# POWER SYSTEM FAULT IDENTIFICATION AND CLASSIFICATION IN FUEL CELLS VIA ARTIFICIAL NEURAL NETWORK

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**MASTER THESIS**
**ELECTRICAL AND ELECTRONIC ENGINEERING**

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I certify that in my opinion the thesis submitted by Rafah Hussein ALZURFI titled "POWER SYSTEM FAULT DETECTION AND CLASSIFICATION BY USING ARTIFICIAL NEURAL NETWORK IN FUEL CELLS" is fully adequate in scope and in quality as a thesis for the degree of Master of Science.

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*"I declare that all the information within this thesis has been gathered and presented in accordance with academic regulations and ethical principles and I have according to the requirements of these regulations and principles cited all those which do not originate in this work as well."*

Rafah Hussein ALZURFI

## ABSTRACT

**M. Sc. Thesis**

**POWER SYSTEM FAULT IDENTIFICATION AND CLASSIFICATION IN FUEL CELLS VIA ARTIFICIAL NEURAL NETWORK**



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**Institute of Graduate Programs**
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The research delineated in this thesis is poised to contribute significantly to the Domain of fault diagnosis in industrial processes, with a specific emphasis on employing sophisticated processing and pattern recognition methodologies for bearing analysis. The primary thrust of the investigation is centered on the application of vibration analysis to discern and diagnose issues in bearings. To this end, an Artificial Neural Network (ANN) is deployed for the analysis of input-output datasets extracted from a Matlab-Simulink-based Proton Exchange Membrane Fuel Cell (PEMFC) model, specifically the 6kw-45Vdc model.

The articulated ANN is designed to furnish steady-state predictions predicated on the provided input. Subsequently, the output of the PEMFC is scrutinized vis-a-vis The model's output, particularly in response to emergent events inducing alterations in the plant's output voltage or current. A residual signal is systematically monitored and employed as a diagnostic tool to identify and characterize defects within the system. The empirical phase of data collection entails meticulous acquisition from a system or test rig, with due consideration accorded to diverse fault typologies, encompassing Abrupt, Incipient, and Intermittent faults.

The steady-state simulation is built around three inputs: heat, fuel pressure, in addition air pressure, as well as two outputs: voltage and current. Matlab's Simulink platform serves as the instrumental medium for comprehensive system modeling.

The subsequent research phase pivots towards the utilization of an Artificial Neural Network for condition categorization. A nuanced exploration and juxtaposition of various supervised learning algorithms, inclusive of support vector machines, random forests, and extreme learning machines, is undertaken to discern the optimal method for effecting bearing fault classification.

In summation, this research orchestrates a methodically comprehensive approach to fault diagnosis, encompassing meticulous data collection, exacting system modeling via Simulink, and the judicious application of advanced machine learning paradigms through an Artificial Neural Network. The overarching objective is the discernment and diagnosis of bearing faults within the context of industrial processes.

**Key Words :** Artificial Neural Network, fuel pressure, fault typologies, Fuel Cell
**Science Code :** 90517

# ÖZET

**Yüksek Lisans Tezi**

**YAKIT HÜCRELERİNDE YAPAY SİNİR AĞI KULLANILARAK GÜÇ SİSTEMİ ARIZA TESPİTİ VE SINIFLANDIRMASI**


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Bu tezde anlatılan araştırma, rulman analizi için gelişmiş işleme ve model tanıma metodolojilerinin kullanılmasına özel bir vurgu yaparak, endüstriyel proseslerdeki arıza teşhisi alanına önemli ölçüde katkıda bulunmaya hazırdır. Araştırmanın temel amacı, rulmanlardaki sorunları ayırt etmek ve teşhis etmek için titreşim analizinin uygulanmasına odaklanıyor. Bu amaçla, Matlab-Simulink tabanlı Proton Değişim Membranlı Yakıt Hücresi (PEMFC) modelinden, özellikle de 6kw-45Vdc modelinden elde edilen giriş-çıkış veri setlerinin analizi için bir Yapay Sinir Ağı (YSA) kullanıldı. Eklemli YSA, sağlanan girdiye dayalı kararlı durum tahminleri sağlamak üzere tasarlanmıştır. Daha sonra, PEMFC'nin çıkışı, özellikle tesisin çıkış voltajında veya akımında değişikliklere neden olan acil olaylara yanıt olarak, modelin çıkışına göre incelenir. Artık sinyal sistematik olarak izlenir ve sistemdeki kusurları tanımlamak ve karakterize etmek için bir teşhis aracı olarak kullanılır.

Veri toplamanın ampirik aşaması, Ani, Başlangıç ve Aralıklı arızaları kapsayan çeşitli arıza tipolojilerine uygun olarak bir sistemden veya test donanımından titiz bir şekilde edinilmesini gerektirir. Kararlı durum simülasyonu üç girdi etrafında inşa edilmiştir: ısı, yakıt basıncı, ek olarak hava basıncı ve ayrıca iki çıktı: voltaj ve akım. Matlab'ın Simulink platformu, kapsamlı sistem modellemesi için araçsal bir ortam olarak hizmet vermektedir.

Sonraki araştırma aşaması, durum sınıflandırması için Yapay Sinir Ağının kullanımına doğru dönmektedir.

Rulman arızası sınıflandırmasını etkilemek için en uygun yöntemi belirlemek amacıyla, destek vektör makineleri, rastgele ormanlar ve ekstrem öğrenme makineleri de dahil olmak üzere çeşitli denetimli öğrenme algoritmalarının incelikli bir şekilde araştırılması ve yan yana getirilmesi gerçekleştirilir.

Özetle, bu araştırma, titiz veri toplamayı, Simulink aracılığıyla titiz sistem modellemeyi ve Yapay Sinir Ağı aracılığıyla gelişmiş makine öğrenimi paradigmalarının akıllıca uygulanmasını kapsayan, hata teşhisine yönelik yöntemsel olarak kapsamlı bir yaklaşımı düzenlemektedir. Kapsamlı amaç, endüstriyel prosesler bağlamında rulman arızalarının tespiti ve teşhisidir.

**Anahtar Kelimeler :** Yapay Sinir Ağı, Yakıt Basıncı, Arıza Tipolojileri, Yakıt Pili
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## LIST OF SYMBOLS AND ABBREVIATIONS

**SYMBOL**

$H_2$ : Hydrogen gas molecule

$H^+$ : Hydrogen proton

$e^-$ : Electron

$O_2$ : Oxygen gas molecule

$H_2O$ : Water molecule

$V_{cell}$ : Actual fuel cell voltage

$E$ : Equilibrium thermodynamic potential

$\eta$ : Over potential

$\eta_{act}$ : Activation over potential

$\eta_{ohmic}$ : Ohmic over potential

$\eta_{diff}$ : Diffusion over potential

ABBREVIATIONS

Abb : Meaning

ANFIS : Adaptive Neuro- Fuzzy Inference System

AFC : Alkaline Fuel cell

ASIC : Application Specific Integrated Circuit

AI : Artificial Intelligence

ANN : Artificial Neural Network

BPNN : Back Propagation Neural Network

DMFC : Direct Methanol Fuel cell

FDD : Fault Detection and Diagnosis

FDI : Fault Detection and Isolation

FTC : Fault Tolerant Control

| | |
|---|---|
| Hwcosim | : Hardware Co-Simulation |
| HNN | : Hardware Neural Network |
| LED | : Light Emitting Diode |
| LMBP | : Levenberg- Marquardt Back Propagation |
| MCFC | : Molten Carbonate Fuel cell |
| MLP | : Multi-Layer Perceptron |
| NN | : Neural Network |
| PC | : Personal Computer |
| PAFC | : Phosphoric Acid Fuel cell |
| PEMFC | : Proton Exchange Membrane Fuel Cell |
| RBF | : Radial Basis Function |
| SOFC | : Solid Oxide Fuel cell |
| UPS | : Uninterruptible Power Supply |
| USB FDC | : Universal Serial Bus Fault Detection and Classification |

# PART 1

# INTRODUCTION AND LITERATURE REVIEW

## 1.1. BACKGROUND

Over the last three decades, a significant effort has been made to improve defect diagnosis tools. Artificial intelligence (AI) involves a popular method for doing diagnosis tasks, whereas diagnosis is a complex intellectual behavior that involves decision making processes and association rules are employed in the same way as the human brain does similar activities. Because of the need for reliability, cost, efficiency, and fault tolerance in dynamic systems, failure detection and diagnosis (FDD) are critical [1]. This thesis presents a novel approach to developing an FD system.

## 1.2. FAULT DETECTION AND DIAGNOSIS

After recognizing the defect and its development, the source of hazard can be averted by making timely actions. Monitoring provides an opportunity to implement a strategic strategy that will make it easier to control the availability and use of equipment. The ideal way to execute the FDI system technology in terms of cost, dependability, and efficiency of fuel cell fulfillment is through the creation of diagnosis based on modeling that utilizes residual fault development of sensitivity [2].

Fault detection and isolation (FDI) as well as fault tolerant control (FTC) are utilized to identify defects, diagnose them, and manage them in order to avoid process deterioration and danger situations [3].

## 1.3. ARTIFICIAL INTELLIGENCE

A variety of methodologies and approaches have been utilized over the last few decades to regulate and enhance a wide range of systems, with hybrid networks, fuzzy logic, neural networks and genetic such as the Adaptive Network Based Fuzzy Inference System (ANFIS) being the most efficient and still in development. Since then, system identification approaches, particularly artificial neural networks (ANNs), have yielded more realistic models of fuel cells.

They are effective tools for mapping complicated systems with nonlinear input-output interactions [6].

Referring to the suggestions of previous studies, use artificial neural networks (ANNs) [27].

Biological networks affected computer or mathematical frameworks known as ANNs [7]. Back Propagation Neural Network (BPNN) represents a controlled technique and the most widely used network proposed by [8].

## 1.4. FUEL CELLS

In the domain of fuel cells, electrical power is generated through the chemical interaction between an oxidizing agent, typically oxygen, and positively charged hydrogen ions. This complex process converts the chemical energy contained in a fuel into electrical power. Notably divergent from electrochemical batteries, which rely on internal chemical reactions to cause an electromagnetic force (emf) to be generated, fuel cells necessitate an uninterrupted supply of fuel as well as oxygen for keeping the chemical reaction going. Given an ongoing provision of these inputs, fuel cells can reliably and consistently generate electrical power [4].

In the context of an expanding global awareness regarding environmental concerns and air pollution, there is a mounting imperative for pioneering solutions to ameliorate the prevailing environmental landscape and assuage the energy crisis. Fuel cells emerge as indispensable contributors to this exigency, offering the expeditious conversion of gaseous chemical energy into electrical power, thereby operating as highly efficient and environmentally benign power generators. Among the spectrum of fuel cell categories, the proton exchange membrane fuel cell (PEMFC) distinguishes itself on multiple fronts, encompassing a low temperature performing range (20 °C to 100 °C), rapid initiation capabilities, elevated power density, lightweight structural attributes, and minimal acoustic emissions. Nonetheless, judicious application of PEMFC in commercial contexts mandates careful consideration, particularly in light of potential safety concerns contingent upon the purity of the utilized hydrogen source [5].

### 1.5. AIM OF THE WORK

The goal of this thesis is to use ANNs to create a defect identification and categorization network for a PEMFC system.

### 1.6. THESIS LAYOUT

The thesis can be separated into the five chapters listed below:

- **Part two** provides a theoretical overview of the most relevant subjects related to the study. Fault detection, fuel cells, and artificial intelligence (ANN). This chapter also mentions the planned system.
- **Part three** covers data collecting and ANN training. Examine the model, design a classification circuit, and test the FDI along with FDC systems for three types of defects.
- **Part four** is about putting the suggested FDC system into action. Changing the voltage at the input to identify fault for each input, as well as creating the entire circuit.
- **Part five** presents the gathered conclusions for the completed study as well as suggestions and recommendations for future work.

### 1.7. PROBLEM STATEMENT

Issues with Other Technologies [27]:

The referenced study [27] underscores certain challenges inherent in alternative technologies; however, the specific nature of these challenges is not explicitly delineated in the current discourse. A thorough examination of the study's findings would offer valuable insights into the limitations of alternative approaches. Such insights can fortify the rationale behind opting for Artificial Neural Networks (ANNs).

Generalization and Response to Unexpected Inputs/Patterns [35]:

- The selection of ANNs for this thesis is underscored by their commendable capacity for generalization and adept handling of unforeseen inputs or patterns [35]. This characteristic resilience positions ANNs as formidable tools capable of discerning and adapting to nuanced data structures, a quality pivotal in scenarios necessitating adaptability and robust learning.
- Mapping Intricate Systems with Nonlinear Input-to-Output Interactions [6]:
- As posited in literature [6], the efficacy of ANNs resides in their proficiency to model intricate systems characterized by nonlinear input-to-output interactions. This distinctive attribute sets ANNs apart, particularly when confronted with intricate datasets where conventional linear models may falter. The application of ANNs is thus aptly tailored for tasks mandating the discernment of complex and nonlinear relationships.

## 1.8. THESIS OBJECTIVES

The objectives of this thesis are as follows:

- The data is collected from a system studied while accounting for the various faults types.
- Use Artificial Neural Network to Classification faults.

## PART 2

## FUNDAMENTAL THEORETIC CONCEPTS AND LITERATURE REVIEW

### 2.1. INTRODUCTION

This section provides a theoretical foundation for defect detection besides its various types and methodologies, fuel cells, particularly the PEMFC category, AI, and ANN, all of which are employed in this proposition.

### 2.2. LITERATURE REVIEW

This section provides an overview of the three most significant issues related to this work: ANN, FDD, as well as fuel cell. The review includes the following ten years of investigation:

SUN, et al., 2005, [12] primary and foremost, an ANFIS identifying simulation of PEMFC was created, then a Neuro-fuzzy PEMFC regulator that works 4 online was created. The result was that an ANFIS model of the complicated Nonlinear PEMFC system may be created and used for online forecasting of heat response.

Luis, et al., 2006, [13] demonstrated how different fault types influenced a PEMFC model. A visualization probability simulation for fault diagnosis is created utilizing databases in addition statistical approaches including as the Bayesian scoring besides Markov chain Monte Carlo. The experiments have shown that the original fault sources and the inference outputs are completely consistent.

Luis A.M. Riasco, et al., 2008, [14] described a system capable of diagnosing several types of defects while a PEMFC is in operation. A diagnosis is developed using Bayesian networks to measure and assess the cause-and-effect relationship within the variables in the development.

Yuedong, et al., 2009, [15] explored the approach to control and fault management to acquire the efficiency of PEMFC under a variety of operational situations while avoiding membranes drying or dehydration, hydrogen and air starvation in the cathode and anode, and membrane leak. The study's application included (UPS) uninterruptible power supply.

T. Escobet, et al., 2009, [8] The study introduces a methodology for model-based fault diagnostics tailored for Proton Exchange Membrane Fuel Cell (PEMFC) systems. The crux of this approach lies in the computation of residuals—indicators derived from a comparative analysis of measured inputs and outputs against mathematical relationships established through meticulous system modelling**.**

M. ELSayed, et al., 2010, [16] created an ANN simulation. The created simulation intends to build a non-parametric simulation. The Levenberg-Marquardt Back Propagation (LMBP) algorithm was used to create the ANN model. The strong consistency with ANN Modeling data obtained allows us to have confidence in the high degree of ANN model dependability that can be applied in applications involving fuel cells.

Djamel Benazzouz, et al., 2011, [17] presented the multi-layer perceptron (MLP) structure and designed an FDI system utilizing the LMBP algorithm. To save money and time on troubleshooting. They focused their investigation on the use of steam turbines for electricity generation. The results demonstrated quick convergence and precision.

Mahanijah and Dingli, 2011, [2] created a model based on FDD that uses (RBF) radial basis function systems to identify and classify faults. The RBF system is utilized to mimic defective and free fault data sets, as well as to implement FDD for 5 faults that typically occur in these types of systems. Faults in sensors, components, and actuators are taken into account.

Aitouche, et al., 2011, [18] suggested a defect system of detection determined by the mathematical PEMFC simulation and employing analytical nonlinear redundancy. The residuals are produced by removing the unknown variables.

Erkan and Osman, 2011, [19] built the internal difficult electrochemical calculations and reactions using an ANN. The LMBP neural network was utilized to create a model with outstanding modeling and performance accuracy when 3 inputs (cell temperature, oxygen flow, hydrogen flow) as well as two outcomes (current and voltage) were used. Meng and Mu-Jia, 2012, [20] suggested a PEMFC condition monitoring FDD system based on ZigBee sensors and a Modbus interface. The study took into account voltage, current, temperature, and fuel pressure characteristics. The system was built using PC-based software. Test findings show that training time is short and accuracy is good.

Ali.Mohammadi, et al., 2013, [21] developed a circuit-based model that takes into account the two-dimensional change in pressure, humidity, and temperature within stacks of PEMFCs. The study attempts to investigate multiple flaws while the capacitance and resistance of the circuit alter in response to changes in system parameters.

Mahanijah and Dingli, 2013, [22] provided an RBF for an FDI system that performs classification, isolation, and identification. In the PEMFC system, one component problem, one actuator fault, in addition 3 sensor faults were investigated. -The fault size was increased from 7% to +10%. The system was designed in a simulation environment, resulting in faster reaction and increased efficiency.

R. Petrone, et al., 2013, [23] presented white-box, black-box and grey-box models for diagnosing PEMFC systems. The grey-box is effective with less energy. The white box is correct. The black-box predicts irregular system parameters and approximations quite well.

Mahanijah and Dingli, 2014, [1] For isolation, employed an MLP network and an RBF classifier. 5 faults with fault sizes of +10% of nominal values were successfully isolated and detected. Michigan University's benchmark model was utilized in conjunction with the modeling environment Matlab R2000aSimulink. All faults were precisely and appropriately isolated.

Ali., et al., 2015, [24] studied a Fuel Cell Electric trains FDD for varied current concentrations in an experimentally calibrated 3D sensitive simulation. The categorization of the flaws was done using ANN based on the three-dimensional model.

The study focused on four main terms: FDI, fuel cells, AI and FPGA. Neither of the research findings in the investigation incorporate all four keywords. Mahanijah and Dingli, 2014, [1] as well as Djamel, et al., 2011, [17] are the most similar studies to ours. Both do not have a hardware representation, which makes our investigation unique, particularly when utilizing the ANN.

H. A. Tokel, et al., 2018, [25] A critical responsibility for a reliable operation is the identification and classification of defective circumstances in power systems. Recently, some academics have suggested using high-resolution synchronized phasor measurements for identifying and categorizing faults.

A novel method for detecting and classifying faults in power systems using machine learning.

S. M. Chopdar and A. K. Koshti,2022 [26] A progressive growth in the number of transmission lines is also occurring as a result of the rising load demand. The likelihood of faults occurring rises along with the expansion of transmission lines.

Rajiv et al. [50] describe a model-based strategy for robust fault identification and isolation in a pair of continuously stirred tank reactor. For robust defect detection, the scheme employs sliding mode observers.

In an instance of parameter uncertainty in the system model, detection is performed.

Simulated defects in sensors, actuators, and plant parameters of operation validate the detection of fault with isolation strategy. Additionally, the technique gives a way for evaluating the system's parameter error.

Dexter, A.L., 1995, [51], presents a model-based fault diagnosis approach that employs explicit fuzzy models of reference to characterize the indications associated with faulty and fault-free plant operation. The diagnosis approach computes an indicator of the fundamental ambiguity in the diagnosis and gives an interval of trust for every one of possible diagnoses. This method displayed an air conditioning plant's mixing box.

Garcia and Frank [52], 1997, provide an overview of the major observer-based fault diagnosis methodologies for nonlinear systems. Some schemes are discussed for expanding commonly used diagnostic techniques for linear structures to the nonlinear case. This scheme's resilience in the case of uncertain inputs is examined. The study concludes with an explanation of some outstanding issues.

Mechefske (1998) [53] discusses the application of fuzzy logic approaches to categorize frequency spectra reflecting distinct rolling element bearing problems. A wide range of fuzzy set shapes were used to process the frequency spectra indicating various fault states. The use of fundamental fuzzy logic approaches has resulted in the generation of fuzzy numbers that indicate the similarity of frequency spectra. When the suitable mix of fuzzy set shapes and membership domain ranges was utilized, accurate categorization of different bearing failure spectra was found.

Weber, et al., 1999, [54], propose model-based fault detection approaches that enable the creation of the residuals as the fault indications and isolation that typically depend on an incidence matrix structure. The decision technique is carried out by qualitative reason based on fuzzy logic by aggregating the complimentary information provided by the 1 and 0 of the probability matrices. The incidence matrix structure's qualities have been utilized to reason about many flaws without verifying each combination. This algorithm's implementation has been used in an automobile engine.

Commault et al., 2000, [55]. This research looked at an array of observer-based residuals in which the transmission of disruptions to remainders is zero while The transfer of faults to residuals enables fault isolation. The required and adequate requirements for generally resolving these problems are defined by means of input and output pathways in the related graph of the system and are frequently satisfied in practice.

BARTY and KOCIELNY, 2002, [56], offer four fuzzy logic isolation of faults techniques appropriate for use in smart final controls elements. These methods allow for the consideration of symptoms of ambiguity as well as real-time applicability. The techniques are distinguished by immunity features that protect against measurement noise. The more the immune components, the more the diminished or "flatness" diagnostic can be detected.

Abdelkader et al., 2003, [57], describe a sliding mode with multiple observers' architecture that allows estimating the vector representation for a nonlinear dynamical structure. The last one is impacted by unknown inputs acting on it via an established transmission matrix. The assessment of the state, and hence the estimation of output, can be utilized to detect and isolate faults. This method was shown using a popular three-tank setup.

Sotomayor et al., 2004, [58], present the design of a fault detection and isolation (FDI) system to monitor failures in sensors and actuators of a Fluid Catalytic Cracking (FCC) unit Model Predictive Control (MPC) system. The control system is based on an infinite-horizon MPC algorithm. The fault detection technique is built on two banks of robust observers, while the fault isolation task is completed using a structured residual approach.

Xing-Gang and C. Edwards, 2005, [59], provide powerful actuator failure detection as well as isolation for a group of a sliding mode observer is used in nonlinear uncertain systems. The observer in sliding mode is initially built using a Lyapunov equation with restrictions. The analogous output error injecting signal is then used to rebuild the signal for the fault using properties of the mode of sliding observer and the composition of the uncertainty. The HIRM aviation system simulation study is given. Rolink et al., 2006, [60], describe the construction of a three-tank FDI method based on sliding mode approaches. This paper emphasizes the a high-order sliding mode observer was designed to analyze the occurrence of actuator failures, and it covers two well-known algorithms for implementing sliding mode techniques: twisting and super-twisting. Both approaches provide very accurate fault estimation.

J. Juan and Rafael, 2007, [61], observed a fault diagnosis problem for a system that is not linear, the results are used for assessing fault diagnosability using a differential algebraic approach, and one nonlinear investigator employing a sliding method approach is provided for calculating faults; a different nonlinear investigator is also handled for purposes of comparing results.

Siahi et. al., 2008, [62], describe a novel adaptive methodology for identifying faults besides isolation. This method obtains an estimation of the fault signal, which offers important information on fault characteristics such as the scope and impact of the problem, which is required for many applications. The suggested approach is tested on an airplane model, and a rebuilt fault signal is gathered. The findings from simulation are compared to those obtained using the sliding mode technique.

Mendonca et al., 2009, [63], provide a model for fault identification and isolation that utilizes an architecture using a fuzzy technique. Fuzzy modelling is implemented to drive nonlinear mathematical models for the procedure while it is running normally and for each fault. When a problem occurs, the residual is used to detect the fault. The defective fuzzy models are then utilized to isolate a flaw. This article utilized a fuzzy making choices approach based on residual analysis to isolate defects. Several sudden and incipient defects are obtained using an industrial valve simulator.

Padmakumar. et al., 2010, [64]. For fault detection, the Kalman filter technique, together with along with residual calculations and hypothesis testing, and an alteration in residues for the current signal is monitored for detection. The study only considers incipient flaws. This work employs an extra order linear space of states model of a DC motor.

Luca. et al., 2011, [65], describe an FD method for manipulating robots that utilizes the idea of second-degree sliding modes. It is conceivable to detect a defect that may occur on a certain system constituent. Sliding modes of higher order Unknown Input Observers (UIO) have been suggested to provide the required analytical redundancy for detecting actuator problems. Instead, sensor defects are detected using a Generalized Observers Scheme (GOS).

Chang et al., 2012, [66], present a defect diagnostic scheme for nonlinear systems that combines a slide-mode observer with a Luenberger observer. Initially a nonlinear structure is divided into two distinct subsystems., one of which is unaffected by the disruptions; a Luenberger spectator is built for this subsystem, and a sliding-model spectator is built for the second, that is affected by the disruptions; an LMI-based method is used for designing the observer. A single-link automated arm is used to test the efficacy as well as practicality of the suggested method.

## 2.3. DETECTION OF FAULTS

The provisions that follow explain the classification, types, definition and procedures of defects.

### 2.3.1. Definition of Fault

It is described as an unallowable modification in no less than one system characteristic attribute from the acceptable, standard condition or typical [25].

For FDD, a model-based method based on a threshold constraint and residual generation is the best way to get an acceptable choice. The discrepancy between predicted and actual values is the residual vector [2].

Model-based fault diagnosis is based on the generation of signals that indicate inaccuracies between conventional and defective system operation circumstances [26].

### 2.3.2. Failure, Malfunction and Fault

After a defect occurs, it can become a malfunction, depending on the circumstances. A failure is a continuing disruption of the system's ability to implement a desired function.

A malfunction is an intermittent inconsistency in the system's ability to perform a function.

There is a distinction among failure with fault; failure denotes full component breakdown, while fault denotes just divergence from the standard features, as illustrated in Figure2.1 [27].

- Fault: is an unallowable divergence of at least that's the minimum one system distinguishing attribute or parameter from the adequate, customary, or standard situation. Detection of flaws.
- Failure: occurs when a system's capability to fulfill an essential function within operational conditions stated is permanently disrupted.
- Malfunction: refers to an occasional inconsistency in a system's ability to perform its intended function.
- Error: A difference in a measurable or calculated value for an output variable from its real or theoretically accurate value.
- Disturbance: uncontrolled and unknown input operating on a system.
- Residual: An indication of failure based on the variation between observation and model-equation calculation.
- Symptom: A deviation from normal behavior in an observable quantity.
- The subsections that follow explain the definition, types, classification, and procedures of defects.

There is a distinction between fault and failure; failure denotes full component breakdown, whereas fault denotes just divergence from usual features. Figure (2.1) depicts the relationship between malfunctions, failures, and faults. The appropriate system feature associated with the fault is considered to be proportionate to the fault's progress. When the range of typical ranges is exceeded, the features signal a defect. A malfunction or failure of a system occurs at a particular time te, depending on its size.

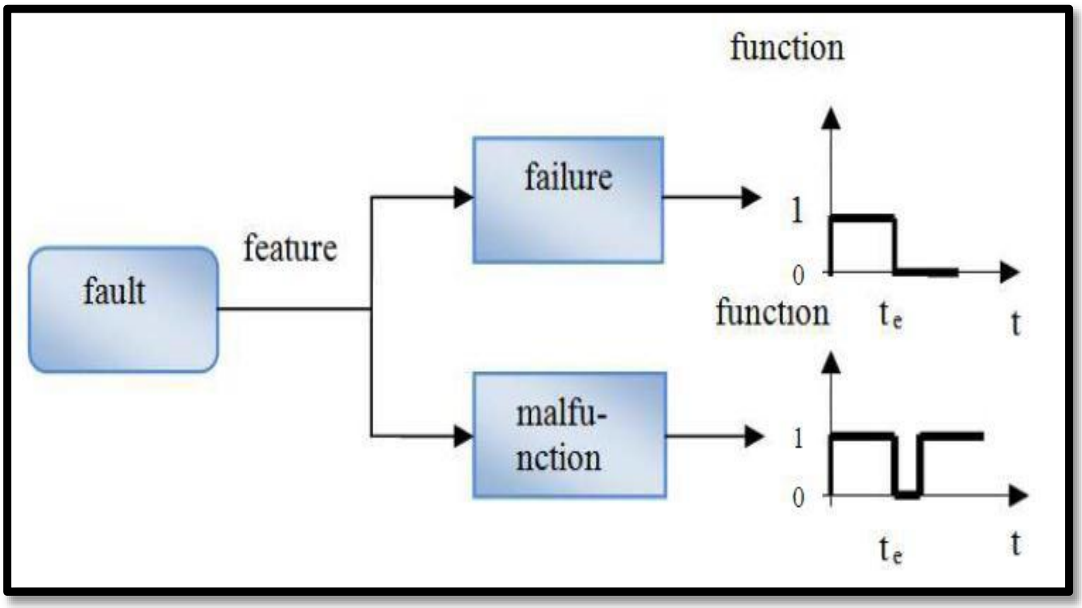



Figure 2.1. Malfunction due to the development of a fault.

### 2.3.3. Fault classifications

As illustrated in Figure 2.2, the temporal dependency of faults may be differentiated, with the three types denoted by letters a, b, and c depending on the fault type [28]:

- a) A severe and perhaps fatal flaw.
- b) Emerging flaw.
- c) Intermittent failure.

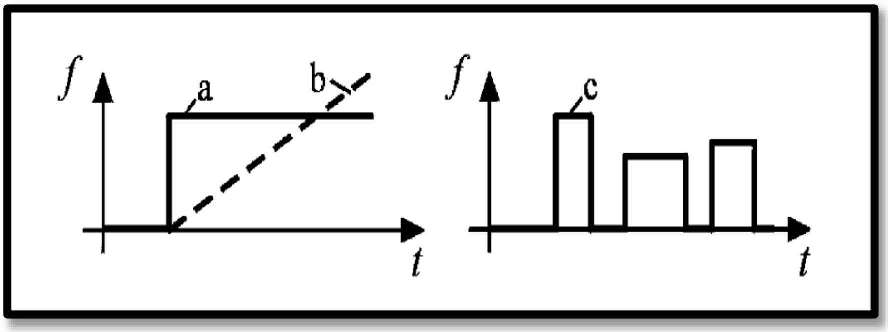



Figure 2.2. Types of time-dependent faults.

According to their occurrence location:

- Actuator errors result in either a complete or partial absence of control action.
- faults of sensor represent inaccurate sensor readings from the system's sensors.
- Component faults are problems in the plant's components. A component fault is defined as any failure that is not an actuator or sensor fault.

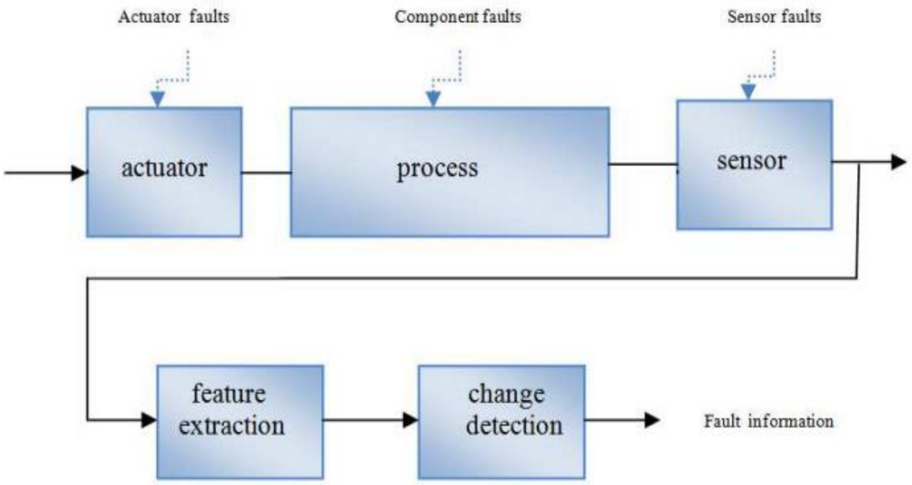



Figure 2.3. Signal-Based Fault Detection Schematic Diagram.

As stated by their illustration:

- Fault multiplication is utilized to depict actuator besides sensor faults, as observed in Figure 2.3. Specimens of this category of problem are a leak in a pipeline with an electromagnetic proportionally the flow of acting control valve [29].

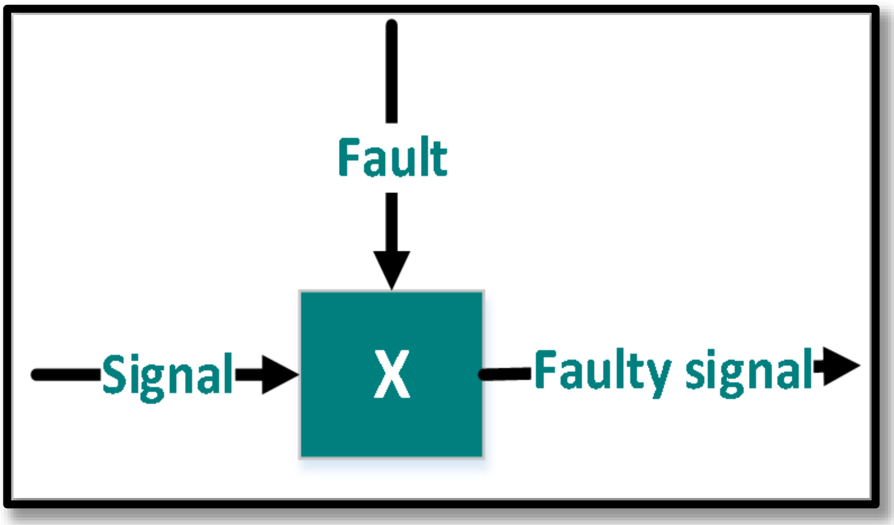



Figure 2.4. Fault multiplication.

- As illustrated in Figure 2.4, additive faults reflect additional shortcomings in general than multiplicative faults. A bypass in the conductivity of a power contact is a prime instance of this sort of defect [29].

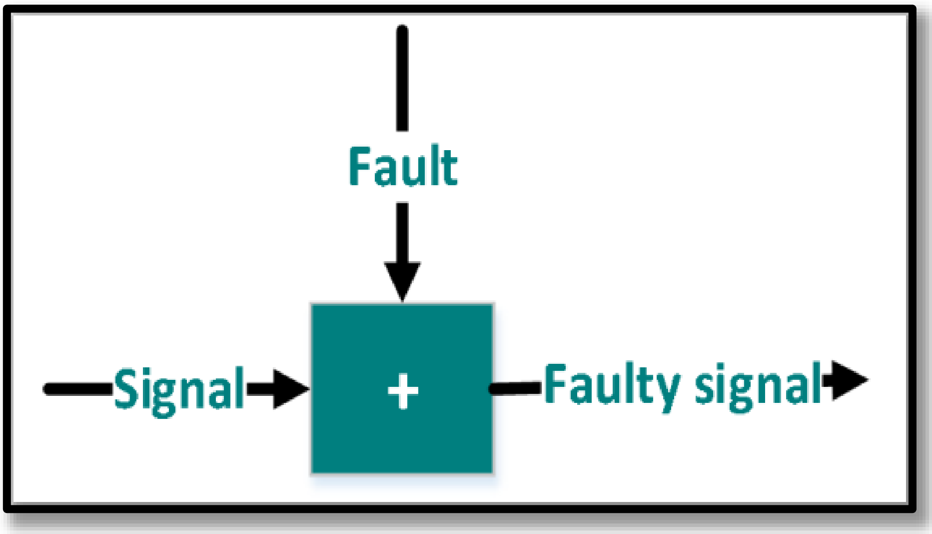



Figure 2.5. Additive fault.

The physical characteristics and models of the defect determine whether the fault is additive or multiplicative. Many sensors and process failures are classified as additive. Actuator failures are multiplicative rather than additively modelled [29].

### 2.3.4. Summary of Diagnosis Techniques [30]

- To diagnose problems, rule-based approaches rely on professional expertise expressed as a collection of established rules.
- Model-based methods define a mathematical description of a system in addition comparison it to the detected state to see if it matches.
- For diagnosis, statistical approaches such as connection, histogram comparison, and probability theory are used for summarizing and interpreting empirical data.
- Machine-learning approaches use clustering to find behaviors patterns or utilize data for training to evaluate if the system is unwell and the probable cause.
- Threshold and Count methods distinguish among transient and periodic problems.
- The presentation tools enable operators to observe data trends and detect aberrant activity.

The redundant analysis FDC approaches are classified as quantitative or qualitative model-based methodologies. The observer-based approaches for generating residues for FDC are qualitative techniques based on modeling that use explicit mathematical frameworks and control theories. The use of AI techniques is seen as a quantitative model-based method [31]. Figure 2.5 depicts the model-based FDC block diagram.

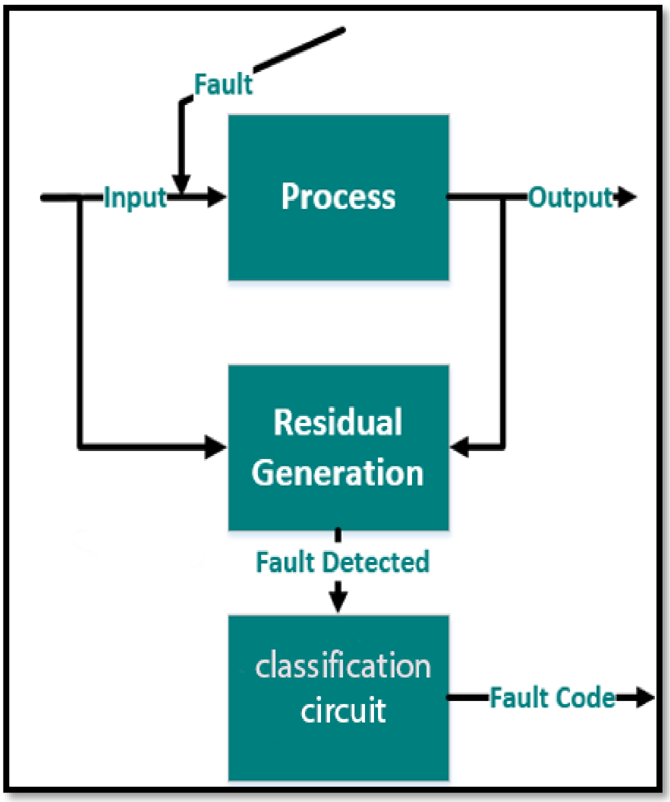



Figure 2.6. Diagram of a model-based fault detection block.

### 2.3.5. Isolation of Faults

It is not just detecting the defect but similarly unique the sorts of fault. One of the following methods can be used to generate residuals. The first approach is the direction residual approach, in which the type of defect is determined by the vector direction. The second way is the structured residual approach, in which Each defect has its own vector pointing to it, i.e. each vector relates to a specific fault type [31].

## 2.4. CELLS OF FUEL BASED ON PEM

In the subsections below, a quick theoretical description of the PEMFC is provided.

### 2.4.1. Introduction

Fuel cells are classed by means of Alkaline Fuel Cells (AFC), PEMFC, Direct Methanol Fuel Cells (DMFC), Molten Carbonate Fuel Cells (MCFC), Phosphoric Acid

Fuel Cells (PAFC), and Solid Oxide Fuel Cells (SOFC) based on the substance of the electrolyte. The PEMFC is highly effective in many processes, including small-scale generating and transportation, as well as portable energy storage.

devices. PEMFC has several advantages, including fast initialization, a high-power weight, high efficiency, low temperature of operation, and a simple structure [32].

As shown in Figure 2.6, PEMFC has a dual electrode the anode and the cathode, divided by solid of electrolyte membrane. The hydrogen gas passes through a system of pipes to the anode, wherever it splits into protons, which flow to the cathode across a electrons and membrane, which are gathered as a voltage by a circuit from the outside connecting the two electrodes. Oxygen goes down through an analogous system of tubes to the cathode, wherever it mixes with electrons that are in the circuit outside and proton flow across the membrane to form water [33].

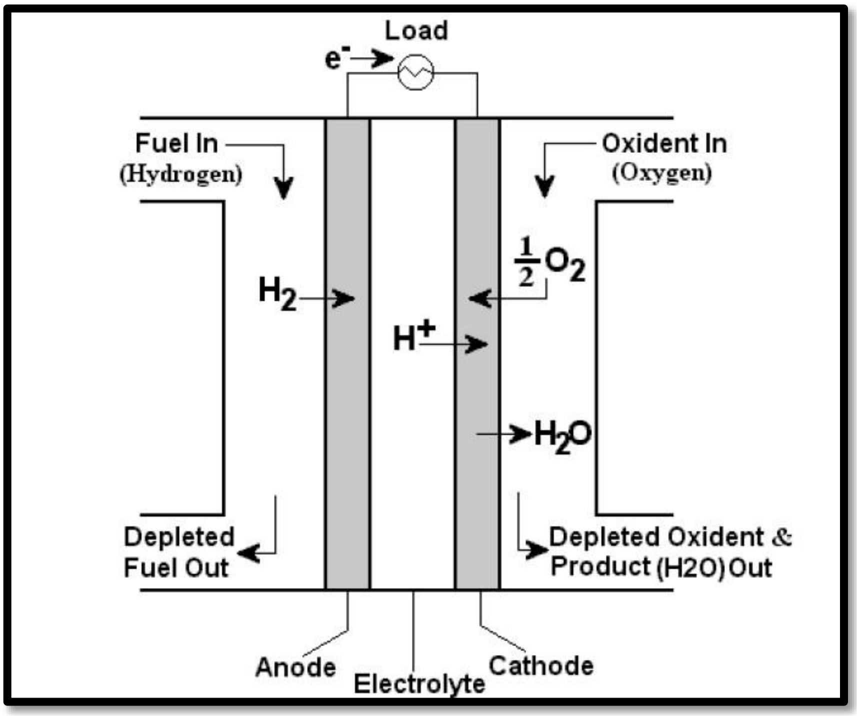


Figure 2.7. Diagram of a PEMFC.

The following reactions of chemicals occur at both the cathode and anode electrode of a PEMFC [33]:

Reaction of anode: $H_2 \rightarrow 2H^+ + 2e^- \ldots$ (2.1)

Reaction of cathode: $\frac{1}{2}O_2 + 2H^+ + 2e^- \rightarrow H_2O \ldots$ (2.2)

Reaction of total cell: $H_2 + \frac{1}{2}O_2 \rightarrow H_2O \ldots$ (2.3)

This reaction produces heat, water, and electricity.

### 2.4.2. Mathematical Model

When current is taken and electrical energy is obtained, irreparable losses reduce the real Vcell (fuel cell voltage) from the state of Potential thermodynamic equilibrium (E). When there is a flow of current proportional to the electrical function accomplished by the cell, a departure from the thermodynamics potential appears. The difference between the equilibrium value and the excess potential is denoted by the symbol (). Over potentials are largely caused by potential activation (act), overpotential ohmic (ohmic), with over potential diffusion (diff). The equation for one Single fuel cell system is [33]:

$$V_{cell} = E + \eta_{act} + \eta_{ohmic} + \eta_{diff} \cdots \tag{2.4}$$

wherein E is the permanent thermodynamic possibility of the $H_2$+$O_2$ process.

### 2.4.3. Fuel Cells Faults

There are numerous flaws in fuel cells, nonetheless, the most prevalent are [14]:

- Air-reaction blower faults.
- A problem with the refrigeration system.
- Boost the fuel crossover.
- Pressure of hydrogen fault.

Table 2.1 compares different types of fuel cells [48]:

Table 2.1. PEMFC against other forms of fuel cell technology.

| Category | Heat ◦C | Output (Kw) | Electrical efficiency (%) |
|---|---|---|---|
| **Alkaline (AFC)** | 90 to 100 | 10 to 100 | 60 |
| **Phosphoric Acid (PAFC)** | 150 to 200 | 50 to 1000 | Less than40 |
| **Solid Oxide (SOFC)** | 600 to 1000 | 1 to 3000 | 35 to 43 |
| **Molten Carbonate (MCFC)** | 600 to 700 | 1 to 1000 | 45 to 47 |
| **Polymer Electrolyte Membrane (PEM)** | 50 to 100 | 1 to 250 | 53 to 58 |
| **Direct methanol fuel cell (DMFC)** | 60 to 200 | 0.001 to 100 | 40 |

## 2.5. ARTIFICIAL NEURAL NETWORKS (ANN)

An ANN is a mathematical framework that utilizes the system and functioning of biological networks of neurons. The data that travels through the network alters the framework of the ANN since the network of neurons changes or learns in some ways according to the input and output [34].

### 2.5.1. Summary

AI approaches are increasingly being used to model environmental systems. Swarm information, systems based on rules, fuzzy theories, ANN, neural networks, cellular automata, genetic algorithms, multi-agent systems, a reinforcement learning, case-based reasoning, as well as hybrid systems are all types of AI techniques used in this dissertation because of their generalizability and respond to unanticipated inputs/patterns [35].

An ANN is made up of several units of processing. According to the ANN design type, each unit is linked to other units via numerous additional weighted connections.

Each unit's role is to receive information from neighbours or external sources, perform simple calculations, and then output the results to other units. Many units work in parallel at the same time; Figure 2.7 depicts the three kinds of activation processes found within each unit [36].

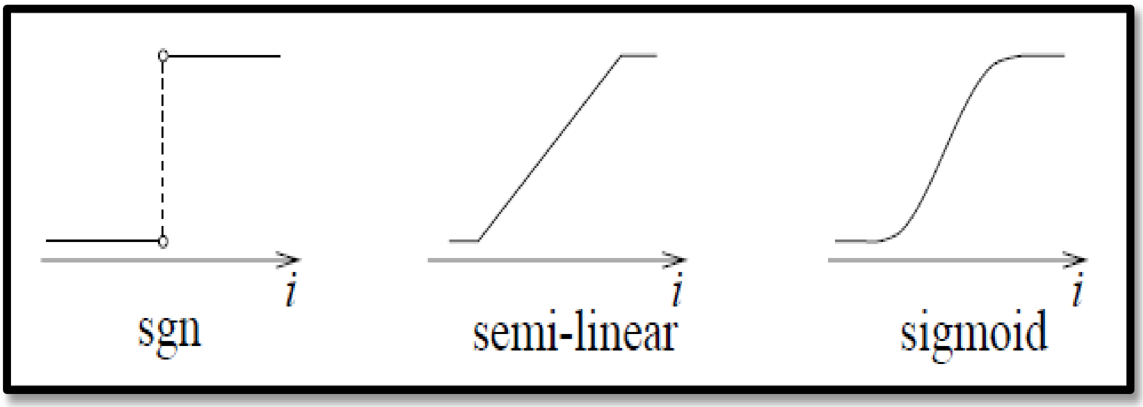



Figure 2.8. A unit's several activation functions.

The error signal is used by an algorithm to adjust the relative weights of each connection in order to improve system performance. The traditional BPNN is depicted in Figure 2.8. Algorithms are widely utilized to solve a wide range of actual issues [37].

### 2.5.2. The Algorithm of Levenberg-Marquardt

It was established separately via Kenneth Levenberg as well as Donald Marquardt, and it presents a numerical approach to the problematic of reducing a function that is nonlinear. It is fast and has constant convergence. This approach is appropriate for problems with training of small and medium size in synthetic neural networks [38].

This technique is an iterative approach for locating the smallest value of a multidimensional function defined as the total number of squares of non-linear actual in value functions [39].

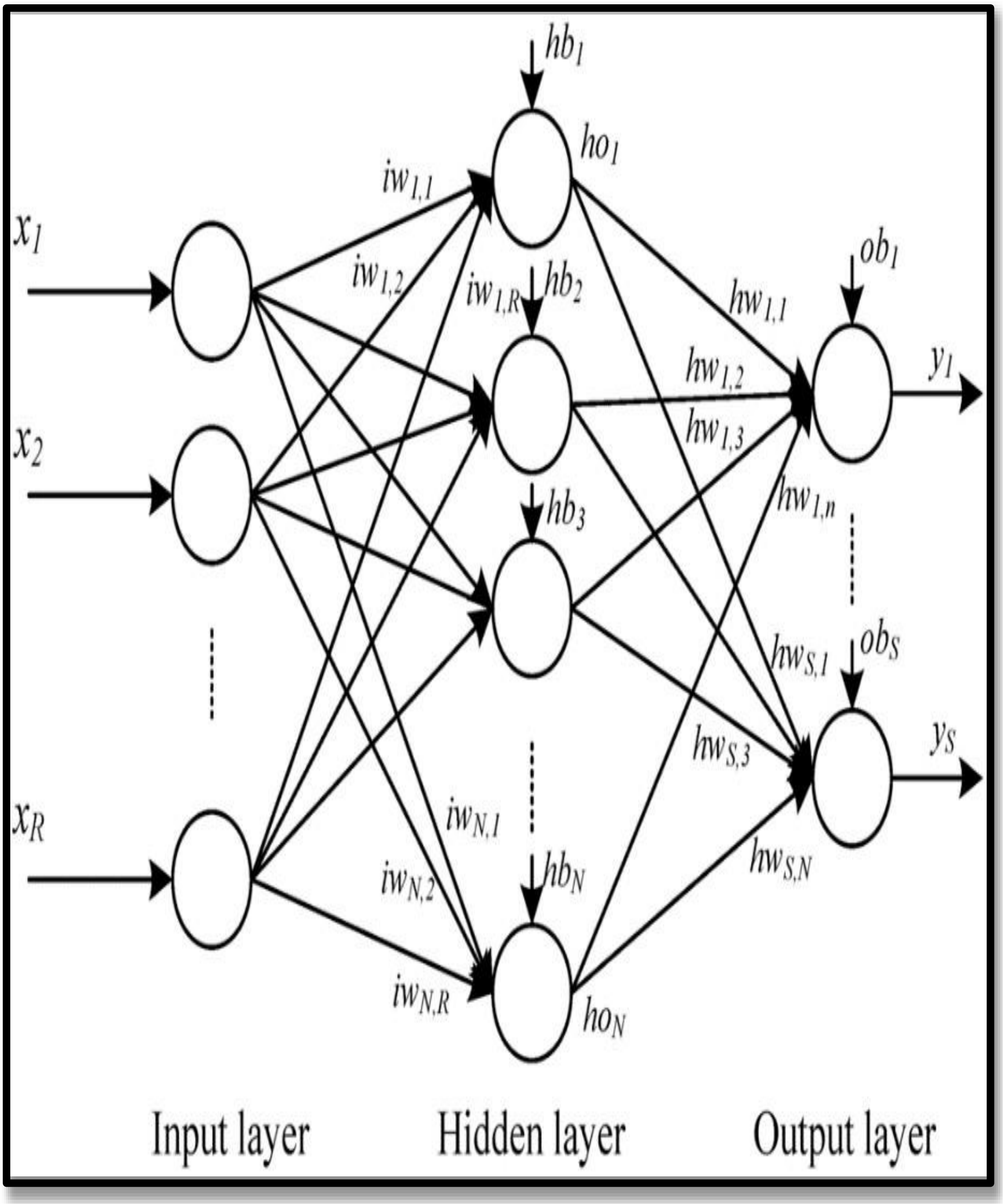



Figure 2.9. Structure of BPNN.

## PART 3

## PEMFC FDC SYSTEM SIMULATION

### 3.1. INTRODUCTION

This chapter describes the proposed system's specifications and details, including the types of fuel cells employed and the neural network chosen.

### 3.2. PROPOSED FRAMEWORK

Figure 3.1 depicts a flowchart of the entire proposed system simulation phases.

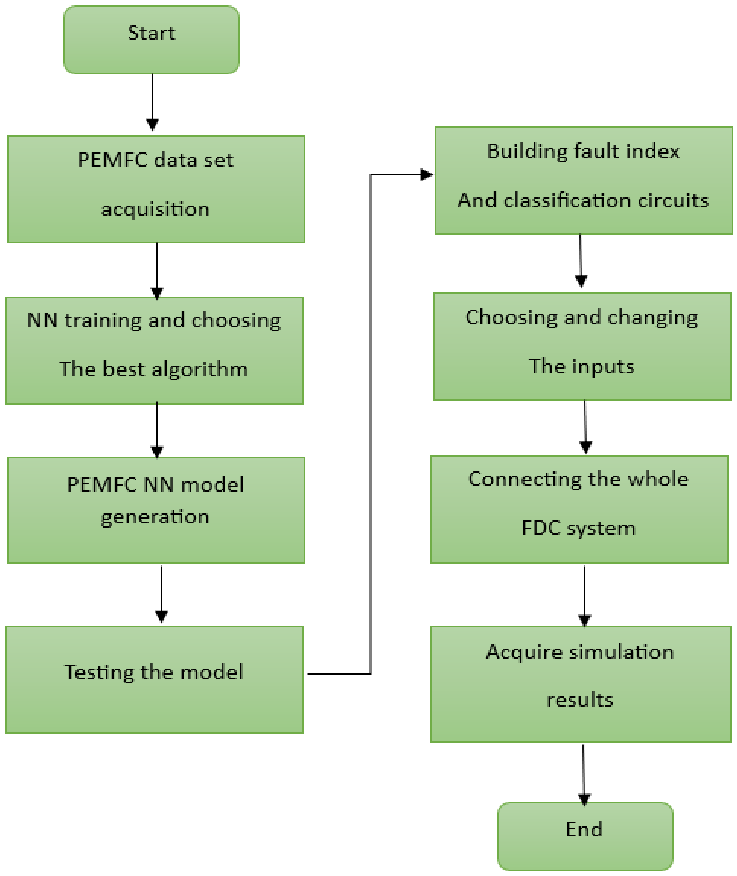



Figure 3.1. Flowchart of the proposed system.

## 3.3. MATLAB'S PEM FUEL CELLS

The PEMFC was selected as a model to be researched and controlled due to its benefits over other forms of fuel cells.

The data set was collected, and the experiments were carried out in the Matlab/Simulink environment. Njoya's [48] PEMFC model is depicted in Figure 3.2.

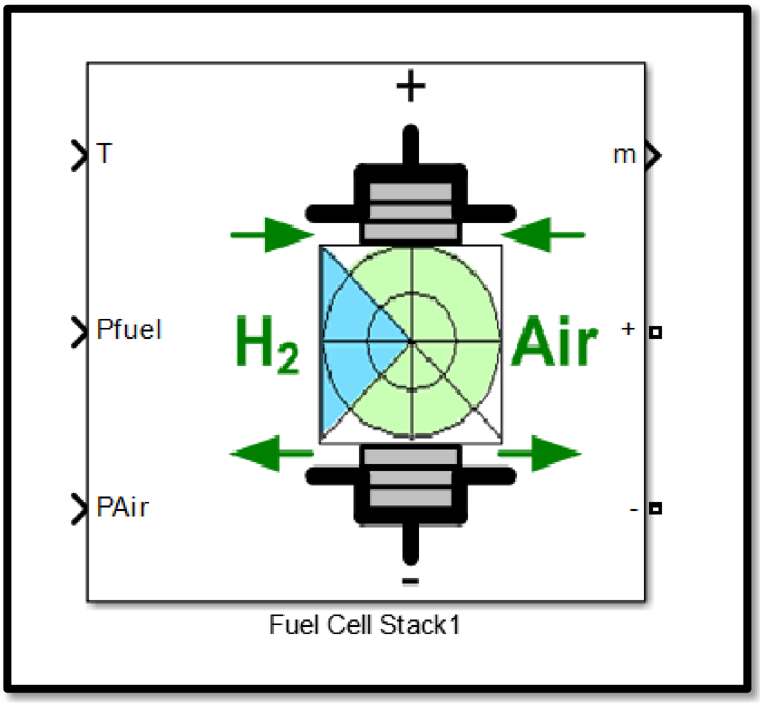



Figure 3.2. PEMFC Block in MATLAB Simulink.

Fuel pressure 0.1 to 5 bar, Heating from 322 to 372 kelvin, , and air pressure 0.1 to 5 bar are the data ranges, with two outputs recorded for every reading (Current and Voltage).

Table 3.1 illustrates the parameters of the (6kw-45Vdc) model that was employed.

Table 3.1. Model parameters for PEMFC in Matlab.

| **Current version** | **6 kw 45Vdc** | |
|---|---|---|
| **Voltage at 0 and 1 amps** | 65volt | 63volt |
| **Operating point nominal** | 133.3 amp | 45volte |
| **The highest operational point** | 225 amp | 37volt |
| **cells Number** | 65 | |
| **Stack nominal performance** | 55% | |
| **Operation Heat** | 65 Celsius | |
| **Fuel provides constraints** | 1.5 bar | |
| **Provide of air pressure** | 1 bar | |

The connection indicated in Figure 3.3 was used to get the inputoutput set of information for the fuel cell. The set constant block number (here 359 kelvin and the air and fuel pressures equal to 2 bar) can be used to change the inputs or parameters, as shown in the picture.

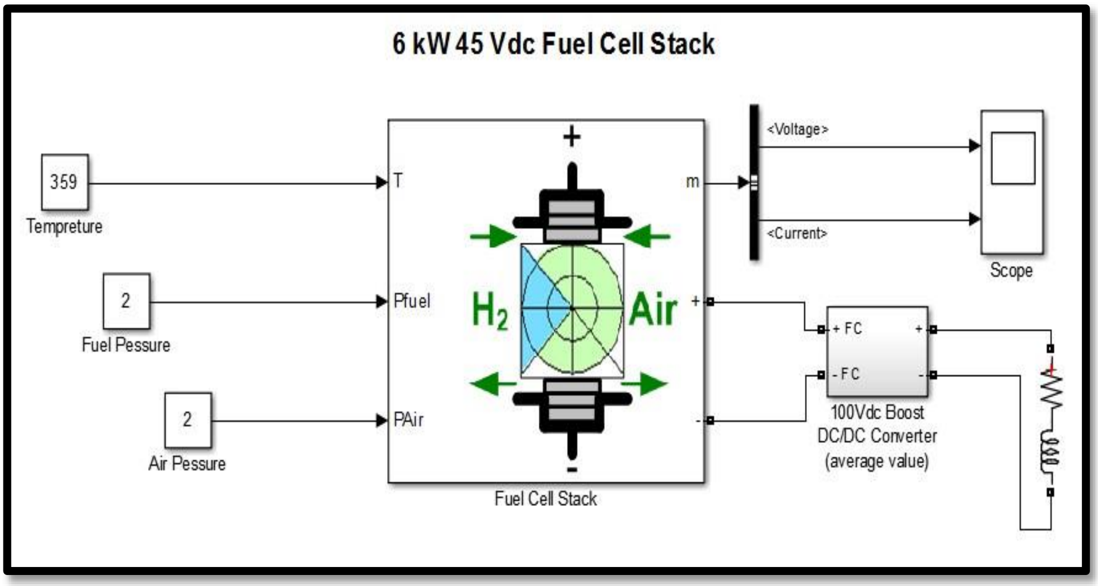



Figure 3.3. Connection for data acquisition.

### 3.4. DESIGN OF A NEURAL NETWORK

There are other networks and structures, but the MLP Network is the most often utilized since it is simple and produces excellent results.

The Levenberg-Marquardt algorithm was employed to train the network since it provides faster ANN training than other reasonable gradient techniques, as evidenced by experimental findings.

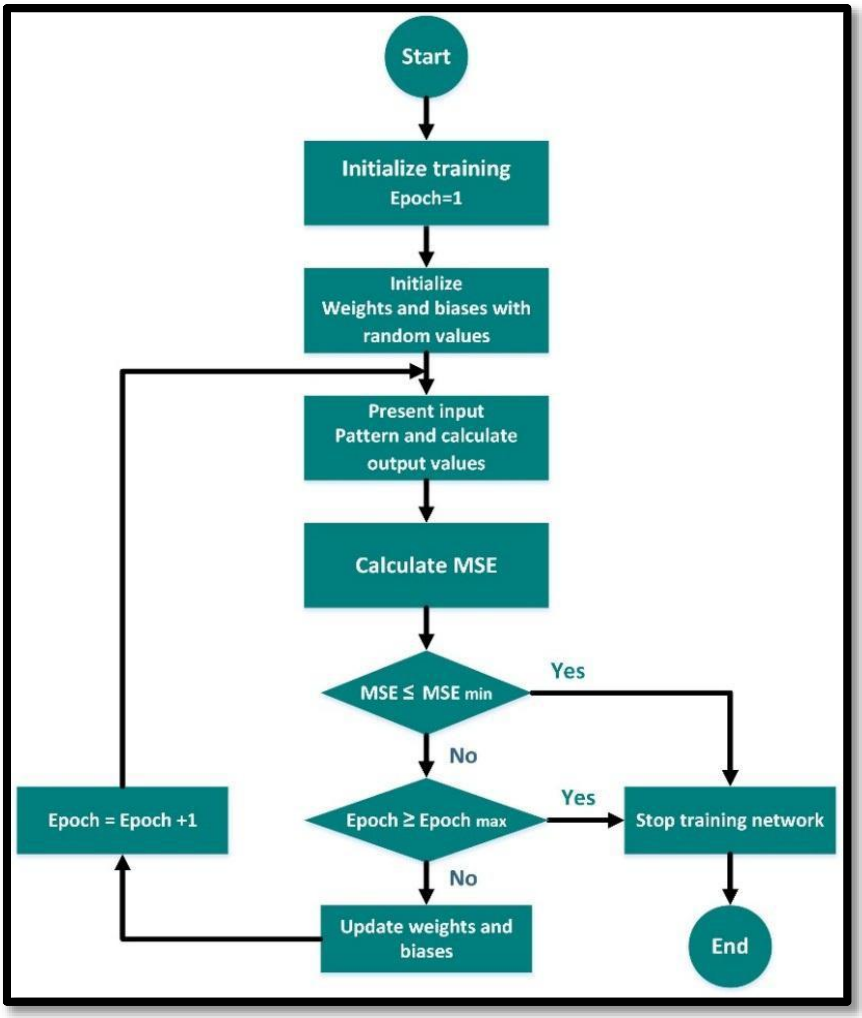



Figure 3.4. Flowchart of the back propagating algorithm training process.

A more generalized version of logistic regression is called SoftMax activation function.

The function is supplied by [49]: the model of neural networks built in Simulink with the sequence (gensim) in order that it may be tested and used in the next section's fault analysis. Figure 3.6 shows the NN Simulink block.

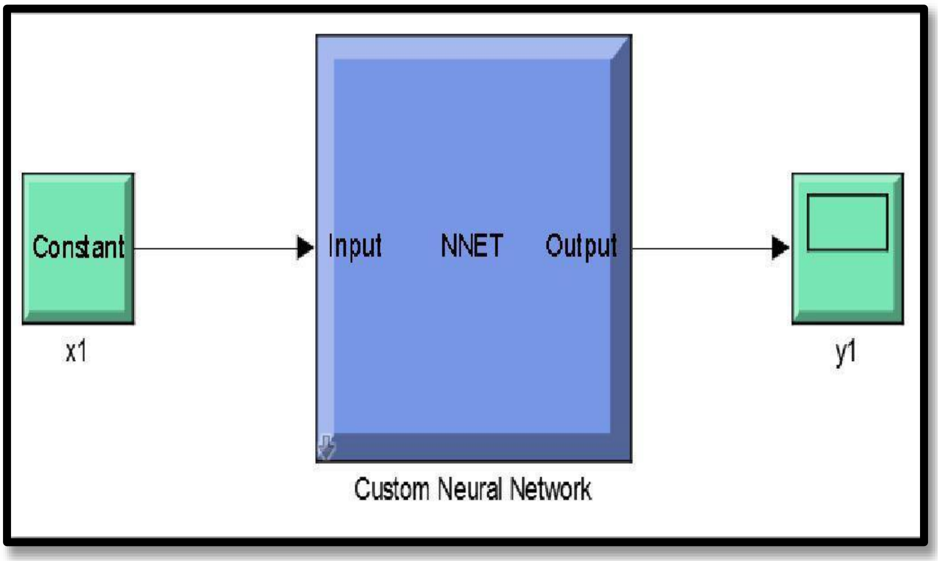



Figure 3.5. Block for creating a neural network Simulink.

The weights of the blocks besides the full ANN model are illustrated in Figure 3.7, whereby the starting hidden layer has 10 neurons, every single one which has an overview of the input data multiplication and the equivalent weight, that is only the Dot outcome process of vectors.

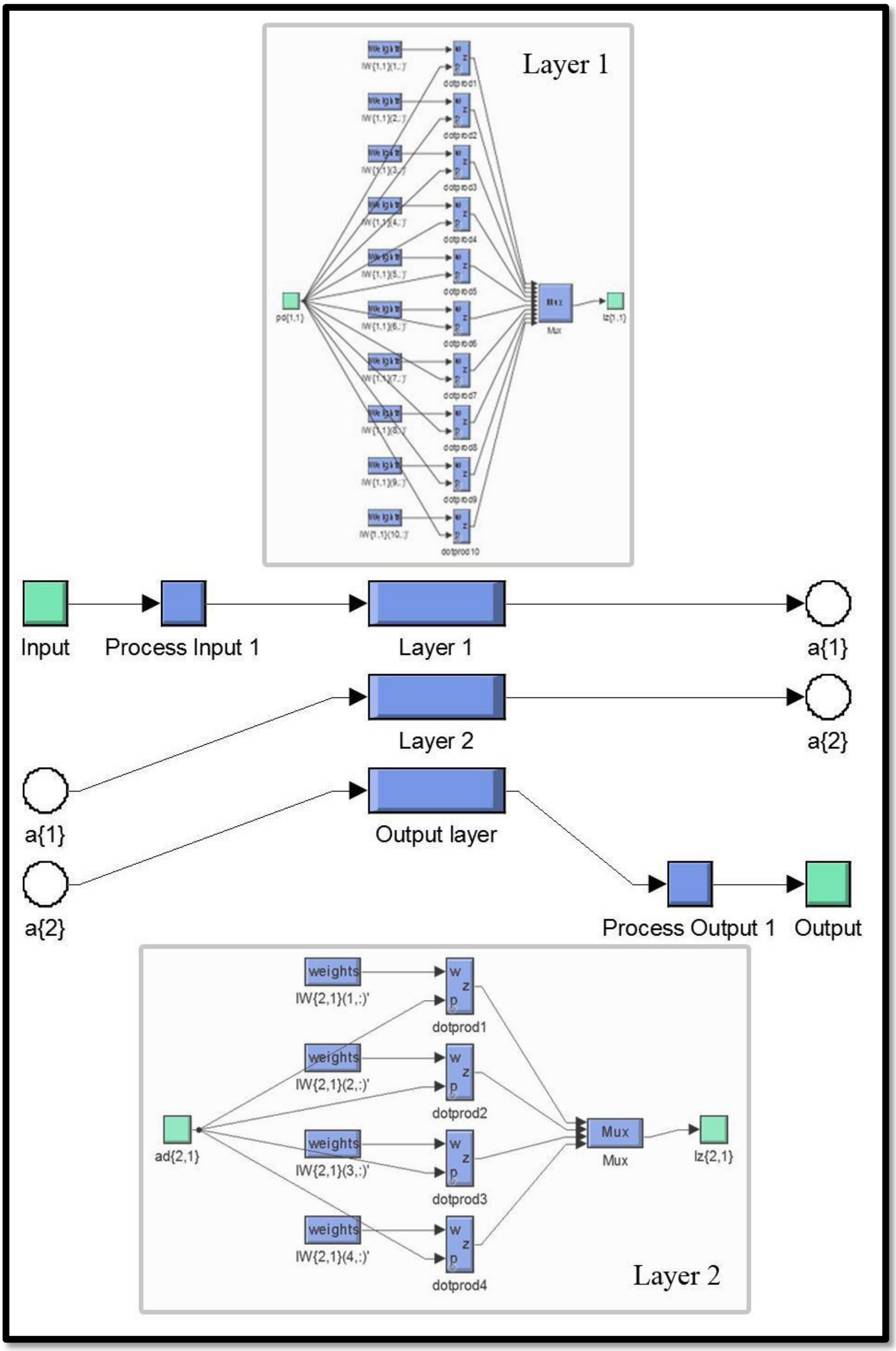



Figure 3.6. The NN model's internal structure.

### 3.5. FAULTS TYPES

This paragraph describes three sorts of faults, although the ANN must first be manually validated.

#### 3.5.1. Model Examination

When a neural network simulation is established, it has the potential to be replicated a variety of failures. It is first linked to PEMFC Matlab simulator for evaluation, as illustrated in Figure 3.8.

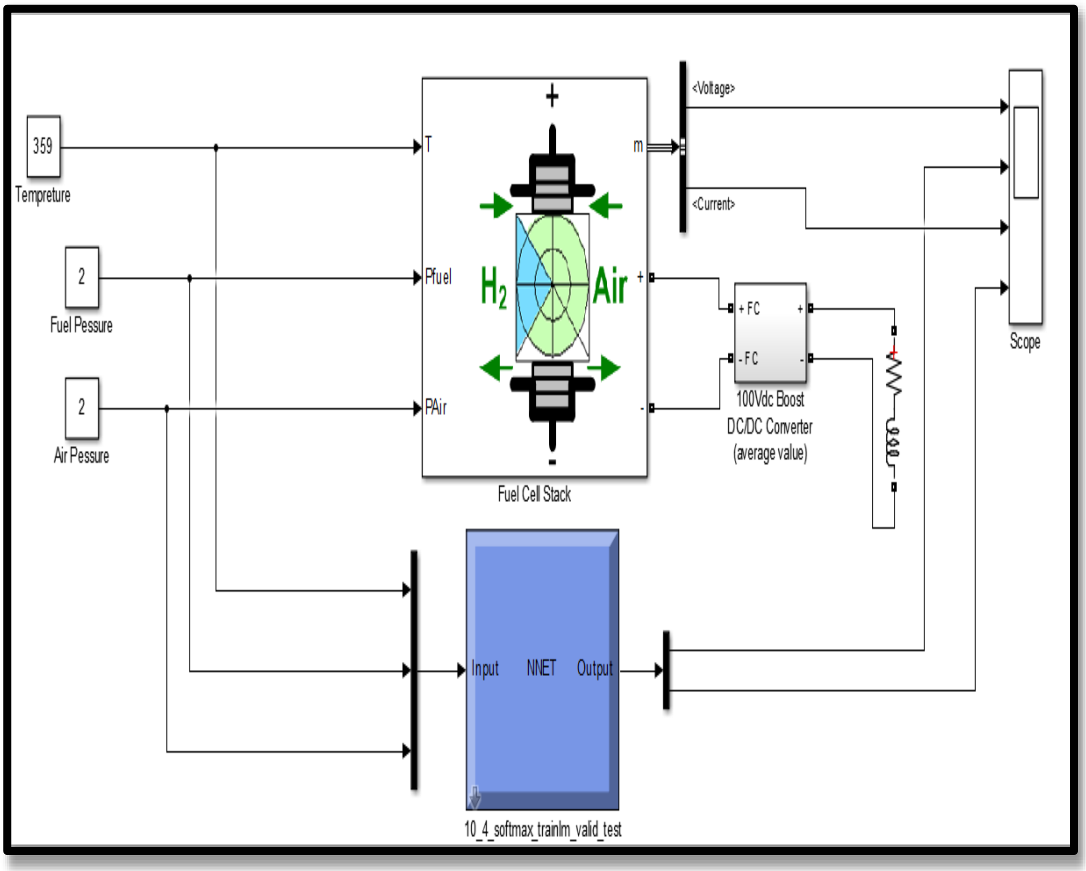



Figure 3.7. Manually evaluating the model's achievement.

#### 3.5.2. Fault Abrupt

As shown in Figure 3.9, this type of problem can be simulated by adding a step signal to the PEMFC's input signal. Look at the fourth input to the scope (the red arrow indication in Figure 3.9). for more details. The PEMFC output voltage has been compared to the NN model output voltage, as well as an additional signal is created by subtraction.

In Figure 3.9, the index of faults indication is produced utilizing two threshold switches, one for positive and one for negative numerical values. For instance, at second 12, a step of 10 magnitude is introduced to ensure that the transitory shift is complete.

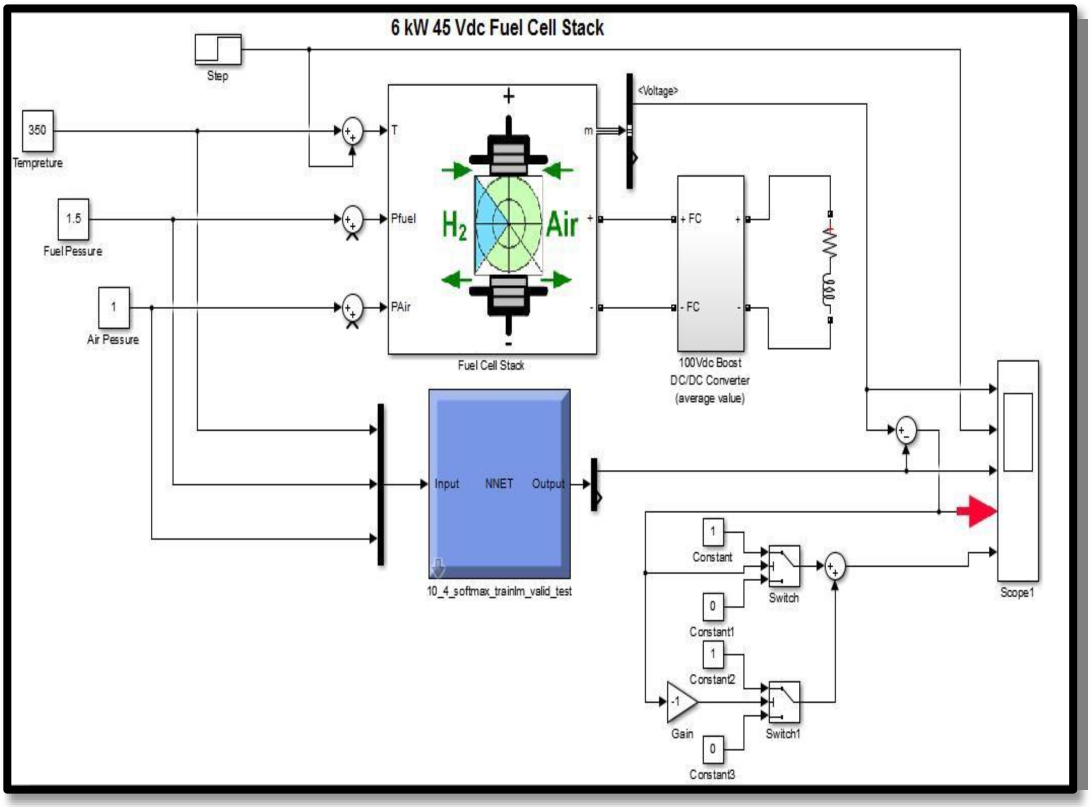



Figure 3.8. Fault Abrupt additional.

### 3.5.3. Fault Incipient

As shown in Figure 3.10, a ramp signal that is introduced to the PEMFC's input signal can simulate this kind of malfunction. The fuel pressure input in this figure has the fault added to it.

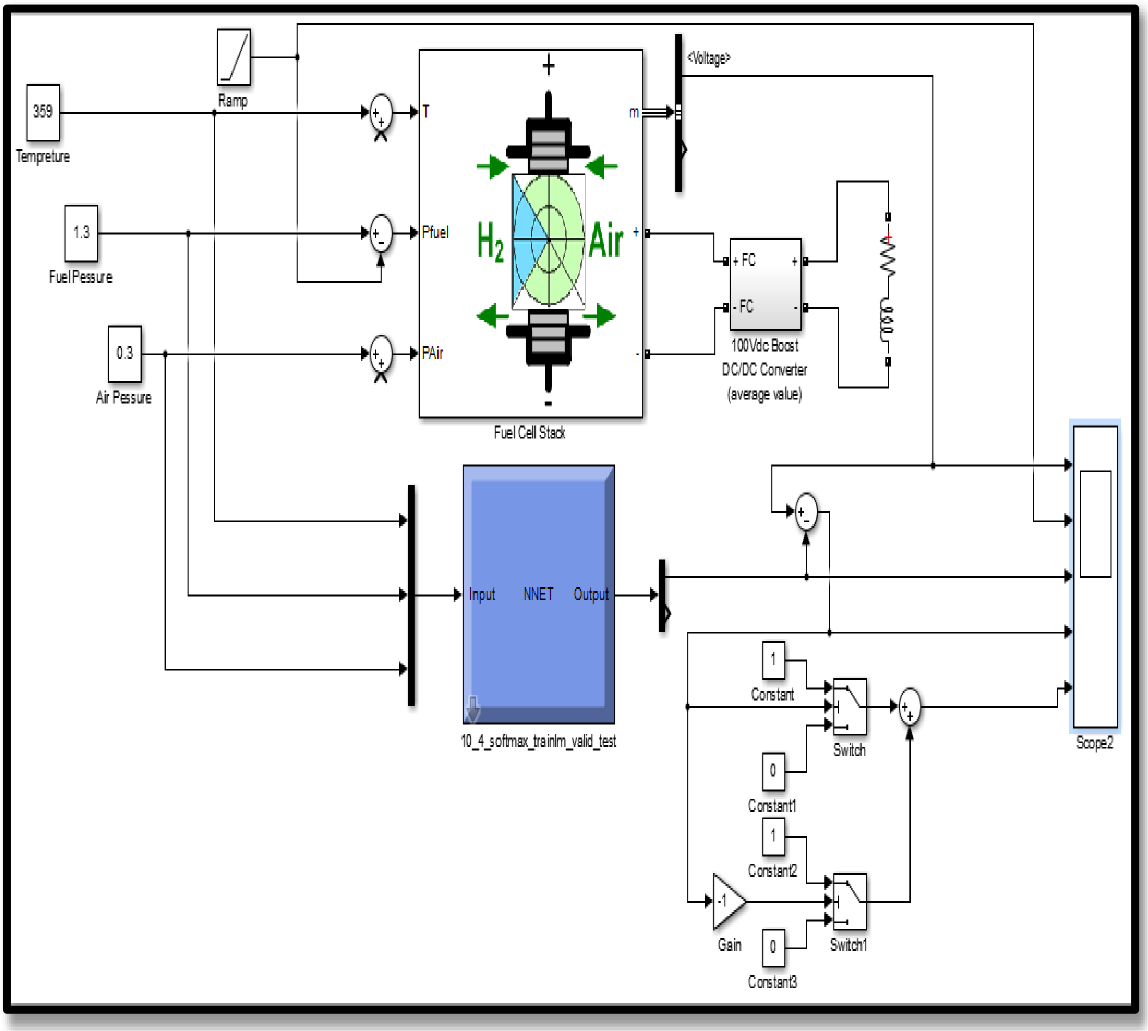



Figure 3.9. Fault Incipient additional.

### 3.5.4. Fault Intermittent

This category of fault can be simulated by adding a arbitrary signal to the PEMFC's input signal, as illustrated in Figure 3.11. The fault is multiplied by the air pressure input in this picture.

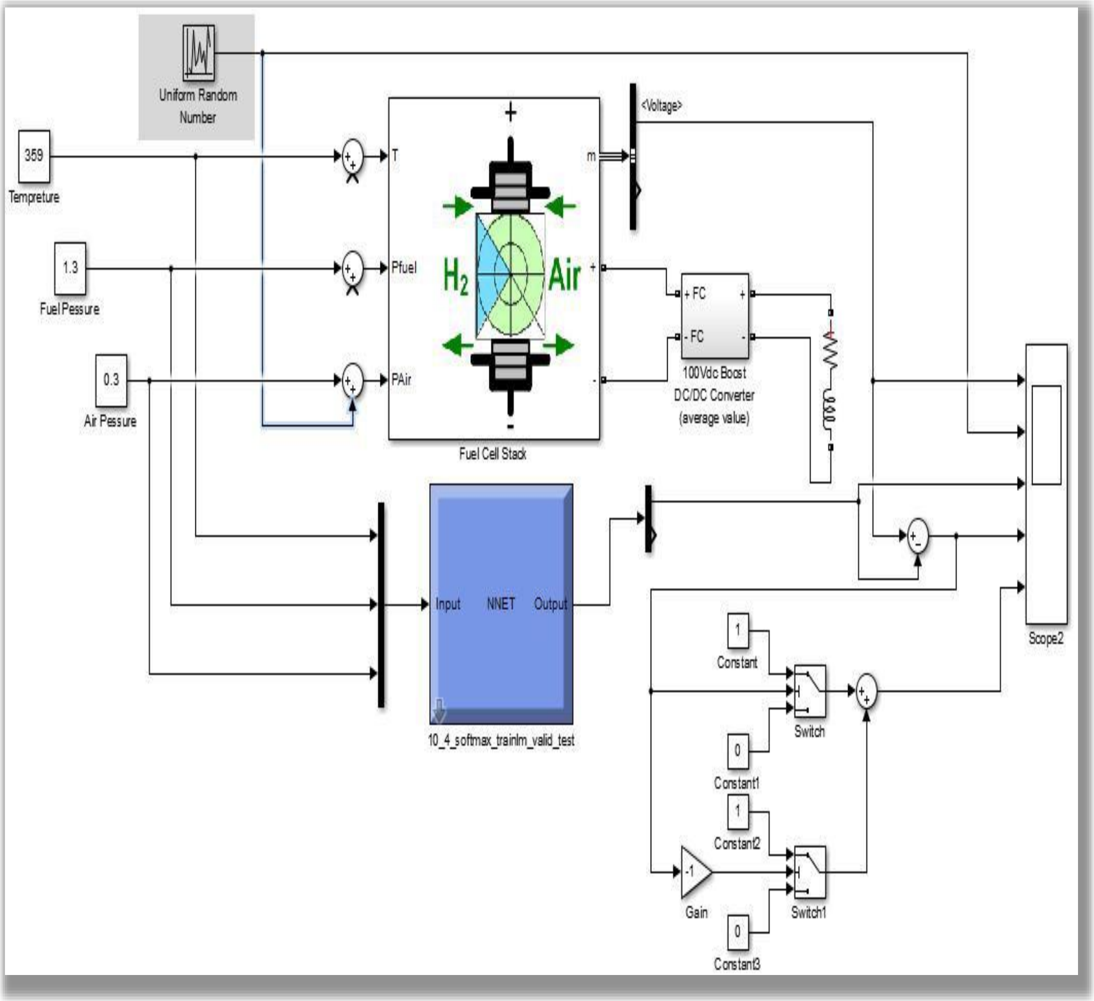



Figure 3.10. Fault Intermittent additional.

## 3.6. SEPARATE AND AVOIDING CIRCUIT

After identifying the fault, the value of the parameter resulting in the fault should be specified separately. As a result, an isolation specifies and identifies the position of the defect.

Figure 3.12 depicts the constructed Isolation subsystem, and Figure 3.13 depicts its internal parts.

According to Table 3.3, the defect is defined by the result of the isolation circuit:

Table 3.2. The isolation circuit's output.

| Code for isolation output (F1F0) | Details |
|---|---|
| **00** | Free Fault |
| **01** | Fault of air pressure |
| **10** | Fault of fuel pressure |
| **11** | Fault of core temperature |

The "Avoid Transient" subsystem is intended to prevent changes in input during startup. Simply said, it blocks detecting faults for five seconds until the system stabilizes. Figure 3.14 depicts the internal organization of this subsystem.

If the fault lasted more than one second, the "Hold" component is utilized to maintain and keep the fault index signal. The inner connection is depicted in Figure 3.15.

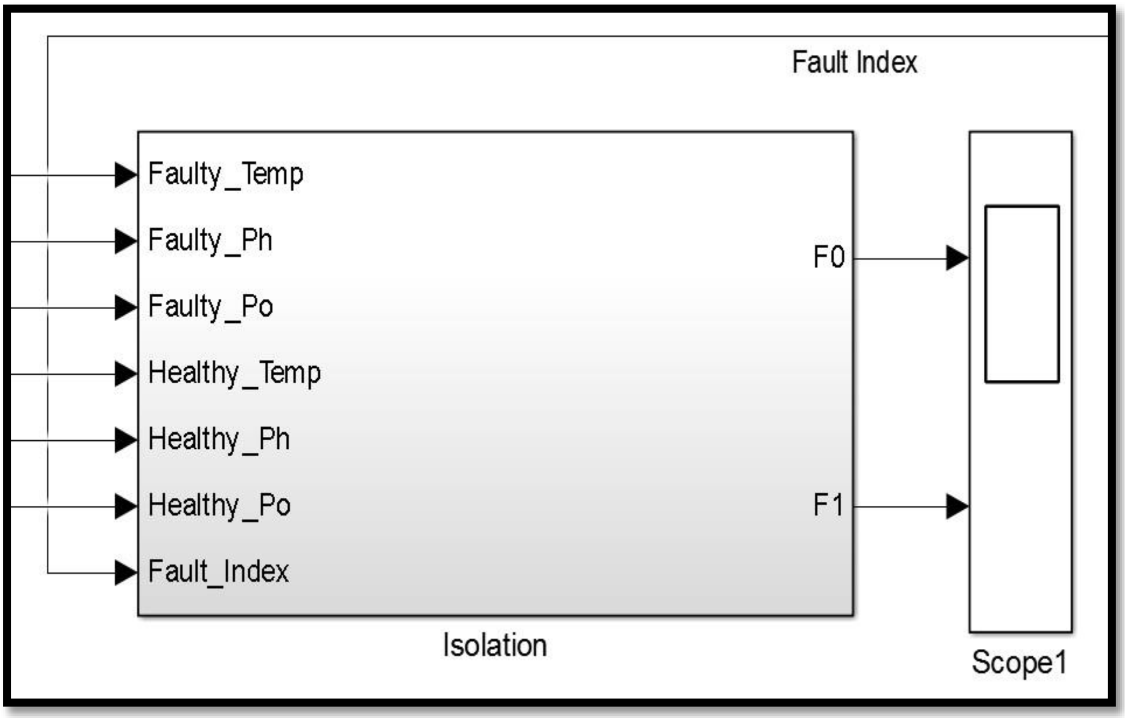



Figure 3.11. Subsystem of separation.

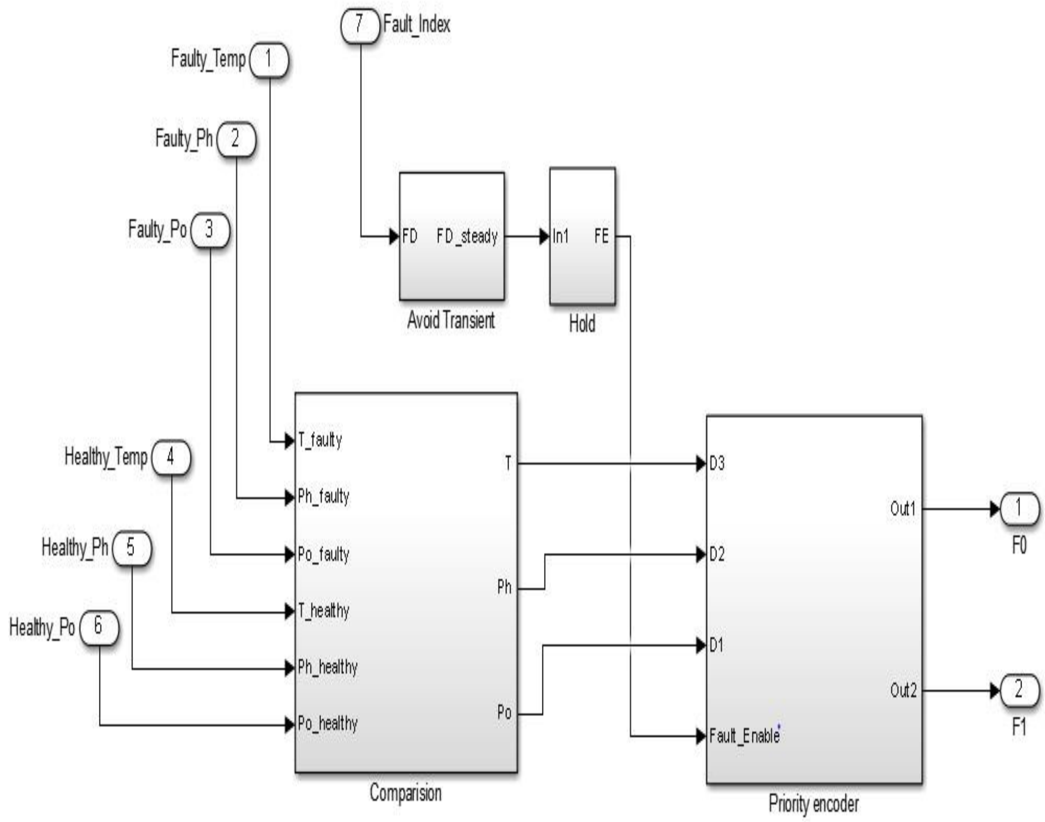



Figure 3.12. Isolation subsystem internal structure.

The internal construction of the prevent transient block is depicted in Figure 3.13, which includes a gate of logic (AND) and the step functional external input. Even after the entire system has been completed and downloaded, the step signal supply can be altered.

The holding block is utilized to hold the failure when it occurs for a short length of time, therefore this block might be updated to hold only faults that occur for a period of 35 seconds or more than a particular time defined by the system as well as its degree of sensitivity. Figure 3.15 depicts the internal construction of the hold block.

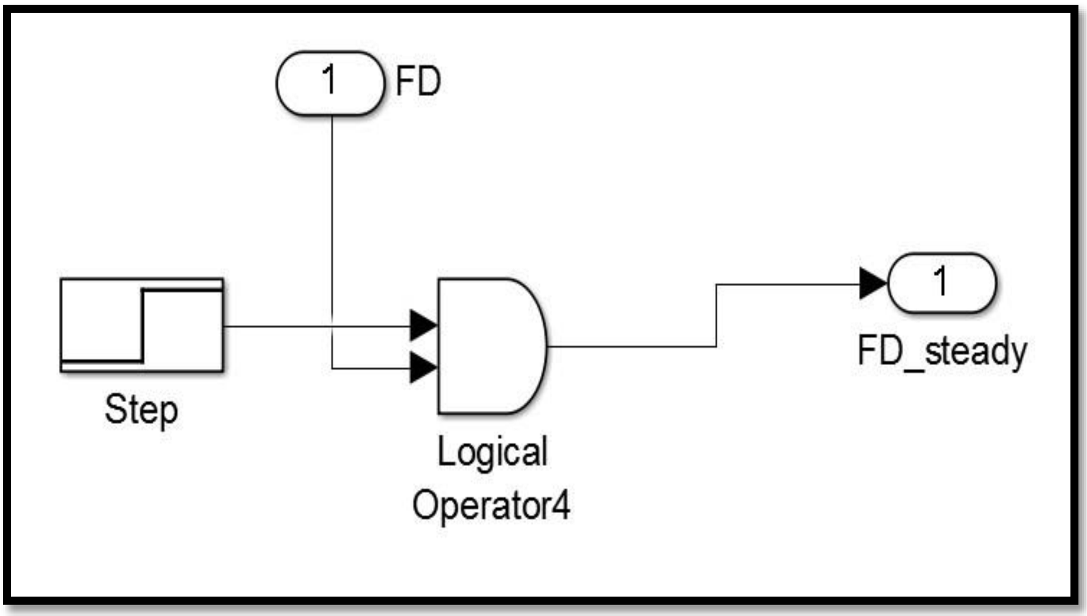



Figure 3.13. The hold block's internal structure.

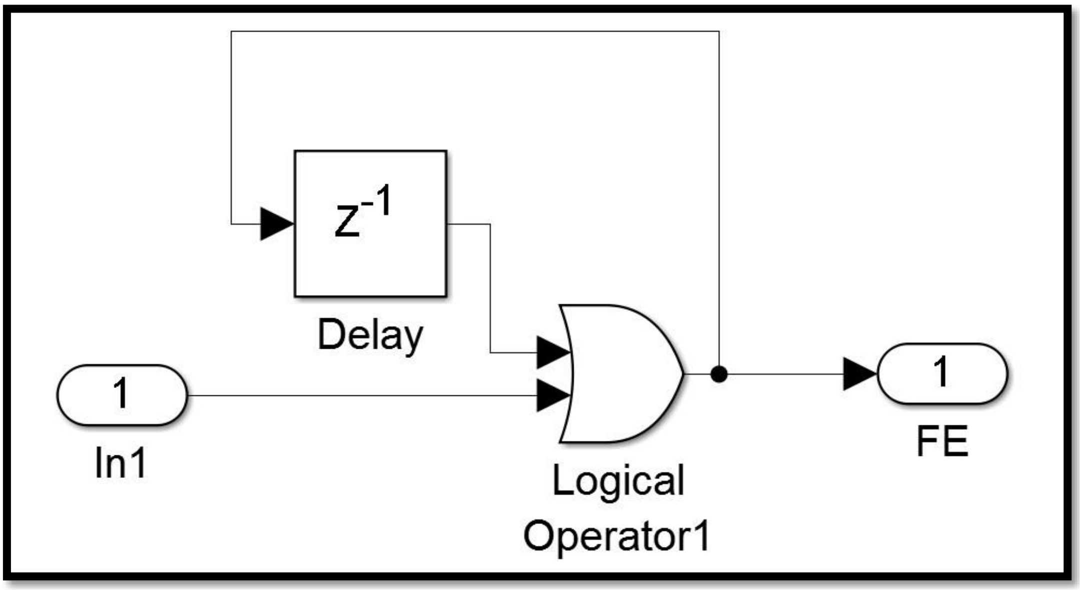



Figure 3.14. Hold circuit.

**3.7. CLASSIFICATION CIRCUIT DESIGN**

Following the separation of the fault, it should be specified which parameter triggered the fault. As a result, a classification the circuit is intended to specify and locate the fault.

The classification circuit is shown in Figure 3.16.

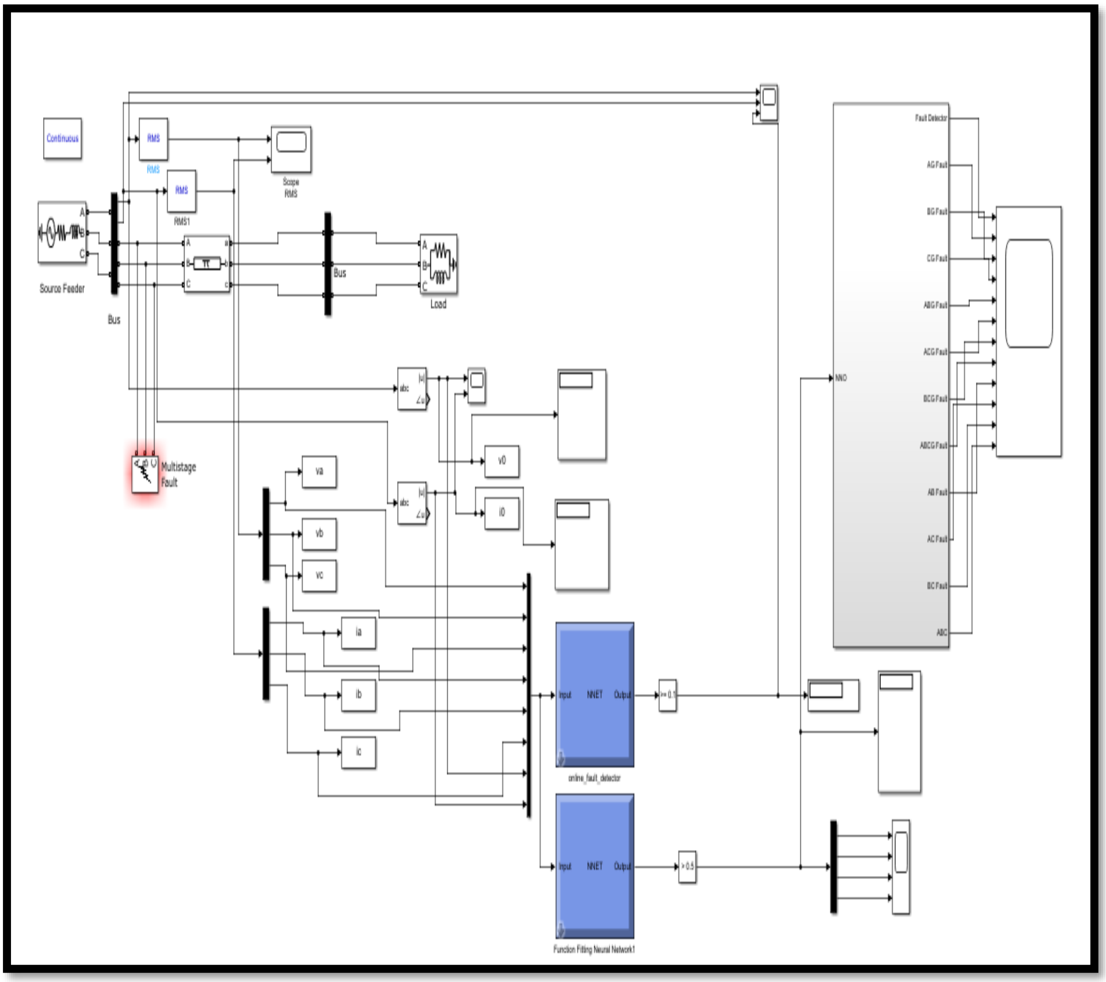



Figure 3.15. Detection and classification circuit.

# PART 4

# FDC SYSTEM SIMULATION RESULTS

## 4.1. INTRODUCTION

This current chapter depicts the Simulation Results implementations of the PEMFC FDC system, including all of its specifics, problems, and software co-simulation configuration. This chapter examines the software system's shortcomings. The linear technology presents numerous challenges to the neural network model.

## 4.2. CONNECTING NN RESULTS

After designing PEMFC with NN have the results and changing.

As demonstrated in Figure 4.1, the transient modification and fuel cell starting are ignored. For current and voltage, the two designs provide roughly the identical steady-state output. The PEMFC output is (51.3V, 116.7A), while the NN model output is (51.25V, 117.08A).

After that, three kinds of faults are introduced into the Matlab framework, which replaces the actual PEMCF in the true connection, in addition its results correspond to the NN model results, after which residual and defect index signals are created.

The fault indicator signal is an electrical signal that increases whenever there is a defect and decreases while there isn't a fault.

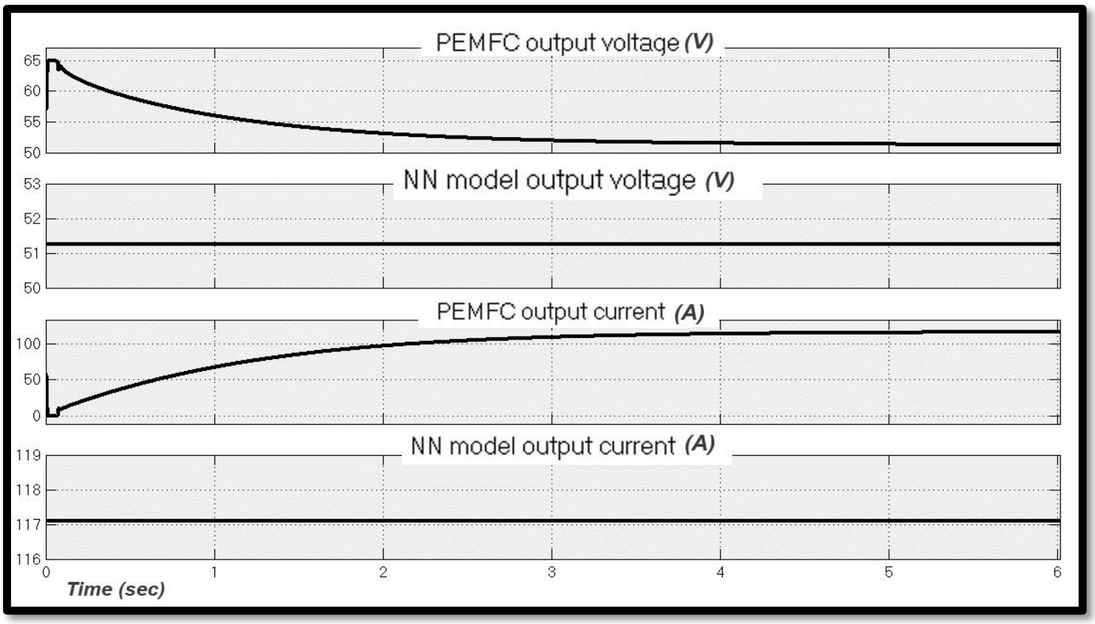



Figure 4.1. Results of NN modeling test circuit.

Three fault types were investigated, and the comprehensive findings are provided below:

### 4.2.1. Abrupt Fault Results

After completing the connecting in this way, we will get the result as shown in the figure 4.2.

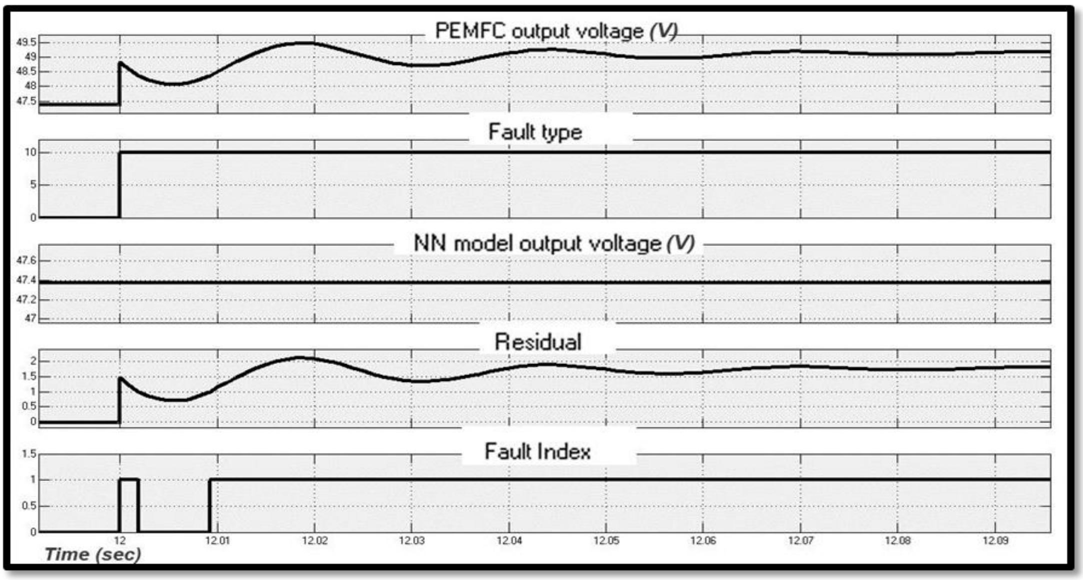



Figure 4.2. Abrupt fault addition signals.

By altering the step amplitude and threshold, similar results are obtained. The second and third inputs can both get the fault.

Examples of abrupt fault in actual, functional PEMFCs are:

- An unexpected crack in a pipe or valve.
- A collision with an outside object that modifies the cell's properties.

### 4.2.2. Incipient Fault Results

After completing the connecting in this way, we will get the result as shown in the figure 4.3.

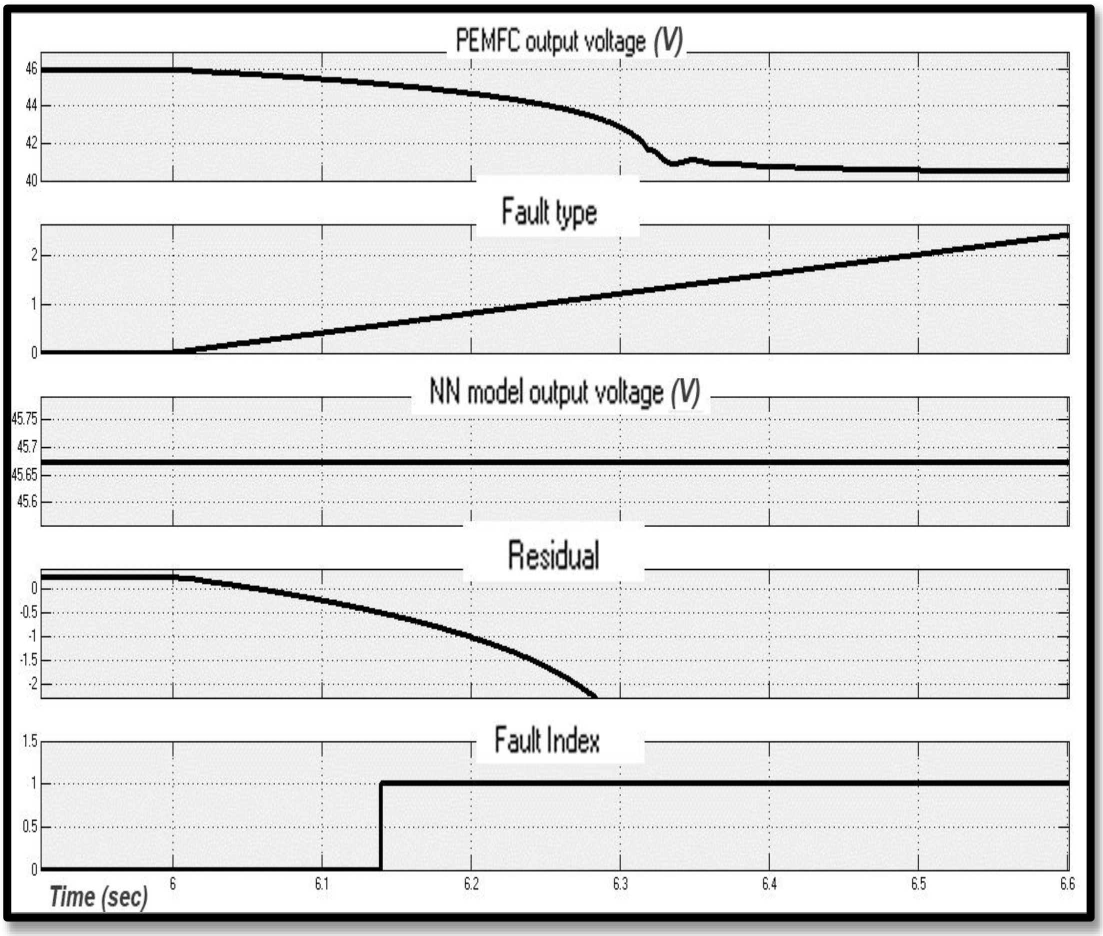



Figure 4.3. Incipient fault addition signals.

For instance, if the ramp has a slope of 4, a start time of 6, and a threshold of 0.5, the initial drop in fuel pressure results in a progressive drop in output voltage. The system detected declines when the residual amount surpassed the threshold value.

Some instances of initiation faults in real-world PEMFCs include:

- A pipe or valve leak that causes the outputs to gradually drop.
- A cooling system malfunction that causes the temperature to rise or fall.

### 4.2.3. Intermittent Fault Results

After completing the connecting in this way, we will get the result as shown in the figure 4.4.

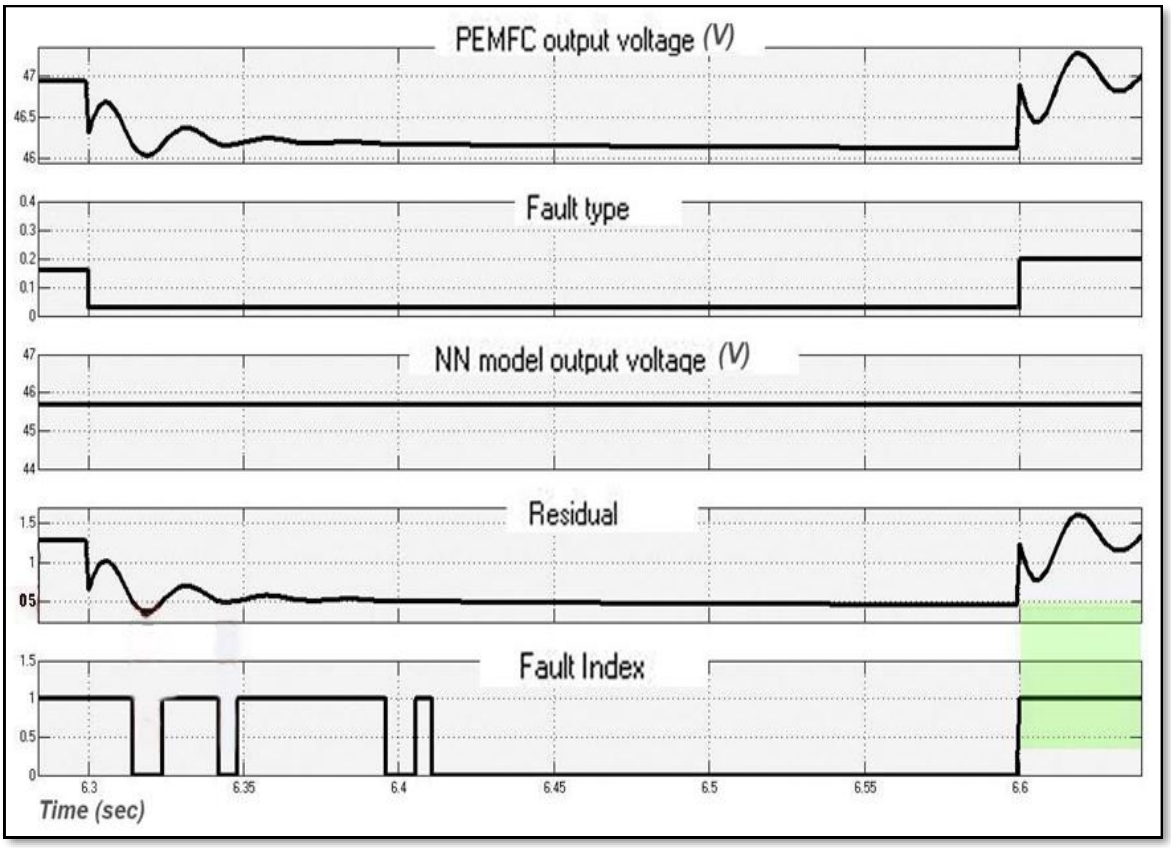



Figure 4.4. Intermittent fault addition signals.

A change in the output voltage results from triggered by an occasional shift in fuel pressure, for instance, by a random signal with an amplitude of 0.3, a sample duration of 0.3, and a threshold of 0.5. The issue is accurately detected by the system. According to that figure, whenever the residual signal exceeds the threshold 0.5 the output is minimal, as indicated by the red dots, and if the residual signal is less than thresholds, the output is high, as indicated by the green spot.

An example of an intermittent fault in a real-world PEMFC is a brief change in heat or any of the parameter values caused by an external factor.

## 4.3. CLASSIFICATION AND DETECTING FAULT RESULTS

After completing the electrical circuit design to classify and detect faults as shown in figure 4.5.

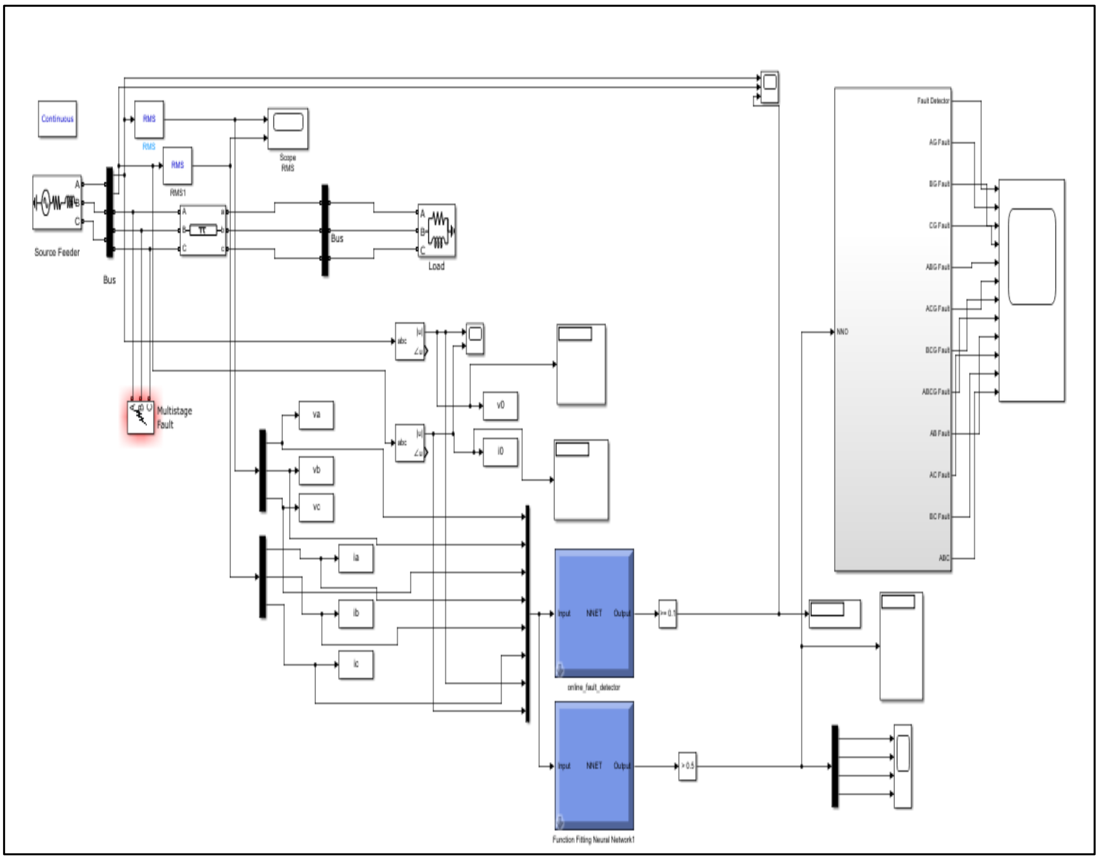



Figure 4.5. Detection and classification.

The input voltages can be classified and detected by changing the input for multistage voltage shown in figure 4.6.

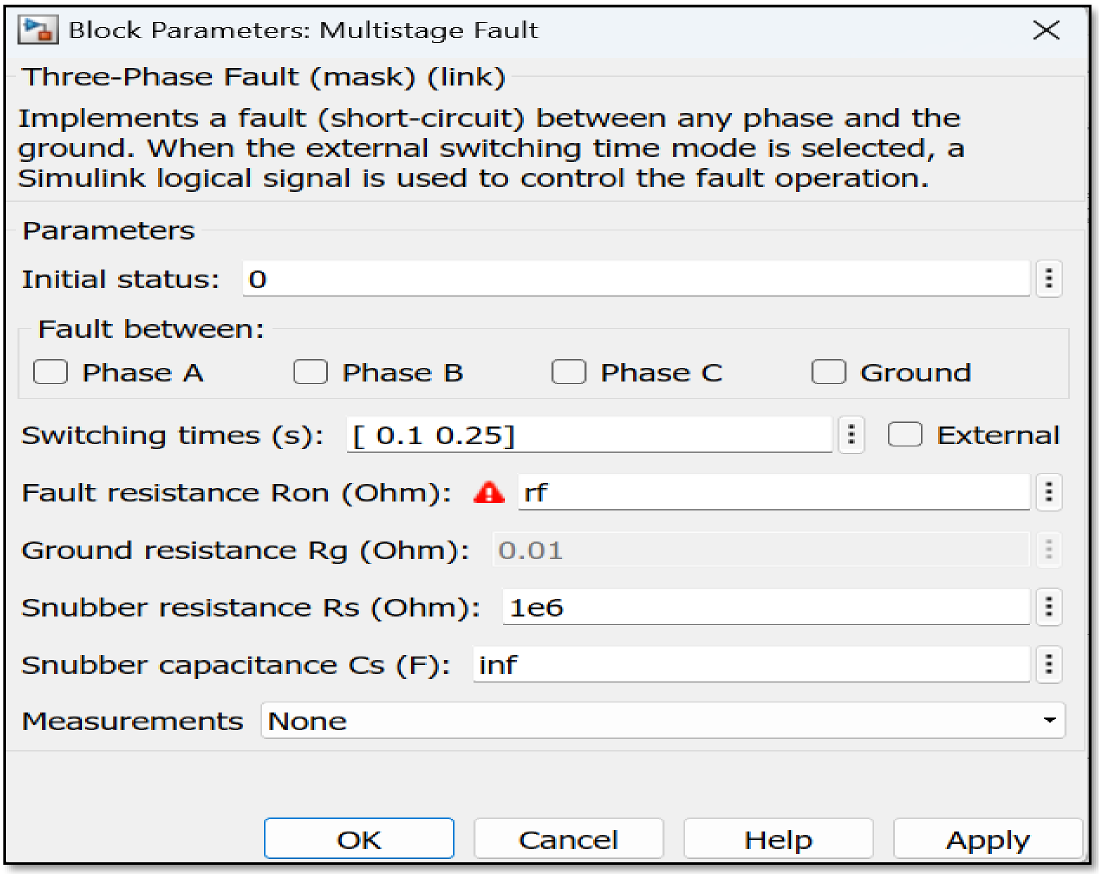



Figure 4.6. Multistage fault.

### 4.4. INPUT CHANGING DETECTING AND CLASSIFICATION

Now we can change the input voltages, classify them, and detect the Faults for each voltage separately.

We can dividing the changing by a cases.

#### 4.4.1. Case A Faut

Choosing A and G (grown) as shown in figure 4.7. showing by the multistage voltage.

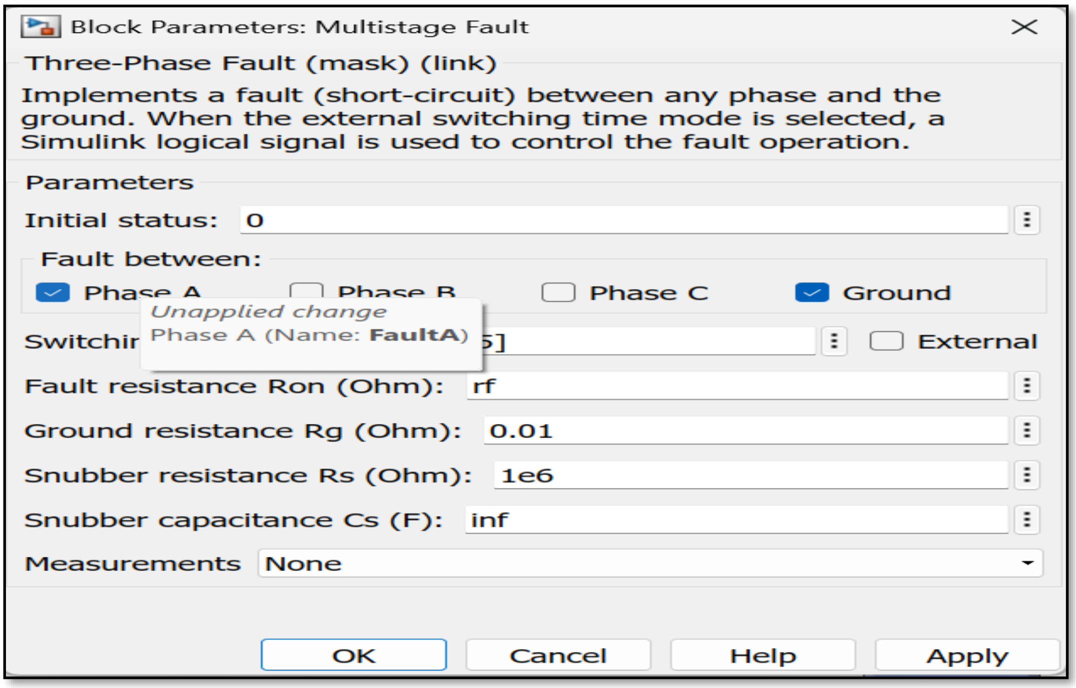



Figure 4.7. Multistage line A.

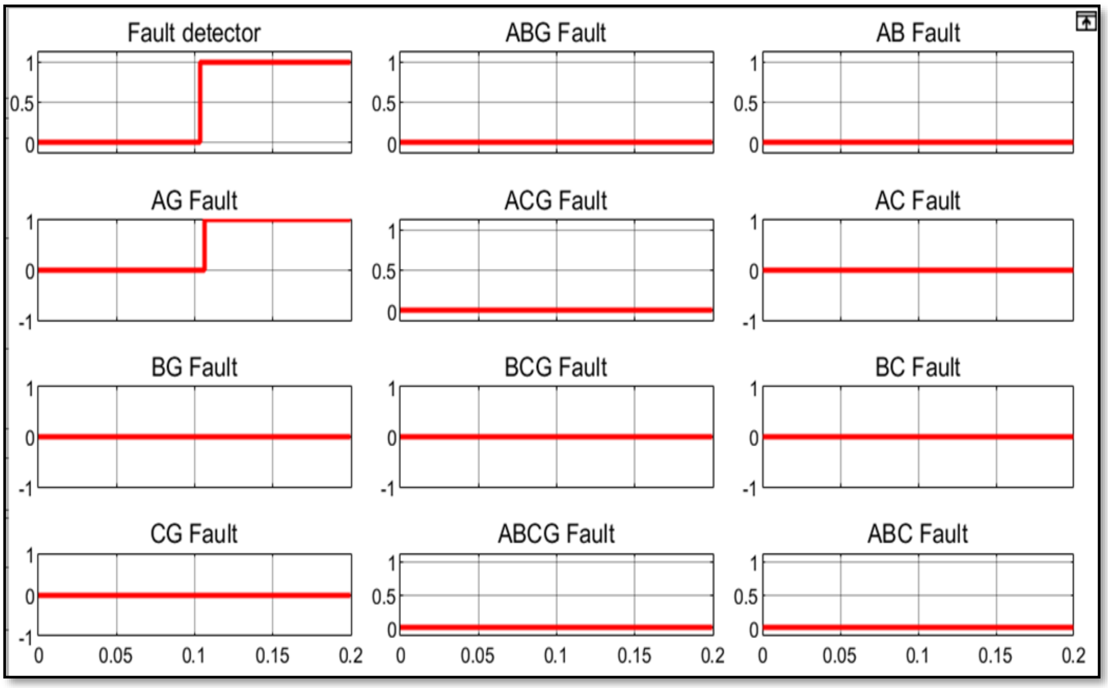



Figure 4.8. Line A fault addition signal.

After choosing A in multistage the fault signal shown just in the line A and the fault detection represented the A faults as shown in figure 4.8.

### 4.4.2. Case B fault

Choosing B and G (grown) as shown in figure 4.7. showing by the multistage voltage.

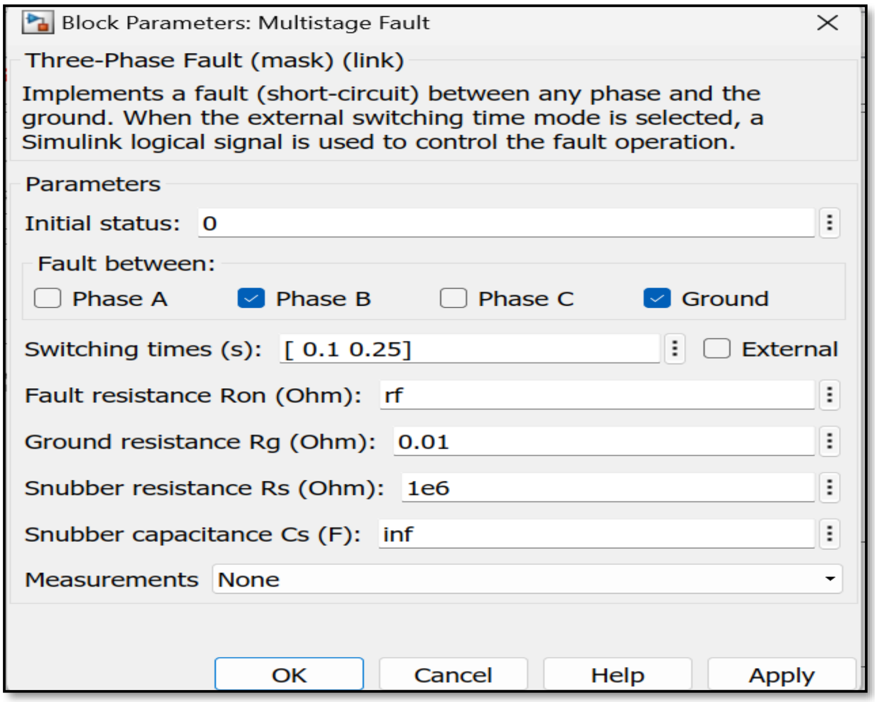



Figure 4.9. Multistage line B.

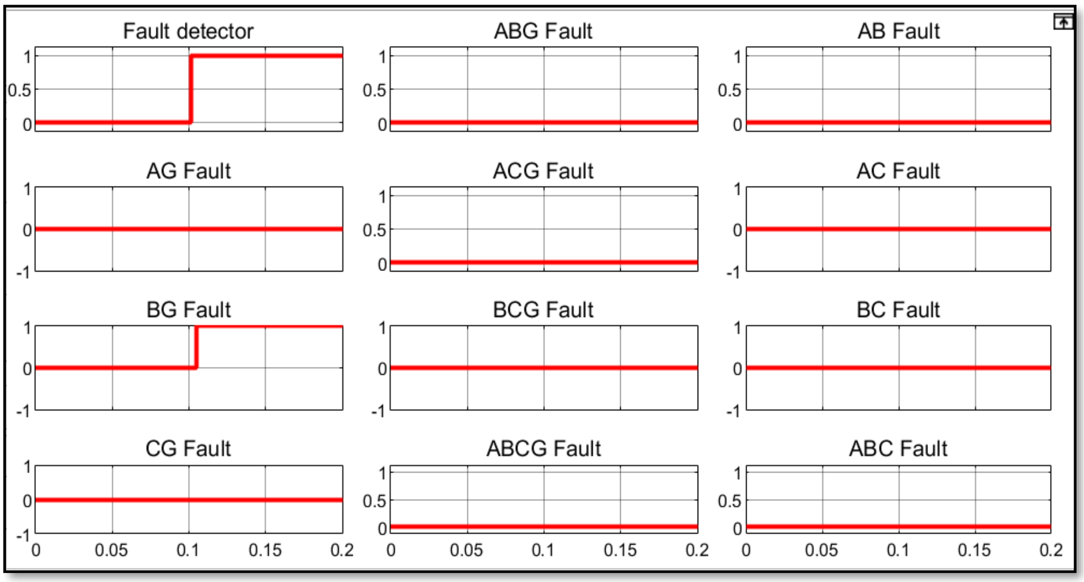



Figure 4.10. Line B fault addition signal.

After choosing B in multistage the fault signal shown just in the line B and the fault detection represented the A faults as shown in figure 4.10.

### 4.4.3. Case C Fault

Choosing C and G (grown) as shown in figure 4.11. showing by the multistage voltage.

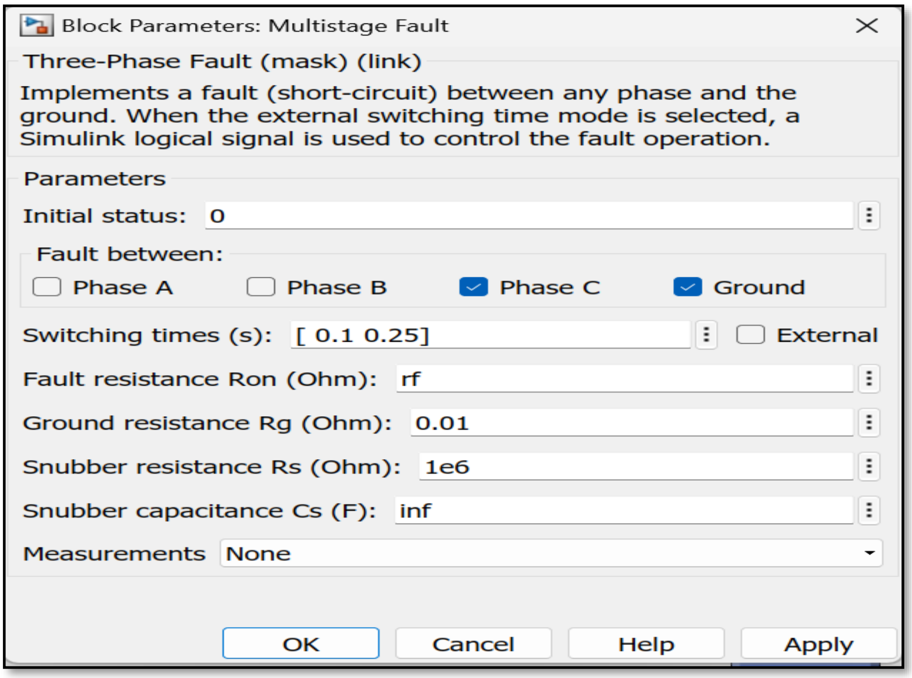



Figure 4.11. Multistage line C.

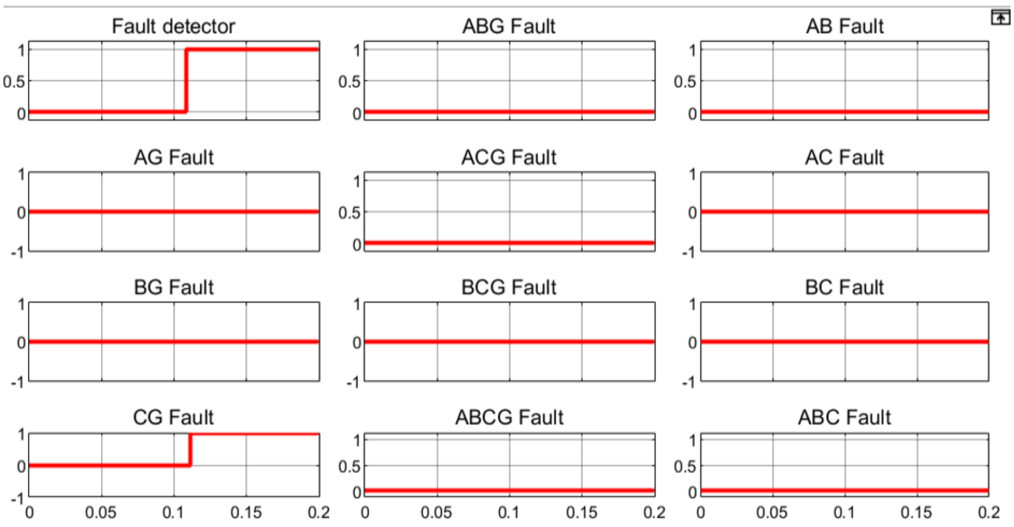



Figure 4.12. Line C fault addition signa.

After choosing C in multistage the fault signal shown just in the line C and the fault detection represented the C faults as shown in figure 4.12.

### 4.4.4. Case AB Fault

Choosing AB and G (grown) as shown in figure 4.13. showing by the multistage voltage.

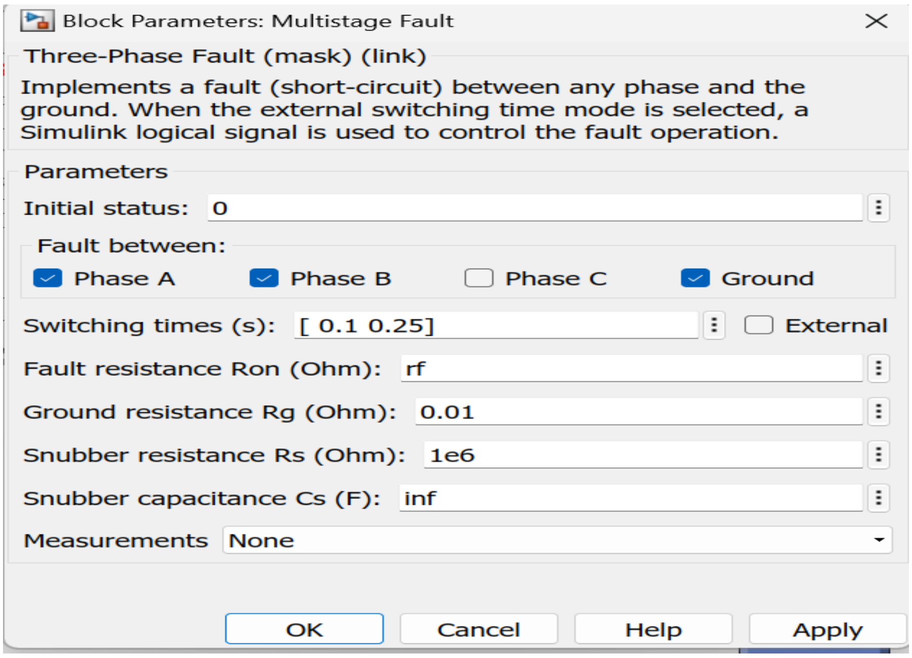



Figure 4.13. Multistage line AB.

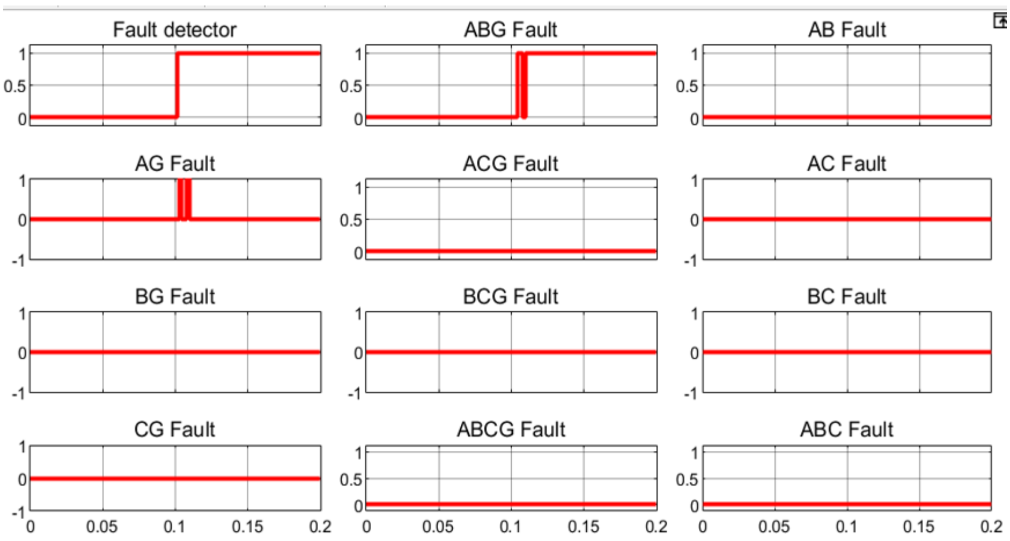



Figure 4.14. Line AB fault addition signal.

After choosing AB in multistage the fault signal shown just in the line AB and the fault detection represented the AB faults as shown in figure 4.14.

### 4.4.5. Case AC Fault

Choosing AB and G (grown) as shown in figure 4.15. showing by the multistage voltage.

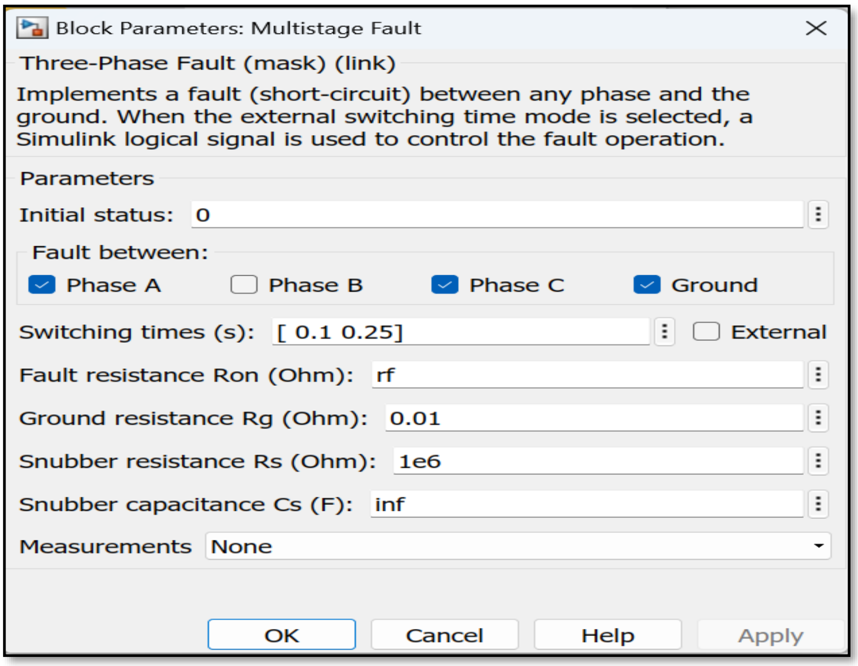



Figure 4.15. Multistage line AC.

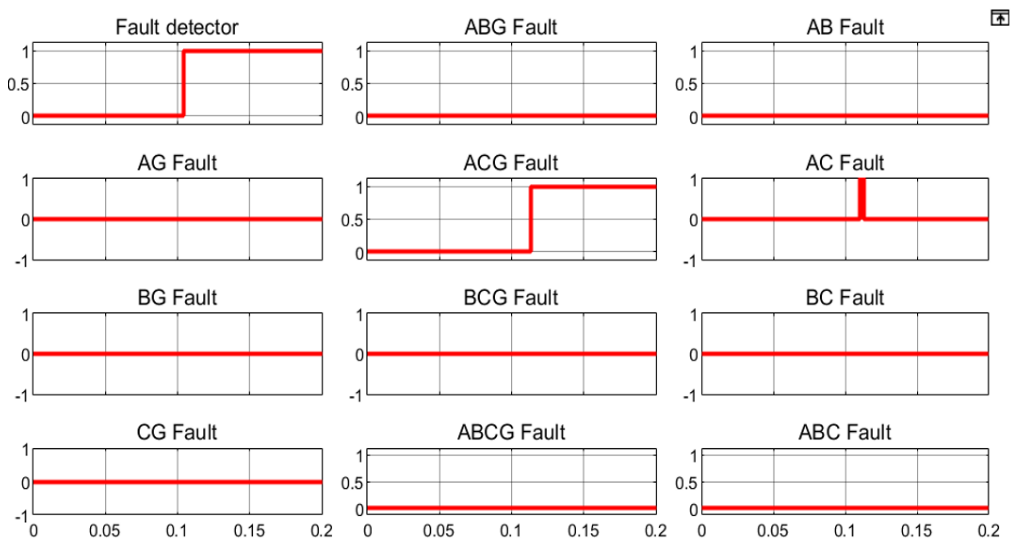



Figure 4.16. Line AC fault addition signal

After choosing AC in multistage the fault signal shown just in the line AC and the fault detection represented the AC faults as shown in figure 4.16.

### 4.4.6. Case BC Fault

Choosing AB and G (grown) as shown in figure 4.17. showing by the multistage voltage.

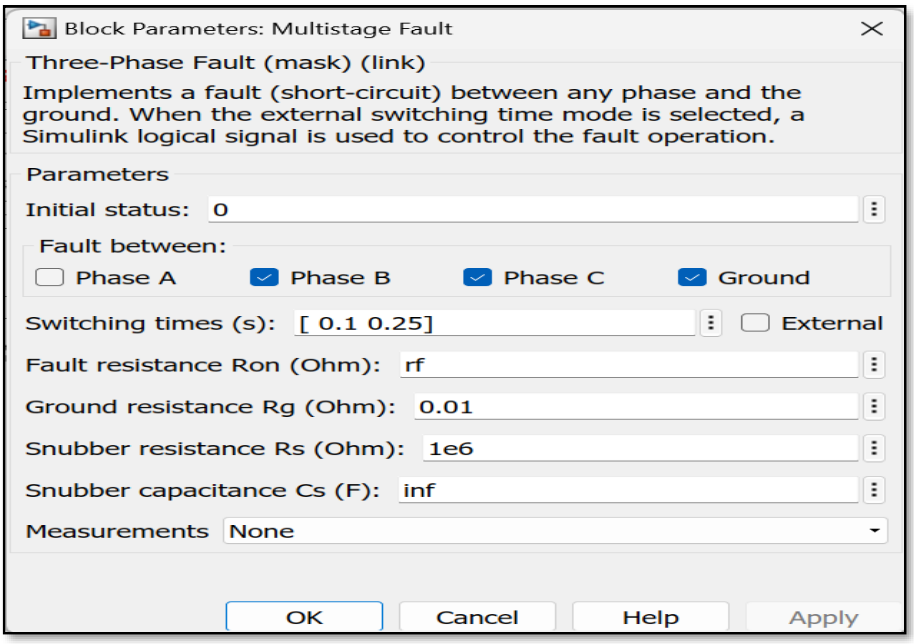



Figure 4.17. Multistage line BC.

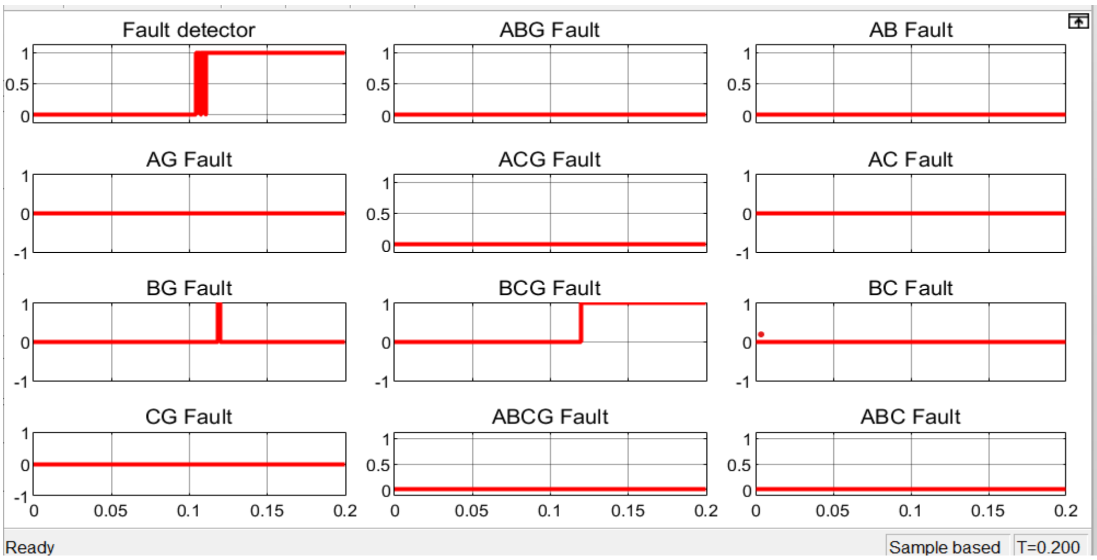



Figure 4.18. Line AC fault addition signal.

When choosing BC in multistage the fault signal shown just in the line BC and the fault detection represented the BC faults as shown in figure 4.18.

### 4.4.7. Case ABC Fault

Choosing AB and G (grown) as shown in figure 4.17. showing by the multistage voltage.

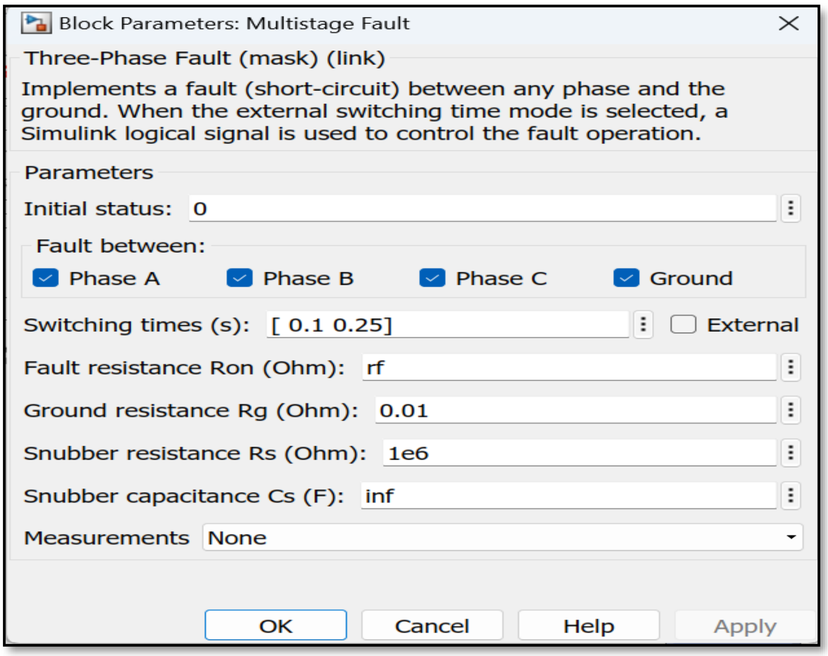



Figure 4.19. Multistage line ABC.

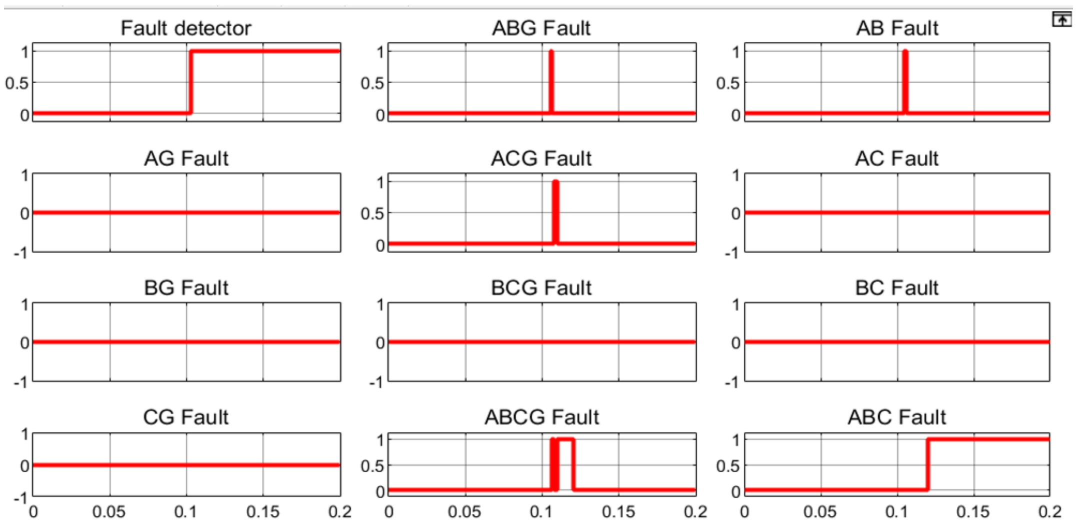



Figure 4.20. Line ABC fault addition signa.

When choosing ABC in multistage the fault signal shown just in the line ABC and the fault detection represented the ABC faults as shown in figure 4.20.

We conclude from these results that we can identify and classify faults by this circuit and we can also add to it the fuel cell.

### 4.4.8. Case AB Fault

Choosing AB as shown in figure 4.21. showing by the multistage voltage.

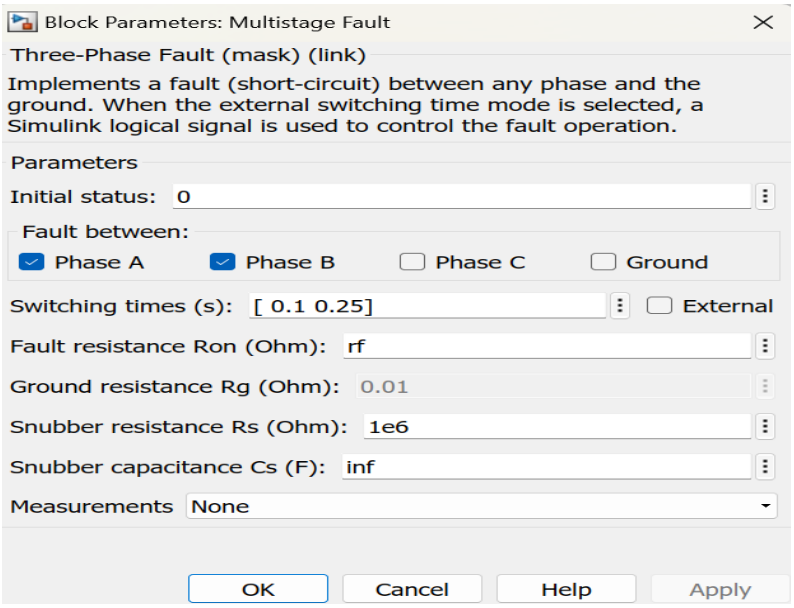



Figure 4.21. Multistage line AB.

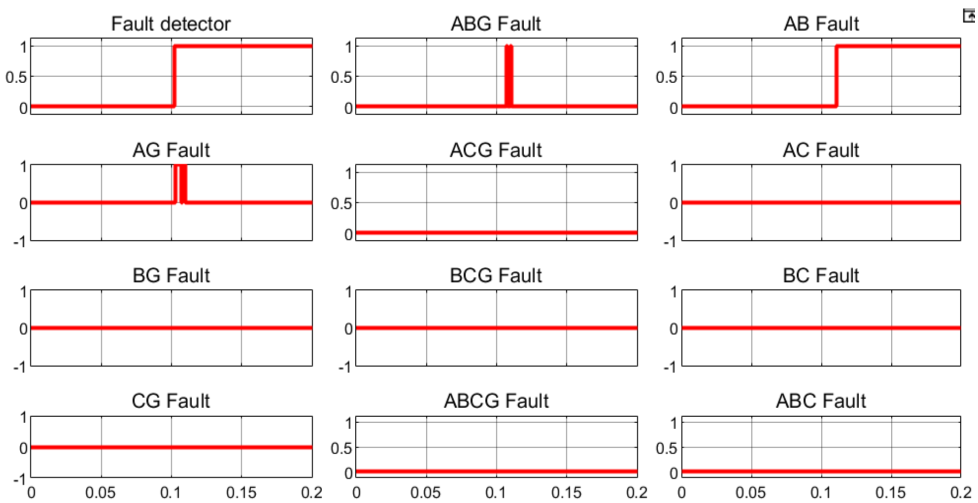



Figure 4.22. Line AB fault addition signal.

After choosing AB in multistage the fault signal shown just in the line AB and the fault detection represented the AB faults as shown in figure 4.22.

### 4.4.9. Case AC Fault

Choosing AC as shown in figure 4.23. showing by the multistage voltage.

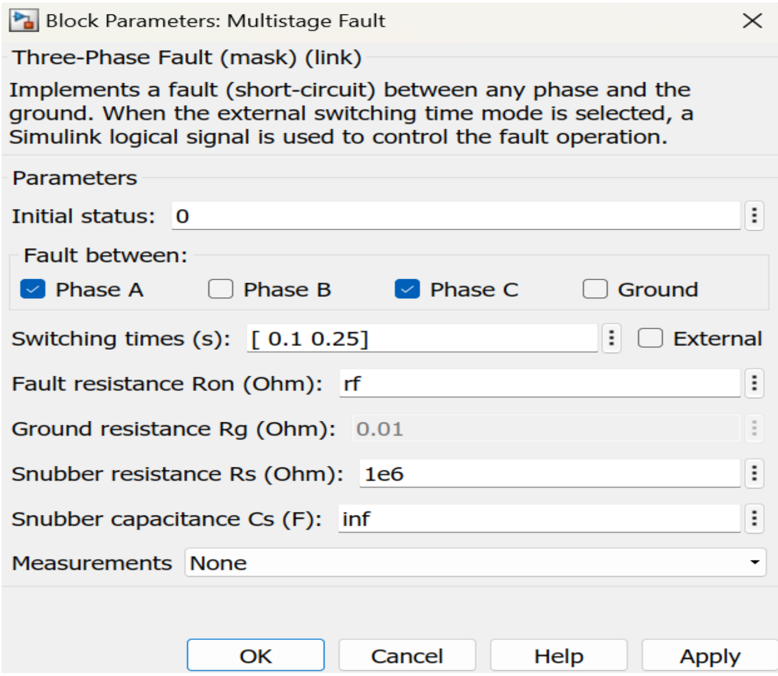


Figure 4.23. Multistage line AC.

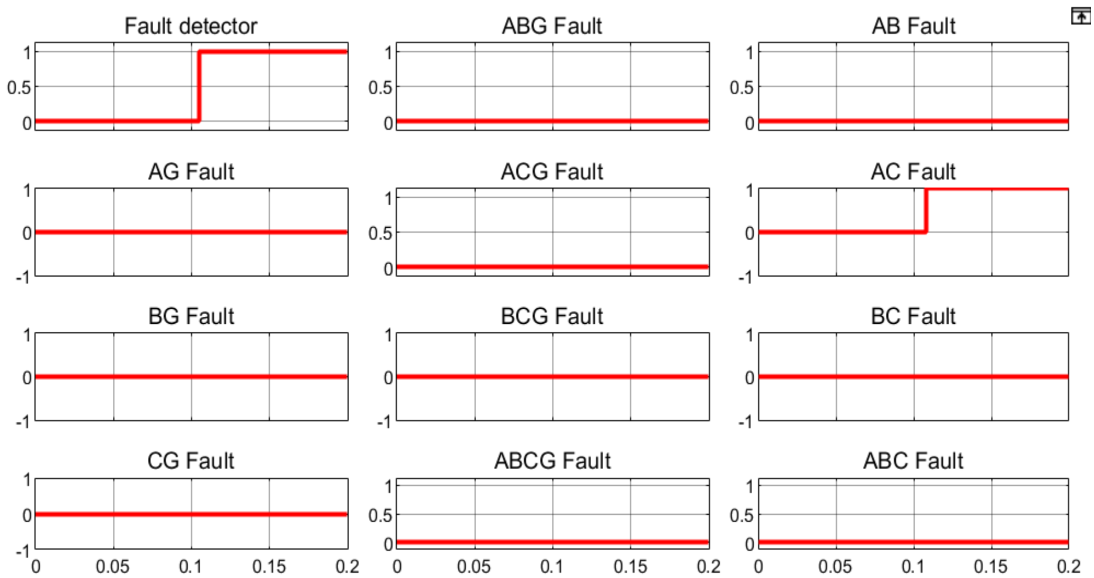


Figure 4.24. Line AC fault addition signal.

After choosing AC in multistage the fault signal shown just in the line AC and the fault detection represented the AC faults as shown in figure 4.24.

### 4.4.9. Case BC Fault

Choosing BC as shown in figure 4.25. showing by the multistage voltage.

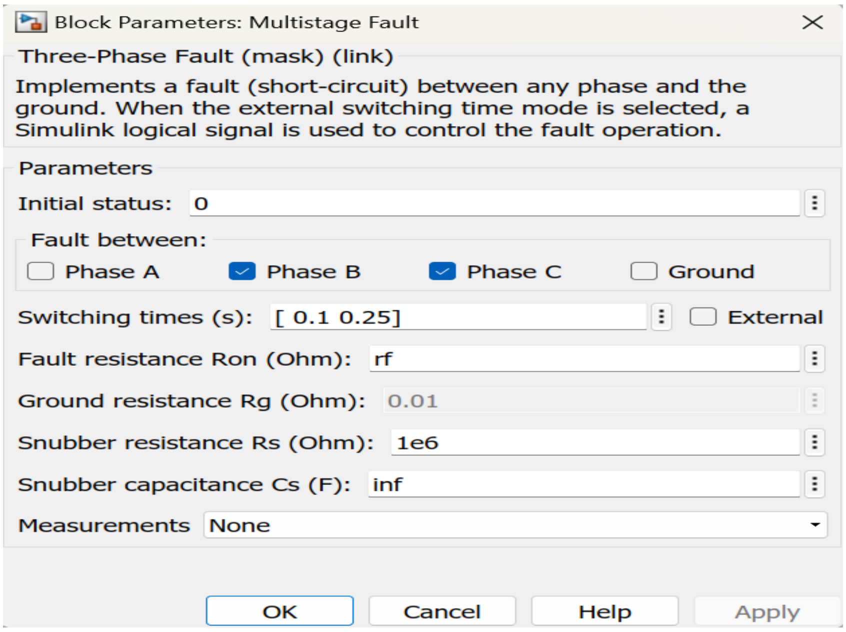



Figure 4.25. Multistage line BC.

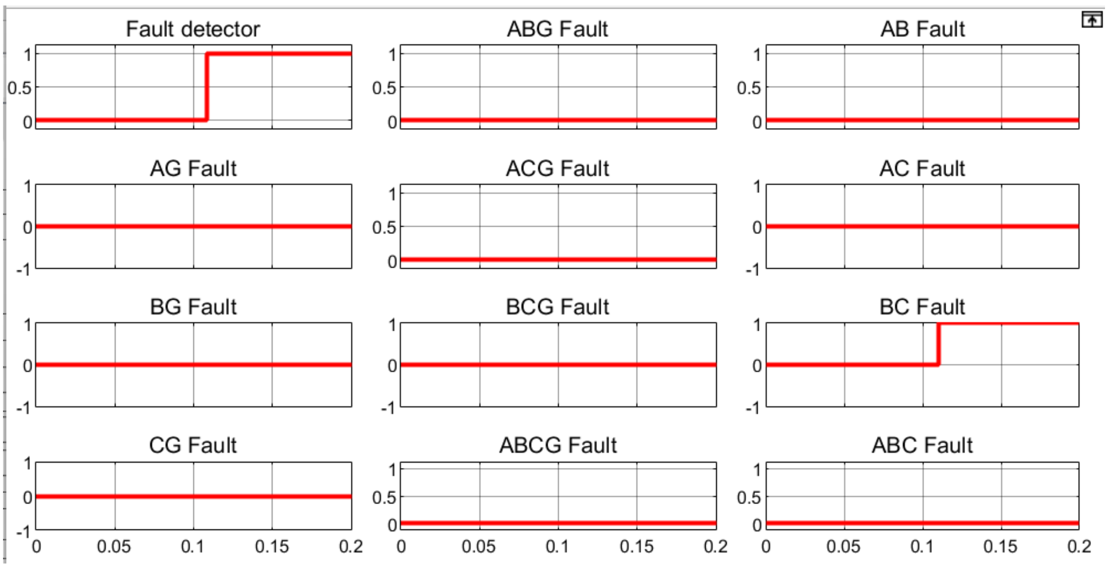



Figure 4.26. Line BC fault addition signal.

After choosing BC in multistage the fault signal shown just in the line BC and the fault detection represented the BC faults as shown in figure 4.26.

### 4.4.10. Case ABC Fault

Choosing ABC as shown in figure 4.27. showing by the multistage voltage.

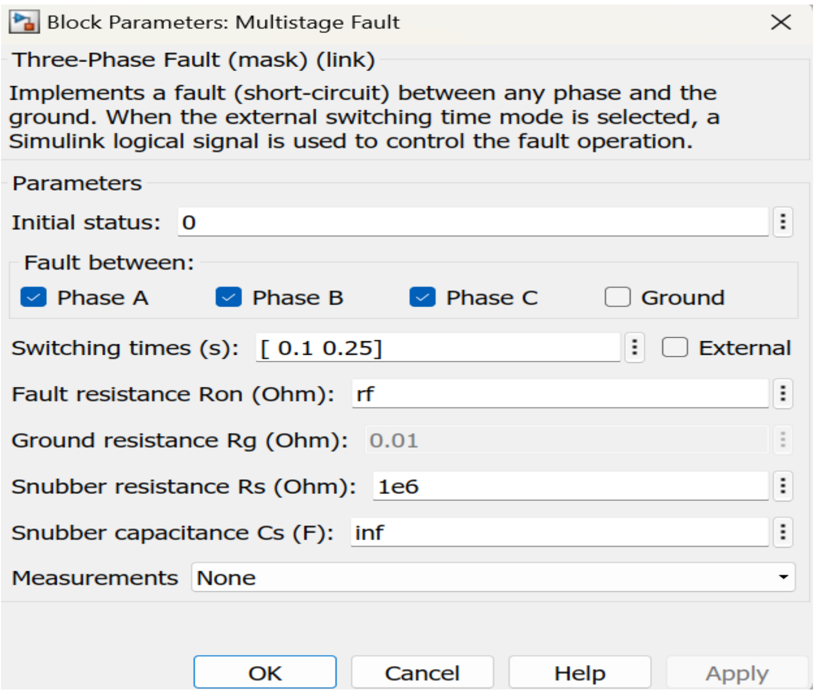



Figure 4.27. Multistage line ABC.

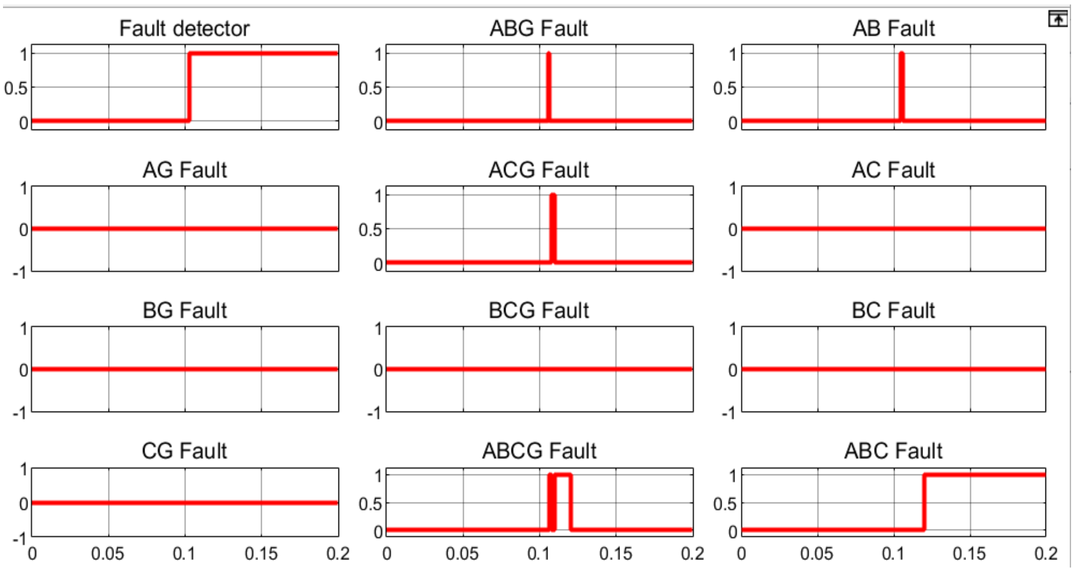



Figure 4.28. Line ABC fault addition signal.

After choosing ABC in multistage the fault signal shown just in the line ABC and the fault detection represented the ABC faults as shown in figure 4.28.

## 4.5. CONNECTION TO THE ENTIRE SYSTEM

As shown in Figure 4.21, the NN framework, fault index, and categorization circuits are all linked together.

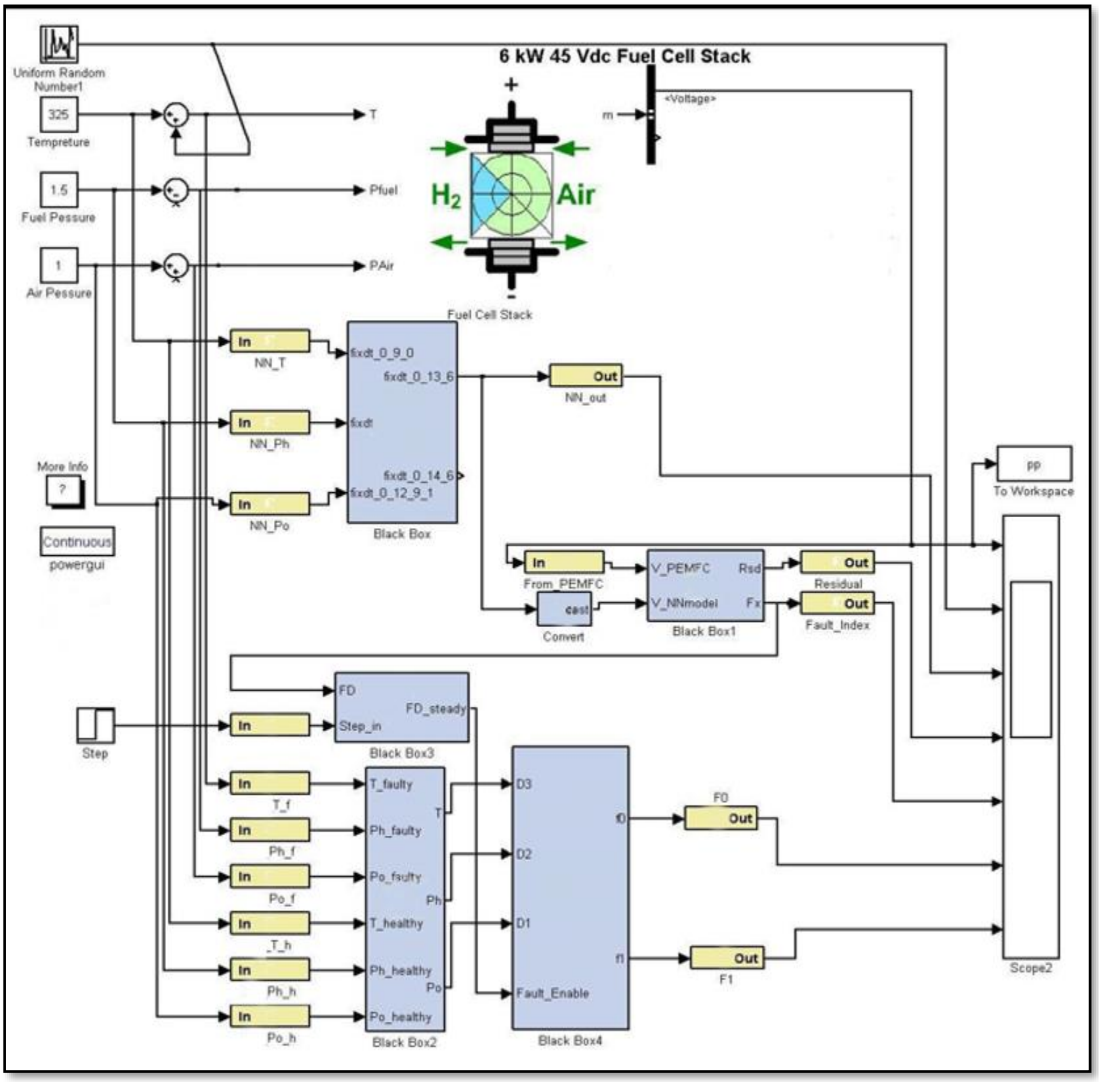



Figure 4.27. All black boxes will be tested.

The names of the blocks in Figure 4.21 have been altered to correspond with the FDC system inputs, which will be produced by utilizing the "system generation" token. Figure 4.22 shows the signals from the scope.

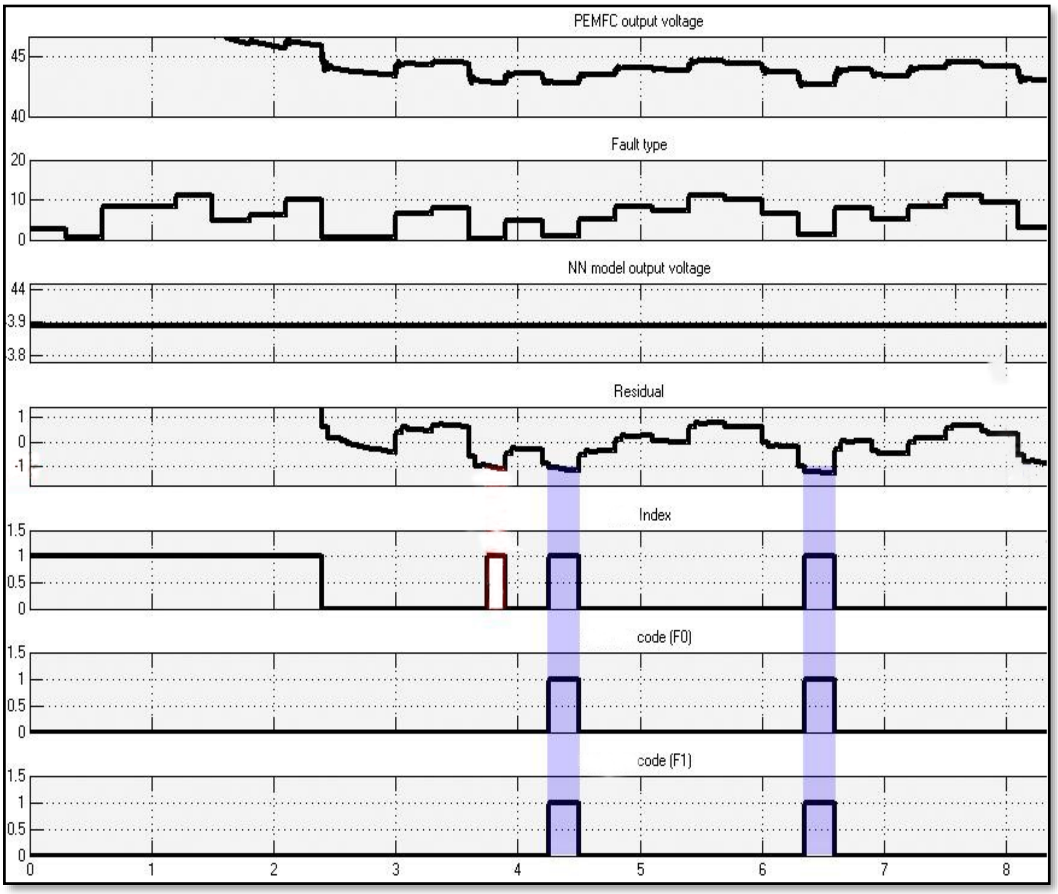



Figure 4.28. Signals of Figure 4.21's scope.

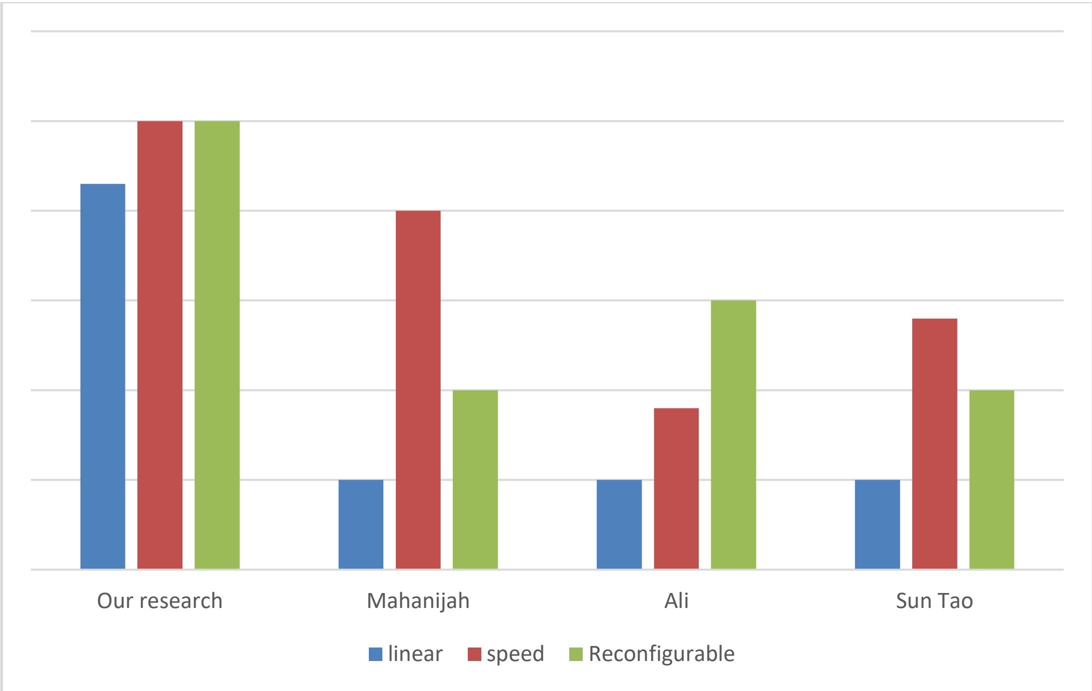
As shown in Figure 4.21, the fault indicator triggers the isolation, revealing the reason of the fault, when the residual signal exceeds the threshold, which has one value (i.e., -1 to +1, which is colored). F0F1=11 indicates the previously observed Core temperature issue. As can be seen, the initial Fault Indicator pulse, which is marked by a red window, was disregarded for four seconds whereas the circuit output is recorded with blue windows.

## 4.6. STUDIES IN COMPARISON TO OTHER LITERATURE

Table 4.1 and flow chart 4.1 show a comparison with the most comparable investigate discovered in the investigation for speed, complication, reconfigurability, in addition hardware application.

Table 4.1. Compared to Other Investigations.

| Investigation | The degree of complexity | velocity | Adaptable |
|---|---|---|---|
| **This study** | linear and Simple | more-fast | yes |
| **Mahanijah [1]** | Simple but nonlinear | Normal PC speed | No |
| **Ali [21]** | Simple but nonlinear | Normal PC speed | No |
| **Sun Tao [12]** | nonlinear and Complex | Normal PC speed | No |




parameters researches

Figure 4.29. Studies in Comparison to Other Literature.

# PART 5

# CONCLUSIONS AND RECOMMENDATIONS

## 5.1. CONCLUSIONS

This research yields numerous conclusions, the most noteworthy of which are:

- Matlab and Simulink are used to study and construct three different types of PEM fuel cell failures. and it is noted that ANNs are effective for FDC systems.
- Using ANNs to classification the fouls.
- Using Matlab to construct the system circuits allows you to categorize the output faults and the input voltage.
- The FDC system designing for this work is adaptable, allowing the threshold window to be modified depending on the application, the level of safety necessary, as well as the NN's MSE. Therefore, Lowering the threshold window enhances safety and sensitivities, but the cost should also be considered. In this thesis, for example, a defect initiation of (10 for heat, 5 for fuel the pressure, with 5 for air pressures) was used in the last phases of the design process with a threshold of (+1 to -1).

## 5.2. FUTURE WORK RECOMMENDATIONS

Many more strategies and additions can be used to improve the system design, some of which are as follows:

- Other innovative approaches, such as fuzzy, ANFIS, in addition RBF ANN, could be adapted to simulate the PEM fuel cell as well as the classification with isolation circuit.
- Investigate the fuel cell's startup, or the initial phase of operation, by adding

more FDC system building blocks.

- The phase of diagnosis can be introduced to make an improved decision while taking into consideration real-world scenarios and past reports by utilizing the code that is output of the isolation as well as classification, residual, in addition fault index signals.
- The method used in the suggested system's design can be applied to different applications, such as wind turbines, photovoltaic cells, etc.
- Making a configurable system so that the settings can be modified for improved functioning and online correction.

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## CURRICULUM VITAE

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