Synchronous Generators and classify LOE from other operating conditions was given in this paper. The LOE fault detection was based on Hotelling's T^2 method. The terminal voltage and reactive power measured from generator terminal were used to calculate HT^2 –FI. During normal operating condition of the generator, the observed data lies within the index. On the other hand during fault the observed data falls out of HT^2 –FI. With this criteria LOE phenomenon is confirmed. As well, the partial LOE and PSC due to 3-phase line fault were also detected in the same manner and the simulation results showcased the same. Afterwards, SVM classification is performed to classify LOE from normal and Power swing condition. Then a classification logic is developed in this study. The test results showcase the efficiency of the classification model in maintaining the dependability, security and accuracy. According to the comparative study performed, the proposed scheme consumes reduced time duration in LOE detection and classification. The proposed method is more reliable and unchallenging in LOE detection and classification of LOE from other operating conditions in a power system network.

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Declarations

Ethical Approval: Not Applicable

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Authors' contributions:

Author1: Main work was carried out and manuscript preparation including figures has been done.

Author2: Manuscript correction and review has been done.

Author 1&2: Final manuscript has been reviewed for submission.

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Availability of data and materials: Not Applicable

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