Semnan University

Journal of Modeling & Simulation in Electrical & Electronics Engineering (MSEEE)

Journal homepage: https://mseee.semnan.ac.ir/

ISSN: 2821-0786

Artificial Neural Network Protection of Synchronous Generators Under Loss of Excitation

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***Abstract*-- Loss of Excitation (LOE) poses a significant challenge for synchronous generators. It can lead to instability, overcurrent conditions, and potentially a loss of synchronization with the electrical grid. Conventional protection techniques based on impedance or power often lack adequate selectivity and are especially vulnerable to voltage fluctuations during major failures. This vulnerability can result in incorrect and undesired disconnections. This article presents an intelligent protection solution that utilizes an artificial neural network (ANN) method to classify and securely identify both entire and partial excitation losses in synchronous generators. The suggested technique uses electrical and electromechanical indications that show how the generator really behaves over time, such as terminal voltage, reactive power, load angle, and load angle derivative. A feedforward NN was trained to classify the difference between four operational states: normal, LOE, partial loss of excitation, and severe symmetric fault. The suggested method can isolate the generator within 0.46 seconds after the LOE or partial LOE (PLOE) happens in the generator terminal.**

***Index Terms*- Loss of Excitation, Artificial Neural Network, PLOE, MATLAB, Synchronous Generators.**

I. Introduction

Synchronous generators (SGs), thanks to their high inertia, controllability, and ability to provide reactive power support, have always been the backbone of large-scale power systems [1, 2]. Thus, the safe operation of such generators is critically important for overall system stability and reliability. Loss of excitation (LOE) is one of the most dangerous and, at the same time, challenging faults that can interrupt synchronous generators. LOE takes place if the excitation system is partially or entirely out of order, which causes a drastic drop in the field current of the generator [3]. Without proper and timely recognition and removal, the situation can lead to rotor overheating, voltage instability, absorbing reactive power when not required, and, in the worst-case scenario, loss of synchronism, resulting in system-wide cascading disturbances [4, 5]. However, traditionally, protection against LOE has been achieved by impedance-based relays, e.g., offset mho or admittance relays that track the generator's apparent impedance path in the R-X plane [5,7]. While these have been the mainstay of practical power systems, their proper functioning relies heavily on correct setting coordination as well as system operating conditions. Today, modern power systems are drastically different from older systems due to their high variability, dynamic loading, and increased integration of renewable energy sources. Therefore, conventional LOE protection schemes may be prone to malfunction, respond slowly, or even misclassify other kinds of disturbances, such as load variations, external faults, or power swings, as LOE events. Hence, these findings highlight the need for robust and adaptive detection methods capable of delivering reliable results across diverse operating scenarios.[8, 9]. Advancements in machine learning and artificial intelligence (AI) have greatly facilitated power system protection and monitoring. Neural

Received; 2026-02-23 Revised; 2026-05-09 Accepted; 2026-06-07

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DOI: https://doi.org/10.22075/MSEEE.2026.40707.1258

Cite this article as:

Mohammed, R; Moravej, Z; Yaghobi, H; and Kadhim Wali, M. (2026). Artificial Neural Network Protection of Synchronous Generators Under Loss of Excitation. *Journal of Modeling & Simulation in Electrical & Electronics Engineering (MSEEE). Semnan University Press . 6 (3), 1-9.*

network (NN) methods, in particular, have shown their effectiveness in understanding nonlinear dependencies and revealing complex dynamic behaviors that are only very limitedly modeled analytically [10-12]. Whereas traditional threshold- or impedance-based methods rely on fixed rules, NNs can classify faults more quickly and accurately by extracting unique predictive features from the data itself. Numerous research works have focused on AI approaches to enhance generator protection; however, many depend on heavy feature extraction, intricate signal modifications, or restrictive assumptions limiting their real-world utility.

In recent years, researchers have employed various methods to detect and monitor the LOE of the SGs using AI and ML techniques. The purpose of the research in [13] is to identify and distinguish the LOE events from the power swing conditions in synchronous generators by means of a machine learning-based framework. The authors derive several time-domain and frequency-domain features from the generator's electrical signals and apply supervised learning classifiers to discriminate between dynamic operating conditions, thereby improving accuracy. The new technique shows better results than traditional impedance-based relays. Nevertheless, their solution heavily depends on feature engineering, which means the necessity of beforehand expert knowledge and the proper choice of signal properties. In addition, the classifier's performance depends on the quality and variety of the training dataset, which may limit its generalization capability when encountering unseen system configurations.

The research study in [14] proposed a method based on dynamic state estimation (DSE) to detect LOE in synchronous generators. The technique uses Kalman filter-based estimation and can therefore be both very sensitive and robust in a noisy measurement environment and when the operating point changes. The method is quite effective in differentiating LOE from external disturbances and transient events. However, the main drawback of the approach is that it relies heavily on the availability of an accurate generator model and exact system parameters.

In addition, a survey of protection challenges and solutions to the issues encountered in distribution-generation-integrated DC microgrids was presented in [15]. The article discusses protection problems in general, arising from the dominance of converter-based systems, the presence of bidirectional power flow, and reduced system inertia. The research aims to organize the various fault detection and protection methods to identify research areas for further development. It introduces genuinely insightful concepts, such as intelligent, self-healing protection systems, and, furthermore, points out the use of AI methods. Nevertheless, its deficiency lies in the fact that shadow is not thrown on synchronous generator-related faults, such as LOE, in traditional AC power systems. The author's argument stays primarily at the level of theory, with only a few examples of quantitative validation or suggestions of the technical implementation. Therefore, the study serves mainly as an overview, providing an introduction to the topic, and does not address excitation-related faults in synchronous generators. The main goal of the study in [16] is to review and summarize the different protection schemes, such as adaptive relays, communication-based methods, and intelligent algorithms. It points out how various signal processing and artificial intelligence tools have been increasingly used to make protection systems more reliable. On the other hand, the study adopts a top-level view of the system to provide the presented issues, such as excitation loss in synchronous generators. The study provides detailed comparisons of different LOE detection methods, such as the practical difficulties of using advanced techniques for real-world generator protection.

The purpose of the study in [17] is to remove the relay setting coordination requirement by taking the estimated air-gap flux behavior as the main detection criterion. The method improves performance under variations in operating conditions and has lower complexity compared to the traditional impedance-based settings. The study provides a reliable detection that is feasible under different LOE situations. However, the method depends on correct flux estimation, which may be influenced by measurement noise, parameter inaccuracy, and saturation effects. Besides, the technique may have some difficulties separating LOE from other incidents that drastically change flux features, such as heavy external faults. The proposed method in [18] is simple, fast, and easy to implement, and it detects the LOE of the SGs. These features highly increase the practical protection application attractiveness. Test results demonstrate faster detection compared to traditional impedance-based relays. Nevertheless, the method has low sensitivity to variations in operating conditions, as reactive power behavior is also affected by load, voltage control, and network topology changes. It is possible, in a weak network or under heavy load, that similar reactive power changes may occur even without LOE, leading to misclassification.

The authors in [19] have described a protective LOE detection scheme that operates smoothly during power swing conditions. To avoid the false tripping of LOE protection during stable or unstable swings, the method introduces additional discrimination logic. Essentially, it improves protection by using generator electrical quantities together with swing features. The testing results indicate that the new method has better selectivity than the conventional relays. Major changes in system settings or generator runs beyond expected conditions could compromise its effectiveness. Besides, the rule-based characteristic of the method restrains its flexibility and capacity to learn from complex, nonlinear power system environments. In [20], different LOE methods are presented to classify the state-of-the-art methods and clarify the advantages and limitations. The study observes that AI- or ML-based LOE methods have the potential to enhance both the efficiency and the functioning of the SGs.

The study in [21] proposed a new setting-free method to monitor and detect the LOE of SGs. The suggested method does not require any threshold to represent the fault protection. The results of the LOE with the rate change of the resistance measured by the relay are implemented.

The authors in [22] have presented a new approach for an LOE detection scheme based on an adaptive neuro-fuzzy inference system (ANFIS) by exploiting only the positive-sequence voltage and current components. The goal is to incorporate the respective strengths of fuzzy logic and neural networks to target accuracy enhancement under uncertain operating conditions. The findings show that performance in terms of sensitivity was significantly better, and the response was quicker compared with that of the conventional methods.

Moreover, the extra computational workload introduced by the ANFIS method may even prevent the practical implementation of relays in real-time, particularly in those protection devices that are embedded. The authors in [23] introduced a method for detecting LOE based on the digital phase comparator algorithm. The authors have detected power loss using phase shifts between electrical quantities in a more reliable manner. The procedure is quite straightforward and ideally fits a digital relay implementation.

In [24], a fuzzy logic method was presented to figure out complete and partial LOEs in synchronous generators. It attempts to deal with the uncertainty and nonlinear nature of excitation-based faults. This method shows the capability to separate cases of partial and complete excitation loss. The authors in [25] have proposed a convolutional neural network (CNN) to detect LOE in the SGs. The study aims to take advantage of deep learning's feature-learning capability with manual feature extraction to enhance classification accuracy. The simulation results indicate a high detection accuracy and excellent discrimination capability under different operating scenarios. However, the method requires large annotated datasets for training, which may not always be the case in real situations. Furthermore, the CNNs' computational requirements may hinder their installation in the traditional protection hardware that does not have special processing units.

In this paper, an intelligent protection solution employing an artificial neural network (ANN) is presented to rapidly and safely detect complete and partial excitation loss in synchronous generators. The method presented here makes use of a small set of physically meaningful dynamic features, such as terminal voltage, active and reactive power, load angle, and the rate of change of load angle, which allow the method to distinguish between normal operation, partial LOE, complete LOE, and three-phase short-circuit faults. In addition, by adding load-angle-based measurement, the ANN has been able to detect the LOE, especially under very challenging transient situations (extreme transient conditions). The proposed method was objectively evaluated using the training, validation, and testing datasets collectively, achieving a classification accuracy of 89.8%, which demonstrates strong generalization capability. Furthermore, the simulation results show that the proposed safety measures operate correctly in the presence of faults without any false tripping, while providing a rapid response to loss-of-excitation (LOE) detection. The entire MATLAB/Simulink solution verifies the proposed scheme's feasibility for using smart generator protection online.

II. Methods and Materials

The LOE of the SG was studied in MATLAB/Simulink, and the one-line diagram of the studied system is shown in Fig. 1. It consists of a synchronous generator connected to an infinite bus load through a 13.8/230 kV high-voltage transformer and transmission lines. This figure shows the mechanical and electrical connections between the generator, the step-up transformer, and the grid. As observed, the LOE relay uses the generator terminal voltage and current to derive the impedance curve for the first LOE detection method. The LOE relay conceptually determines the impedance curve for the LOE detection using conventional methods with the aid of the generator's voltage and current terminals. Fig. 2 shows the equivalent circuit of SG connected to the infinite bus. The modeling of this system was conducted using (1)-(3). At the LOE state, the internal voltage of the SG becomes zero. Therefore, the first part of (3) is removed, and the total impedance $(-jX_G I)$ which is calculated by the LOE relay [25].

$$V = E_G\angle\delta - jX_G I \quad (1)$$

$$I = \frac{E_G\angle\delta - E_G\angle 0}{j(X_G + X_T + X_{sys})} \quad (2)$$

$$Z = \frac{E_G\angle\delta}{I} - jX_G I \quad (3)$$

where E_G is the internal voltage of the SG, X_G is the reactance of the SG, δ is the power angle, Z is the impedance seen by the relay, and X_T and X_{sys} are the reactance of the transmission line and the infinite bus.

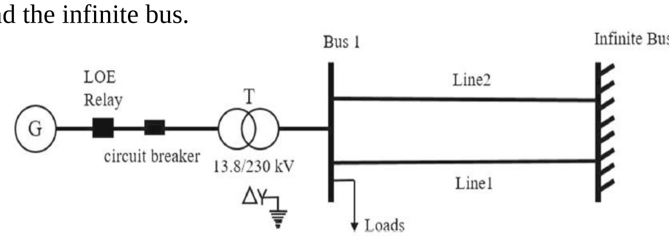

Fig. 1 The suggested studied system

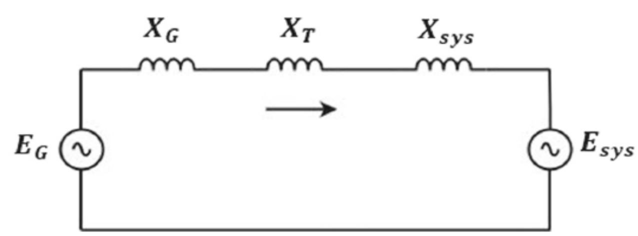

Fig. 2 Equivalent circuit of the system.

III. Loss of the excitation concept

A. LOE overview

LOE in a synchronous generator is an abnormal operating scenario when the generator's field current is lost partially or fully because of the malfunction of the excitation system. The excitation system is the component that provides direct current to the rotor winding, thus producing the magnetic field necessary for synchronous operation and reactive power control. If excitation is lost, the rotor magnetic field either collapses or is considerably weakened, and the generator is unable to produce the electromagnetic coupling needed to operate as a synchronous machine [24, 26]. In the situation of LOE, the synchronous generator starts acting like an induction generator that takes reactive power from the power system rather than delivering it. This instant change causes a typical variation in the flow of reactive power, usually from positive (generation) to negative (absorption). Hence, the generator's terminal voltage might be lower, and stator currents could rise, leading to the overheating of rotor and stator windings. Therefore, if an LOE condition persists for a long time, it may lead to a generator being damaged both thermally and mechanically beyond repair. A generator's dynamic LOE behavior depends very much on conditions such as the level of loading, the strength of the network, and the fault severity. With strong grids, a generator can remain synchronized for a short while even when excitation is lost, but in weak grids or under heavy loading, LOE can very quickly produce a loss of synchronism and pole slipping. In addition, partial LOE might pose a significant challenge to detect because the generator can still function with reduced performance and only become unstable over time.

B. Impedance Relays

Impedance relays were used in the protection methods by calculating the impedance with current and voltage transformers. In 1975, Berdy introduced a two-zone relay including a smaller zone with a reduced time delay (1 pu diameter) to identify LOE and prevent SPSs from venturing into the zone, beside a bigger zone with an extended time delay (Xd diameter), both incorporating an offset value of X'd/2 [25]. Common time delays are around 0.3 to 0.4 seconds for the small zone and 1 to 2 seconds for the big zone. Fig. 3 illustrates a two-zone loss-of-excitation relay. However, the MHO offset relay with a directional element incorporates the beneficial features of the Berdy design while eliminating its limitations. This relay is equipped with a directional feature that continues to alert system faults while the LOE conditions are the primary focus of the relay. The directional element is configured at an angle of 10-15 degrees; if the leading power factor exceeds this range, an alarm will activate [25, 26]. Furthermore, (4) describes the impedance locus of the generator connection.

$$\check{Z} = \frac{V^2}{P-jQ} = \frac{V^2\times(P+jQ)}{P^2+Q^2} = \frac{V^2\times P}{P^2+Q^2} + \frac{j(V^2\times Q)}{P^2+Q^2} = R + j\,X \qquad (4)$$

where P and Q are the active and reactive power, respectively. The real and imaginary parts of the impedance are denoted by R and X, respectively.

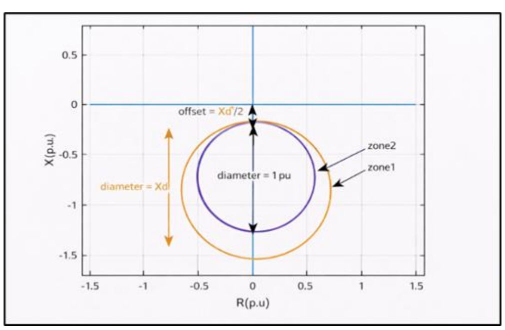

Fig. 3 Offset relay for two-zone LOE.

IV. Methodology of the Research

A. Set up and LOE testing

Fig. 4 illustrates the single-line diagram of the analyzed system. The SG is equipped with an LOE relay, a current transformer (CT), a voltage transformer (VT), a high-voltage transformer (13.8 KV / 230 KV), a circuit breaker, and two transmission lines linked to the infinite bus. In this work, MATLAB/Simulink was used to model and test the SG as presented in Fig. 5. This figure shows that the proposed ANN-based LOE detection scheme works when an SG is connected to a high-voltage transmission network. The model is designed to accurately capture the electromagnetic and electromechanical behavior of the synchronous generator under normal operation, with partial LOE, with LOE, and with a three-phase fault. The parameters of the system are presented in Appendix I.

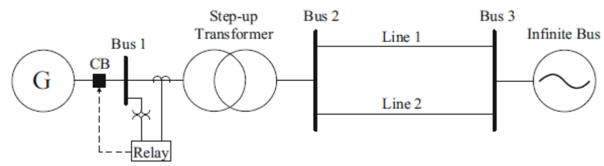

Fig. 4 The single-line diagram of the studied system with SG

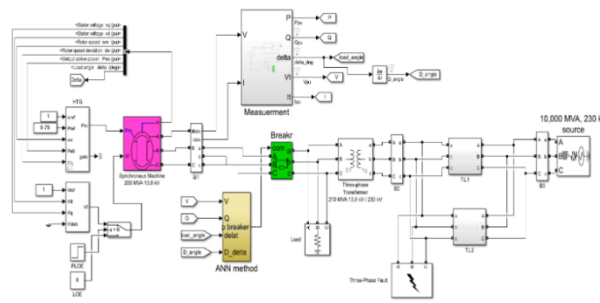

Fig. 5 Proposed power system diagram under MATLAB. Simulink.

This study conducts PLOE, LOE, and symmetrical fault (SF) analyses, along with a three-phase fault, to validate the proposed ANN detection method over a simulation duration of 8 seconds. Moreover, Figs. 4 and 5 show that the synchronous generator behaves under an LOE event in simulation at t = 2 s. The active power and reactive power responses are shown in Fig. 6. The response of the terminal voltage and current of the SG are presented in Fig. 7. Also, the load angle of the generator under LOE is shown in Fig. 8. Under normal operating conditions, the generator supplied active power at a steady level close to the rated power, and reactive power (Q) was positive, i.e., the grid received magnetizing and excitation power. At t = 2 s, the excitation is curtailed to initiate the LOE condition, and the resulting effect on reactive power is a drop in the value, eventually becoming negative in the course of time as it continuously trends downward. This pattern validates the model, in which the machine is forced to take reactive power from the system as a characteristic feature of the under-excited and LOE operation, which is known to be distinctive.

Moreover, the active power increases slowly as the rotor angle grows, with a weakening in electromagnetic coupling. This gradual rise in power illustrates the fact that the LOE causes a mismatch between the mechanical input and the electrical output power. When the LOE condition is severe, the transient response curves for P and Q show pronounced oscillations at around ≈ 6 s, the exact moment when generator synchronization with the grid is lost. Thus, the generator loses the ability to operate stably in synchronism with the grid, which results in fluctuations of the electrical power. After the LOE, the terminal voltage will slowly reduce as the excitation power decreases. However, the stator current will increase markedly, most especially close to the moment when the loss of synchronism occurs.

In general, the paper discloses the physical dynamical behavior of the synchronous generator during the LOE using the developed MATLAB/Simulink model. The different transitions depicted, from normal operation to under-excitation and loss of synchronism, provide enough evidence that the signals via simulation (active power, reactive power, voltage, and current) are appropriate for the design and implementation of advanced protective devices such as the proposed ANN-based LOE relay.

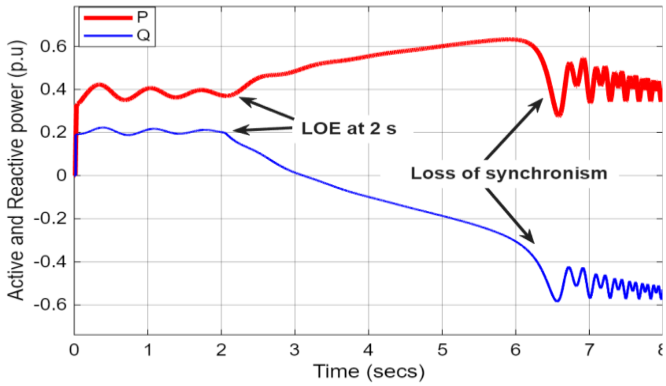

Fig. 6 Active and reactive power response under LOE.

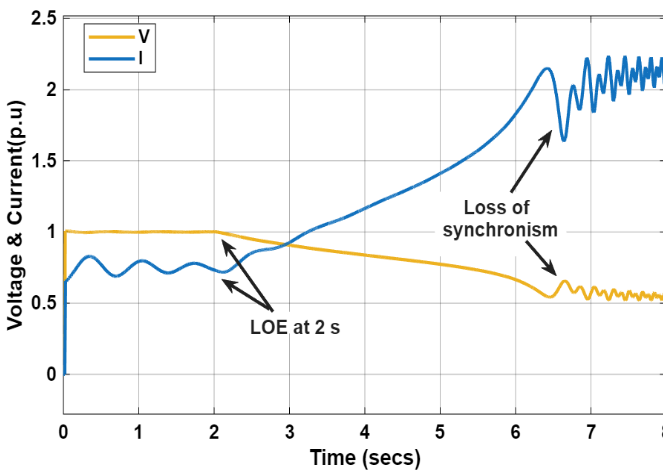

Fig. 7 Voltage and current response under LOE.

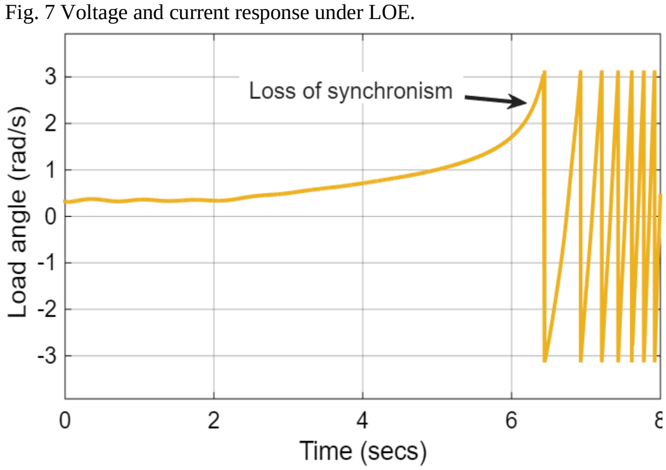

Fig. 8 Load angle of the generator under LOE

B. Design the ANN protection method

The proposed approach for LOE detection and protection is essentially a supervised ANN closely integrated with a comprehensive SG model developed in MATLAB/Simulink. The objective of the ANN framework is to obtain prompt and reliable identification of the normal mode of operation, PLOE, complete LOE, and three-phase short-circuit faults (SF) under different power system operating conditions. The ANN algorithm diagram and its flowchart are shown in Figs. 9 and 10, respectively. The procedure of the implementation is summarized as follows:

-Step (1)-Modeling of the power system: Using MATLAB/Simulink, a detailed power system model was developed that reflects the operating conditions of the real-world system. The synchronous generator of 200 MVA at 13.8 kV is modeled with the same SG model so as to render the transient and sub-transient electromechanical dynamics accurately.

The step-up transformer and the double-circuit transmission line were used to connect the generator to a strong grid that was modeled as an infinite bus (10000 MVA, 230 kV). This arrangement not only ensures the stability of the grid but also exposes the operation of the generator during LOE events.

-Step (2)- Simulation of LOE, PLOE, and SF scenarios: LOE conditions are achieved by directly changing the generator field voltage signal within the excitation system. generator field voltage signal within the excitation system. Both partial LOE (field voltage is reduced) gradually) and complete LOE (excitation is suddenly collapsed) are simulated to represent actual excitation system failures. In this paper, the field voltage was V_f=0.3 p.u. at PLOE. Moreover, An asymmetrical three-phase short-circuit fault is set on the transmission line to test the robustness of the proposed protection scheme against very harsh external disturbances. The occurrences happen at different times, and the points of operation are used to extend the training dataset.
dataset.

-Step (3)- Feature measurement and parameters extraction: The terminal voltage (V), current (I), reactive power (Q), load angle (δ), and the change in the load angle ($d\delta/dt$) are extracted from the simulation for each LOE or fault scenario. The selected features are used to train the ANN method. The angular features are particularly important where LOE leads to continuous rotor acceleration and progressive angle divergence. Moreover, the operation under SF results in transient oscillations that clear and classify the SF against the PLOE or LOE. All measured data are expressed in p.u and collected within a predefined post-event decision window of the curves.

-Step (4)- Data collection and labeling: In this step, the ***extracted*** features are normalized based on the extracted feature vectors and labeled into four operating classes: normal operation, partial LOE, complete LOE, and three-phase fault. The dataset is randomly split into training, validation, and testing subsets to ensure unbiased performance evaluation and the robust generalization capability of the ANN.

-Step (5)—training the ANN method: In this study, a feed-forward neural network (FFNN) has been developed to classify and protect the SG against the LOE, PLOE, and SF scenarios. The input feature ***set*** was collected from time-domain simulation measurements such as $V, I, \delta,$ and $d\delta/dt$. In this work, a sliding window is used to improve the robustness and prove the training approach under LOE or transient disturbances. The measured signals are sensed and sampled at 20Hz, and the suggested ANN inputs are formed using a 0.3-second window, resulting in 6 samples per parameter. The total inputs to the ANN block are 24 features per training scenario. The structure of the ANN comprises an input layer with 10 neurons. These have nonlinear activation functions, whereas the output layer has 4 neurons, corresponding to the target classes.

To facilitate multi-class probabilistic classification, the output layer was given a SoftMax activation function. The network was trained using a cross-entropy loss function, which is highly efficient for classification problems, and optimization was done through the backpropagation algorithm. The dataset was collected directly from MATLAB/Simulink time-domain simulations under different operating and disturbance scenarios, ensuring consistency between the training data and the real-time implementation environment. To avoid overfitting and to check the ability to generalize, the dataset was split into training, validation, and testing sections.

***-Step (6)—implementation and logic decision*:** to enhance the ANN protection scheme, the suggested ANN block in Simulink was integrated with a decision logic model**.** The decision logic is mainly geared towards protection. A confirmation counter is part of this logic, which requires detecting LOE or PLOE continuously through several consecutive windows before a trip command can be given. Besides, a swing restraint mechanism using the size of dδ/dtd was added to prevent ANN decisions during severe electromechanical oscillations. The developed ANN via the *gensim* function was imported into Simulink for real-time deployment as an intelligent relay without any issues. This combination of ANN-based protection features offers a high level of classification accuracy and fast response with great security. Hence, it can be used for practical generator synchronous protection. However, the presented flowchart denotes a protection-centric decision mechanism in which generator electrical and electromechanical measurements first undergo a sliding-window feature extraction stage, and then an ANN classifies the features into normal, LOE, PLOE, and symmetrical fault conditions. Then, the ANN method protects the SG via fault-blocking, swing-restraint, and time-confirmation logics to achieve fast, secure, and reliable tripping without malfunction even during deep voltage depressions or transient power swings.

The dataset is a result of extensive MATLAB/Simulink time-domain simulations operating under different fault times, and excitation conditions were used to make the dataset rich and help the ANN learn well. The resulting dataset was split into training, validation, and testing parts following the standard ratio of 70%, 15%, and 15%.

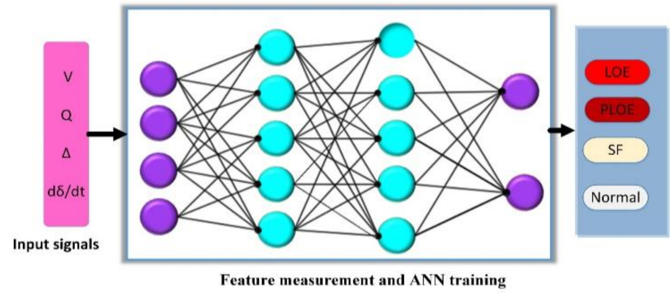

Fig. 9 ANN algorithm

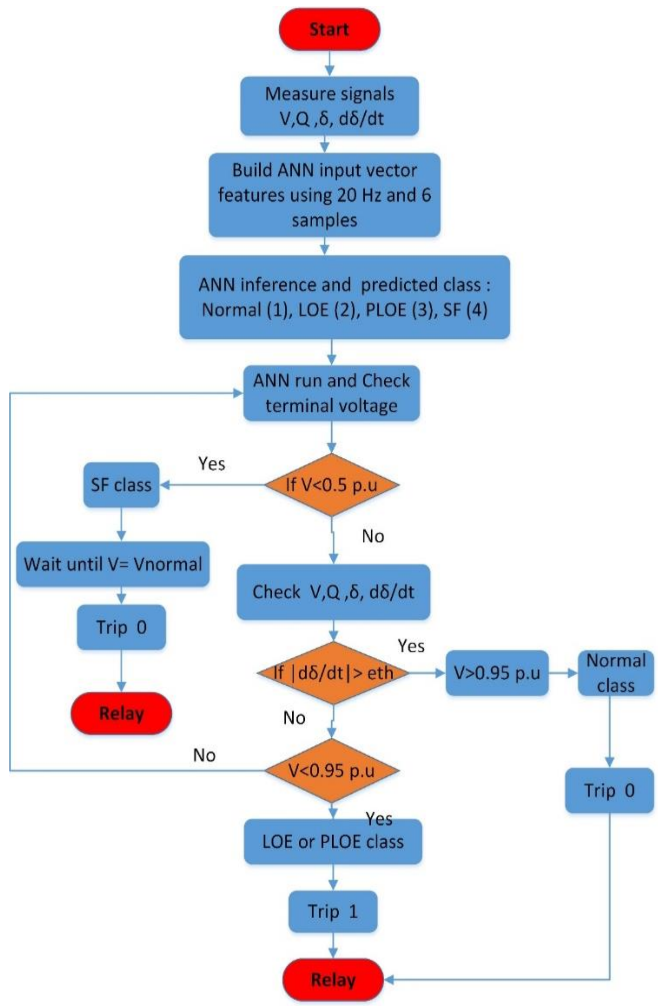

Fig. 10 Flowchart of the ANN protection method.

V. Results and Discussion

This section presents the results of the ANN protection method for the fourth case study's normal, LOE, PLOE, and SF conditions. The FFNN was trained using the procedure in section 4.2, and the results are displayed in Figs. 11-13. The confusion matrix for the ANN algorithm is shown in Fig. 11. These matrices offer a comprehensive overview of the ANN's performance in classification tasks, its reliability, and its ability to generalize to new situations. The recognition rates exceed those of all operating classes, with several classes achieving 100% accuracy, clearly indicating that the ANN has successfully captured nonlinear dynamic patterns of excitation loss and fault conditions. Only minor confusions for misclassifications among the neighboring excitation-loss states are seen, especially between partial and complete LOE, which is physically explained by the progressing and continuous nature of these two states.

The validation confusion matrix shows very good generalization, and thus, fault conditions can be easily differentiated from LOE-related classes, thereby indicating the strength of the chosen feature set. The test results also emphasize the feasibility of the method since even under severe disturbance, such as three-phase faults and complete LOE events, which are the most important from a security perspective, the ANN preserves flawless classification. The complete confusion matrix has revealed an average accuracy of nearly 90%, with no confusion between the fault and excitation-loss classes. Thus, excellent security against false tripping is highlighted. The small misclassification at the early stage of LOE essentially reflects the ANN being conservative and protection-oriented, not a lack of modeling. In a nutshell, it has been demonstrated that the suggested ANN can deliver rapid, reliable, and secure LOE detection that can be used for protecting real-world generators.

Fig. 12 illustrates the cross-entropy FFNN performance after 60 epochs. From the chart, it is clearly observed that the cross-entropy drastically fell in the early epochs, reflecting that the main loss features of the excitation have been quickly learned. The validation graph is almost indistinguishable from the training graph, indicating that the model not only stably converged but also effectively generalized without overfitting. The least loss on the validation set, which was 0.12503, occurred at the 50th epoch.

Fig. 13 demonstrates the error histogram of the proposed ANN-based LOE detection method with a 20-bin partition for the training, validation, and test datasets. The fact that most samples lie very close to zero error indicates effective learning and the model's capability to generalize to all data.

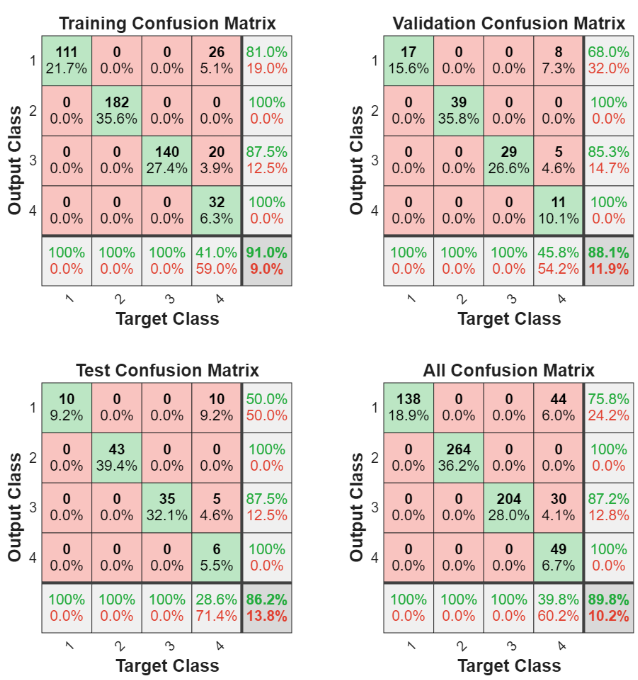

Fig. 11 Confusion matrix of the ANN algorithm

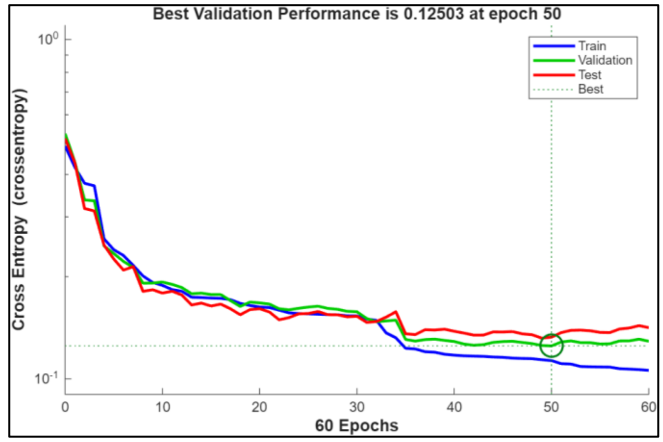

Fig. 12. The cross-entropy FFNN response of the ANN algorithm

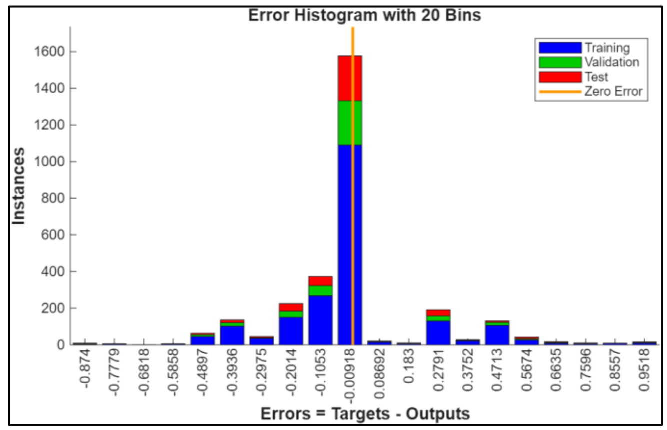

Fig. 13. Training, validation, and test datasets of the ANN algorithm

In Fig. 14, the response of the synchronous generator using the ANN-based protective relay decision is presented during the LOE case. Initially, the generator is in steady state as the terminal voltage is kept near 1.0 p.u.; the reactive power shifts slightly to 0.2 p.u., and the load angle remains quite stable at about 0.3 rad. The LOE starts at approximately 2 s, and a sharp record is made in the three variables of excited radii. At t = 2 s, the excitation loss starts, and all monitored variables exhibit a wide deviation.

After the LOE event, the terminal voltage drops sharply from 1.0 p.u. to 0.4 p.u. at t = 8 s due to insufficient field current, which weakens the air-gap flux; consequently, the flux in the air gap is gradually depleted. At the same time, the reactive power starts to fall immediately from approximately 0.2 p.u. to almost zero. The load angle returns to zero after a sudden jump, and the rapid drop is followed by the loss of synchronism, thus confirming severe electromechanical instability. The LOE is applied at time t=2 s. The ANN-based dynamic feature recognition scheme indicates that the trip command occurs at approximately 2.46 seconds, resulting in a detection time of about 0.46 seconds after the LOE began. The rapid and well-coordinated reaction refers to the capability of the proposed ANN approach, which can identify the excitation loss correctly and disconnect the generator before widespread instability emerges, showing its efficiency for real generator protection applications.

Fig. 15 reports the response of the SG during a three-phase short circuit fault (SF). The figure demonstrates the protection scheme's ability to distinguish between a fault and the LOE condition. Before the fault, the system was in a steady state with a terminal voltage close to 1.0 p.u., reactive power around 0.25 p.u., and the load angle was about 0.35 rad. When the three-phase short circuit was applied at t = 2 s, the voltage dropped sharply to almost 0.5 p.u. and then recovered quickly after the fault was cleared. These are the typical characteristics of symmetrical faults in a strong grid and differ from those of LOE, in which the voltage gradually decreases. The load angle also showed a sudden transient peak and hence increased to almost 0.75 rad, but once the oscillations were damped, the load angle returned to its pre-fault condition, indicating that the generator remained in synchronism. Likewise, reactive power showed a tremendous transient peak of over 0.8 p.u., and then Q started to oscillate and finally settled near its normal value, thus showing that the electromechanical recovery of the generator occurred after the fault was cleared. Importantly, the ANN trip signal remained inactive during the whole period of the event, thus verifying that there was no false tripping during the fault condition.

These outcomes unequivocally show that the proposed ANN-based LOE protection scheme can correctly differentiate between transient fault dynamics and excitation loss even when voltage and power quantities undergo severe disturbances. The fact that the method is able to meet the security requirements in three-phase faults and, at the same time, be sensitive to genuine LOE events makes it a viable choice for reliable generator protection in modern power systems. Table I lists the results obtained under the studied scenarios.

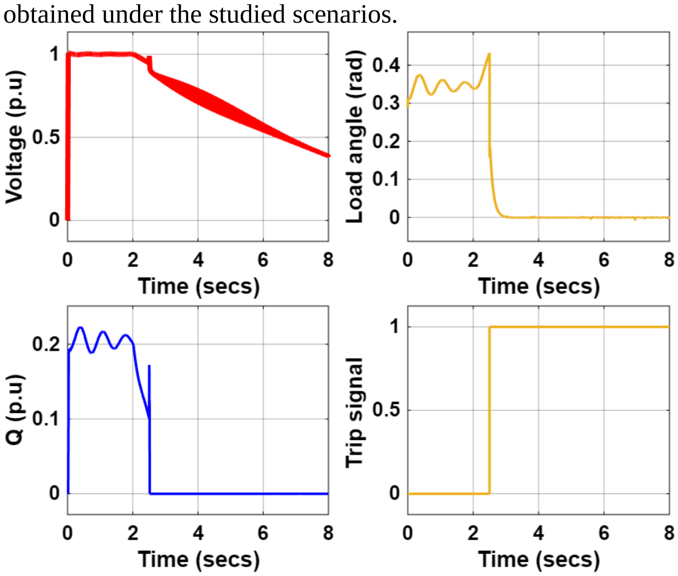

Fig. 14 Obtained results of the system under the LOE scenario.

To clear the novelty of the work, a comparison analysis with the LOE detection method is presented alongside other methods in terms of trip time, input parameters, detection accuracy, and computational complexity, as shown in Table II. The results show that the proposed method strikes the best balance between quick detection, high accuracy, and a moderate computational cost. In terms of trip time, the proposed ANN finds LOE in 0.5 seconds, which is much better than classical machine learning (5.3 seconds) and fuzzy-based methods (1.1 seconds). In synchronous generators, quick detection is very important to prevent the rotor from overheating and the system from becoming unstable. The proposed ANN has medium complexity compared to CNN, which requires a lot of computing power, making it easier to use in real time.

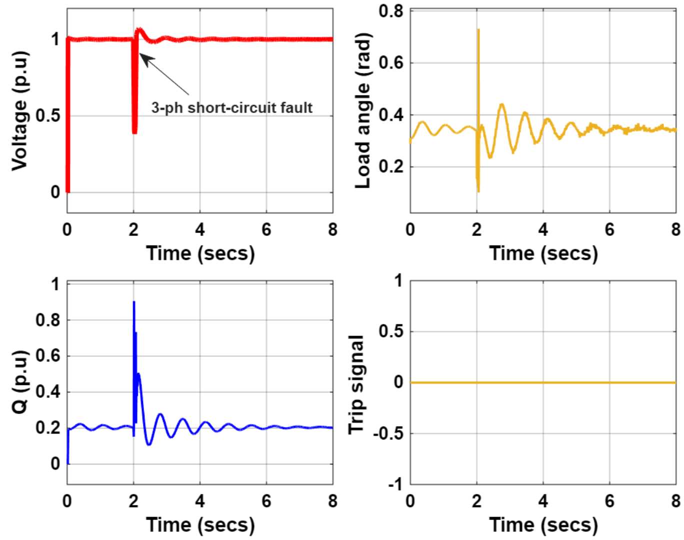

Fig. 15 Obtained results of the system under the SF scenario.

TABLE I
Obtained Results Under the Studied Scenarios

Case	No. of class	Load level (P+jQ)	Fault occurrence time (s)	Excitation voltage $(p.u)$	Trip time (s)
LOE	2	$30+0j$	2	0	0.46
		$100+50j$		0	
		$70+70j$		0	
PLOE	3	$30+0j$	2	0.4	
		$100+50j$		0.4	
		$70+70j$		0.4	
SF (3-ph Fault)	4	$30+0j$	2	1.0	-
		$100+50j$			
		$70+70j$			
Normal	1	$30+0j$	-	1.0	-
		$100+50j$			
		$70+70j$			

TABLE II
Comparison Between the Proposed Method and Existing Methods.

LOE strategy	Trip time (s)	Parameters considered	Accuracy	Complexity
ANN [2]	0.5	V, P, Q	Moderate	Medium
ML [13]	5.3	V, Q	Moderate	High
ANFIS [22]	0.5	V	Low	Medium
DPC [23]	0.5	V, I	High	High
Fuzzy [24]	1.1	V, Q, δ	Low	Low
CNN [25]	0.2	V, I	High	Very high
Proposed	0.5	V, Q, δ, dδ/dt	Very high	Medium

As observed, the proposed method for feature selection uses V, Q, δ, and dδ/dt, which allows for a more detailed dynamic representation than methods that use only voltage or current. This strategy with multiple parameters improves the ability to tell the difference between things, which leads to very high accuracy, better than traditional ANN and fuzzy systems.

Overall, the proposed ANN method is better than current LOE protection strategies because it is faster, more reliable, and more efficient at handling complexity.

VI. CONCLUSIONS

This work presents a robust ANN-based method for identifying LOE and PLOE in synchronous generators. Conventional protection schemes, which mainly rely on impedance or power-based indicators, are quite sensitive to voltage depression. In contrast, the proposed model uses both electrical and electromechanical signals simultaneously. The terminal voltage, reactive power, load angle, and derivative of the load angle are the main features, emphasizing the generator's behavior under excitation faults more accurately. A trained feed-forward neural network (FFNN) with a sliding-window feature extraction method was applied. This method allows rapid and precise determination of four modes of operation: normal operation, LOE, PLOE, and severe symmetrical fault. The ANN that was trained worked well when it was placed in MATLAB/Simulink and combined with a protection-oriented decision logic that incorporated fault blocking, post-fault recovery supervision, swing restraint depending on dδ/dt, and a time-confirmation mechanism. All these together make the hybrid architecture sensitive enough to real LOE events and yet immune to false tripping due to severe voltage dips and post-fault swings in power. The performance of the suggested ANN algorithm was tested by simulation on a 200 MVA synchronous generator. It was found that the newly developed relay can detect LOE and PLOE accurately and in a timely manner, and can also operate securely even under symmetrical fault conditions when the terminal voltage falls to very low values. The relay's behavior remained unchanged over different operating level conditions; thus, the proposed method can be considered both reliable and practically implementable.

APPENDIX I. PARAMETERS OF THE POWER SYSTEM.

Generator parameters	$S_G = 200MVA$
	$V_G = 13.8kV$
	$f = 50Hz$
	$X_d = 1.305$ pu
	$X_{d'} = 0.296$pu
	$X_{d''} = 0.252$pu
	$X_q = 0.474$ pu
	$X_{q''} = 0.243$pu
	$X_l = 0.18$pu
	$T_{d'} = 1.01$s
	$T_{d''} = 0.053$ s
	$T_{qo''} = 0.1$ s
	$R_s = 0.00285$ pu
	$H = 3.2\ s$
	$p = 2$
Transformer parameters	$S_{Tr} = 210MVA$
	$V_H = 230kV$
	$V_L = 13.8kV$
	$f = 50Hz$
Transmission line	line 1 & line 2 = 60km
	$R = 0.07\Omega/\text{km}$
	$X = 0.3\Omega/\text{km}$
Infinite bus data	$S_{S.C} = 10000MVA$
	$V_{bus} = 230kV$
	$X/R = 10$

CONFLICTS OF INTEREST

Professor Zahra Moravej, the author of this paper, is the CoEditor-in-Chief of the Journal of Modeling and Simulation in Electrical and Electronics Engineering (MSEEE). Still, she has no involvement in the peer review process to assess this work submitted to the journal. This paper was evaluated, and the Chief Editor of the MSEEE Journal managed the corresponding peer review.

The author declares that there is no conflict of interest regarding the publication of this article.

AUTHORS CONTRIBUTION STATEMENT

Rusul Mohammed: Conceptualization; Methodology; Numerical Implementation; Writing—original draft, **Zahra Moravej**: Supervision; Project administration; Investigation; Validation; Writing—review & editing, **Hamid Yaghobi**: Formal Analysis; Investigation; Validation, **Mousa Kadhim Wali**: Investigation; Validation, Formal Analysis.

AI DISCLOSURE

The authors used ChatGPT (OpenAI, San Francisco, USA) to assist in language editing and improving the clarity of the manuscript. All AI-assisted outputs were reviewed and verified by the authors.

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