Different Types of Faults Detection and Identification in Synchronous Generator Using MFO-based FL Techniques

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ABSTRACT

Synchronous generators (SGs) are expensive and essential parts of power networks that need to be safeguarded from flaws and unusual operating conditions. The performance of the power system as a whole can be negatively impacted by internal and external problems that can seriously harm SGs. Electric utilities utilize numerical, solid-state, and electromagnetic relays constructed on a differential protection scheme to protect SGs. More machine models and analyses of how synchronous machines operate with intrinsic flaws are nonetheless required. Various synchronous generators have been successfully controlled using traditional control theory and nature-inspired metaheuristic stochastic optimization techniques like evolutionary algorithms (EAs), particle swarm optimization (PSO), differential evolution (DE), genetic algorithms (GA), firefly algorithms (FA), and artificial bee colonies (ABC) algorithm. defects. Artificial neural networks (ANNs), wavelet packet decomposition, and MFO-based FLC have all been used to analyze synchronous generators with internal and external ground faults.

Key words: Synchronous Generator , Incipient faults , Artificial Neural Network (ANN) , MFO ,Fuzzy Logics

1. INTRODUCTION

Synchronous generators (SGs) are essential components of power systems that generate electricity and ensure an uninterrupted power supply to consumers[1]. However, SGs are susceptible to various internal and external faults that can cause significant damage to the machine and affect the performance of the entire power system[2]. Traditional protection methods have limitations in detecting and identifying faults in SGs, necessitating the development of new and effective fault detection techniques[3]. This article focuses on the detection and identification of different types of faults in SGs using MFO-based FL techniques[4]. The article highlights the importance of fault detection and identification in SGs and proposes the use of MFO-based FL techniques for this purpose[5]. The article also discusses the application of wavelet packet decomposition and artificial neural networks (ANNs) in conjunction with MFO-based FL techniques to improve fault detection and identification in SGs[6]. The proposed technique was tested on a 3 MW SG, and the results demonstrated its effectiveness in detecting and identifying different types of faults[7]. The article concludes that the proposed technique can be a valuable tool for power system operators to improve the reliability and performance of SGs[8].

Proposed MFO-Based FLC Using Synchronous Generator and Fault Diagnosis

This section discussed the synchronous generator's fault detection and diagnostic technique using the MFO-based FLC. The block architecture of a possible method for diagnosing synchronous generator incipient faults is shown in Figure (1). The synchronous generator, offline process, online process, and diagnosis process are shown in this diagram. In this case, the output signal has produced and controlled the synchronous generator. The alternator’s signal has been double-checked for errors and the data collection representing is saved for the different errors throughout the offline phase.

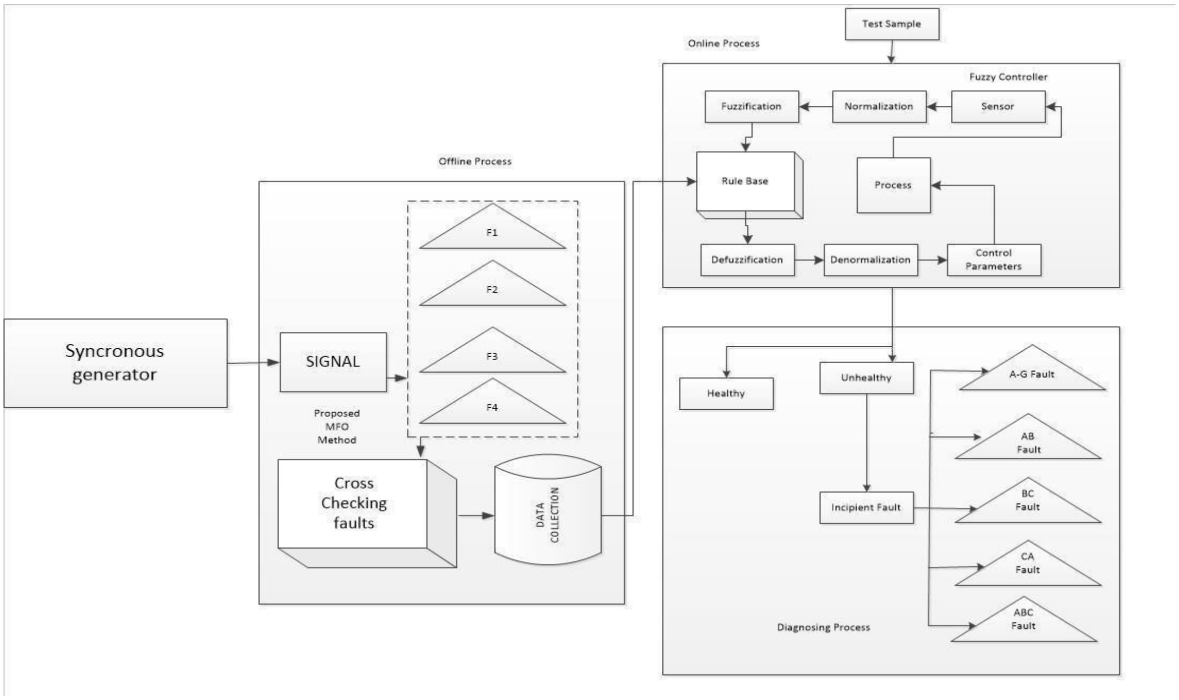


Figure.1 shows a block diagram of the suggested method for diagnosing internal faults in alternators.

The recommended technique is carried out in this case in a synchronous generator collecting data sets and identifying the new issues in two steps. The Moth flame optimization approach is used to identify the best ways to proceed from the open looking for space in light of a function of the objective kind and produce logically plausible data sets first and foremost. The Moth flame optimization technique uses the synchronous generator to provide a range of metrics that are used to determine if the generator is healthy, ill, etc. situations separately. In the second stage, the Fuzzy logic controller applies the finish of a data set and terms the es synchronous generator's nascent problems under various scenarios. The recommended diagnosis technique was developed with the specific genuine purpose of separating the fault concerns from the states of the synchronous generator. the figure1. A synchronous generator's modeling is put together, furthermore, with a combined MFO control technique, finding a synchronous generator's three-phase fault problems is made. For synchronous generator incipient defect diagnosis, the proposed method is the MFO-based FLC. The MFO technique is used in this situation to identify the best courses of action within the confines of the desired capacity and create any feasible coherent datasets. Considering the finished data set, the Fuzzy logic control performs and diagnoses Alternator nascent difficulties in various scenarios. The following are notable steps connected to the recommended calculation:

(a) Stages in the Proposed Algorithm's Optimization:

Stage 1: Initialisation
The voltage(V), speed(N), and torque(T) numbers serve as the initial constraint parameters. The number of iterations is initialized, and the power values begin as the FLC parameters are generated at random.

Stage 2: Random generation
V, N, and T values are used as the beginning values for the restrictions' conditions. Initialize the power values and the number of iterations. using the equation and the random generation of Fozzy logic controller parameters, respectively .

Stage 3: Evaluation
The V and I level that correspond to the value of the produced power are displayed during the assessment Work on. Recommended MFO and FLC method's primary goal is to minimize the deviation of the power signal from the intended location.

Stage 4: Updation
Using equations and the moth's position in proximity to the flame is updated based on the fitness function.

Stage5: Final process

Equation estimates that during the course of repetitions, the number of flaws decreases adaptively . The calculation's output is only available for the data sets that are theoretically possible to predict the optimal parameter. Access is granted to the FLC's rule base of these finished data sets so that it may simulate the fuzzification process and identify any impending problems with the synchronous gene under varied responsibility situations. The FLC is created with the particular objective of diagnosing the synchronous generator's nascent problems.

(b) With FLC, prediction of the ideal parameter:

Identification of impending problems with a synchronous generator is carried out using the fuzzy system. Figure 1 shows that the following succinct explanation of the technique has been provided:

Procedure (i): Fuzzification

This process converts the sharp input into a linguistic element in a fuzzy knowledge base using the membership function acquired. The error and the change of error, are provided as equations (1) and the fuzzy controller's input (2).

$$E(t)=V(t)-V^*(t)$$
$$\triangle E(t)=V_i(t)-V_{i-1}(t) \quad …..(1)$$

V(t) presents the output voltage, V*(t) refers to the standard voltage and i subscripts denote the value taken at the beginning of the process. **Process (ii):** the **system of fuzzy inference** fuzzy input, fuzzy input, and fuzzy output is changed with the help of the "If then" type fuzzy rules. Here, rules are formed with one reflecting the circumstances in which a defect occurs and the other indicating the situations in which the system is fault-free. Both levels of the fuzzy system and demulsifier can be used to recognize the membership function. After the The membership function is pushed out to list phonetic words during the fuzzification and defuzzification layers; it graphs non-fuzzy information values to fuzzy semantic terms and, in contrast, fuzzy linguistic positions to non-fuzzy information values. **Procedure (iii): Decision making** the uncertain values that the fuzzification approach is based on may be used to create fuzzy rules for every component of the methodology. The decision is based on the aforementioned criteria. The common method for the If A, then B is a vague rule. The system is faultless if A and B are both zero, but in the unlikely event that A is positive and B is negative, fault 1 is now active. The rules for the form are unclear

$$\text{If } E \text{ is } X_a \text{ and } \triangle E \text{ is } Y_a, \text{ THEN } X^f_a(t) \text{ is } F_a(t) \quad …..(2)$$

Where Xa and X_y are the vague subsets and consider the singleton values of the fuzzy system. **Procedure 4: Defuzzification**

The decisions made when using the defuzzification process are where the fuzzy values are found. This method converts the output esteems from fuzzy to crunchy . The output variable's potential to include members serves as the foundation for the defuzzification. The framework is provided as a database.

$$F_a(t)=X_a^F(t) \quad ……(3)$$

Where $X_a^f(t)$ is the final result of fuzzification.

As a degree of assistance target is determined for each member of the collection, fuzzification is necessary. The fuzzy system accurately anticipates the outcomes when there is increased participation in the work. Similarly, the proposed MFO with the FLC system determines the precise SG fault while increasing the gain parameter. Figure(2) shows the MFO with FLC flowchart in action.

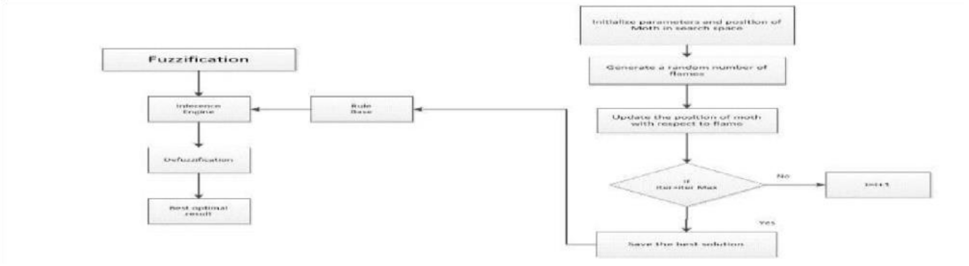


Figure.2: Flowchart of proposed MFO with FLC

By using a variety of approaches, including wavelet packet decomposition, artificial neural networks, and MFO-based FLC, this chapter investigates the synchronous generator's nascent flaws. To diagnose the behavior of the fault at this point, internal faulty signals are analyzed as wavelet packet decomposition to three-phase currents is decomposed into approximate and detailed signals. This method establishes the energy of the approximation signal and the maximum energy of the detail signals. By controlling both regular and irregular signals, the ANN controllers successfully get rid of internal faults. The output performance of the synchronous generator signals is assessed by the MFO-based FLC-based signal analysis to determine whether or not it is initially flawed. The subdivision gets rid of increased inquiries into the developing fault, decreased fault detection, and decreased internal fault. As a consequence, it is possible to raise the issue of the internal fault of the synchronous generator with MFO based FLC much more successfully by presenting an optimization fault issue, followed by fact-finding and the suggested techniques. The recommended MFO-based FLC-based synchronous generator's concept and plan, as well as its implementation next to the internal fault problems, are made evident. The results and discussion of the proposed approach and the existing method have been briefly presented along with comparisons to other methods.

RESULTS:

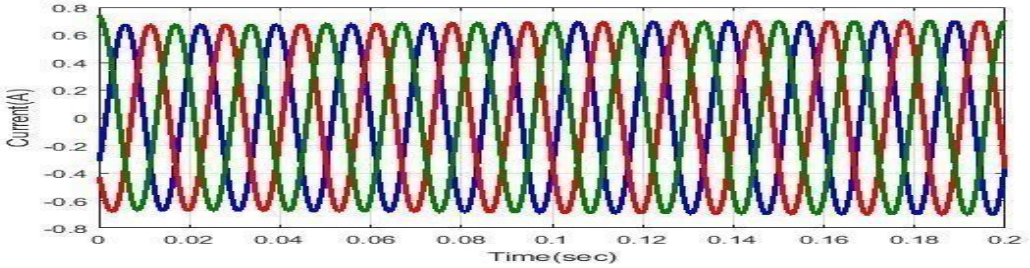


Fig:3 Analysis of current in normal condition

A – Earth Fault

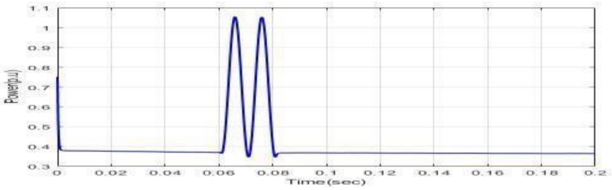


Fig 4: Electrical Energy

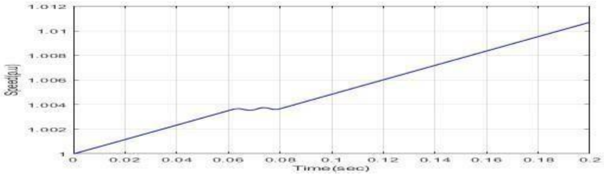


Fig 5: Turning Speed

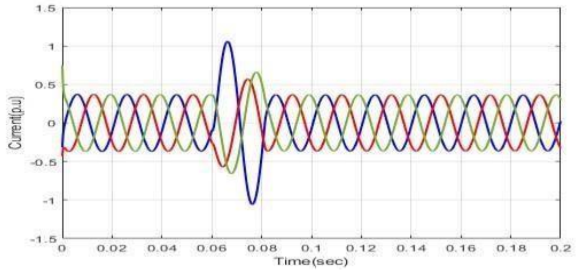


Fig 6: Stator-(I)

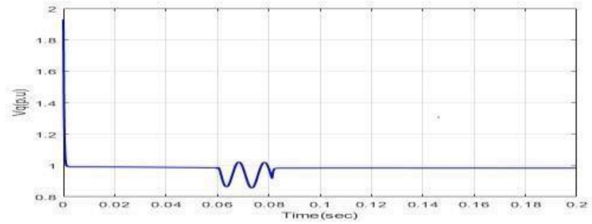


Fig 7: Stator (V) Vd

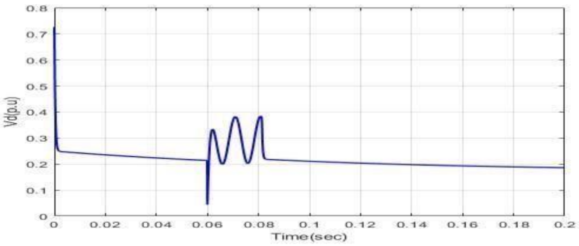


Fig 8: Stator (V) Vq

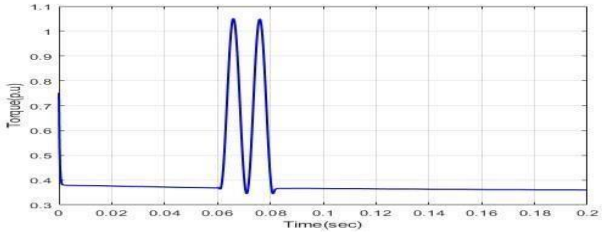


Fig 9: TORQUE (Ʈ)

B – Earth Fault

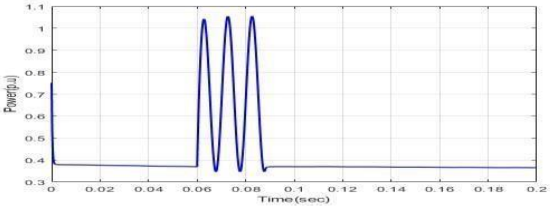


Fig 10: Electrical Energy

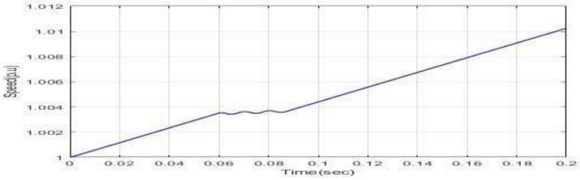
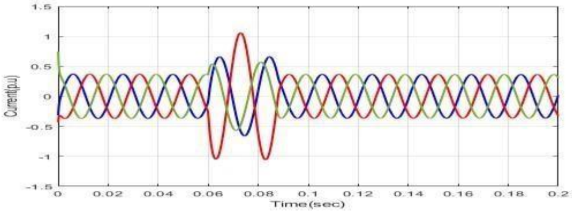


Fig 11: Turning Speed



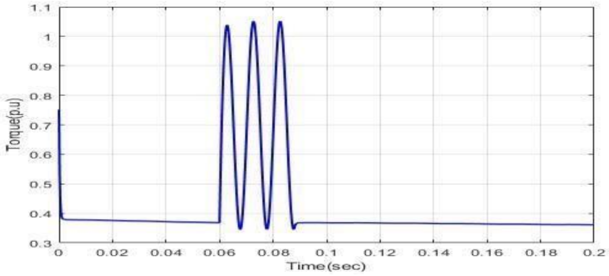


Fig 12: Stator-(I)

Fig 13: Stator (V)Vd

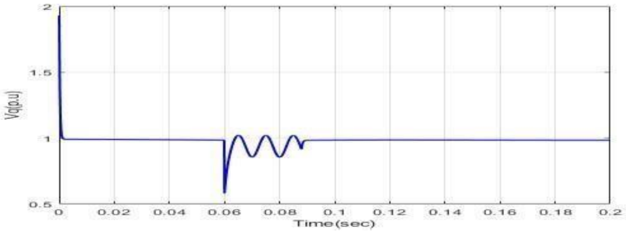


Fig 14: Stator (V) Vq

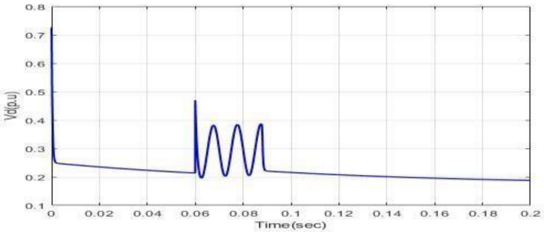


Fig 15: TORQUE(Ʈ)

C – Earth Fault

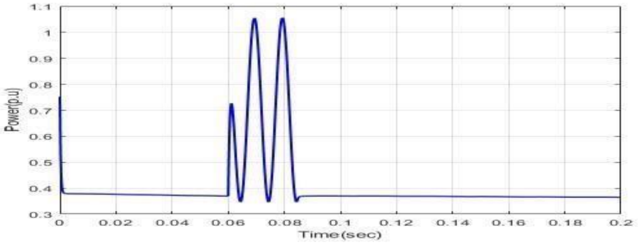


Fig 16: Electrical Energy

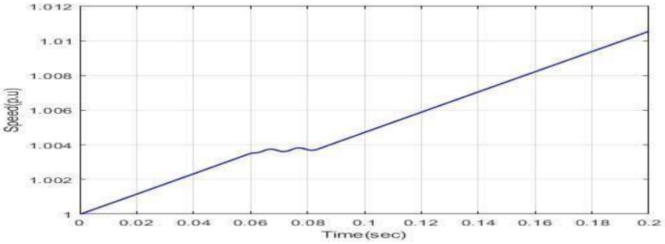


Fig 17: Rotor Speed

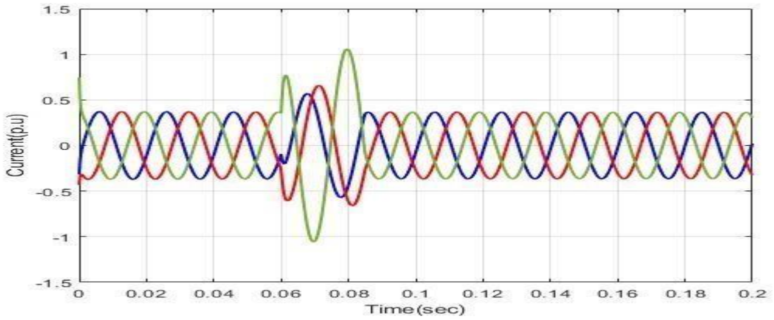


Fig 18: stator-(I)

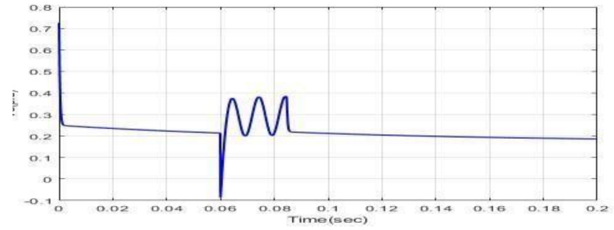


Fig 19: stator (V) Vd

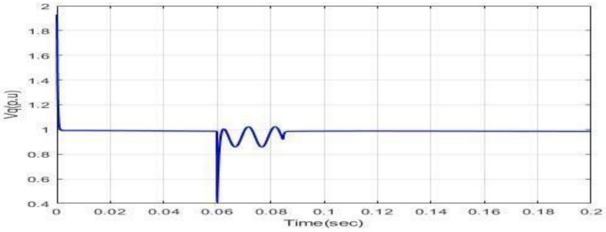


Fig 20: Stator (V) Vq

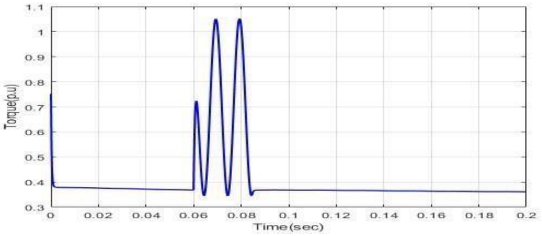


Fig 21: TORQUE (Ʈ)

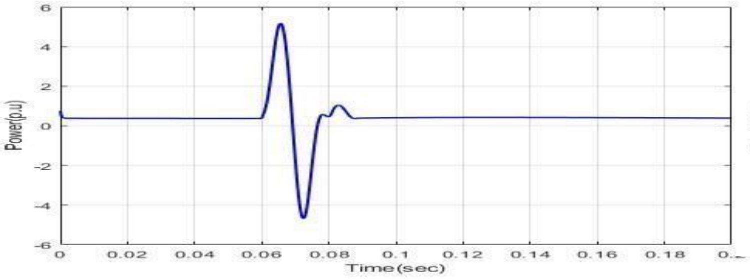


Fig 22: Electrical Energy

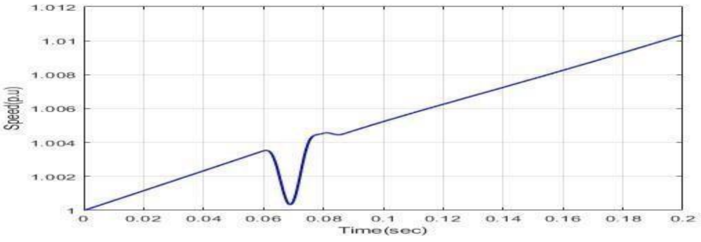


Fig 23: Turning Speed

AB – Earth Fault

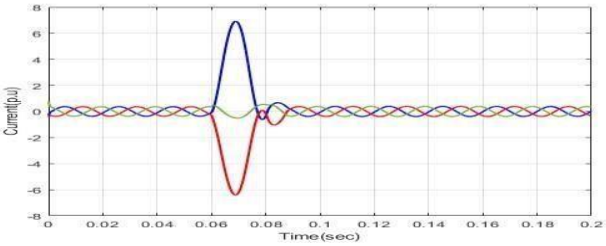


Fig 24: Stator (I)

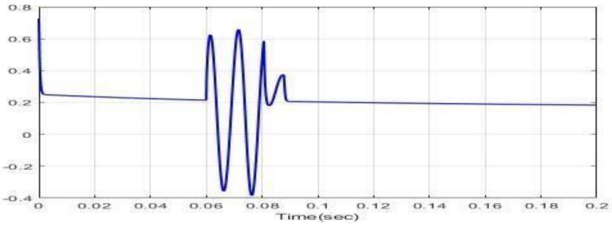


Fig 25: Stator (V) Vd

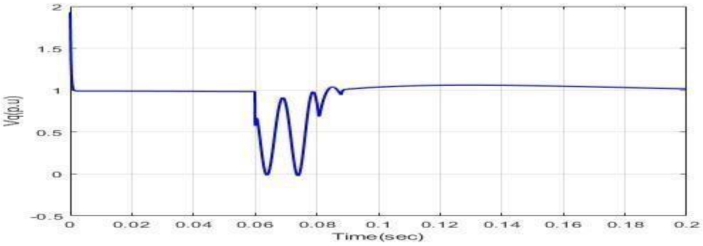


Fig 26: stator (V) Vq

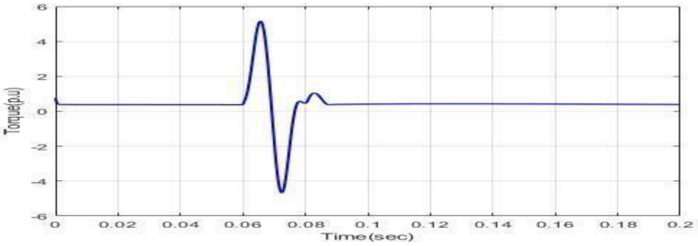


Fig 27: TORQUE (Ʈ)

BC-Earth fault

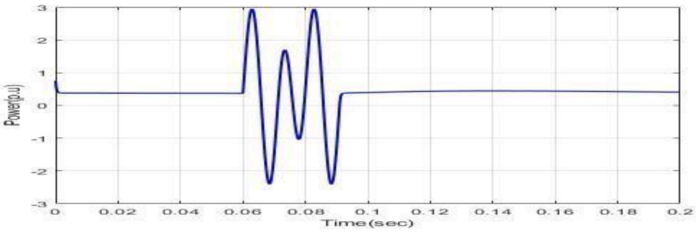


Fig 28: Electrical Energy

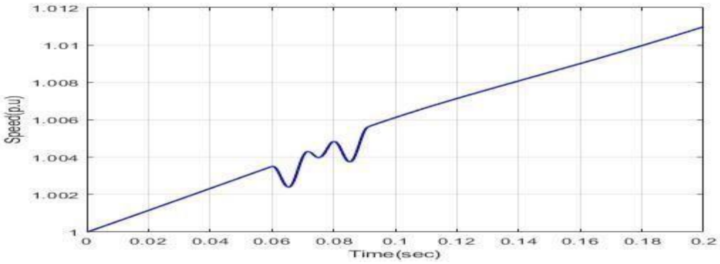


Fig 29: Turning Speed

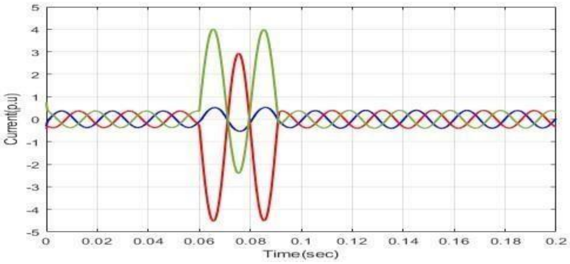


Fig 30: Stator (I)

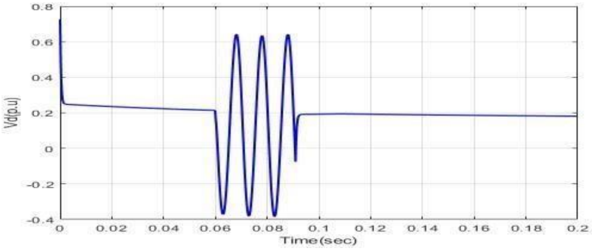
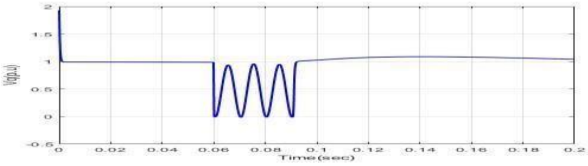


Fig 31: Stator (V) Vd



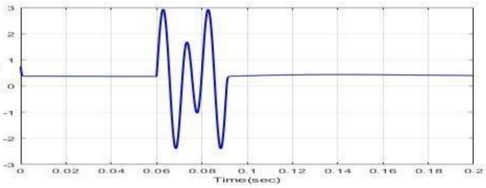


Fig 32:Stator (V) Vq

Fig 33: Torque

CA-Earth fault

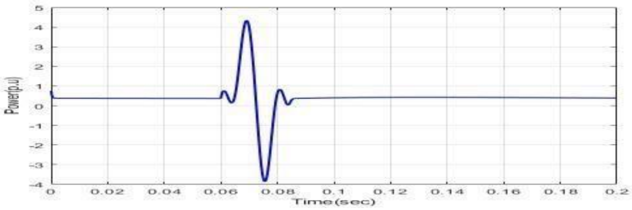


Fig 34: Electrical Energy

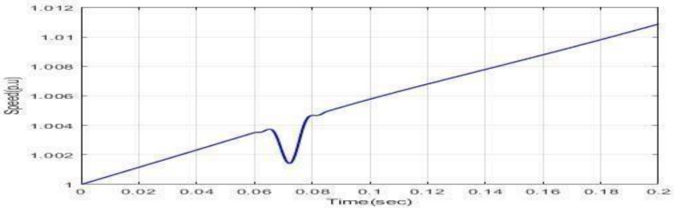


Fig 35: Turning speed

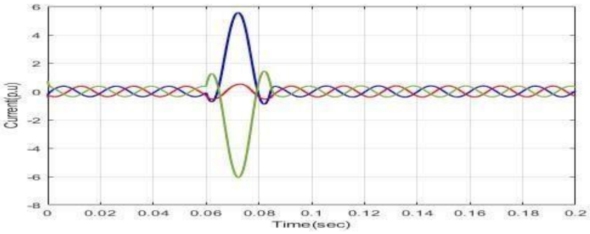


Fig 36: Stator (I)

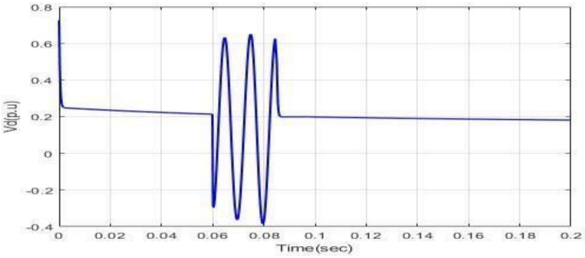


Fig 37: Stator (V) Vd

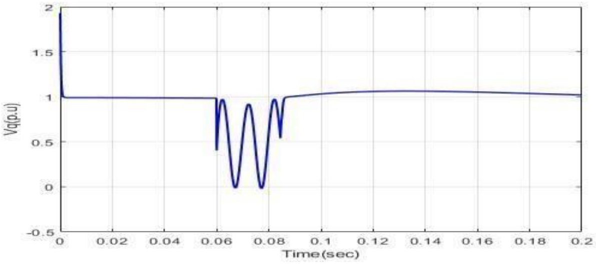


Fig 38: Stator (V) Vq

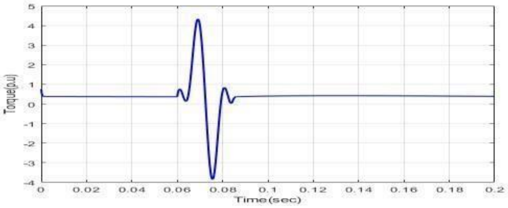


Fig 39: TORQUE (Ʈ)

ABC – Earth Fault

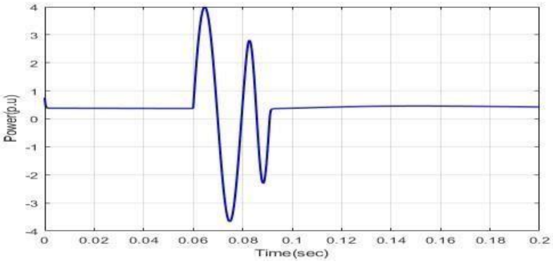


Fig 40: Electrical Energy

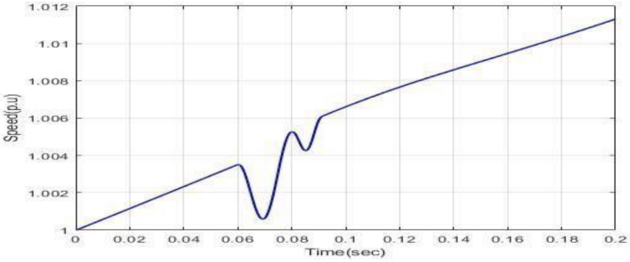


Fig 41: Electrical Energy

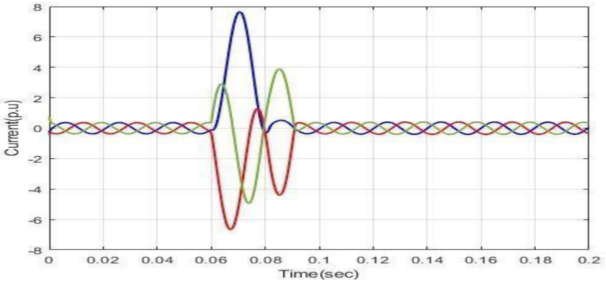


Fig 42: Electrical Energy

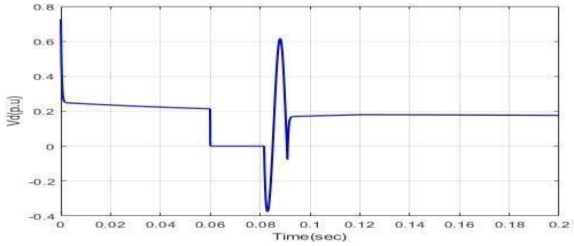


Fig 43: Stator (V) Vd

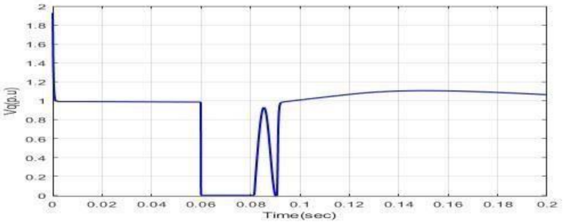


Fig 44: Stator (V) Vq

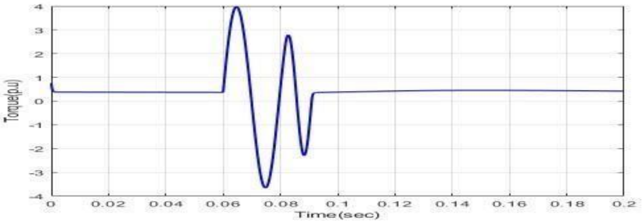
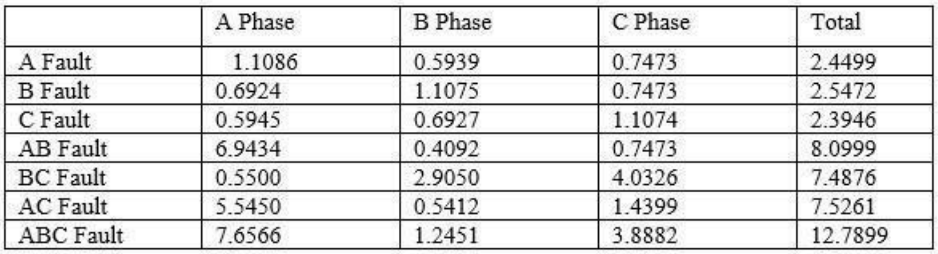


Fig 45: TORQUE (Ʈ)

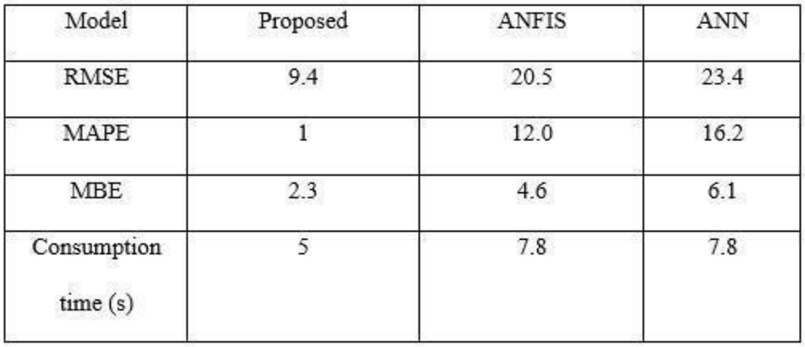
Fig:46 : 3 KVA, 415 V, 4.5 A, 1440 RPM, 3- Phase Alternator

EXPERIEMNTAL DATA:



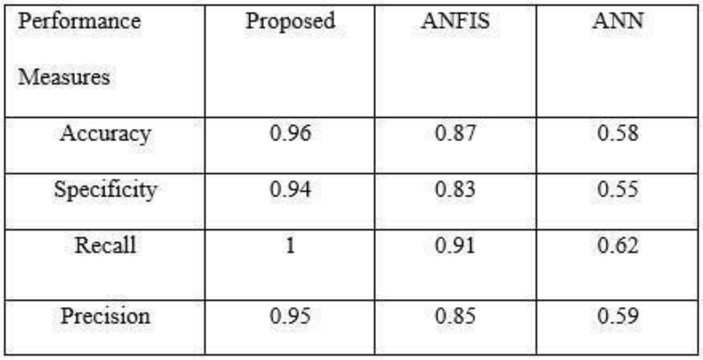
	A Phase	B Phase	C Phase	Total
A Fault	1.1086	0.5939	0.7473	2.4499
B Fault	0.6924	1.1075	0.7473	2.5472
C Fault	0.5945	0.6927	1.1074	2.3946
AB Fault	6.9434	0.4092	0.7473	8.0999
BC Fault	0.5500	2.9050	4.0326	7.4876
AC Fault	5.5450	0.5412	1.4399	7.5261
ABC Fault	7.6566	1.2451	3.8882	12.7899

Table 1: Execution analysis of a suggested method through a developing fault for ten preliminary steps



Model	Proposed	ANFIS	ANN
RMSE	9.4	20.5	23.4
MAPE	1	12.0	16.2
MBE	2.3	4.6	6.1
Consumption time (s)	5	7.8	7.8

Table 2: A statistical analysis of a method proposed by an existing technology that detects a flaw in the first 10 preliminary results



Performance Measures	Proposed	ANFIS	ANN
Accuracy	0.96	0.87	0.58
Specificity	0.94	0.83	0.55
Recall	1	0.91	0.62
Precision	0.95	0.85	0.59

CONCLUSION:

The control calculation for a synchronous generator is shown in the thesis utilizing a variety of methods, including wavelet packet decomposition, artificial intelligence, BA-RNN, ANN-GSA, and MFO-FLC. In this case, the suggested approach is carried out in two stages, such as the first problems with SG-set sorting and data analysis. A synchronous generator is used to study DWT and ANN, fault detection, and character with the GSA system. The mistakes in the synchronous generator then control the RNN technique going ahead. Here, the RNA production process was used to enhance the BA. The ANN is trained using ALO, which improves ANN performance. The improved ANN is used to determine whether or not the signs are faulty. The MFO approach's best course of action is to use the space that is now available to authenticate and maybe store static data packages. The FLC employs SGs and supplementary data sets in both favorable and undesired circumstances. Using factual estimations, such as sensitivity, specificity, recall, and accuracy, has allowed researchers to examine and assess the suggested strategy's practicality. Using statistical measures including MBE, MAPE, RMSE, and use time, the proposed task's execution was verified and compared Using ANN, fuzzy, and ANFIS methods . The suggested methodology was displayed in front of several techniques relating to communication presentation methods and real techniques. The comparison of the MATLAB simulation results with the outcomes of the experimental setup demonstrated the superiority of the suggested AI approaches for fault identification in a Synchronous

Generator The suggested approach is employed to identify the stable and undesired SG states in the presence of an early deficit. Here, the suggested method is employed to diagnose emerging defects and collect informational indexes. The SG rehearsals are divided into good and bad circumstances right away. The stator-torque current views within that are normalized to their estimated peak esteem. At that point, the MFO is used to evacuate the deficiencies that directly correspond to the current symptoms. To offer the precise type of flaw, the extruded components are established using FLC. This proposed method allows for more accurate detection of new failures.

REFERENCES:

[1] B.VIDYASAGAR, Dr.SS.TULASIRAM “Incipient Fault Diagnosis in Stator winding of Synchronous Generator A CMFFLC Technique” IETE Journal of Research (Taylor and Francis online Journal) ISSN: 0377-2063, April 2018

[2] Yushi Miura, Toshifumi Ise, Toshinobu Shintai, and Toshinobu Shintai, "Oscillation damping of a distributed generator using a virtual synchronous generator," IEEE Transactions on Power Delivery, Vol.29, No.2, pp.668-676, 2014.

[3] B.VIDYASAGAR, DR.SS.TULASIRAM “Enhanced ANN with Ant Lion Optimization for diagnose the incipient faults of Synchronous Generator”(JARDCS) Journal of Advance Research in Dynamical Control Systems ISSN 1943-023X, 02 Sep 2019.

[4] Deepak M. Divan and Andrew D. Paquette published a paper in IEEE Transactions on Industry Applications titled "Virtual impedance current limiting for inverters in microgrids with synchronous generators" in 2015.

[5] Lin-Yu Lu, Chia-Chi Chu, and others, "Consensus-based Secondary Frequency and Voltage Drop Control of Virtual Synchronous Generators for Isolated AC Micro-Grids," IEEE Journal on Emerging and Selected Topics in Circuits and Systems, Vol. 5, No. 3, pp. 443-455, 2015.

[6] "Real-time emulation of a high-speed micro turbine permanent-magnet synchronous generator using multiplatform hardware-in-the-loop realization," IEEE Transactions on Industrial Electronics, Vol. 61, No. 6, pp. 3109-3118, 2014.

[7] "Comparison of wind power converter reliability with low-speed and medium-speed permanent-magnet synchronous generators", IEEE Transactions on Industrial Electronics, Vol. 62, No. 10, pp. 6575-6584, 2015. Zhou, Dao, FredeBlaabjerg, Toke Franke, Michael Tonnes, and Mogens Lau

.

[8] Ehsan Nasr-Azadani, Claudio Caizares, Daniel E. Olivares, and Kankar Bhattacharya, "Stability analysis of unbalanced distribution systems with synchronous machine and DFIG based distributed generators," IEEE Transactions on Smart Grid, Vol. 5, No. 5, pp. 2326–2338, 2014.