PREDICTION OF POWER DISTURBANCES BY ARTIFICIAL INTELLIGENCE METHODS

Begüm ÇETİN

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PREDICTION OF POWER DISTURBANCES BY ARTIFICIAL INTELLIGENCE METHODS

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Master's Thesis

Department of Electrical and Electronics Engineering Department

Supervisor: Asst. Prof. Dr. Şener AĞALAR

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FINAL APPROVAL FOR THESIS

This thesis titled PREDICTION OF POWER DISTURBANCES BY ARTIFICIAL INTELLIGENCE METHODS has been prepared and submitted by Begüm ÇETİN in partial fulfillment of the requirements in "Eskişehir Technical University Directive on Graduate Education and Examination" for the Degree of Master's in Electrical and Electronics Engineering Department Department has been examined and approved on 23/01/2023.

Committee Members		**Title, Name and Surname**	**Signature**
Member	:	Asst.Prof.Dr.Şener AĞALAR	
Member	:	Asst.Prof.Dr.Atabak NAJAFI	
Member	:	Asst.Prof.Dr.Mehmet FİDAN	

Prof. Dr. Murat TANIŞLI
Director of the Institute of Graduate Programs

23/01/2023

SUPERVISOR APPROVAL

Master's student Begüm ÇETİN, whom I supervise, has completed this thesis titled PREDICTION OF POWER DISTURBANCES BY ARTIFICIAL INTELLIGENCE METHODS. According to my inspections, the work is scientifically and ethically appropriate for the student to the thesis defense exam.

Supervisor
Asst. Prof. Dr. Şener AĞALAR

ABSTRACT

PREDICTION OF POWER DISTURBANCES BY ARTIFICIAL INTELLIGENCE METHODS

Begüm ÇETİN

Electrical and Electronics Engineering Department

Branch of Electrical Machinery Science

Eskişehir Technical University, Institute of Graduate Programs, January 2023

Supervisor: Asst. Prof. Dr. Şener AĞALAR

Ensuring the continuity of power quality is the most important factor for efficient and reliable operation of a power system. In a balanced three-phase system, voltage and current are sinusoidal and nominal. When any fault is occurred on power systems, the system is unbalanced and power quality disturbances can be occurred. They cause power losses on the transmission and distribution lines, malfunctioning of devices, disasters such as fire that will affect living life and the environment. In this context, the use of predictive artificial intelligence methods in the prediction of power quality disturbances offers an innovative and supportive solution in the process of preventing the possible effects of power quality disturbances, ensuring the efficient and safe operation of the power system, and transition from traditional grids to smart grid and microgrid structures.

The aim of the study is to predict the magnitude of the instantaneous voltage sag in a bus (single fault-7 ones) or buses (double fault-other 7 buses) of the IEEE9 bus test system according to 14 total short circuit faults before defined time duration by homogeneous and heterogeneous machine learning methods. While selecting the methods, firstly load flow analysis was performed to investigate the voltage sag behavior and then a short circuit fault was in order to phase a. When homogeneous (random forests) and heterogeneous (support vector regression, decision tree, K- nearest neighbors) machine learning methods are compared in terms of prediction performance and speed, it is observed that the heterogeneous ensemble training model is generally more successful.

Keywords: Power Quality Disturbances, Voltage Sag, Ensemble Machine Learning, Heterogeneous Machine Learning, Homogeneous Machine Learning

ÖZET

GÜÇ BOZUKLUKLARININ YAPAY ZEKA YÖNTEMLERİ ILE TAHMİNİ

Begüm ÇETİN

Elektrik Elektronik Mühendisliği Anabilim Dalı

Elektrik Makinaları Bilim Dalı

Eskişehir Teknik Üniversitesi, Lisansüstü Eğitim Enstitüsü, Ocak 2023

Danışman: Dr. Öğr.Üyesi Şener AĞALAR

Güç kalitesinin devamlılığının sağlanması sistemin verimli ve güvenilir bir şekilde çalışmasını sürdürmesinde en önemli etkendir. Dengeli üç faz sistemde gerilim ve akım sinüs ve nominal değerdedir. Güç sisteminde arıza olduğunda sistemin yük dengesi bozulur ve güç kalitesi bozuklukları meydana gelebilir. Güç kalitesi bozuklukları iletim ve dağıtım hattında güç kayıplarına, şebekeye bağlı cihazların arızalanmasına, canlı hayatını ve çevreyi etkileyecek yangın gibi felaketlere kadar istenmeyen durumlara sebep olmaktadır. Bu bağlamda güç kalitesi bozukluklarının olası etkilerini önlemek, güç sistemin verimli ve güvenli bir şekilde çalışabilirliğinin sağlanması, geleneksel şebekelerden akıllı şebeke ve mikroşebeke yapılarına geçiş sürecinde öngörücü yapay zekâ yöntemlerinin güç kalitesi bozukluklarının tahmininde kullanımı yenilikçi ve destekleyici çözüm sunar.

Çalışmanın amacı IEEE 9 baralık test sisteminde oluşturulan toplamda 14 adet kısa devre arıza senaryosuna göre güç sisteminin bir barasında (7 adet tekli) veya baralarında (7 adet ikili arıza) meydana gelen kısa süreli gerilim çökmesi büyüklüğünü diğer baralarda belirlenen zaman ufkundan önce homojen ve heterojen topluluk makine öğrenmesi metodları ile tahmin etmektir. Yöntemler seçilirken gerilim düşümü davranışını incelemek için öncelikle yük akışı analizi yapılmış sonrasında sisteme kısa devre arızası verilmiştir. Homojen (rastgele orman) ve heterojen (destek vektör regresyonu, karar ağaçları, en yakın komşu) makine öğrenmesi yöntemlerinin tahmin performansı ve eğitim hızı karşılaştırıldığında heterojen topluluk eğitim modelinin daha başarılı olduğu gözlemlenmiştir.

Anahtar Sözcükler: Güç Kalitesi Bozuklukları, Gerilim Çökmesi, Topluluk Makine Öğrenmesi, Heterojen Makine Öğrenmesi, Homojen Makine Öğrenmesi

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In addition, I believed that every person carried with excitement and had a potential waiting to reveal. This study has been a study that I believe that I could give direction to the future.

I dedicate my thesis to my dear mother, father and brother Cemil Can ÇETİN who always support me in my continuous learning and development, to everyone who loves to learn and teach. I hope that will be useful and inspire for future studies.

Begüm ÇETİN

23/01/2023

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Eskişehir Technical University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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GLOSSARY OF SYMBOLS AND ABBREVIATIONS

a	: Phase Unit Vector
AC	: Alternating Current
ADN	: Active Distribution Network
ANN	: Artificial Neural Networks
ANSI	: American National Standard Institute
APF	: Active Power Filter
B_{kn}	: Sum Susceptances Connected Between k^{th} Bus and n^{th} Bus
C	: Control Parameter
CART	: Classification and Regression Tree
CNN	: Convolution Neural Network
CV	: Cross Validation
D	: Reversible Matrix
DC	: Direct Current
DNN	: Deep Neural Network
DT	: Decision Tree
DVR	: Dynamic Voltage Restorer
DWT	: Discrete Wavelet Transform
ΔP	: Active Power Mismatch
ΔQ	: Reactive Power Mismatch
$\Delta \delta$	: Voltage Angle Mismatch
ΔV	: Voltage Mismatch
Δy	: Power Mismatches
ε_i	: Constraint Factors (Support Vector)
ξ_i	: Outlier
E_i	: Transformer Voltage
EMC	: Electromagnetic Compatibility
EMD	: Empirical Mode Decomposition
EMI	: Electromagnetic Interference
EWT	: Empirical Wavelet Transform
FFT	: Fast Fourier Transform

γ : Control Parameter (trade off bias-variance)

G_{kn} : Sum Conductance Connected Between Bus k and Bus n

GCNN : Graph Convolutional Neural Network

GBM : Gradient Boosting Machine

GNN : Graph Neural Network

HAPF : Hybrid Active Power Filter

HHT : Hilbert Huang Transform

HT : Hoeffding Tree

I : Current

I_a : a Phase Current

I_b : b Phase Current

I_c : c Phase Current

I_g : Phase Currents of Matrix Input

I_k : Symmetrical Components of Matrix Input

I_1 : Positive Phase Component of Current

I_2 : Negative Phase Component of Current

I_0 : Zero Phase Component of Current

I_k : k^{th} Bus Current for Load Flow Analysis

I_X : Inductive or Capacitive or Both Current

I_R : Resistive Current

I_{unb} : Unbalance Current

IBk : k-Means Algorithm

IEC : International Electrotechnical Committee

IEEE : Institute of Electrical and Electronics Engineers

i : i^{th} Sample

J_{kn} : Partial Derivation of Active and Reactive Power According to Angle and Voltage Connected Between Bus k and Bus n

J_{kk} : Derivation of Active and Reactive Power According to Angle and Voltage Connected to Bus k

J48 : Decision Tree Algorithm

k : kth Bus for Load Flow

k : Number of Decision Tree

K : Number of Observation Data for K-Nearest Neighbor k- nn : K-Nearest Neighbor

LSTM : Long Short-Term Memory

L : Transformation Matrix

l : Loss Function

LGF : Line to Ground Fault

LLGF : Line to Line Ground Fault

LLF : Line to Line Fault

LLLF : Three Line Fault

LMS : Least Mean Square

m : Number of Observation Samples for Decision Tree

m_L : Number of Left Samples

m_R : Number of Right Samples

MAE : Mean Absolute Error

ms : Milli Seconds

MSE : Mean Squared Error

MSRF : Multiple Synchronous Reference Frame

N : Turn Ratio

n : Number of Buses for Load Flow

n : Number of Samples

NB : Naive Bayes

NN : Neural Network

Ω : Omega (Penalty Number for GBM)

P : Power

P_k : Net Active Power for Connected to kth Bus

P_{kl} : Sum of Load's Active Power Connected Between kth Bus and Load Bus

P_{gk} : Sum of Generator's Active Power Connected Between kth Bus and Generator Bus

PF : Power Factor

PPF : Passive Power Filter

PLC : Programmable Logic Controller

p.u : Per Unit

PQ : Power Quality

PQ : Load Bus for Load Flow Analysis

PV : Voltage Controlled Bus for Load Flow Analysis

PV : Photovoltaics

Q : Reactive Power

Q_k : Net Reactive Power

Q_{kl} : Sum of Load's Reactive Power Connected Between k^{th} Bus and Load Bus

Q_{gk} : Sum of Geberator's Reactive Power Connected Bwetween k^{th} Bus and Generator Bus

Q_{kn} : Sum of Reactive Power Connected Between Bus k and Bus n

Q_{kk} : Sum of Reactive Power Connected to Bus k

RELU : Rectifier Linear Unit

RF : Random Forest

RMS : Root Mean Square

RMSE : Root Mean Square Error

RPP : Reactive Point Process

R2_Score : Regression Score metric

S : Appearance Power

s : Seconds

SNR : Signal Noise Rate

SST : Solid State Transform

STATCOM : Static Synchronous Compensators

SVC : Static VAR Compensator

SVM : Support Vector Machine

SVR : Support Vector Regression

σ : Standard Deviation

δ : Voltage Angle

δ_k : kth Bus Voltage Angle

δ_n : nth bus Voltage Angle

(t) : Iterative Number for Gradient Boosting Machine

t : Time

T : Number of Leaves

T : Period

t_k : Threshold for Decision

V : Voltage

V_a : a Phase Voltage

V_b : b Phase Voltage

V_c : c Phase Voltage

V_1 : Positive Phase Component of Voltage

V_2 : Negative Phase Component of Voltage

V_0 : Zero Phase Component of Voltage

V_n : n^{th} Bus Voltage

V_k : kth Bus Voltage

V_g : Phase Voltages Matrix Input

V_k : Symmetrical Components of Matrix Input

Van3_4_a : Ex. Voltage Sag Magnitude at 3^{rd} Bus in Faulted 4^{th} Bus (Labeled Voltage Data)

VAR : Volt- Ampere Reactive

VA : Volt- Ampere

V_{UF} : Voltage Unbalance Factor

V_{unb} : Unbalance Voltage

w : Angular Frequency

W : Watt

w_i : Weight

w_0 : Bias

WT : Wavelet Transform

x_i : Inputs (Attributes)

x' : Observation Data for k-nn

y_{kn} : Sum Admittance Connected Between the Bus k and Bus n

y_{kk} : Sum of Admittance Connected to Bus k

y_i : Expected (Actual) Value

$\hat{y}$: Predicted Value

$\bar{y}$: Mean of Samples

Z_1 : Positive Sequence Impedance

Z_2 : Negative Sequence Impedance

Z_0 : Zero Sequence Impedance

Z_f : Three Phase Faulted Impedance

1. INTRODUCTION

Is it possible to predict power quality disturbances for other buses early when a failure occurs at any bus in a power system? There are many reasons for asking this research question. Firstly, automation has been started to systemic process for production, energy and workforce optimization. Then, technologic developments move towards to big data management with information and communication technologies for each technical or social fields. In this way, result of focusing on aim with big data management, multi-agent systems which is field of artificial intelligence branch can develop and may provide fully controlled grid structure like smart grid with increasing of electric car and integration of renewable energy resources.

Additionally, for supply-demand management, meeting the electricity demand is very important for efficiently,safely,economically. One of the solutions is providing optimum energy management option between the producer and the consumer with feedback thanks to bidirectional data flow. In the light of these developments, there will be many advantages of proactively predicting the power disturbance ahead of time when a failure occurs in the power system that will deteriorate the power quality. The continuity of power quality in the power system will provide despite the integrated new power supplies and power disturbances that may occur in the system, and therefore the grid will gain more resilience. This paves the way for safer and more efficient operation of the power system and allows for early intervention in the event of a disturbance.

One of the important works developed in practice is the development of power quality analyzers that allow the development of predictive methods in the grid by providing real-time energy generation, consumption, storage of power quality disturbances, notification of power quality disturbances, remote control of the system.

Three phase AC power systems generate pure sinusoidal voltage signals in a balanced condition. Stability of power quality is protected, and the power system works efficiently and safely. However, when any fault is happened on the power system, power quality and stability of system are disturbed, because of these, power quality disturbances occur due to drawing high current in generally. The situation leads to malfunctions of devices (programmable logic devices, motor drivers, computers) on the power grid. Elements of semiconductor, power electronics circuits, arc and welding machines consuming high level energy, induction machines during starting time, short circuit faults cause power quality disturbances. Result of the events, power losses happen on distribution and transmission networks. The problem is undesired case, because operating power system and stability of demand-supply are affected negatively, using of devices can be disturbed, demanded energy needs are not enough and the situation reflects on electric bills so, power outages increase. Besides, if reactance frequencies of capacitor and inductor in harmonic systems are equal each other or power system frequency equals to capacitor or inductor frequency, resonance occurs and it causes dangerous situations like fire disaster. According to IEEE 1159 standards in 2019, power quality disturbances split 7 different categories, they are transients, short duration root mean square (RMS) variation, long duration RMS variation, imbalance, waveform distortion, voltage fluctuation, power frequency variation respectively [17].

Depending on the type of power disturbances and the structure of the power system, when fault occurs, filtering types for harmonics, interharmonics, noise, buck-boost power electronics devices, voltage regulators(transformers), dynamic voltage restorers (DVR) for overcurrent-induced power quality disturbances such as voltage sag, voltage swell, overvoltage and undervoltage are used. Static var compensators (SVC) and static synchronous compensator (STATCOM) are used to provide reactive power compensation, adjust power factor, regulate voltage fluctuation and voltage flickers, this topic is explained in more detail in Chapter 2.

When any fault is occurred on any bus or buses and transmission or distribution electrical networks, prediction of power quality disturbances before fault occurs on other buses or lines has many advantages in order to take precautions early, decrease power failures, malfunctions, prevent dangerous situations for living creatures and environmental things and decrease response time of the mitigated devices. In this way, power quality continuity is provided and power system operates efficiently and safely with increasing of fault tolerance and decreasing maintenance cost.

In order to adapt this study to smart grids, microgrid structures, complex systems with larger bus numbers, along with traditional grids, AC three-phase IEEE 9 bus power system was initially preferred when evaluated together with data acquisition, system dynamics to define data and preprocessing steps. When instantaneous short-circuit fault is given to the system, the behavior of voltage sag disturbance which is one of the most common power quality disturbances, was examined and how much voltage sag can be in which bus according to 14 different short-circuit fault scenarios before optimum time range was predicted by heterogeneous and homogeneous ensemble learning methods.

Knowing how the power quality disturbance reacts in the whole system when the system fails makes it clear which methods can be effective. Therefore, first of all, the load flow analysis of the 9-bus system should be made and the balance of power quality in the system should be ensured. MATLAB/Simulink program was used to analyze the load flow analysis, to examine the behavior of short-circuit fault and to obtain the fault (voltage sag) data from the power system. After the balanced operation of the system was ensured by the load flow, a short-circuit fault was given to phase a of the power system with a three-phase circuit breaker for 0.1 seconds instantly, with the fault start time being at 1 second. As a result of the failure, it was observed that the voltage sag was of different magnitudes in the time intervals in which the entire system was faulted without faulted buses, because the buses which given a phase fault have interruption events in the fault time. Additionally, only 2nd bus has voltage sag, although a phase fault is applied to the bus. The three-phase voltage sag data obtained were simulated for 3 seconds and the sampling frequency was determined as 20kHz to capture the characteristics of the instantaneous, nonlinear and nonstationary signal, and the short-circuit faults given to the single and double buses in total are ($14\times9\times3+1$) and 379 features, 60000-time dependent voltage sag data (379×60000). The suitability of three-phase voltage sag data for the estimation of the voltage sag magnitude is also explained by the symmetrical components analysis approach. All of the data are labeled one by one to introduce to artificial intelligence algorithms which bus was faulted and voltage sag was observed for which bus after each fault scenario. The type of failure to be predicted was removed from the features and made a target (dependent) variable and the remaining data was used as an independent (input). The reason for giving a double fault to the system at the same time is to increase the type of fault and to enable the artificial intelligence system to better introduce the location-related pattern of the magnitude of the voltage sag in the power system at the same time interval.

According to problem definition, when the short circuit fault is occurred on any bus in defined fault time range, voltage sag phenomena can be understood before 100ms. Optimal time horizon is determined with ratio of splitted data for train and test, because fault time has only one range and the voltage sag event must be recognized at the same time. Therefore, before voltage sag, the period is defined about 5 and after voltage sag, recovery period is defined about 2, according to response of the power system. In other words, inception time (predicted time horizon) is about 0.35 seconds, end of time is 1.13995 seconds.

When the behavior of the voltage sag in the 9-bus system is evaluated, it is observed that the voltage sag increases at the buses closer to the faulted area as a result of the fault, while it decreases with distance from the fault. In other words, the situation depends on the closeness- distance to the faulted area. Another connection is that a voltage sag that occurs at the same time intervals as a result of a fault in the system creates a voltage sag in all other buses at the same time interval without faulted bus or buses. The magnitude of the voltage sag is caused both by the distance relationship depending on the fault area and also causing a voltage sag for the whole system (cumulative effect). Therefore, it is important to find machine learning methods that can connect a correct pattern between the determined independent (input) or attribute values and the dependent (output) or target variables. In this context, it is thought that they are appropriate to prefer homogeneous random forest machine learning method, which is one of the ensemble learning methods with close applicability to fractal pattern finding and real life. Heterogeneous ensemble learning methods consisting of nearest neighbor, support vector regression and decision trees that can establish both of distance-dependent relationship of voltage sag magnitudes and effect of different voltage sag magnitudes on the power system as a fractal pattern for decision tree. Actually, if fractal pattern is defined, it depends on initial condition sensitively and it repeats with low scale, so according to 14 fault scripts, voltage sag magnitudes of chosen 10 experiment script happens different each other depending on distance of the buses or location of them. Also, SVR method is useful for with Kernel functions to find pattern nonlinear and nonstationary data structure. The main reason for choosing ensemble learning methods is the combination of basic (weak) classical machine learning methods to create a more powerful algorithm structure with higher generalizability and a focus on optimization for the predicted data.

As a result of the targeted estimation, it was observed that the heterogeneous ensemble learning model performed better in general, and when the training time was evaluated, the heterogeneous models were again higher in speed. Better generalizability of heterogeneous models can be deduced from the variation of the magnitude of the voltage sag of the strongest context between the predicted and trained data, and the distance from the fault. Besides, the performance metrics are evaluated with K-Fold Cross

Validation scores. Using of the software program is Anaconda /Jupyter Notebook application.

Estimating both the time dimension and magnitude of power quality disturbances saves time for any human or device-induced intervention in the system, providing more accurate and controlled, reliable and technological solutions. As a result, positive results can be obtained in increasing energy and production efficiency in the industrial field, increasing fault tolerance and using the installed system and the devices in the system for a longer time, thus reducing maintenance costs and increasing production. In this context, investment in innovative solutions for both producers, consumers and electricity networks are supported.

First part is related to work aim, content of work, using of methods with reasons of them, literature reviews that explained works past to future and contribution of future works; second part is related to power quality definition, examination of power quality disturbances, effects of power quality disturbances and using of techniques to decrease effects of them; third part is related to short circuit faults, symmetrical component analysis and application on IEEE9 bus test system; fourth part is related to load flow analysis and its importance, fifth part is related to the birth of the artificial intelligence concept, mathematical model of brain, some advises about that and explanation of using of machine learning methods and last part is related to data preprocessing steps, chosen suitable methods with reasons for the work aim, discussion, some advises and aimed future works.

1.1. Literature Review

Power quality problems occurs at several forms and different time horizon on pure sinusoidal signals due to source of reasons. They are undesired events because initially, they can cause serious problems for human and environment. It affects balance of load flow, so power loss can happen on transmission and distribution networks. In short, this situation is becoming more important with integrated renewable energy resources due to probabilistic nature of it and adding of control devices effects. Based on artificial intelligence method is important in terms of being compatible with evolution of grid topologies and intervening in a timely manner. Thus, it will increase the reliability of the grid and effects the operation life of the networks and the connected devices. Particularly, using of predictive compensation methods, a solution that will benefit both the electrical network, producers and the consumers will be reduced the malfunctions and their effects

[12]. There are studies on which methods and how to find solutions to prevent these and ensure the continuity of power quality.

Magnitude of voltage or current or both and also frequency changes when any fault case occurs. When we look at the studies that will be source for current to future studies, voltage flickers, voltage sag, harmonics, interharmonics, transients, fault variation(LGF, LLGF, LLF, LLLF) predictions are observed by using begin of Wavelet Transform (WT), Fast Fourier Transform (FFT) and Hilbert Huang Transform (HHT) from main signal processing methods in order to separate time and frequency components of the power quality disturbances and in this way, magnitude, start - end point of power quality disturbances are detected in early. Additionally filter method is applied with signal processing methods for same purpose. If the methods are compared each other, especially in Kalman Filter approach is better to extract signal features and detect power quality disturbances in generally.

In 1995, of Girgis A.A., Stephens J.W., and Makram E.B., estimates of voltage flicker magnitude and frequency with Kalman Filter predictive approach. According to their works, filter operation is more successful than Fourier and Wavelet transforms because, filter methods especially in Kalman Filter captures frequencies and magnitude of disturbance signal against to noise and harmonics. In this work, voltage flicker data is obtained from arc furnaces. Kalman filter is modulated the signals as random frequency and magnitude. Then, prediction of voltage flicker magnitude and frequency is made by the method in 50 milliseconds early [1]. In 1999, Chung J.,Powers E.J., Grady W.M and Bhatt S.C. detect voltage sag time envelope during fault with e new detection system by using of Adaptive prediction error filter and Wavelet Transform(WT) . The methods are executed to extract start and end point of voltage sag event. Noise and harmonics are added to disturbance signal. Adaptive prediction error filter is more successful to eliminate harmonics and find noise signal according to wavelet transform. After that, in detection system, result of multiplication of fault alarm probability (chosen constant) and local mean noise cells, a threshold value is obtained with Stop and Go Cell Average Constant False Alarm Rate (CA CFAR) algorithm. If detected signal and mean noise signal are compared in counter detect system, when threshold value is more than 1, this situation is stop, disturbance signal time(start-end) is detected, in contrast, the system is continued until finding voltage sag time period. It is emphasized that the effect of the fixed failure probability value determined is important to obtain more successful model

[2]. Other similar study is that in 2001, Dash P.K., Pradhan A.K. and Salama M.M.A. use adaptive Least Mean Square (LMS) algorithm, Kalman Filter and Fourier Linear Combiners Kalman Filter algorithm to estimate voltage flicker magnitude and frequency. Modulation of voltage flickers are made as magnitude and frequency with adding harmonic components and noise. When the methods are compared, adaptive LMS algorithm is better solution than Kalman Filter and FLC Kalman Filter algorithms respectively [3].

Hilbert Huang Transform (HHT) is more effective method to find magnitude, frequency and time points of nonstationary signals, because this method can ensure against to noise, harmonics, when prediction, detection or classification is made, in other words, it has more accurate ratio to find variety of the dynamic signals. Additionally, the method has wide capacity to find frequency, magnitude and time components of the signals [15]. In 2014, Önal Y., Ece D.G. and Gerek Ö.N. execute Hilbert Huang Transform 10kHz sampling modulated voltage flicker signals. Firstly, square of voltage flicker is obtained to find symmetrical components of the waves. Empirical Mode Decomposition (EMD) method captures case envelope and separates harmonic components in order to detect wide range frequency of the signal. As a result of process, Intrinsic Mode Functions (IMFs) represents frequency components (highest to lowest frequencies). Then, magnitude and frequency of voltage flicker signals emerge with Hilbert Huang Transform (HHT) as a spectral analysis because the found parameters are detected in time-frequency plane of energy spectrum [4].

As it is seen, if above methods are evaluated in generally, various signal processing methods with spectral analysis on nonlinear signals to find magnitude, frequency and time point of them (power quality disturbances) from aspect viewpoint of chronological.

Prediction, detection and classification process are executed by signal processing or artificial intelligence method or combined of two methods to improve power quality according to kind of problem and power grid structure. When the methods developed until today are examined, by gaining robustness, speed, and performance in solving problems; the accuracy of the results obtained with certain metrics is also calculated.

The point that needs to be emphasized here is that the electricity grid, which plays a role in the development of the early warning system, turns into a more controlled, that is, intelligent network, and can it create a fully self-controlled network structure with predictive methods, which also contributes to PQ devices? Multi agent system, which is branch of artificial intelligence, can provide self-healing in smart grid topologies. When any fault happens on power system, information of fault location is shared with device protection tools and the system demands closest tool to prevent fault. In this way, needed data is shared and managed in wide area and operation of power system is improved selfly [36].

A statistical model can be developed in a more real-life pattern for failures at the point of access of power cables that cause harm and damage to the environment and threaten safety for humans and other living things. In 2015, Ertekin Ş., Rudin C., McCormick T.H. work on the prediction of fire, explosions and power failures that occur as a result, the disasters damage the underground cables in the manholes in New York City. The statistical approach is Reactive Point Process (RPP) as a method which examines natural behavior of these failures. In other words, the past disasters effects probability of occurred vulnerability of same events in future. Based on this information, main four functions are defined to adjust vulnerability of occurred the catastrophic events. Self-exciting function is defined that past failure cases increases vulnerable of occurred events, so saturation function provides to turn back baseline level; self-regulating functions is explained that decreasing vulnerable level with control and repair gradually and also other defined saturation function turn back baseline vulnerability level. Features is obtained from Con Edison at NYC. They are past cases, past control report and specifications of manhole's cables to estimate future vulnerability of the events. Function parameters are found by various statistical approaches. In order to explain the complex order of the problems in real life, the K_L Divergence statistical model is used to simulate how often, where and when it will occur. Besides, Bayesian approach is used to share information between similar manholes, so self-exciting function is not needed to use. Then, Maximum Likelihood model is used to measure difference between simulated result and real result. If the study is compared with related to similar studies, it emerges with more successful results. Hence, developed predictive system give information about which manhole is vulnerable, where and when the failures can occur early. Additionally, the estimated failures affect cost [5].

The integration of renewable energy sources into electricity networks with its structure that supports increasing population and technological development is effective in the development of predictive artificial intelligence methods to improve power quality. Particularly, prediction of power quality disturbances early has more important for the electrical system. In 2017, Kaitovic I. estimates voltage sag with proactive approach by using of artificial neural network methods. Active Distribution Networks (ADNs) are suitable for developing innovative and proactive solutions for power quality disturbances and faults due to renewable energy sources and bidirectional power flow. The system is modified IEEE 14 bus with distributed generators (wind and photovoltaic (PV)) and compensation tools. Data frame of disturbances, short circuit fault injections to different buses are obtained with PSAT which is an interface of MATLAB/Simulink. Faults are occurred between 20 seconds and 60 seconds with a sampling period of 0.5 cycles for each busbar. For the input features, real power, reactive power, bus voltage and phase angle are used as the current is not used for input feature, because it changes all the measurable parameters. When short circuit is executed on any bus, length of sampled data is 100 cycles and while lead time (start time for sag prediction) is defined as 30 cycles, prediction window size (considering data size for prediction) is 50 cycles as a proactive method. In this method, lightning and bell are used to explain early sag prediction. When bell explains proactive prediction for sag signal, lightning is sign of detected voltage sag. Prediction algorithms are Naïve Bayes, logistic regression, support vector machine (SVM), k-means algorithm (IBk) and decision tree algorithm (J48). According to determined different lead time and prediction window size, metrics show that IBk is better to predict sag [6].

To ensure the continuity of security and power quality in power systems with more complex network structure, power quality analyzers are placed in certain parts of the network and parameters related to power quality can be monitored, including power quality disturbances. Especially in recent studies, the increase in prediction, classification and recognition studies on power quality disorders in these networks has attracted attention. In 2018, Liao H., Milanovic J.V., Rodrigues M. and Shenfield A. estimate voltage sag magnitude level in IEEE68 bus active distribution network (photovoltaic and wind turbines). PQ monitoring systems are placed certain part of the grid. Bus matrix is occurred according to relationship between distance and compatibilities of close monitoring bus. In other words, the matrix gives information about topological features of the grid. Voltage sag event is obtained from Line to Ground Fault (LGF), Line to Line Ground Fault (LLGF), Line to Line Fault (LLF) and Three phase fault (LLLF) by DIgSILENT/PowerFactory. Besides topological features and voltage sag magnitude, symmetrical component of phase voltages and differences of pre-fault voltage and voltage sag are consisting of to predict the sag magnitude level with using of CNN (Convolutional Neural Network). According to validation accuracy, prediction success reaches to 100% [7].

Another study that will be mentioned an “Early Warning Project” to provide sufficient time to take necessary precautions by notifying the system earlier before a power quality deterioration occurs. In 2019 Vemund M.S works to predict voltage sags, interruptions, rapid voltage changes and ground faults early. The study provides early warn to compensate or order to operational system during the fault and selecting amount of time horizon is important to interfere the power grid and electrical devices by equipments, so time horizon is certained 10 minutes. Phase voltages are used for features to predict the disturbances. Data are obtained from Norwegian power grid (PQ analyzer). Support Vector Machine (SVM), Random Forest (RF) and Multiple Neural Network methods are used to predict the power quality disturbances. According to metrics, random forest method outperforms. Python 3.6 tools are used to develop the models [8].

Ensemble methods can adjust trade-off underfitting-overfitting better. The terms are interested in variance and bias. The methods tend to reduce variance and bias so, it can prevent overfitting, occurred model learn better from data, so it can prevent underfitting. In this way, model performance increases, better prediction can made. This may be one of the reasons why ensemble learning methods are preferred in various power quality disturbances. In 2019, Sahani M. recognizes and classifies wide various power quality disturbances with using of Empirical Wavelet Transform (EWT)- Hilbert Huang Transform (HHT) that is signal processing method in order to extract time - frequency components of the disturbance signals and Random Forest Classifier to classify the 16 different disturbances according to getting EWT-HHT output features. These disturbances are voltage sag, voltage swell, harmonics, voltage flickers, notching, transient, spike, interruption, DC Offset and its combines. Other classification method is Discrete Wavelet Transform (DWT) – HHT -RF classification. When two methods are compared, EWT-HHT RF is more successful performance because, it can detect various power quality disturbances simultaneously and has the ability to predict quickly in noisy environments [9].

Stacking ensemble is various of meta ensemble learning. Most importance ability of it is that stack ensemble is providing of collective learner in successfully. It can be used to design model both of homogeneous and heterogeneous ensemble machine learning

[14]. In 2021, Radhakrishnan P., Ramaiyan K., Vinaygam A., Veerasamy V. detect and classify voltage sag, voltage swell, harmonics, transients; voltage sag with harmonic and voltage swell with harmonic by using of DWT-Stacking ensemble method. Power grid is designed with PV generator, boost converter and voltage source inverter in two bus system. The disturbances data are by using of MATLAB/Simulink. Firstly, features are extracted with DWT method to solve the signals in frequency -time plane. Then output of the process is given to stack ensemble algorithm. The algorithm is combined of decision tree, logistic regression and Naïve Bayes machine learning algorithms. After first prediction is made (level 0) with base learners, suitable model is occurred with meta learners (level 1). Both ensemble classification approach (level 0) with base learners and stack ensemble classification (level 1) approach with meta learners are used, as a result of them, stack ensemble approach is robust and better performance, according to classification metrics [10].

Graph Convolutional Neural Networks (GCNN) can learn relationship connection between embedded features(nodes) and edges. Besides, the method can make spectral analysis(time-frequency). Thus, the method is suitable for wide range area related to improve power quality. In 2021, Tong H., Qui R., Zhang D., Yang H., Ding Q. and Shi X. observe more successful than other classical machine learning algorithms to detect and classify transients and with Graph Convolution Networks (GCNs). GCN algorithm captures spatio-temporal features from the graph structure of the system. Thus, bus topology information and relationship between the nodes which is embedded bus features is learnt from bus graph structure. Firstly, IEEE 9 bus test system is used to detect and classify transients and faults with the method as a case study. One of important calculation for this work is occurring edge weights in order to learn correlation between nodes. LGF, LLF, LLGF, LLLF and non-fault data is used to identify the event and classify the executed faults. Then, IEEE 39 bus system is used for the same purpose. The data is labeled due to different fault resistances, fault locations and fault impedances. PSCAD/EMTDC and python program are used for simulation of model and classification faults and detection of transients respectively. Data samples are obtained 4kHz, fault duration is 0.1 seconds and fault types are 5 in total with as same as IEEE 9 bus graph structure. In addition, this work is done with adding signal to noise rate (SNR). As a result of it, when machine learning algorithms (SVM, logistic regression, k-nearest, decision tree, CNN, Naïve Bayes and RF(Random Forest)) are compared, according to classification metrics, GCN technic is most successful performance and generalized[11].

Arc furnaces are main cause of several power quality disturbances. It spends high energy to process heavy loads. Hence, providing both continuous energy and cost efficiency is important issue. In 2022, Salor Ö., Balouji E. and McKelvey T. develops deep learning based predictive compensation model against to voltage flicker, interharmonics, voltage sags and harmonics. Current and voltage waveform which draw from arc furnace separates to frequency components for more accuracy and easy prediction of interharmonics, flickers, harmonics and voltage sags. Interharmonics and harmonics frequencies can cause voltage flickers or fluctuations. Therefore, based on interharmonics model is designed. Frequency modulation is done with adding different frequencies of flicker, interharmonic and harmonics to fundamental power signal. Besides, their amplitude is adding to the signal with same way. After, dividing frequency component (dqo) with multiple synchronous reference frame (MSRF) method, butterworth low pass filter is used to pass low frequencies and then, future values of these passed components are predicted by linear FIR based prediction method. Prediction horizon is chosen 40 ms. Other method is time series model. Long Short-Term Memory (LSTM) is better result regard to other methods. Time series models can show better generalization and performance for time-varying dynamical systems. The filter and CNN, LSTM methods are used together in order to estimate the disturbance frequencies. CNN extracts feature of the components. When these methods execute at the same time, prediction accuracy is lower than LSTM. After estimating prediction horizon, active power filter is used to eliminate the interharmonic, harmonic frequency. In this way, voltage flickers and voltage sags are compensated at the same time [12].

Signal processing, classical machine learning models and GCNNs can predict fault envelope as a time, magnitude, frequency and location of power quality disturbances. Also, Random Forest(ensemble) method is effective method for same aim. In 2022, When El Mrabet Z., Sugunaraj N., Ranganathan P. and Abhyankar S.predict time duration and location of (three phase fault)LLLF power failure in a 9 bus system ,according to other machine learning algorithm , Random Forest (RF) ensemble approach outperforms. The faults are executed, and observation of the bus system is made on GridPack simulation program. Simulation time of the system is 10 seconds and features are voltage magnitude, generator supply frequency and phase angle. Machine learning methods are out of

Random Forest Regressor (RFR) approach, Support Vector Machine (SVM), K-nearest neighbors(K-nn), Deep Neural Network (DNN), Neural Network (NN),Naïve Bayes(NB), Decision Tree(DT) and Hoeffding Tree(HT). According to regressor metrics, random forest algorithm is most robust and accurate method for the study [13].

In this thesis, the voltage sags that occur on the IEEE 9 bus test system by giving a single-phase fault in a certain time interval are estimated by collective homogeneous and heterogeneous learning methods before the determined time duration. Prediction performance was compared with R2_score, Mean Squared Error (MSE), Mean Absolute Error (MSE), Root Mean Squared Error (RMSE) metrics. After the voltage sag estimation is expressed visually, the differences between the estimated and expected results are shown in the table.

As it can be understood from the studies in the literature, one of the most important aims of the study is to raise awareness for the continuity of the studies on this subject. In addition to the "Early Warning System" in ensuring the continuity of power quality, attention was paid to provide innovative contributions to support technological development and to be a source for future studies.

2. POWER QUALITY

Power quality (PQ) can be used for load balance between the power plant or utilities and end users (residential, industrial, commercial) with electrical equipment connected in a power system. When balance of power quality provides in a power system, the electricity flows in the system reliably and efficiently from production side to consumption side. In this sense, it is very important to ensure the continuity of power quality. PQ means that is protection of sinusoidal waveform at rated frequency and voltage technically.

Power quality is expressed with certain PQ standards at the same time. These standards provide to work on power quality and interested issues about all examinations of it, to illustrate; mitigation, detection, prediction, classification of power quality disturbances, increasing power quality etc. with scientific measurements. When load stability of a power system is destroyed due to power quality disturbances or other reasons, many various methods are executed (e.g., artificial intelligence methods, compensation) to improve power quality according to examinated fields.

2.1. Power Quality Definition

Power quality means balanced sinus waveform at rated voltage and frequency from feeded by a power supply. It is interested with voltage quality, current quality, reliability of service and quality of power supply[19].

According to IEEE Standard 1159, power quality can be defined that giving suitable power and grounding to power system to work safely [20].

Table 2.1. *Some Power Quality Standards* [4]

IEEE 100	Standard dictionary of electrical and electronics engineering
IEEE 493	Applied for design of reliable industrial and commercial power systems
IEEE 519	Applied for harmonic control and reactive compensation of static power converters
IEEE 1048	Guides for protective grounding of power lines

IEEE 1159	Electromagnetic events categories of power system on monitored electric power quality
IEEE 1250	Service to equipment sensitive for momentary voltage disturbances
IEEE 1346	Applied for compatibility of power systems and electronics equipment
IEC 38	Standard voltages
IEC 868_0	Evaluation of flicker meter for force of voltage flicker and fluctuations on light flicker
EN 50160	Voltage characteristics of electricity
IEC 6100	Electromagnetic compatibility (EMC)
IEEE/ANSI C57.110	While feeding non sinusoidal charge to develop transformer capacity
ANSI C84.1	American national standard for operating of electric power systems and equipment in fundamental frequency (60 Hz)
ANSI 70	Code of National Electric

2.2. Power Quality Disturbances

Short circuit failures in transmission and distribution lines in the power grid, failure of generators, electric motors, especially high power electric arc furnaces, induction machines or sensitive equipment (computers, power electronic circuits, communication cables and devices) as well as some external factors such as weather conditions, lightning strikes, interference with power lines, people, trees, birds, etc. can cause power quality problems in the system. As a result, power quality disturbances, power losses, power outages, various faults, unbalance operations and other catastrophic events may occur in the power system.

According to IEEE standard 1159 – 2019 standards, power quality problems are separated with seven events aspect from sources of voltage and current [17].

1.Transients

2. Short Duration Root Mean Square (RMS) Variation

2.a.Voltage sag

2.b.Voltage swell

2.c.Interruption

3.Long Duration RMS Variation

3.a. Undervoltage

3.b. Overvoltage

3.c. Sustained Interruption

4.Imbalance or Unbalance

5.Waveform Distortion

5.a. Noise

5.b. Harmonics

5.c. Interharmonics

5.d. Notching

5.e. DC Offset

6.Voltage Fluctuation

7. Power Frequency Variation

2.2.1. Transients

Transient events happen with sudden change in voltage, current or both of them between nanoseconds and milliseconds. This phenomenon can be observed unidirectional and bidirectional variations in voltage and current. While impulsive transients occurs with unidirectional polarity, oscillatory transients occurs with bidirectional polarity in voltage, current or both of them. When oscillatory transients include different frequencies in signals, impulsive transients include instant frequency [17].

Transients are reverse of steady state condition on electrical power systems. Capacitance, resistance and inductance parameters of the system specify behavior of transient and the condition is related to transient magnitude [19].

Major cause of transient is lightning strikes. It effects aspects from electrical coupling between the transmission lines. Also, resonance during capacitor switching is other factor of the phenomena [20].

According to Figure 2.1, various of the event is oscillatory transient due to bidirectional variation on three phase voltage signals.

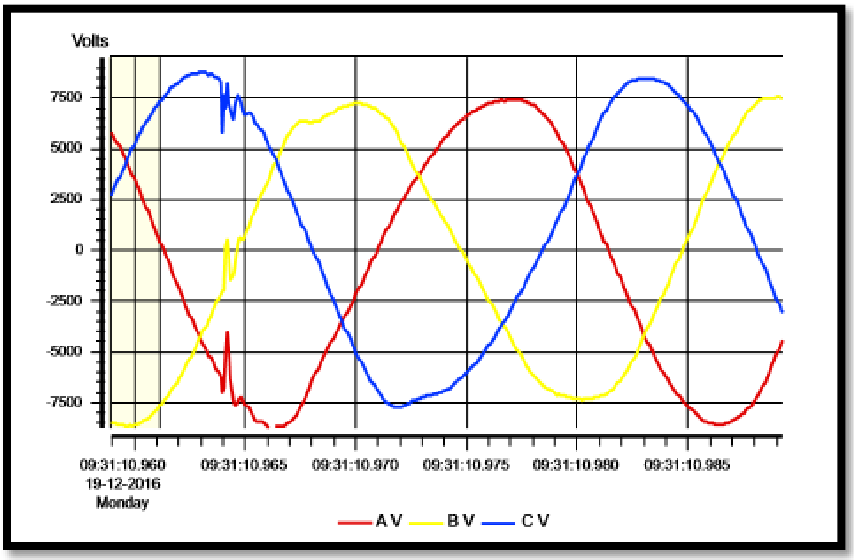

Figure 2.1. *Transients* [2]

2.2.2. Short duration RMS variation

RMS voltage variations occurs between 0.5 cycles and 1minute as instantaneous, momentary and temporary. Voltage sag, voltage swell and interruption cases takes place in this category. If these categories are explained briefly, time period of instantaneous event is between 0.5 cycle and 30 cycles; momentary period is between 30 cycles and 3 seconds; temporary one is between 3 seconds and 1minute.

RMS value is related to heat value on resistive loads. It means AC average power equals to DC circuit power. Mean of AC signal is zero “0”, because the signal changes periodically. However, if square of voltage or current is get to calculate root mean square or effective value, average of the signals can be found [32]. According to formulas, V, I, $R, T, w,$ t are voltage, current, resistance, period, angular frequency and time.

$$V^2 = \frac{1}{T}\int_0^T v^2\, dt \tag{2.1}$$

$$I^2 = \frac{1}{T}\int_0^T i^2\, dt \tag{2.2}$$

$$\mathrm{P} = \frac{1}{T}\int_0^T \frac{v^2}{\mathrm{R}} dt \quad = \frac{1}{T}\int_0^T i^2 R\, dt \tag{2.3}$$

$$v(t) = \sqrt{2}|V|\sin(wt) \tag{2.4}$$

$$i(t) = \sqrt{2}|I| \sin(wt) \quad \textbf{(2.4a)}$$

$$|V| = \sqrt{\frac{1}{T}\int_0^T v^2 \, d\mathrm{t}} \quad = \quad \sqrt{2}|V|\sqrt{\frac{1}{T}\int_0^T \sin^2(wt) \, dt} \quad \textbf{(2.4b)}$$

$$|I| = \sqrt{\frac{1}{T}\int_0^T i^2 \, dt} \quad = \quad \sqrt{2}|I|\sqrt{\frac{1}{T}\int_0^T \sin^2(wt) \, dt} \quad \textbf{(2.4c)}$$

$$|V| = \sqrt{2}|V|\sqrt{\frac{1}{2}} \quad \textbf{(2.4d)}$$

$$|I| = \sqrt{2}|I|\sqrt{\frac{1}{2}} \quad \textbf{(2.4e)}$$

As can be seen from above equations, $|V|\ and\ |I|$ are rms or effective values.

2.2.2.1. Voltage sag

Voltage sag defines reducing from nominal RMS voltage magnitude (1.0 p.u) to between the 0.1 and 0.9 p.u. Time duration of the phenomena lasts 0.5 cycles to 1min[17].

Voltage sag magnitude depends on location or distance of fault buses and impedances of transmission line, supply voltage and transformer, in a power system [17].

Main causes of the sag are high current drawing the electrical system. In this situation occurs with switch on heavy loads (e.g., arc furnaces), starting of large induction machines, symmetrical and unsymmetrical faults on transmission and distribution networks. Morever, switching off frequency and speed motor drivers effects on the system [18],[19].

According to Figure 2.2., while sag happens about 0.10 ms and reducing 80 percent for rms voltage, it happens nearly 60ms and reducing 90 percent for AC voltage.

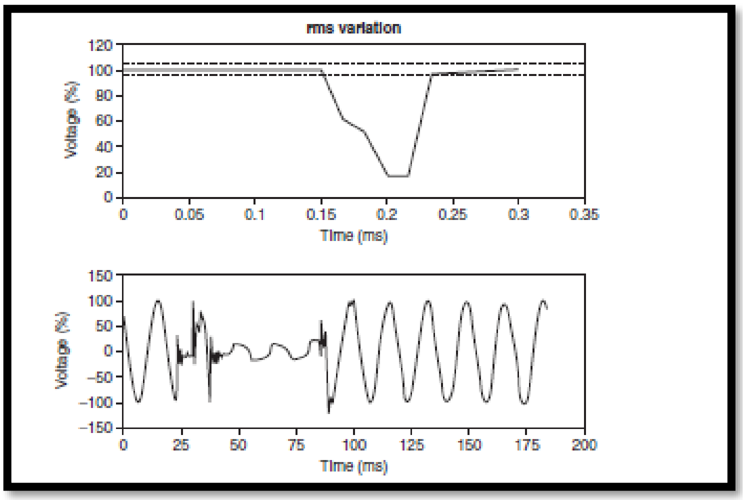

Figure 2.2 *Voltage sag definition* [20]

2.2.2.2. Voltage swells

Voltage swell occurs increasing of RMS nominal voltage from 1.0 p.u to between 1.1 and 1.8 p.u at between 0.5 cycle and 1minute[19].

Main causes of swells are energizing capacitor bank, single line to fault, switching off large loads and strike variations like lightning, tree etc. Common factor of the causes actually is inrush current [19],[21].

According to Figure 2.3, voltage swell case happens between about 0.075 and about 0.23 seconds and magnitude increases to about 1.15 p.u.

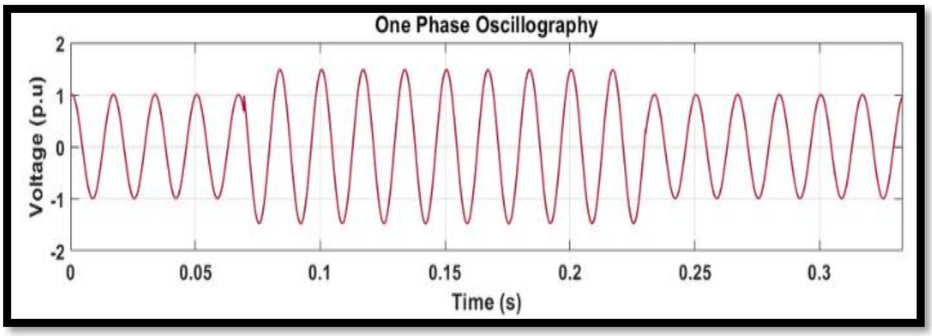

Figure 2.3. *Voltage swell definition* [19]

2.2.2.3. Interruption

Interruptions occur as short-term, momentary and temporary various. Definition of the event that voltage or current reduces less than 0.1 p.u and time duration lasts between 0.5 cycle and 1min[21].

Causes of interruption are equipment failures, power system(electrical) faults, control equipment malfunctions [17].

According to Figure 2.4., interruption occurs and voltage magnitude is zero “0” in a fault time range.

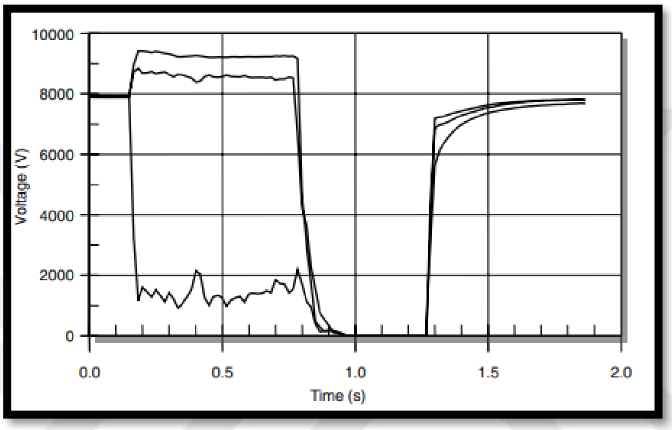

Figure 2.4. *Interruption phenomena* [25]

2.2.3. Long duration RMS variation

According to IEEE 1159 standards, if time period of power quality disturbances lasts longer than 1 minute for RMS voltage or current or both of them, these events counts long duration RMS variation. Undervoltage, overvoltage, sustained interruption and unbalance or imbalance cases are in the category.

2.2.3.1. Undervoltage

Undervoltage is defined that RMS voltage decreases from 1.0 p.u to in between 0.8 and 0.9 pu. Time duration is more than 1 minute [20].

Main causes of undervoltage are instability loads between the utilities and end users(overload), switching off capacitor banks and switching on loads in a power system [18],[19].

According to Figure 2.5. The case lasts about 75 seconds (long time) and the magnitude reduces percentage of ten 10% .

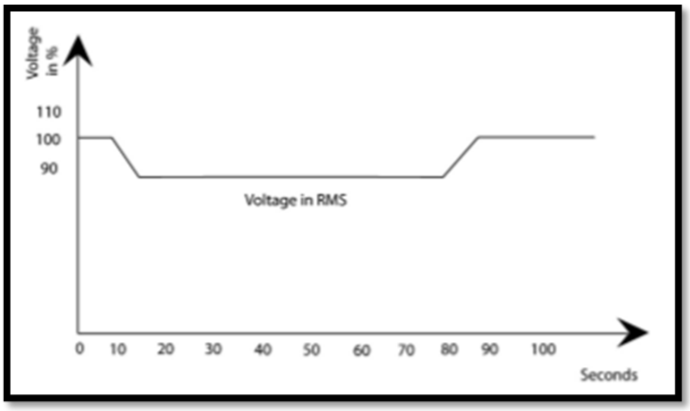

Figure 2.5. *RMS undervoltage* [17]

2.2.3.2. Overvoltage

Overvoltage means that voltage magnitude increases from 1.0 p.u to 1.1 p.u or 110% of nominal voltage in RMS , and time duration lasts more than 1 minute[20].

The phenomena is like swell but time variation lasts quite long. Main causes are capacitor energization, switching off loads, insulation fault, lightning strikes [18],[19].

If Figure 2.6. is observed, RMS voltage increases 100Vrms to 110Vrms for time duration is about 75 seconds.

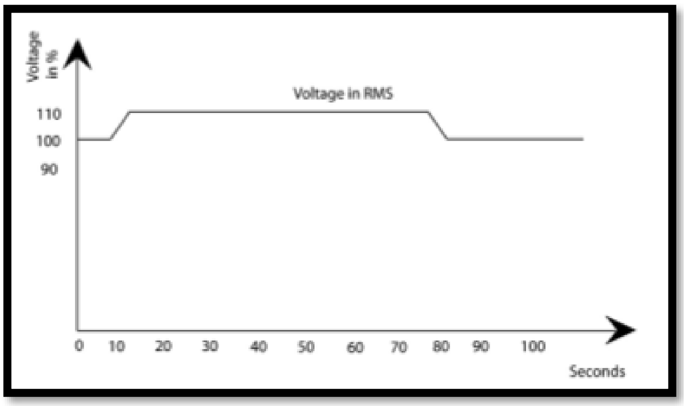

Figure 2.6. *Overvoltage in RMS* [17]

2.2.3.3. Sustained Interruption

Sustained interruption defines RMS voltage reduces less than 0.1 p.u and time duration lasts more than 1minute[17].

Main causes of sustained interruption are failure of system equipment and protection devices, early planned interruption [19].

According to Figure 2.7, system RMS voltage reduces zero “0” at more than 1 min.

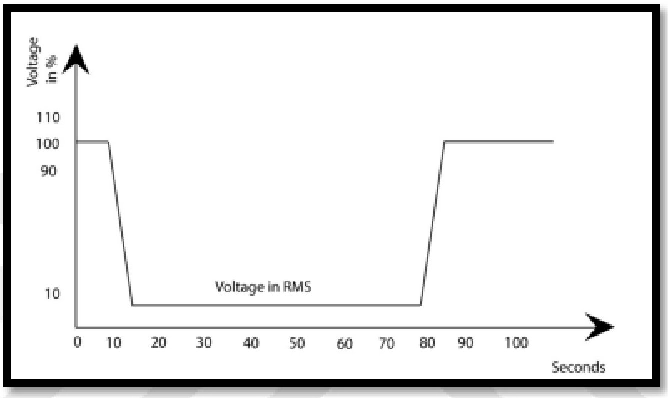

Figure 2.7. *Sustained interruption in RMS* [17]

2.2.4. Unbalance or imbalance

Voltage unbalance is obtained negative sequence component divided by positive sequence component of three phase voltage as a percentage, as well as current unbalance is get ratio of negative sequence component to positive sequence component like the voltage imbalance formula [2]. In other definition, if magnitude of three phase voltages and their degrees (not 120 degree) are not equal to each other, the phenomena can happen [28].

$$V_{unb}(\%) = \frac{V_{neg}}{V_{pos}} \times 100\% \quad \textbf{(2.5)}$$

$$I_{unb}(\%) = \frac{I_{neg}}{I_{pos}} \times 100\% \quad \textbf{(2.6)}$$

The stable operation of the electrical network is important for the safe operation and efficiency of the systems that make up the grid. With some standards, this situation has been preserved. While according to ANSI C84.1 standards, recommended voltage imbalance amount is 3%, regarding to national equipment manufacturers association, its ratio is 1% [22],[18].

Major cause of instability in voltage is large load on single phase system instead of three phase source. Others are increasing heat losses, nonequal impedances, generation failures etc [20],[22].

According to Figure 2.8., V+ shows positive sequence voltage, whereas V- shows negative sequence voltage and also VUF is voltage unbalance factor calculating with equation (2.5) [22].

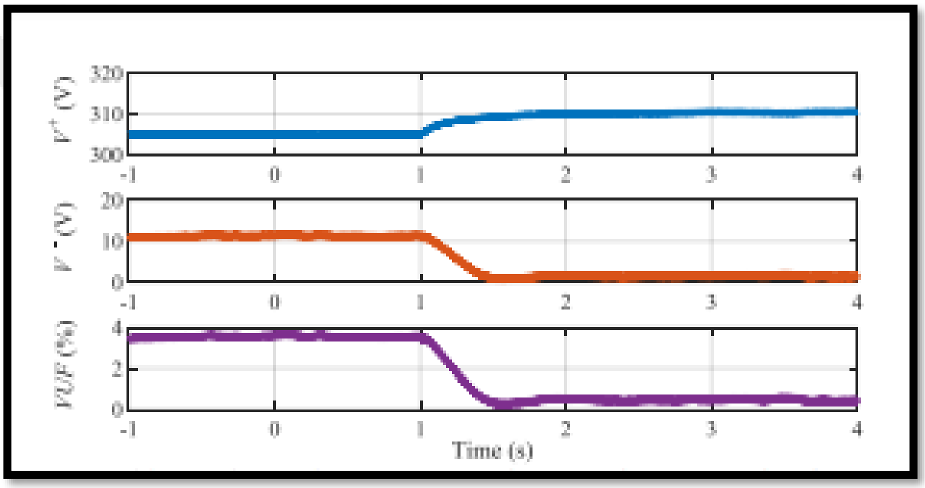

Figure 2.8. *Voltage unbalance definition* [22]

2.2.5. Waveform distortion

According to IEEE 1159 standards, waveform distortion defines deviation from ideal sinus waveform. Noise, harmonics, interharmonics, notching and DC offset are consisting of distortion.

2.2.5.1. Noise

Noise event is observed in voltage or current or both as undesired signal. In other words, if another signal having different frequency is added main voltage includes undesired noise signal [31].

In addition, main reasons of the phenomena are electromagnetic interference (EMI), corona interference, radio frequency interference, power electronic devices and switching power circuits[16]. Besides, arc furnaces, electrical furnaces and welding equipment having large load are reasons of the event [19].

According to Figure 2.9, noise effect is shown on a voltage signal.

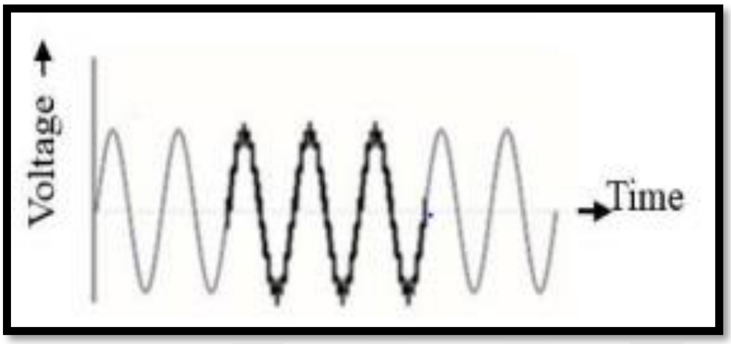

Figure 2.9. *Noise definition* [31]

2.2.5.2. Harmonics

Harmonics are adding fundamental frequency of periodic wave as multiple integer frequencies in voltage, current or both signals. Fundamental frequencies are 50Hz or 60Hz in a power system. To illustrate, if the system includes 100Hz ,150Hz,200 Hz or 250 Hz, it means observable second, third, fourth and fifth harmonics respectively. In addition, odd harmonics include odd numbers (e.g.,3,5,7…) and even harmonics include even numbers (e.g.,2,4,6,8…). Harmonic number one "1" is defined as fundamental component of a periodic wave, besides harmonic number zero "0" is defined as DC component or constant of the periodic wave [41].

Most important cause of the harmonics is static power electronics devices (e.g., inverters, converters) and switched control circuits. Other causes are AC and DC speed drivers, lightining strikes and electrical arc furnaces [41].

According to Figure 2.10, third order harmonics adds to fundamental frequency on voltage signal. Result of summation signal is shown in Figure 2.11. Voltage waveform destroys periodically with harmonic signal.

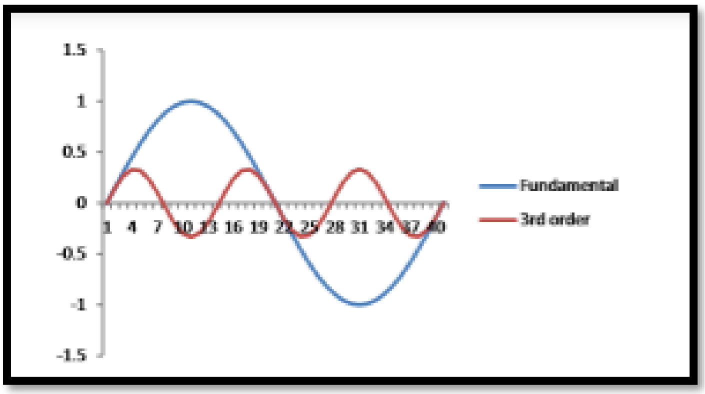

Figure 2.10. *Harmonics in voltage* [18]

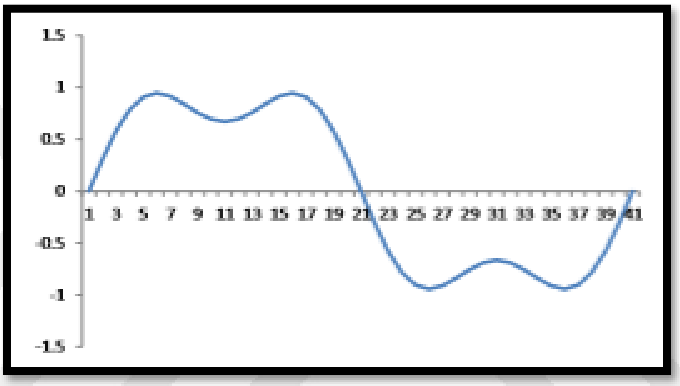

Figure 2.11. *Result of signal summation* [18]

2.2.5.3. Interharmonics

Interharmonics do not comprise of integer multiples of fundamental frequency. In other words, some frequencies can be observed that do not have a coefficient of fundamental frequencies and waveforms with intermediate frequency are nonperiodic [25],[26]. They cannot define with certain standards as limit values. Besides, interharmonics cause voltage fluctuations and voltage flickers [27].

Main causes of interhormanics are arc furnaces, converters, semiconductor devices like switching technologies etc. Especially in, interharmonics detection and its control are very important for connected power grid sensitive loads (e.g.communication, programmable control devices), integrated renewable energy sources and its control(e.g.microgrid,smart grid) due to intermittent nature.

According to Figure 2.12, interharmonic frequencies and harmonic frequencies were shown and interharmonics are outside of fundamental frequency and multiplied integer coefficient of it.

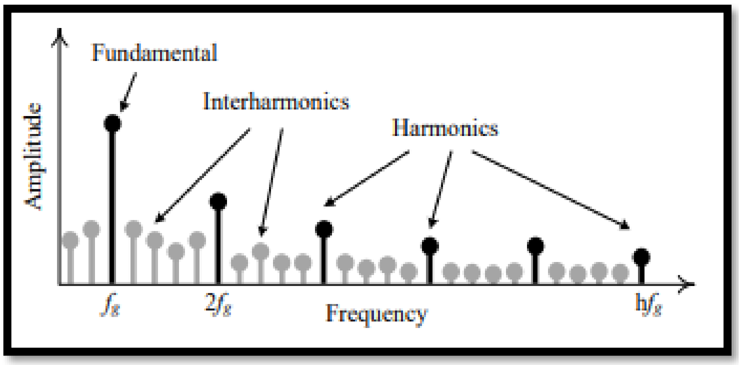

Figure 2.12. *Interharmonics definition* [23]

2.2.5.4. Notching

Notching happens due to change of commutator current in power electronics devices (e.g., controlled rectifiers etc.) in voltage signals. When a commutation occurs between the phases, short circuit can happen between the two phases. This situation can lead to notching disturbances in three phase voltages. Furthermore, it is iterative event and magnitude of notching depends on current flow, line impedances and commutation angle. In addition, it lasts in microseconds [17].

Notching observes speed drivers and Uninterruptible power supply (UPS) units frequently due to power electronics regulators [26].

According to Figure 2.13., the notch continues throught the phase. The phenomena lasts very short time(microseconds).

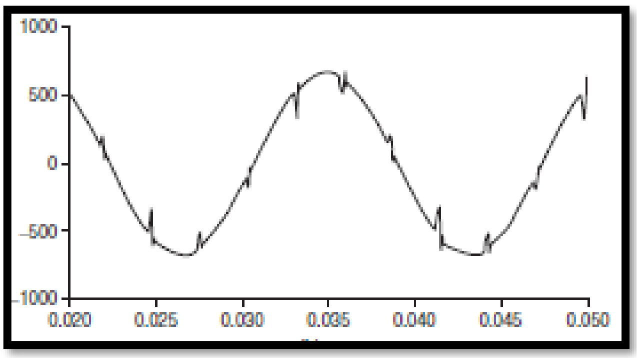

Figure 2.13. *Notch definition* [20]

2.2.5.5. DC offset

DC offset is the existence of a DC current or voltage component or both of them in an AC system [19].

DC offset can due to operation of rectifiers, other electronic switching devices and geomagnetic disturbances [21].

According to the Figure 2.14., as a result of applying a nearly zero DC current, the AC voltage is slightly shifted proportional to the amount applied.

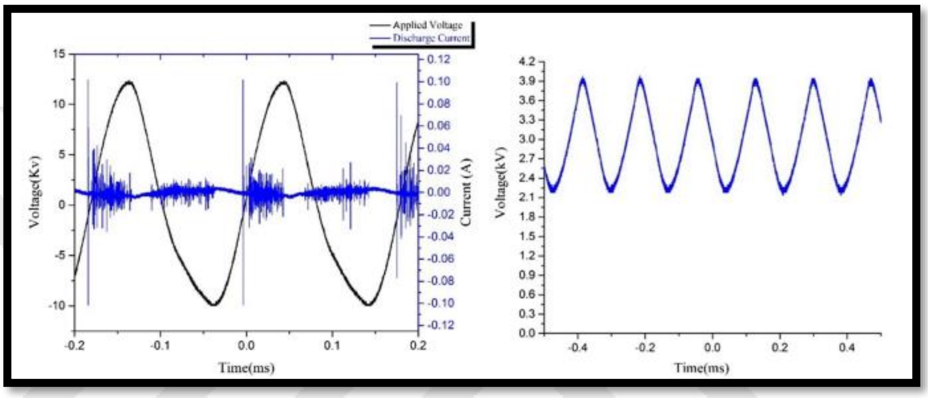

Figure 2.14. *DC offset definition* [24]

2.2.6. Voltage fluctuation

According to ANSI C84.1 standards, voltage fluctuations occurs in range of certained voltage magnitude (e.g., 0.9 p.u to 1.1 p.u) or random voltage variations on periodic wave. In other words, it can be explained as continue RMS voltage change. While under percentage of ten (10%) in voltage fluctuation does not effect on electronics equipment, it causes instability voltage and current on the equipment with increasing of magnitude of fluctuations. As a result, performance of the electrical system and the equipments decreases. The most important cause of the phenomena is arc furnaces because of using of huge power during heavy weightless process. This case has sudden change in system loads. In the same way, welding machines, motor drivers and pulsed power output can lead to voltage fluctuations [17],[18].

Unwanted result of voltage fluctuations can cause voltage flicker. It means that .continues and fast change in load charge can lead of voltage flicker. If flicker frequencies are range of 6Hz and 8Hz, the case is able to represent with human eye like lamp fluctuations. Causes of voltage fluctuation also same effects with voltage flicker [28].

According to Figure 2.15, U_{mean} is average RMS voltage of a power system and the voltage fluctuation goes on through in phase.

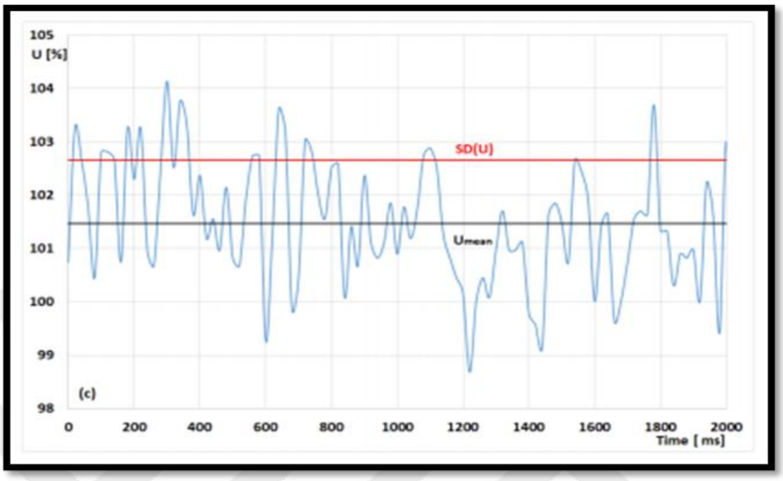

Figure 2.15. *Voltage fluctuations* [30]

2.2.7. Power frequency variations

Power frequency variation event is deviation of fundamental frequency in a power system (50Hz or 60Hz) [19]. Deviation limit frequency is 50 Hz or 60 Hz(-,+)1.5Hz.[31].

Power frequency depends on rotational speed of generator and frequency deviation is related to load features [31].

According to Figure 2.16., fundamental frequency (average) is 60Hz and while one of frequency variation is between 60.03Hz (max) and 59.951Hz(min) [25].

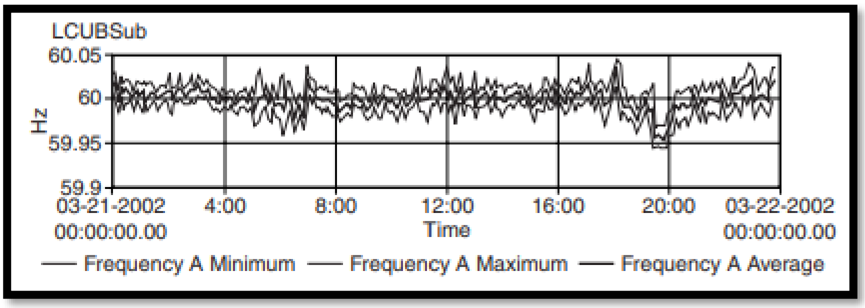

Figure 2.16. Frequency deviation [25]

2.3. Effects and Solutions of Power Quality Disturbances

Electrical power system comprises linear and nonlinear loads (complex loads). When electrical connection consider in the system, It includes power utilities, transmission and distribution networks, electrical devices transmitted energy and end users(residential, industrial and commercial).Linear loads means that relationship between the voltage and current signal is proportional each other and have ideal sine waveform at constant fundamental frequency. It can be said that the energy quality of the grid, which maintains its linear load status, is ideal and it is a reliable system with high efficiency by ensuring the production-consumption balance.

Protecting the power system from non-linear loads is very important for many reasons. Non-linear load is a condition in which the sine waveform is distorted, in which there is a non-proportional charge exchange between voltage and current, where the frequency varies. These loads can count required heavy-duty arc furnaces, heavy load electrical machines, power electronics devices (e.g., converters, inverters, rectifiers) and switching elements, adjustable speed drivers, UPS (Uninterruptible Power Supplies), PLC (Programmable Logic Controller) devices, computers and printers as a sensitive load devices. When the devices are used in the electrical power systems, it can draw harmonic current. Besides, according to failure type in the devices and other external factors (e.g., strike of tree, human, animal or weather conditions), inrush or less current draw from the system. This case causes various power quality disorders in transmission and distribution networks and this situation affects both producers and consumers negatively. Harmonic currents or voltage or both have many differences frequency component. In addition, noise phenomena is consist of several frequencies at the same with harmonics. When one of the harmonic frequencies is equal to capacitor or inductor, resonance can happen. Besides, the situation can be observed between capacitor and inductance impedances during equality of impedances and magnetic and frequency interferences can cause the phenomena. It is important issue, because high energy turns up during the resonance. It affects overheat on electrical devices and electrical networks, device malfunctions and also it can bring about fires. Furthermore, high current can bring about undervoltage, voltage sag, voltage swell and overvoltage phenomena. The events can affect same with other disturbances. Other important effect is weather conditions. It brings about undesired problems in the traditional and smart grids. Especially in, wind and solar energy which are the main distributed(renewable) energy resources have intermittent and probabilistic nature. Both the case and using of power electronic devices can cause variety power quality problems like transients, notching, harmonics, voltage disturbances etc. Therefore, these situations lead to power losses on transmission and distribution lines and power system cannot work safely and efficiently and various malfunctions in the system. Furthermore, the disturbances affect the power factor and it is reflected as a penalty fee on the invoices in the businesses. Then, interruption and especially in sustained interruption events can bring about stopped production at industrial area. It causes loss of production along with loss of workforce. Lastly, operational time can be extended and lifetime of the using of devices can reduce.

Suitable and effective solutions are executed the power system in order to prevent, eliminate and mitigate the power quality distortions. Meanwhile, using of some compensations or methods are explained for traditional power grids and smart grids.

Firstly, line voltage regulators arrange output voltage if input voltage changes. It works same method with transformers. It compensates the voltage disturbances (voltage sag, swell and transient) with below formula [21].

$$\frac{E_1}{E_2} = \frac{I_2}{I_1} = \frac{N_l}{N_2} \tag{2.7}$$

The regulators include tap changers, buck – boost regulators and constant voltage transformer. While tap changers provide to order voltage distortions, buck- boost regulators increase output voltage during boost mode, decrease output voltage during buck mode and constant voltage transformer provides to hold constant for output voltage.

Static var compensators (SVCs) prevents from voltage sags, flickers and fluctuations in transmission and distribution networks.

Static synchronous compensators (STATCOMs) eliminate voltage fluctuations and provide load compensation.

Dynamic voltage restorers (DVRs) inject required voltage during voltage sag and swell phenomenas rapidly [38].

Isolation transformers eliminate noise, transient and hold harmonic frequencies caused by power plants or utilities [21].

Noise filters prevent unwanted frequencies. It is called low pass filter at the same time. In other words, it passes low frequency components thanks to inductor and capacitor which is connected parallel. In this way, it eliminates harmonics at power grids [21].

Active power filter (APF) and passive power filter (PPF) suppress harmonics but hybrid active passive filters (HAPF) is more effective technology than other filters because of injecting resonance as a solution [38].

Solid state transformers (SSTs) prevent power quality disturbances passing through from consumption side to distribution side [21],[38].

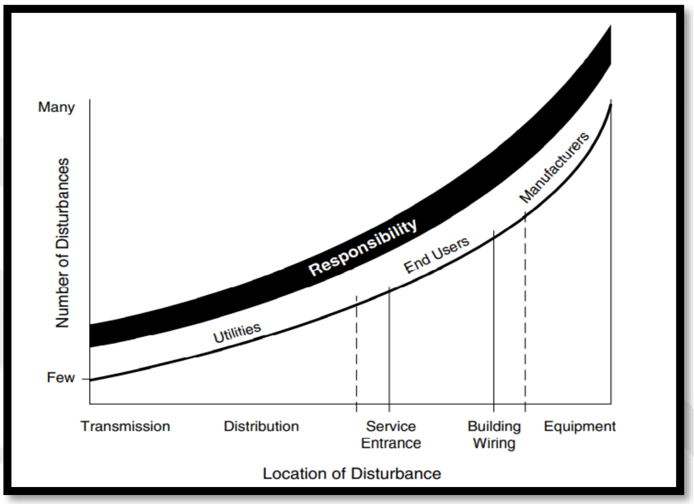

Figure 2.17. *Responsibility amount for preventing power quality disturbances* [6]

Artificial Neural Networks algorithms can provide estimating power quality disturbances early, so we can take measurements against to power quality problems. In other words, power quality can protect and improve with using of effective the algorithms. Ensemble learning algorithms (bagging, boosting, stacking) are robust and outperformance regarding to other machine learning and artificial neural network (ANN) methods to predict fault varieties (phase and ground faults), optimize for decreasing power loss , arrange power factor on transmission and distribution electrical networks. If reason of the situation is explained briefly, these algorithms comprise many different machine learning algorithms at the same time, and advantage of it is especially in effective features of the algorithms are shown in that time, as a result, these methods generalize better [39],[44] In recent years, Graph Neural Networks (GNN) algorithm is one of the effective solutions. It is recommended for prediction of power quality disturbances, solar and wind power, failures and power flow analysis to capture spatial-temporal features of the bus systems. While nodes(buses) include features, edges (power lines) express relationship between the node features. Locations and distances of both nodes and edges can be certained for topologic features. The features are transmitted by communicating in each iteration(k-loop) to neighboring nodes, until summation of node features reach target node As a result, all features are aggregated to target node. This method is called "message passing method". Moreover, dynamic parameters which changes in time can hold with Long-Short Term Memory (LSTM) as a time series model, so LSTM based GNNs predictions can be made like voltage stability, fault location and load shedding. The algorithms are useful and robust [42],[43],[45].

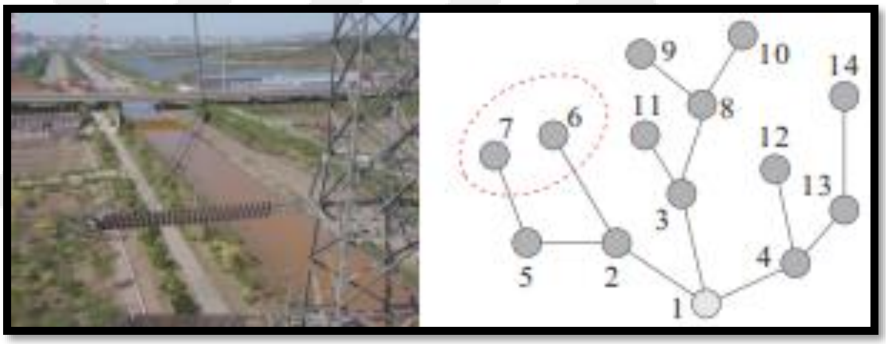

Figure 2.18. *Graph structure on 14 bus power grids* [43]

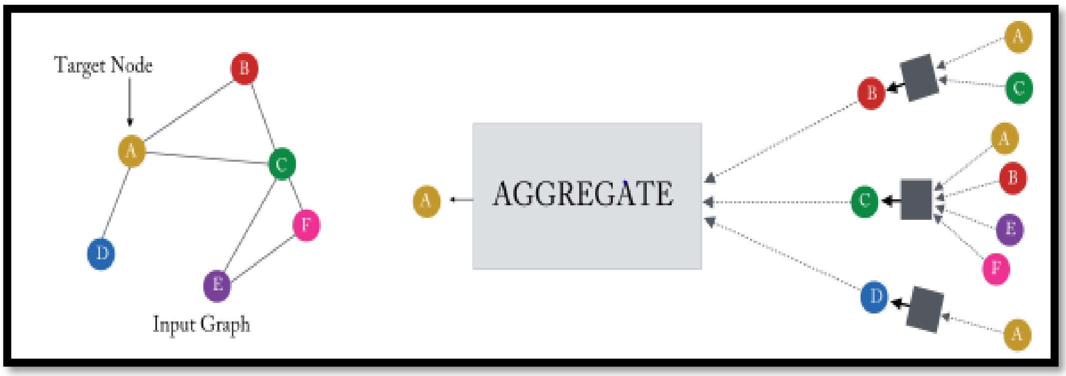

Figure 2.19. *Message passing for GNN* [45]

Lastly, in grid structures where distributed energy sources such as smart grid and microgrid are used, the use of energy storage units and integrated power electronics technology (e.g., buck-boost converter) makes it possible to perform a balanced and controlled bidirectional load exchange. Consumption-controlled, cleaner, quality and economical power system for both the producer and the consumer can be one of the effective solutions [50].

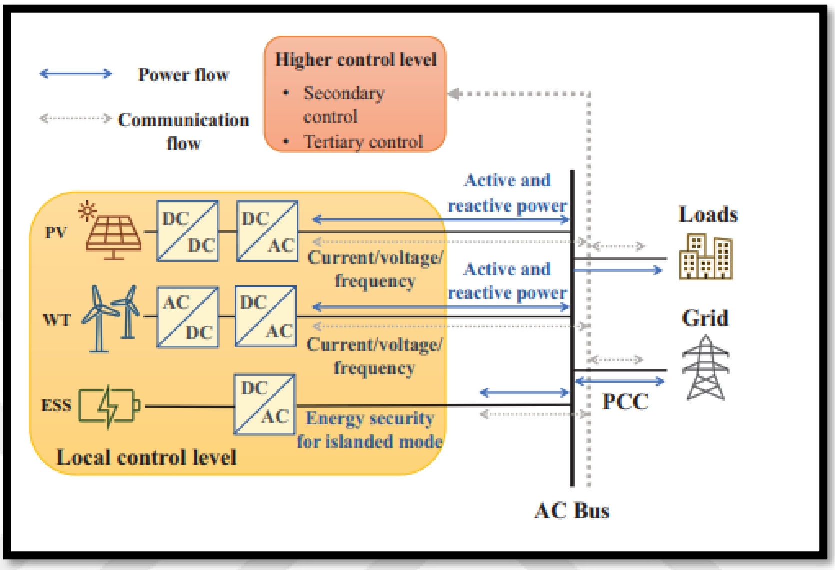

Figure 2.20. *Microgrid structure* [37]

3. SHORT CIRCUIT FAULTS

Short-circuit faults are the most common type of fault that causes unbalanced load flow in a power system, causing power quality problems and preventing the efficient operation of the power system and the connected devices. High current emerges in a power system during short circuit faults. The high fault current produces huge electromagnetic force in electrical machines (e.g., transformers, motors, generators). The situation leads to power loss, overheating and isolation error on windings of the devices. The short circuit currents can show up result of the contact of lines without insulation at the same time [48].

Short circuit faults are four varieties including single phase ground fault (LGF), two phase ground fault (LLGF), two phase fault (LLF) and three phase fault (LLLF).

In this chapter, when short circuit fault occurs in any of the power system, an examination will be made on how the fault analysis is done and how the current and voltage are affected by the power magnitudes. These analysis and calculations are defined regards to IEEE, IEC and ANSI standards [47].

3.1. Investigation of Short Circuit Faults

Power supplies produce voltages that phase angles are 120 degrees displaced and magnitudes are equal each others in a balanced three phase system. If the system is balanced, it means that load flow provides efficiently and the power system continues to work reliability. In this way, energy production and consumption are stable. However, when short circuit fault show up due to any reason or injected fault, the system is unbalanced, in other words, power supplies produce voltages that phase angles are not sequence and voltage magnitudes are different from each others. Providing stability of energy production-consumption (load flow) must require again. Dr.Charles LeGeyt Fortescue offers “Symmetrical Component Analysis” to solve case of unbalanced three phase system in 1918 at American Institute of Electrical and Electronics Engineering Conference[48].

3.2. What is symmetrical(sequence) component method?

Positive, negative and zero components of voltage or current phasors are existed on both symmetrical(balanced-sequence) and unsymmetrical (unbalanced) in three phase system. Only positive sequence can be demonstrated for sequence(balanced) electrical systems because all of components are independent from each other so, voltage magnitudes of the system are equal, phase angles are displaced with stable 120 degrees. However, all of components are appeared for unbalanced power system, because the components connect each other due to connection of fault regions during the short circuit fault [46]. The occurred components are calculated by using of circuit of positive, negative and zero components. Impedances of power components in power lines are neglected to calculate simply. The condition is assumed that their magnitudes does not change in time [47].

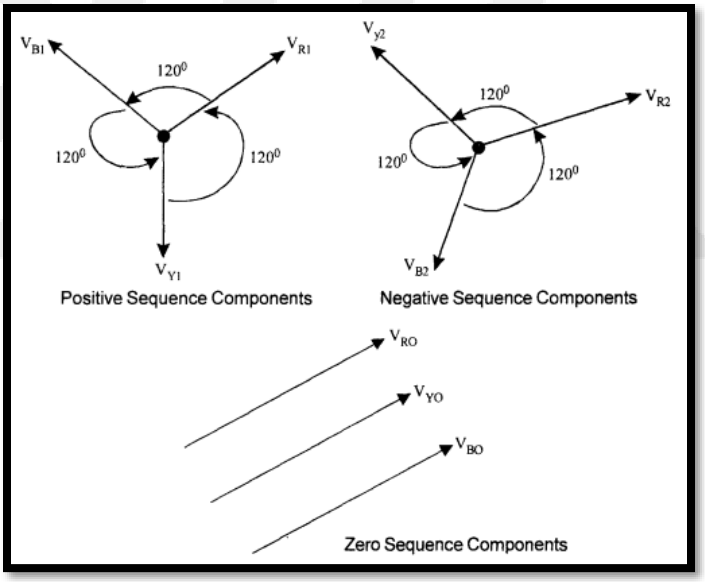

Figure 3.1. *Sequence components* [48]

As it is seen in Figure 3.1., in balanced power system, positive and negative sequences of voltage phasors are equivalent, and differences of phase are 120 degrees displaced. Then, zero sequence components are magnitudes are same but, phase angles are zero, so they are parallel to each others. Besides, positive sequence and negative sequence components forwards to direction of anti-clockwise [47].

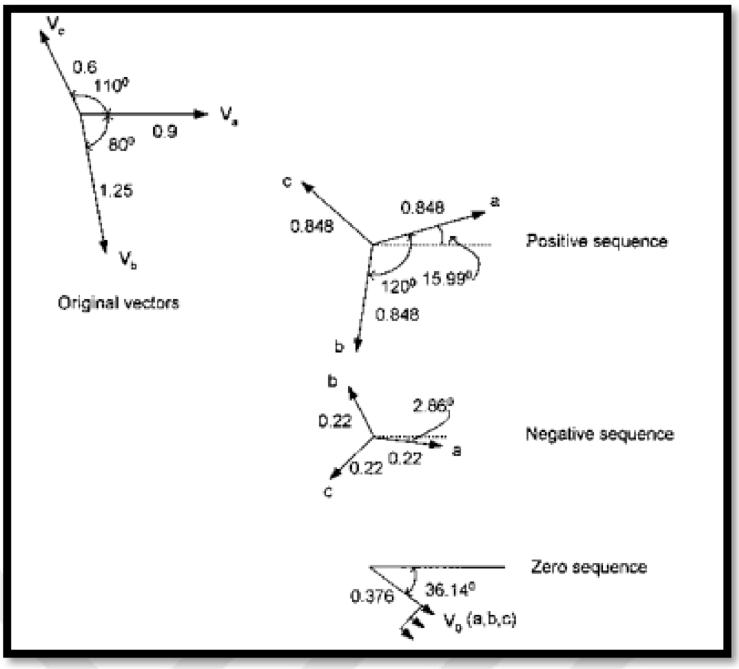

Figure 3.2. *Unbalanced components* [47]

According to Figure 3.2, unbalanced components three phase voltages are demonstrated. Magnitudes of V_a, V_b, V_c phasors equals to 0.9,1.25 and 0.6 respectively and phase angles are different from each others. The symmetrical component method is executed to analyze the unbalanced situation. Hence, unbalanced phasors are separated to symmetrical components.

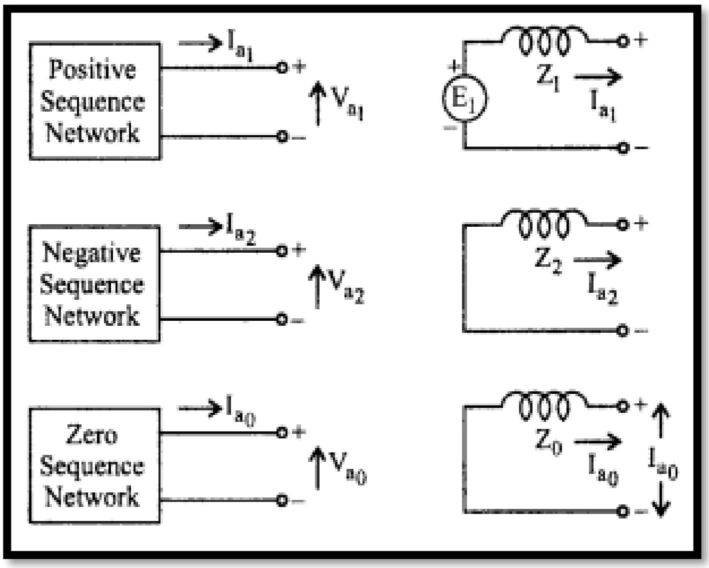

Figure 3.3. *Sequence circuits* [48]

Sequence circuits do not merge because of without short circuit fault. In this way, the voltages values are equal to the voltage provided by the power system since only positive component is observed for balanced power systems in Figure 3.3.

The sequential circuits mentioned above are Thevenin equivalent circuits. In the case of a short circuit, these circuits integrate with each other according to the type of short circuit fault.

When voltage and current phasors and their symmetrical components calculate, phasor V_a and a unit vector are referenced. If the calculation is made for unbalanced component of the voltage and current phasors, equations in matrix form are created as follows.

$$\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \begin{bmatrix} v_0 \\ v_1 \\ v_2 \end{bmatrix} \qquad (\mathbf{3.1})$$

According to above matrix formulation, V_a, V_b and V_c show phasors of voltage in an unbalanced three phase power system , V_0, V_1 andV_2 are symmetrical components of the phasors and also a is unit vector whose magnitude is one(unit) and phase angle equals 120 degrees[49].

$$a = 1\angle 120 \qquad \textbf{(3.1.a)}$$

$$a^2 = 1\angle 240 \qquad \textbf{(3.1.b)}$$

$$V_a = V_0 + V_1 + V_2 \qquad \textbf{(3.1.c)}$$

$$V_b = V_0 + a^2 V_1 + aV_2$$

$$V_c = V_0 + aV_2 + a^2 V_2$$

Phasor components of voltages are found from result of matrix solution in equation (3.1.). Then, reverse of L (transformation) matrix is get to symmetrical component of the phase voltages. It is shown that how to solve the matrix equations in below.

$$L = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \;,\; L^{-1} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix} \tag{3.2}$$

$$V_g = \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \;,\; V_{k=} \begin{bmatrix} v_0 \\ v_1 \\ v_2 \end{bmatrix} \tag{3.3}$$

$$V_k = L^{-1} V_g \tag{3.4}$$

From equation (3.4), sequence components are shown up like below matrix.

$$\begin{bmatrix} v_0 \\ v_1 \\ v_2 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \tag{3.5}$$

$$V_0 = \frac{1}{3}(V_a + V_b + V_c) \tag{3.5.a}$$

$$V_1 = \frac{1}{3}(V_a + aV_b + a^2 V_{c)}$$

$$V_2 = \frac{1}{3}(V_a + a^2 V_b + aV_c)$$

As seen in the above equations, the phase components and symmetrical components of the voltages can be written in terms of each other. Besides, same equivalents can be constituted for phase currents.

$$\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix}\begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} \tag{3.6}$$

Phase components of the current are expressed in equation (3.6.a). Symmetrical components of the phase current can be solved in the same way.

$$I_a = I_0 + I_1 + I_2 \tag{3.6.a}$$

$$I_b = I_0 + a^2 I_1 + aI_2$$

$$I_c = I_0 + aI_1 + a^2 I_2$$

$$L = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \;,\; L^{-1} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix} \tag{3.7}$$

$$I_g = \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \;,\; I_k = \begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} \tag{3.8}$$

$$I_k = L^{-1} I_g \tag{3.9}$$

$$\begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{3.10}$$

$$I_0 = \frac{1}{3}(I_a + I_b + I_c) \tag{3.10.a}$$

$$I_1 = \frac{1}{3}(I_a + aI_b + a^2 I_c)$$

$$I_2 = \frac{1}{3}(I_a + a^2 I_b + aI_c)$$

3.2.1. Explanations of short circuit faults

Three phase currents and voltages are separated zero, positive and negative symmetrical components during the any short circuit fault [46]. Aim of using of symmetrical component analysis, after occurred the fault, in an unbalanced power system, the current and voltages can be provided representation of sequence components and then the sequence phase voltages and short circuit currents can be computed simply.

Short circuit faults are divided two parts to be symmetrical(balanced) short circuit fault and unsymmetrical short circuit faults. Symmetrical fault is three phase (LLLF) fault because it includes only positive sequence component as same as balanced power system. Therefore, during the fault, the voltages and phase angles are equal and sequential to each other. Unsymmetrical faults are single phase ground fault (LGF), two phase ground fault (LLGF) and two phase fault (LLF). The sequence components can be calculated according to varieties of short circuit faults. Phase angles are not sequence and phase voltages are not same magnitudes during the fault. As a result, unbalanced phasor magnitudes are solved to symmetrical components by using of symmetrical component analysis.

Simulation of IEEE9 bus test system is made in order to observe how to effect phase voltage magnitude during the short circuit fault with using of MATLAB / Simulink tool.

If general information is given about the system briefly, three generators that feeds the AC system and supply voltage values are 18kV,13.8kV, 16.5kV. Then, the system has three step up transformers in order to rise mid voltage level to high voltage level and three constant PQ loads are connected. Besides, structure of IEEE9 bus was explained in 6th chapter in detail. Fundamental frequency of the system is 50Hz. While external short circuit fault is executed to phases on 6^{th} bus, effects of short circuit faults are observed on $6^{th}$and 3^{th} buses. In addition, executed time horizon is between 1 and 1.1 seconds and fault resistance value is 0.001 ohm.

In short, when single phase ground, two phase ground, two phase and three phase short circuit faults are applied to the 9 bus test system with simulation tool respectively, relationships between the effects of short circuit current and phase voltage magnitudes can be observed easily.

3.2.1.1. Single phase ground fault (LGF)

The fault occurs during contacting of any one phase and earth or neutral zone. It is the most common type of fault in the electrical network. It is less dangerous than other faults. During the fault, short circuit current happens on only faulty phase, it does not emerge on other phases [46]. When single phase short circuit is evaluated, Z_f is fault impedance, Z_0 ,Z_1 and Z_2 are zero, positive and negative sequence impedances respectively. In addition, V_f is fault voltage. As it is seen, zero, positive and negative sequence components connect series with each other and only fault current passes through in the circuit so, I_0 = I_1=I_2 and symmetrical components of voltage phasors (V_0, V_1,V_2) are calculated from this circuit. As it is seen, V_a is reference phase voltage for symmetrical component methods.

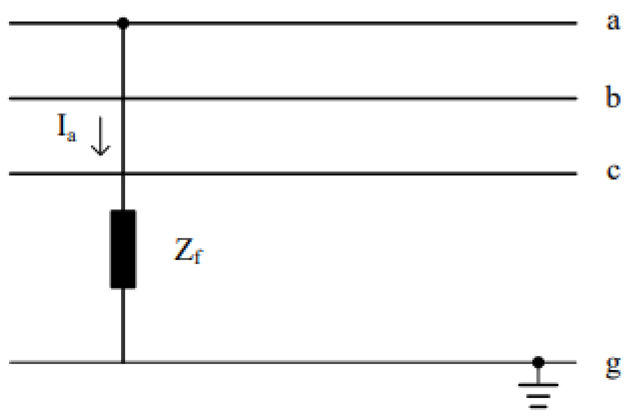

Figure 3.4. *Representation of LGF* [46]

$$I_b = I_c = 0 \tag{3.11}$$

$$V_a = I_a Z_f \tag{3.12}$$

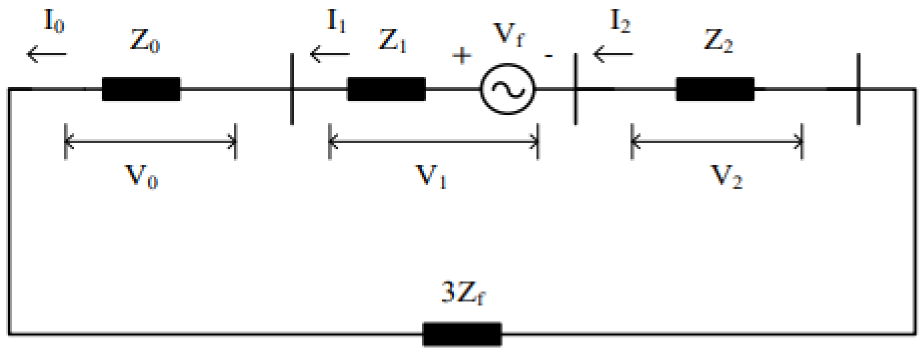

Figure 3.5. *LGF circuit* [46]

$$\begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} I_a \\ 0 \\ 0 \end{bmatrix} \tag{3.13}$$

$$\frac{1}{3} I_a = I_0 = I_1 = I_2 \tag{3.13.a}$$

$$V_0 + V_1 + V_2 = 3Z_f I_0 = V_f \tag{3.14}$$

$$I_0 = \frac{V_a}{Z_0 + Z_1 + Z_2 + 3Z_f} \tag{3.15}$$

When single phase short circuit fault evaluates on IEEE 9 bus test system as an example in time axis, as seen in Figure 3.5, since there is no fault in phases b and c, the phase voltages are equal to the voltages coming from the generators.

The voltage is measured 0.1819 p.u approximately at 1.028 seconds in Figure 3.6. , when a phase short circuit fault is occured on 6th bus. The interruption phenomena is happened on fault time range.

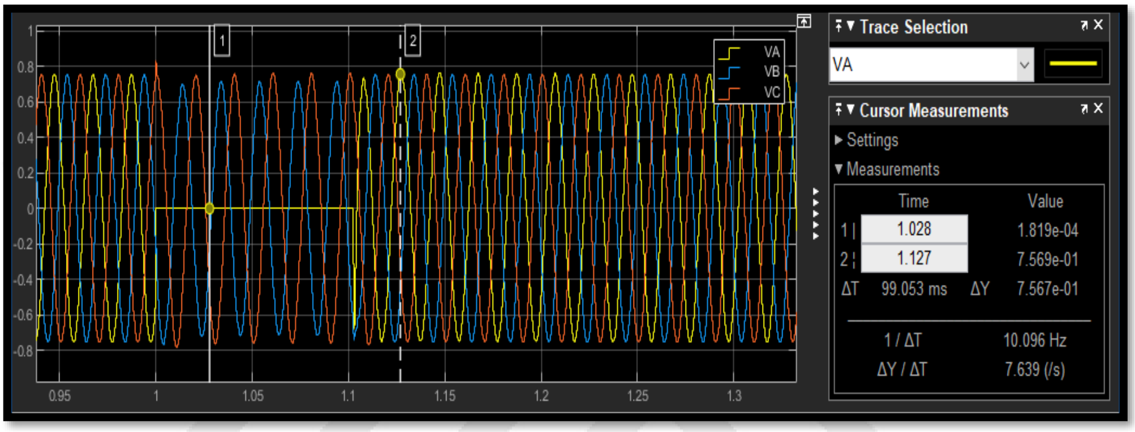

Figure 3.6. *LGF on 6th bus of IEEE 9 bus test system*

Supply voltage value of the system is about 0.7962 p.u. While the b and c phases are at the nearly same value as the voltages supplied from the sources, it is observed that the voltage value in phase a, which has an error, drops to 0.3923 p.u. during short circuit fault for Figure 3.7.

Figure 3.7. LGF on 3rd bus of IEEE 9 bus test system

3.2.1.2. Two phase ground fault (LLGF)

The fault happens between any faulted two phases and ground in the power system. When the sequence circuit investigates, Z_1 and Z_2 impedances are connected parallel and Z_0 is connected to series in the sequence circuit. Furthermore, I_b and I_c currents are short circit currents because phase *b* and *c* are faulted but I_a (non fault phase) equals to zero.

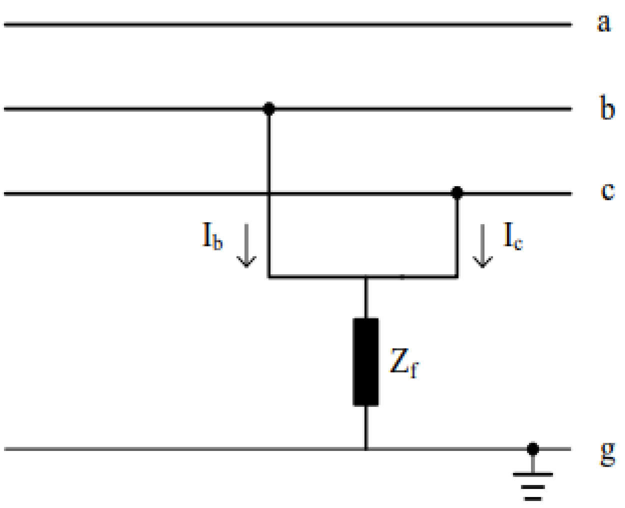

Figure 3.8. *Representation of LLGF* [46]

$$V_b = V_c = (I_b + I_c)Z_f \tag{3.16}$$

$$I_0 = \frac{1}{3}(0 + I_b + I_c) \tag{3.17}$$

$$V_b = V_c = (3I_0)Z_f \tag{3.18}$$

From matrix equivalent equation (3.1.c):

$$V_0 + a^2V_1 + aV_2 = V_0 + aV_1 + a^2V_2 \tag{3.19}$$

$$V_1 = V_2 \tag{3.19.a}$$

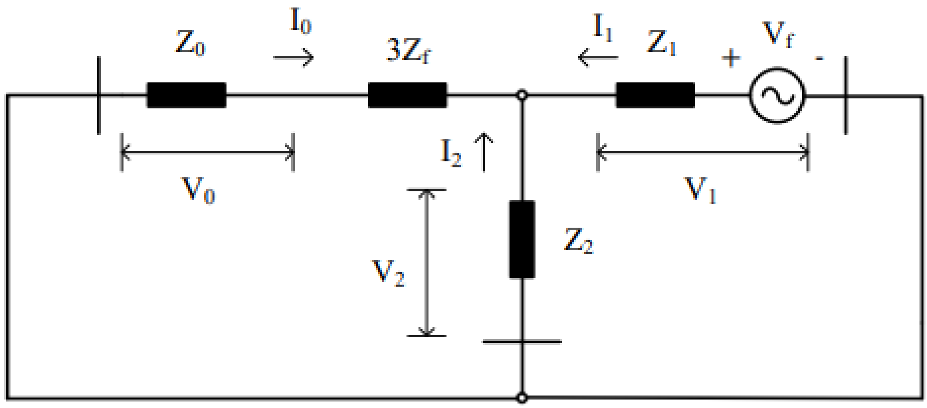

Figure 3.9. *LLGF circuit* [46]

According to the equivalents, LLGF can be draw. In addition, I_0, $I_1$and I_2 are calculated according to node voltage method (voltage equality) or according to the series and parallel connection of the impedances.

$$I_0(Z_0 + 3Z_f) = I_2Z_2 = V_{f-} I_1Z_1 \tag{3.20}$$

$$I_0 = \frac{V_{f-}I_1Z_1}{Z_0 + 3Z_f} = \frac{I_2Z_2}{Z_0 + 3Z_f} \tag{3.20.a}$$

$$I_1 = \frac{V_{f-}I_2Z_2}{Z_1} = \frac{V_{f-I_0}(Z_0 + 3Z_f)}{Z_1} \tag{3.21}$$

$$I_2 = \frac{I_0(Z_0 + 3Z_f)}{Z_2} = \frac{V_{f-I_1Z_1}}{Z_2} \tag{3.22}$$

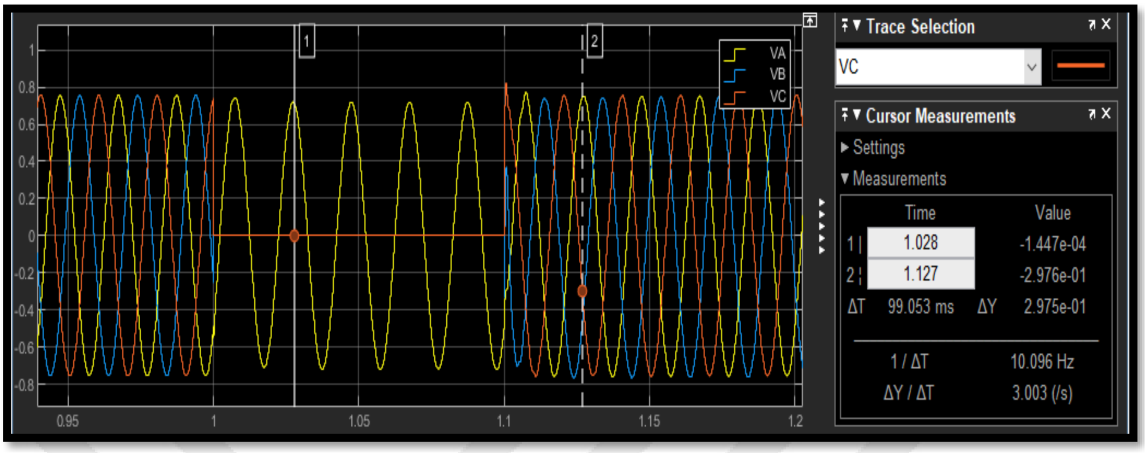

Figure 3.10. *LLGF on 6th bus of IEEE 9 bus test system*

According to the Figure 3.10, a phase voltage is the same magnitude with supply voltages, it does not change during the short circuit fault. Fault current is maximum for *b* and c phases so, V_b and V_c magnitudes are (-0.1447) zero p.u. approximately. Also, while V_a is same magnitude with supply voltages, V_b and V_c magnitudes drops about 0.3444 p.u during the fault in Figure 3.11.

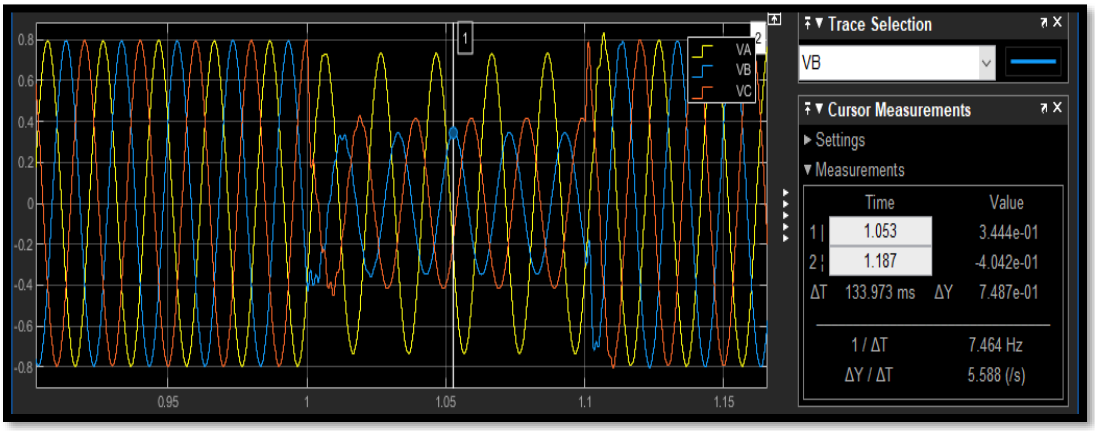

Figure 3.11. *LLGF on 3rd bus of IEEE 9 bus test system*

3.2.1.3. Two phase fault (LLF)

The fault happens between any faulted two phases. When the solution is made according to the representation of LLF on Figure 3.12 and defined matrix equations, the LLF circuit can be drawn. Then, the symmetrical components of the unbalanced current and voltage phases can be calculated. Actually, base of all of calculations is related to general representation of varieties of short circuit faults.

According to the figure below, the fault occurs between phases b and c, so short circuit current does not happen on I_a.

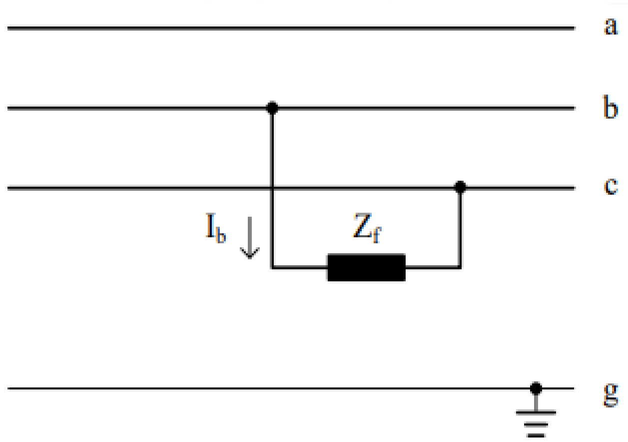

Figure 3.12. *Representation of LLF* [46]

$$-I_{b=}I_c \quad \textbf{(3.23)}$$

$$Z_f I_{b\,=}\, V_b - V_c \quad \textbf{(3.24)}$$

If the above equations are replaced in matrix of symmetrical components method:

$$I_0 = \frac{1}{3}(0 + I_b + -I_b),\ I_0 = 0 \quad \textbf{(3.25)}$$

$$I_1 = \frac{1}{3}(0 + aI_b - a^2 I_b)$$

$$I_2 = \frac{1}{3}(0 + a^2 I_b - a I_b)$$

$$I_2 = -I_1 \quad \textbf{(3.26)}$$

Hence, LLF circuit can be draw like below figure:

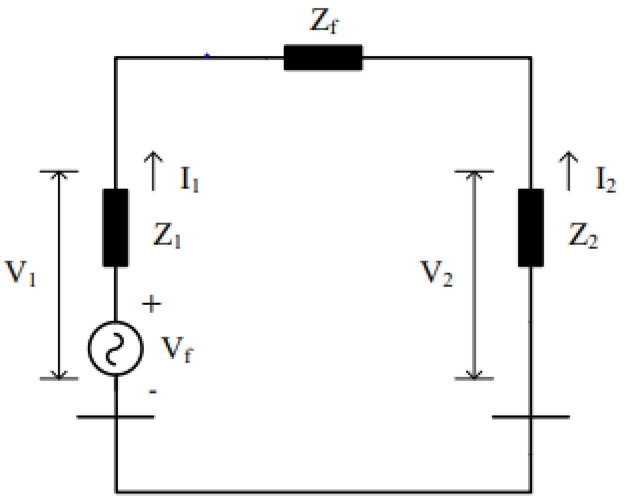

Figure 3.13. *Representation of LLF* [46]

Since current and voltages are directly proportional to each other, similar results are obtained.

$$V_0 = \frac{1}{3}(0 + V_b + V_c) \quad \textbf{(3.27)}$$

$$V_1 = \frac{1}{3}(0 + aV_b + a^2 V_c)$$

$$V_2 = \frac{1}{3}(0 + a^2 V_b + aV_c)$$

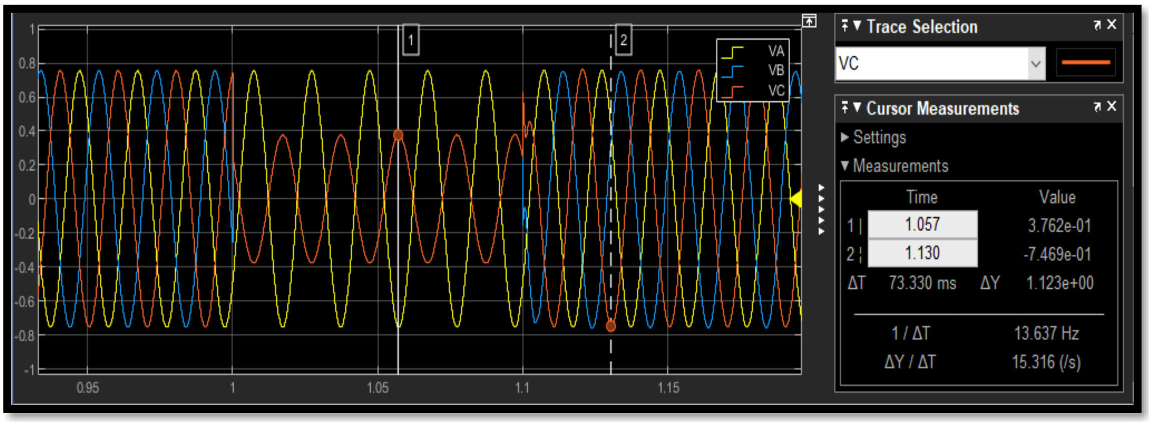

Figure 3.14 *LLF 6 th bus of IEEE 9 bus test system*

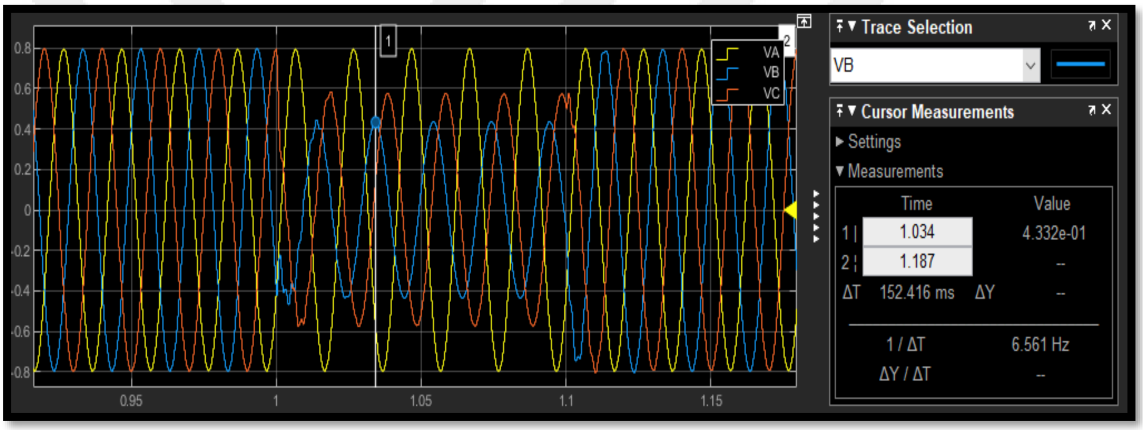

Figure 3.15. *LLF 3rd bus of IEEE 9 bus test system*

When the 9 bus test system, where the 6th bus is faulted, is evaluated, a phase voltage does not change because of nonfault phase but, b phase and c phase voltage magnitude drops to about 0.3762 p.u. due to fault. Furthermore, as it is seen b phase voltage is not able to appear. General reasons of that is can which the bus system feeds from three AC power supplies and three step up transformers, so they convert generator voltage values to 230kv high voltage to work system. When the fault happens on the power system, observing different effects can expected with change of impedances.

If the condition of the fault in the 3^{rd} bus is observed, $V_a$magnitude is same again and V_b and V_c magnitudes are different from a phase voltage because of faulted phases. While V_b magnitude is about 0.4332 p.u., V_c is about 0.5711 p.u. during the fault.

3.1.3.4. Balanced three phase faults (LLLF)

The fault (LLLF) is given or injected on all phases of the power system. Only positive component is shown due to variety of balance fault. It is the fault that causes the most damage to the power system and can lead to catastrophic events, because it draws too much current. Its incidence is less than other types of failures [46].

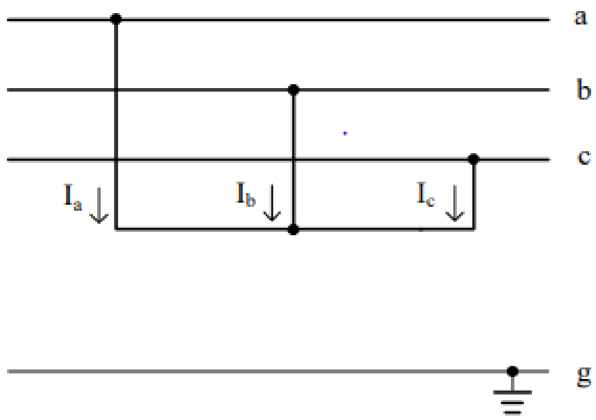

Figure 3.16. *Representation of LLLF* [46]

$$V_a = V_b = V_c = 0 \tag{3.30}$$

$$V_0 = \frac{1}{3}(0+0+0) \tag{3.31}$$

$$V_1 = \frac{1}{3}(0 + a0 + a^2 0)$$

$$V_2 = \frac{1}{3}(0 + a^2 0 + a0)$$

$$V_0 = V_2 = 0 \tag{3.32}$$

The faulted voltages (V_a, V_b and V_c) are equal magnitude with proportional to positive sequence impedance. However, as seen in the equations, since the positive phase component of V_1 is also equal to zero, the matrix equation with sequence impedances is recommended to find the values in the positive component [46].

$$\begin{bmatrix} v_0 \\ v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 0 \\ V_f \\ 0 \end{bmatrix} - \begin{bmatrix} Z_0 & 0 & 0 \\ 0 & Z_1 & 0 \\ 0 & 0 & Z_2 \end{bmatrix} \begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} \tag{3.33}$$

$$I_1 = \frac{V_f}{Z_1} \tag{3.34}$$

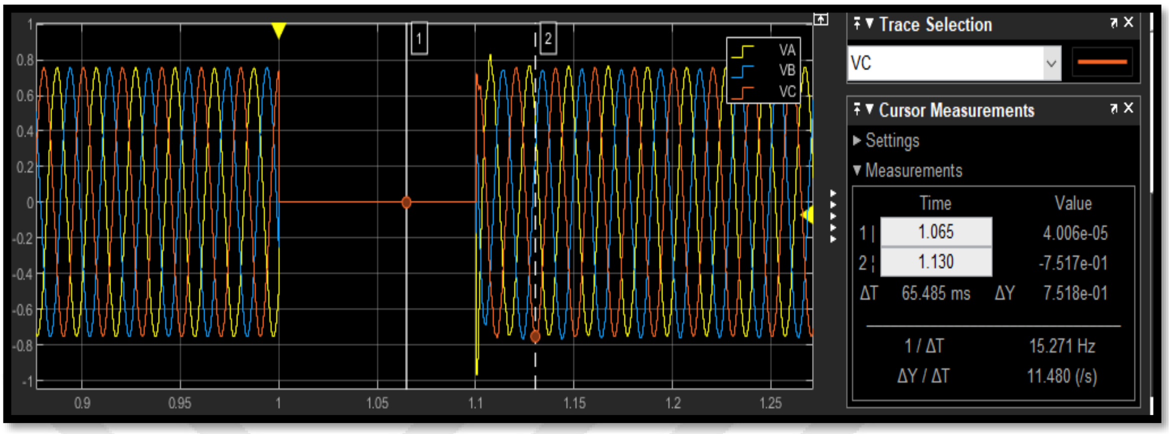

Figure 3.17. *LLLF 6th bus of IEEE 9 bus test system*

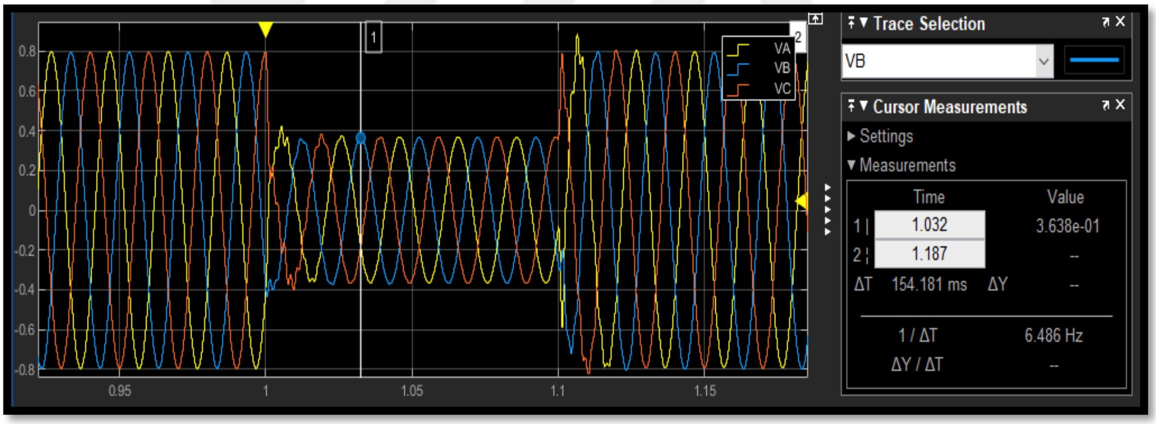

Figure 3.18. *LLLF 3rd bus of IEEE 9 bus test system*

When the sixth bus is faulted, the phase voltages give results close to zero during the fault. It is where the short-circuit current is maximum for Figure 3.17.

Failure to observe the faulty phases b and c during the fault may result in high voltage operation of the system and changes in impedances during fault, as indicated in two phase short circuit faults. In addition, it may be difficult to find the components of faulted currents and voltages by feeding the system with more than one generator, electrical network structure and static power components with using the symmetrical components method. If 3^{rd}bus observe during the fault, according to distance from fault location, the magnitude of phase voltages can be changes at equal amount, because this fault is balanced short circuit fault for Figure 3.18. As it is seen, magnitude of balanced fault voltage phases is 0.3638 p.u.

4. LOAD (POWER) FLOW ANALYSIS

Stability of produced and consumed active and reactive power is important in a power system. When the condition can not able to provide, power losses, power quality disturbances, electricity interruptions and undesired faults can occur on the system. It creates a dangerous situation for both the devices in the circuit and the living things. Particularly, the decrease in the active power and the increase in the reactive power reduce the working efficiency in the electrical system and it is reflected in the electricity bills as a penalty in the utilities that have the electrical machines that produce and consume reactive power. It is the magnitude power factor that shows that the loads are compensated for this occasion. In such cases, since the load flow of the system is calculated, it can be calculated and observed at which point of the power system failure occurs and the risks that may occur. Depending on this situation, malfunctions can be eliminated by using various methods (artificial intelligence methods, compensators, filters etc.) as stated in Chapter 2, according to kind of power problems.

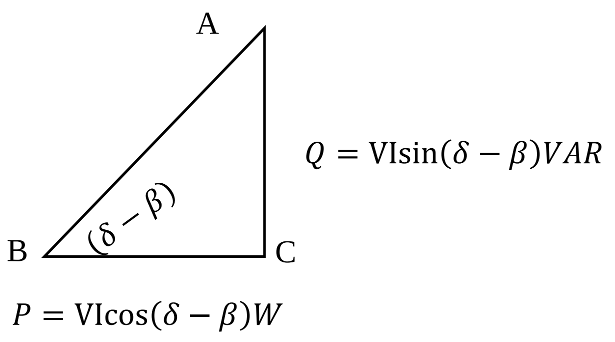

Figure 4. 1. *Power compensation*

$$|AB| = S = VI^* = |V\angle\delta|\ |I\angle\beta|^* = VI\angle\delta - \beta \quad \textbf{(4.1)}$$

$$|BC| = P = VI\cos(\delta - \beta)W \quad \textbf{(4.2)}$$

$$|AC| = Q = VI\sin(\delta - \beta)VAR \quad \textbf{(4.3)}$$

$$S = P + jQ = VI\cos(\delta - \beta) + jVI\sin(\delta - \beta) \quad \textbf{(4.4)}$$

$$S = \sqrt{P^2 + Q^2} \quad \textbf{(4.4.a)}$$

$$\mathrm{pf} = \cos(\delta - \beta) = \frac{P}{S} = \frac{P}{\sqrt{P^2 + Q^2}} \quad \textbf{(4.4.b)}$$

$$I_R = I\cos(\delta - \beta) \quad \textbf{(4.5)}$$

$$I_X = I\sin(\delta - \beta) \quad \textbf{(4.6)}$$

As can be seen in the above equations, the relationship between active power equation (4.2), reactive power equation (4.3) and apparent power equation (4.4) are explained. Power factor formula equation (4.4.b) is produced from these equations. If capacitor or inductor or both are connected to AC power system, the system has capacitive or inductive loads or both of them equation (4.5). Thus, active and reactive power stability can be understood according to these loads. $(\delta - \beta)$ represents angle between voltage and current in the system. When the system current lead from the voltage, the load is capacitive and angle is $(\delta < \beta)$, so reactive power is delivered to the power system. When the system current lags from the voltage, the load is inductive loads and angle is $(\delta > \beta)$, so reactive power is absorbed by the power system. Therefore, it is important that magnitude of $\cos(\delta - \beta)$ is close to 1 to compensate the active and reactive power [49].

Integration of electric vehicle charging stations, renewable energy sources, smart and microgrid transformation cause increase in sensitive loads. Therefore, more innovative solutions can be produced in load flow analysis. Recently, artificial intelligence applications such as graph convolution neural network method has been executed instead of Newton Raphson and Gauss Seidel which are classical and frequent methods. An advantage of GCNN method can be capture spatio-temporal features of any power system successfully [43].

4.1. Computation of Load Flow

Generators that are supplies balanced voltage for system and electrical devices, static power devices (transformers), constant PQ load that absorbs active and reactive power, transmission and distribution networks that have line impedances and buses that hold power magnitudes and deliver to power system in needed are content in general three phase AC power system. The elements of the system have certained power magnitudes. The magnitudes are active power, reactive power, voltage and angle. Main idea of load flow analysis is computation of voltage and angle magnitudes for each buses and providing of stability of active and reactive power in a power system. Thus, while computation of load (power) flow is made, varieties of bus are found for calculation of two unknown parameters of these four main magnitudes. These buses are three kinds as slack (swing)bus, voltage controlled bus (PV) and load buses (PQ)[49].

Slack bus is reference bus, because before computation of load flow, voltage and angle of the bus are certain as a reference for calculation of the magnitudes for each bus. Voltage magnitude equals to 1 p.u and its angle is zero($V = 1\angle 0$). After calculations of voltage, angle, active and reactive power at other buses, active and rective power is calculated for swing bus. Number of swing bus is one. The active and reactive power calculation (net power), which balances the last system, is made in this bus. [49].

Voltage controlled bus (PV) has certained active power and voltage magnitude. After load flow analysis is executed, reactive power and angle of voltage is found.

The last kind of bus is load (PQ) bus. While active power and reactive power are defined as values, voltage and angle values are computed after load flow analysis. Besides, load bus draws active and reactive power, so any power production cannot be observed [49].

These calculations are made by various iterative methods. The used methods are Newton Raphson, Gauss Siedel and Fast Decoupled in generally. As mentioned before, GCNN, which is one of the artificial intelligence methods, offers a more accurate and faster solution than classical methods. Reason of that is GCNN learns load flow computation itself thanks to neural network structure, while classical methods work iteratively [28]. How to solve an iterative method will be explained as an example in mathematically. In addition, computer programs are used for same aim [49].

4.1.1. An iterative method: Newton Raphson

Firstly, how to use iterative method with Newton Raphson is explained step by step and then, Newton Raphson Method is shown. F(x), x and y are context from N vectors [49].

$$y=f(x),\ y-f(x)=0 \qquad \textbf{(4.7)}$$

D is a reversible matrix. If Dx adds on both side of equations:

$$Dx + y - f(x) = Dx \tag{4.8}$$

Reverse of D matrix is obtained (D^{-1}) in order to solve x (unknown) parameter and it is written both side of the equation:

$$D^{-1}(Dx + y - f(x)) = D^{-1}Dx \tag{4.9}$$

$$x = x + D^{-1}(y - f(x)) \tag{4.9.a}$$

When iterative method is executed to new value of x parameter, equations occur like below:

$$x(i+1) = x(i) + D^{-1}(y - f(x(i))) \tag{4.10}$$

y is left alone to occur differential equation:

$$x(i+1) - x(i) = D^{-1}y - D^{-1}f(x) \tag{4.11}$$

$$y = D[x(i+1) - x(i)] + f(x) \tag{4.11.a}$$

$$y = f(x) + \frac{df}{dx} \mid x(i+1) - x(i) \tag{4.12}$$

If Taylor Series approach is used for solution:

$$y = f(x_0) + \frac{df}{dx} \Big|_{x=x_0} x - x_0 \tag{4.12.a}$$

In order to find x parameter:

$$x = x_0 + \left[\frac{df}{dx}\Big|_{x = x_0}\right]^{-1}(y - f(x_0)) \tag{4.13}$$

Jacobi matrix is used to apply transform quadratic iterative solution for unknown load flow parameters:

$$J(i) = \frac{df}{dx}\Big|_{x=x(i)} \tag{4.14}$$

According to equation (4.14), in order to calculate V and δ .

$$x = \begin{bmatrix}\delta \\ \mathrm{V}\end{bmatrix},\ x(i) = \begin{bmatrix}\delta(i) \\ \mathrm{V(i)}\end{bmatrix} \tag{4.15}$$

$$\mathbf{y}=\begin{bmatrix}P \\ \mathrm{Q}\end{bmatrix},\ y=f(x) = \begin{bmatrix}P(x) \\ \mathrm{Q(x)}\end{bmatrix} \tag{4.16}$$

$$\mathbf{y(i)} = \begin{bmatrix}P(i) \\ \mathrm{Q(i)}\end{bmatrix},\ \Delta y(i) = \begin{bmatrix}\Delta P(i) \\ \Delta \mathrm{Q(i)}\end{bmatrix} \tag{4.16.a}$$

$$\Delta y(i) = \begin{bmatrix}P - P[x(i)] \\ \mathrm{Q - Q[x(i)]}\end{bmatrix} \tag{4.16.b}$$

Y(admittance) is adopted for solution of Newton Raphson Method:

$$Y_{kn} = G_{kn} + jB_{kn} \tag{4.17}$$

k and n define which bus participates in load flow calculation, they are bus numbers (k,n=1,2,3…N)[49].

$$I_{k=}\sum_{n=1}^{N} Y_{kn}V_n \tag{4.18}$$

$$S_k = P_k + jQ_{k=} V_k {I_k}^* \tag{4.19}$$

$$S_k = V_k\left(\textstyle\sum_{n=1}^{N} Y_{kn}V_n\right)^{*} = V_k \textstyle\sum_{n=1}^{N} Y_{kn}V_n\, e^{j(\delta_k-\delta_n-\theta_{kn})} \tag{4.19.a}$$

$$P_k = P_k(x) = V_k \sum_{n=1}^{N} Y_{kn}V_n \cos(\delta_k - \delta_n - \theta_{kn}) \tag{4.20}$$

$$Q_k = Q_k(x) = V_k \sum_{n=1}^{N} Y_{kn}V_n \sin(\delta_k - \delta_n - \theta_{kn}) \tag{4.21}$$

Equation (4.14) is represented Jacobian matrix is put on to solve unknown load flow parameters:

$$\text{J(i)} = \begin{bmatrix} J_1(i) & J_2(i) \\ J_3(i) & J_4(i) \end{bmatrix} \tag{4.22}$$

$J_1(i)$ takes the partial derivative of the active power according to the angles, $J_2(i)$ takes the partial derivative of the active power according to the voltages, $J_3(i)$ takes the partial derivative of the reactive power according to the angles, and $J_4(i)$ takes the partial derivative of the reactive power according to the voltages.

If "n "does not equal to "k", Jacobian equivalent is written like below at that time:

$$J_{1kn} = \frac{\partial P_k}{\partial \delta_n} = V_k Y_{kn} V_n \sin(\delta_k - \delta_n - \theta_{kn}) \tag{4.23}$$

$$J_{2kn} = \frac{\partial P_k}{\partial V_n} = V_k Y_{kn} \cos(\delta_k - \delta_n - \theta_{kn}) \tag{4.24}$$

$$J_{3kn} = \frac{\partial Q_k}{\partial \delta_n} = -V_k Y_{kn} V_n \cos(\delta_k - \delta_n - \theta_{kn}) \tag{4.25}$$

$$J_{4kn} = \frac{\partial Q_k}{\partial V_n} = V_k Y_{kn} \sin(\delta_k - \delta_n - \theta_{kn}) \tag{4.26}$$

If "n "equals to "k", Jacobian equivalent is written like (k=n) :

$$J_{1kk} = \frac{\partial P_k}{\partial \delta_k} = -V_k \sum_{\substack{n=1 \\ n\neq k}}^{N} Y_{kn} V_n \sin(\delta_k - \delta_n - \theta_{kn}) \tag{4.27}$$

$$J_{2kk} = \frac{\partial P_k}{\partial V_k} = V_k Y_{kk} \cos(\theta_{kk}) + \sum_{n=1}^{N} Y_{kn} V_n \sin(\delta_k - \delta_n - \theta_{kn}) \tag{4.28}$$

$$J_{3kk} = \frac{\partial Q_k}{\partial \delta_k} = V_k \sum_{n=1}^{N} Y_{kn} V_n \cos(\delta_k - \delta_n - \theta_{kn}) \tag{4.29}$$

$$J_{4kk} = \frac{\partial Q_k}{\partial V_k} = -V_k Y_{kk} \sin(\theta_{kk}) + \sum_{n=1}^{N} Y_{kn} V_n \sin(\delta_k - \delta_n - \theta_{kn}) \tag{4.30}$$

When calculated unknown parameters are written with Jacobian (J(i)) matrix, The equations will be as follows:

$$\begin{bmatrix} \Delta P(i) \\ \Delta \mathrm{Q(i)} \end{bmatrix} = \begin{bmatrix} J_1(i) & J_2(i) \\ J_3(i) & J_4(i) \end{bmatrix} \begin{bmatrix} \Delta\delta(i) \\ \Delta \mathrm{V(i)} \end{bmatrix} \qquad \textbf{(4.31)}$$

As a result of all given equations, the parameters can be computed by iterative Newton Raphson method:

$$x(i+1) = \begin{bmatrix} \delta(i+1) \\ \mathrm{V(i+1)} \end{bmatrix} = \begin{bmatrix} \Delta\delta(i) \\ \Delta \mathrm{V(i)} \end{bmatrix} + \begin{bmatrix} \delta(i) \\ \mathrm{V(i)} \end{bmatrix} \qquad \textbf{(4.32)}$$

$$P_k = P_{gk} - P_{kl} \qquad \textbf{(4.33)}$$

$$Q_k = Q_{gk} - Q_{kl} \qquad \textbf{(4.34)}$$

Equations (4.33) and (4.34) define net active and net reactive power, in other words, P_{gk} is generator's active power connected to k^{th} bus, P_{kl} is load's active power connected to k^{th} bus, so, net active power is P_k from differences between P_{gk} and P_{kl}. Q_k (net reactive power) is found with the same way such in equation (4.34). While unknown power magnitudes are found with Newton Raphson, the reactive power value $(Q_{gk}) is$ specified in equation (4.34) is taken as the tolerance value. The voltage, angle, active and reactive power parameters required in the system are solved according to the tolerance value obtained in the iterative methods. If this tolerance value is approached, the results stop because the voltage compatibility, active and reactive power balance sent by the generators to the loads is completed. However, if this limit value is exceeded in the PV bus, this time the bus is considered as the load bus and the solution is continued from the excessive reactive power of PV bus [49].

5.ARTIFICIAL INTELLIGENCE FROM THE PAST TO FUTURE

The feature that distinguishes humans from other living and non-living beings is the ability to use their minds and think. That is, a self has a mindset and consciousness to develop awareness. A person who can develop different personal characteristics by nature, has soul consciousness, questions, acts with intuition and instincts, when necessary, finds the equivalent of his / her inner world as a simulation in the outer world, and is in constant relationship with the outer world, for himself / herself the right, wrong, morality, purpose of life and it is a living creature that discovers life. At the same time, it has been able to create different civilizations and has a special psychology and biochemistry. In other words, from the mitochondria organelle, to which we owe the energy of our cells, to the circulatory, respiratory and other biological systems, which are marvels of engineering, we are such complex but organized beings... Except for the pessimistic scenarios that we have heard of this concept and possible pessimistic scenarios, why not use our power of thought for the benefit of humanity with the awareness of our needs, based on the concept of trans plus humanism, that is, based on our own value and the importance of our togetherness? In fact, it is not a new concept, the biologist Huxley, who first used the concept of transhumanism in the 15th century, can say that the definition of "A person who remains human but overcomes himself / herself and discovers new possibilities of human nature for his/her own nature" gives the full meaning of this concept. Technology is the art of transcending and realizing a design that sometimes seems impossible, according to the current situation of a civilization and the societies and individuals that make up the civilization. When transhumanism is looked at as a narrative, it is described within the patterns of prolonging and improving human life, which is not filled, and it is reflected as if there is only a superhuman creation effort in the form of an ideology. First of all, there cannot be an ideological movement because scientific and technological developments are used. It offers a free space with the resources that people and societies benefit from for self-realization. Humans are already in a structure that reinforces their existence when they help or meet a need, creating a product with a sense of curiosity by using their mind and self in all conditions that are not static by nature. When evaluated holistically, if a person can transform his potential existence as a self-aware individual into the universal benefit, which is the highest level of service, this can be the concept of idealistic transhumanism, and every person is born with the potential to realize himself / herself in this context. Here, benefit is not focused on profit. Let's consider efficiency in a power system. When there is a power loss due to a fault in the system, energy cannot be used efficiently and as mentioned before, it causes negative consequences for both the user (industrial, commercial, residential) and the devices connected to the grid. In this context, it is natural to find solutions by being inspired by the techniques developed to take effective measures, mostly from nature and the living body, which is a magnificent architectural work, as scientists, and it will contribute to the development of a positive perspective in every sense.

What should be stated as an argument is that it is not appropriate to compare robots and humans within the framework of certain competencies, and even in the worst scenario of taking over the world, having more control areas, even if there is malware, it is also made by humans. As stated in the previous paragraphs, when the value of the consciousness of being human, freedom and the power of free thought is considered, there will be no point in imagining negativities. Along with abstract concepts such as love, belief and intention whose mathematical dimension will be discussed, there is nothing that a person cannot do with the power of thought. In this context, if an introduction is made to why artificial intelligence can be so important, it can be understood that even this is the reason for the brain in head, one of the most valuable organs considered as the management center of existence in humans and other living things. Before moving on to studies on the working system of the brain, it is necessary to know about Al-Jazari, the architect of automatons and robotics, who grew up in the field of cybernetics in the 12th century in Mesopotamia and collected his 25 years of effort in the book "The Book of Knowledge of Ingenious Mechanical Devices". From water clocks to musical instruments, all of which are works of art at the same time, and movable systems produced for a purpose, started to be made in this period. In the Industrial Revolution, which was the first revolution in the industry in the 18th century, the process of mechanization aiming at automatic control in production was entered and locomotive vehicles were started to be produced, especially by obtaining energy from water vapor. In the 19th century, in the process of transferring alternating current (AC) from its use in induction motors to city grids, developed by Tesla, electrical systems started to be developed in industry. During the transition to information technologies in the 20th century, automation systems have developed with the development of the concept of efficiency (energy, labor, production) in the industry, and now, in the 21st century, as a natural result of these advances, information based on optimization has been more needed. Because now, after human beings have reached a certain productivity, our changing perspective with scientific developments has brought with it the question of whether systems can be connected with each other, that is, can they be in communication. This period is also a process in which the benefits of multidisciplinary work will be seen. In fact, at this point that should be emphasized, the concept of artificial intelligence emerged as a result of social, need-oriented, natural transformation and cumulatively triggering each other, and we can see that scientists and engineers have developed with productive and creative thinking in the realization of industrial revolutions.

Artificial intelligence is a scientific approach to find smart solutions for needs by transferring the working system of the brain to physical systems. This structure, which enables the brain to carry information, use it when necessary, forget it, and manage the human body as a complex, continuous, regular and intelligent system, necessitated the design of a mathematical model for intelligent solutions to the questions. The brain consists of neurons through which information is transmitted by trillions of electrical and chemical impulses. While establishing a connection in the brain, the impulse is transmitted to the cell body of the neuron by communicating with chemical molecules called neurotransmitters that occur in the gap (synapse) between the axon and the dendrite. Whether the message goes or not is evaluated according to whether the neuron cell is electrically polarized ($Na^{+}$and K^{-}).

Firstly, artificial intelligence term starts with mathematical modelling of biological neuron. “A Logical Calculus of the Ideas Immanent in Nervous Activity, Bulletin of Mathematical Biophysics” by McCulloch and W.Pitts in 1943[57]. A single neuron is called a perceptron. The mathematical model of a perceptron is given below.

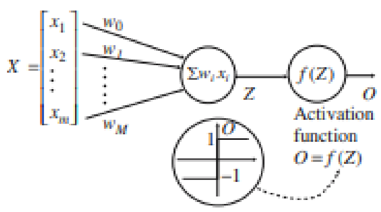

Figure 5.1. *Perceptron mathematical model* [57]

$$h(x) = \sigma(\sum_{i=1}^{m} w_i x_i + w_0) \tag{5.1}$$

x_i is the signals (inputs) that must be sent from the axon to the synapse and the dendrites for transmission, w_i (weight multiplied by the inputs) is the coefficient that gives weight for the transmission of the stimulus in the synaptic connection (depends on the importance of the information to be transmitted). Activation functions (Sigmoid, Rectifier Linear Unit (RELU), Hyperbolic tangent, Softmax) enable the information carried by neurons to be activated in adaptation to nonstationary (dynamics) real-life problems. Different activation functions are preferred according to the characteristics of the data used and the type of problem. After all the inputs are multiplied and summed with the weights, w_0 (bias) is the value that contributes to the activation of the neuron for the message to pass. The purpose of the artificial neural network is to calculate the optimum values of unknown weight parameters and bias until the error function is minimum during training. The multi-layer perceptron architecture is shown below. In deep learning, communication between neurons is realized and solutions are produced to complex problems. The greater the number of layers, the greater the depth and processing load.

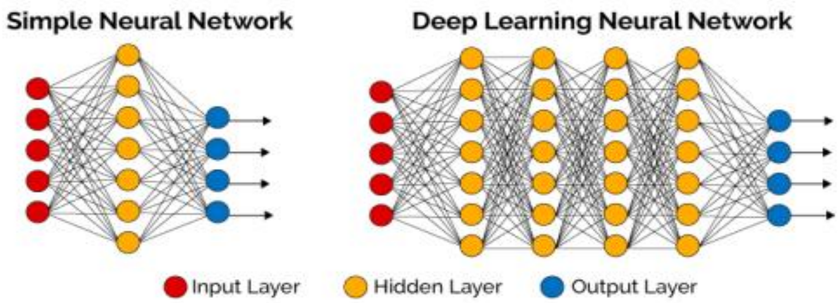

Figure 5.2. *Multiple layer perceptron structure* [8]

Studies on graphical convolutional neural network and prediction and classification in power networks were mentioned in Chapter 2. In terms of performance, the success of this method over basic classical artificial intelligence and machine learning algorithms may be that it can capture detailed spectral connections, namely space, time and functional connections. Examining the brain, which has the ability to communicate with the whole universe as a door opening from the inner world to the outer world, 5 sense organs, the working rhythm of the body, enzymatic arrangements, dreams, subconscious, conscious level, in short, in all branches of science, necessitating a multidisciplinary approach and solving problems. It should be emphasized that it is important to present. In recent studies, GCNN examines the structural, functional and formal similarities of the brain in this sense, making it a mostly preferred method for the treatment of various diseases such as Alzheimer's and motor neuron diseases, which is actually a ray of hope for every study [56]. By bringing together different brains with a complex operating system, the change in the time-dependent brain can be examined, and it can provide detailed analysis without the need for distance connection calculations like Euclidean, compared to other classical algorithms. Therefore, the estimation and classification of various power disturbances and power parameters can be easily made with artificial neural networks, just as the brain solves complex problems with electrical connections and establishes the balance and internal stability for our body in a certain plasticity, and in the same way, ensuring the continuity of power quality in the network operating at the nominal frequency and voltage where electricity flows. On ensemble learning methods, we are familiar with the studies on the random forest method, one of the decision trees that Breiman had previously developed in 1996, but it should be seen in studies about what kind of scenario will emerge when artificial neural networks are included in heterogeneous ensemble learning methods.

In 1950, cryptographer, mathematician and philosopher Alan Turing conducted an experiment to answer the question of whether machines could think like humans. The Turing test was the beginning of human-machine interaction and the use of natural language in machine communication. Turing test applications have continued in different forms since the development of the Eliza machine in 1966. In addition, scientific studies conducted as a prediction, communication between people without speaking, any situation, past event, and even a dream that the person does not remember can be reflected visually by connecting with any person, perhaps with the effect of mirror neurons in the temporal lobes. Because in practical terms, while Elon Musk is developing the brain-machine interface, he is producing technology that can store electrical information in the brain. In addition, the development of quantum computers in this context can pave the way for many seemingly impossible developments. Since mirror neurons are effective in learning by imitation, empathy, coordinated behaviors and especially in learning purposeful moving behaviors, focusing on studies on this subject can contribute to artificial intelligence studies. It is useful to look at technological developments and the understanding of science as both advantages and disadvantages, in this context, it can be said that a new social order is being formed with a transhumanist perspective on unemployment and intelligent robots. Robots may be controversial in terms of "intelligence", but since they will have an impact on other areas for mission purposes, new legal and ethical regulations can be introduced. There is no doubt that great progress will be made in all branches of science as studies to unravel the mystery of the brain continue.

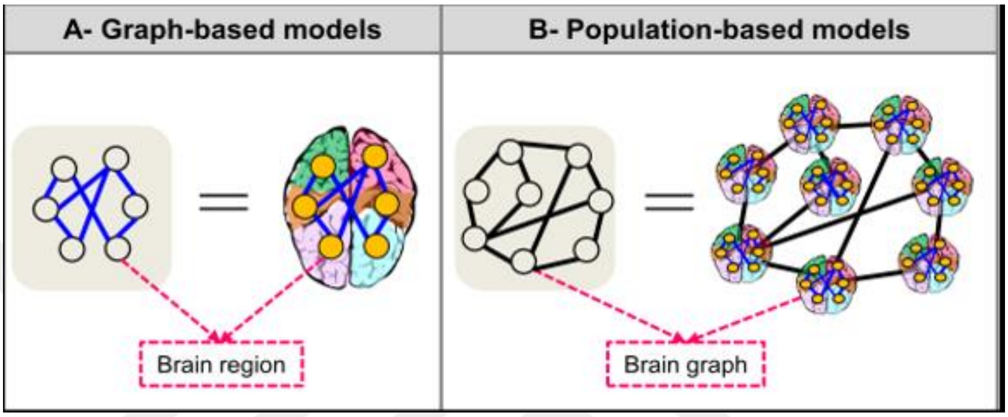

Figure 5.3. *GCNN for brain research* [56]

Finally, in the information and communication age, the main purpose of the "Dark Factory" approach, which emerged by learning the communication between cloud computing and robots performing sensitive tasks in production lines with artificial intelligence methods to provide high level energy, production, workforce and cost optimization. It can be said that a sustainable future that supports more efficient, uninterrupted, renewable energy is aimed by developing demand-oriented energy management with bidirectional smart meters in smart grids, minimizing failures with predictive compensation methods in case of any malfunction, extending the life of the networks and the devices used and reducing maintenance costs [12].

Artificial neural networks (deep learning) and machine learning are sub-branches of artificial intelligence. In machine learning, the data needs to be introduced to artificial intelligence, while artificial neural networks discover the semantic relationship between the data on their own because they are capable of self-learning. Therefore, as a result of a wrong prediction, it does not need to be retrained as in the machine learning method. Artificial intelligence, which has data (information) in its nature and can relate to all disciplines in the universe, is an artistic science that offers technological developments for the benefit of humanity for a more sustainable future.

5.1. Basic Machine Learning Types

Machine learning is an artificial intelligence method that can make a target-oriented prediction and classification after training on the data based on the ability of humans to learn, making a sense of the future from the past information. The concept of machine learning was first used in 1959 with Arthur Samuel's study titled "Some Studies in Machine Learning Using the Game of Checkers". It can be said that this concept of beating the computer in the game of checkers is a pioneer in the studies carried out so far [58].

5.1.1. Supervised learning

It is the type of learning in which the data to be trained and predicted or classified is known and meaningful information can be extracted from them. Examples include decision trees, k- nearest neighbor, support vector machines, neural networks, and random forests.

5.1.2. Unsupervised learning

It is a type of unlabeled learning in which the semantic relationship between the data is given to machine learning methods such as clustering and principal component analysis (PCA) for feature extraction.

5.1.3. Semi supervised learning

There may not be enough labeled data to predict or classify targeted, which in some studies can take a very long time to label data. Optimum results are achieved by using labeled and unlabeled data together during training. While tagging pictures as a case study, tagging only one person allows it to be seen in other pictures as well or studies about natural language processing takes long time as examples, so semi supervised learning can be suitable for the occasions.

5.1.4. Reinforcement learning

According to a policy, orienting object choose an action during current occasion. If it is not suitable for aim, it gets punishment and it does not do same action again. In this way, it reaches true aim with providing of feedback. Training robots for purpose, computer game programs work on a reward-punishment-based experiential learning mentality.

5.2. Machine Learning Methods

For nonlinear and nonstationary data structures, optimization-oriented support vector regression (SVR), decision trees(CART) and k-nearest neighbors (k-nn) machine learning methods, which can better find and perform the pattern between the input data and the predicted output data, providing solutions with kernel functions in the estimation of multidimensional data, are explained. Methods are changed according to the type of problem and data structure.

5.2.1. Classification and regression tree (CART)

Breiman, Friedman, Olshen, and Stone were developed the Classification and Regression Tree (CART) method in 1984[59]. While performing regression in decision trees, the division continues from root node to leaf node by minimizing the error according to the mean squares of the errors (mse). Decision trees are divided into three parts: root node, intermediate node and leaf node. The following equation shows how the decision tree regression is calculated according to the size of the split criterion mse for each node. $J(k, t_k)$ is loss (minimization) function , t_k is threshold, m is number of sample, m_r is right sample, $\hat{y}$ is predicted value, is $y^{(i)}$ is (i)th sample and $\hat{y}_n$ is each node prediction [51].

$$J(k, t_k) = \frac{m_L}{m} \cdot mse_L + \frac{m_r}{m} \cdot mse_R \qquad \textbf{(5.1)}$$

$$mse = \Sigma\left(\hat{y}_n - y^{(i)}\right)^2 \qquad \textbf{(5.2)}$$

$$\hat{y}_n = \frac{1}{m_n} \sum_{i \in n} y^{(i)} \qquad \textbf{(5.3)}$$

5.2.2. Support vector regression (SVR)

Support vector regression is an optimization method that works with objective (minimization) and constraint functions. Constraint is determined according to Epsilon(ε) and outlier vectors (ξ_i). The goal here is that the difference between the expected value and the predicted value is not greater than the sum of a given epsilon and outliers. The Gaussian Radial Based kernel function is functional in estimation and classification problems for multidimensional dynamic data types as shown in equation (5.6). Penalty parameters γ and C adjust overfitting and underfitting in training and x and y input(attributes) and output(target) respectively [40].

$$y = \omega x + b + \varepsilon \tag{5.4}$$

$$\frac{1}{2}\|w\|^2 + c\sum_{i=1}^{m} \varepsilon_i + \xi_i \tag{5.5}$$

$$k(x, y) = exp - \frac{|x - y|^2}{\gamma} \tag{5.6}$$

5.2.3. K-nearest neighbors (k-nn)

The distance between the vectors to be estimated and all the vectors in the training set is calculated with the preferred distance formulas one by one. They can be calculated with Euclidean, Minkowski and Manhattan. Then, the closest "k" observation is selected according to the nearest neighbor "k" number and the average of the "k" observations is taken. Thus, the vectors to be estimated are found. According to below formulas, y_i is observed predicted values and K is observed selected nearest values to predicted sample for equation (5.7) and Euclidean formula is defined in equation (5.8) [59].

$$f(x') = \frac{1}{K}\sum_{i \in N_k(x')} y_i \tag{5.7}$$

$$\sqrt{\sum_{i=1}^{K}(x_i - y_i)^2} \quad \textbf{(5.8)}$$

5.3. Basic Ensemble Machine Learning Methods

One of the important reasons why collective machine learning methods are different from other classical machine learning methods is that by training all efficient classical machine learnings collectively in parallel (bootstrapping) or sequence (boosting) for better prediction performance, the generalizability of the data to be predicted can be increased. Stacking method, which is one of the collective learning methods, is one of the robust algorithms. In this section, explanations and comparisons of how the methods work are made.

5.3.1. Bagging (Bootstrapping) ensemble method

Since the generalizability of the decision trees was low due to overfitting in 1996, Breiman decided to try more than one decision tree consisting of random samples and different subsets from the training set in which the bootstrap and random subspace techniques were included. As a result, overfitting was prevented by randomly training different tree groups together independently from each other. This method is called Random Forest. In other words, it is an ensemble learning model that works with a bootstrapping or bagging method that includes more than one decision tree in the random forest structure. Below is the function used to estimate random trees. $h_k(x)$ is total decision tree predictions and k is total decision trees in a random forest [55].

$$RF = \frac{1}{k}\sum_{k=1} h_k(x) \quad \textbf{(5.9)}$$

Random Forest ensemble model is example of homogeneous ensemble model. If the ensemble methods include different multiple base learners, the method can be called heterogeneous ensemble machine learning method. If the method includes only one kind of base learner, it is called homogeneous machine learning method. Homogeneous neural network model is shown in Figure 5.4.[60].

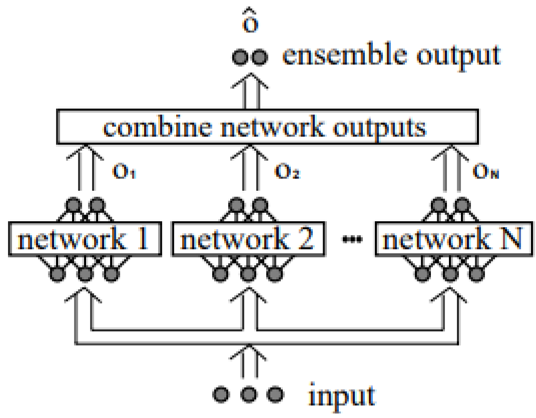

Figure 5.4. *Neural networks homogeneous ensemble model* [60]

5.3.2. Boosting ensemble method

The main idea of the boosting method is that after each base learner has been modeled, the error-causing data is retrained with a base learner, thus reducing the average prediction error and so on until the average error reaches the optimum result. Varieties of main boosting ensemble machine methods are adaboost, gradient boosting machine (GBM) and XGBoost. In the adaboosting method, weights are assigned according to the size of these prediction errors of samples, and while the amount of weight is reduced for the correct predicted sample, it is increased for wrongly predicted samples. It continues untill prediction error is optimum. Learning rate is used to increase prediction ratio of predicted samples instead of weights for GBM. The method uses decision tree as a base learner. Initially, average prediction is calculated for predicted samples. Then, each faulted predicted samples are multiplied by learning rate and the results are added average and previous predictions. When prediction error is decreased, gradient descend is used. In this context, gradient descend optimization algorithm is used. The difference of XGBoost from GBM is that it was developed to be faster and with higher prediction performance [62]. As they are seen in equation (5.10), (5.11) and (5.12), GBM equations are given. GBM equations are increasing of increase the generalizability capacity. In other words, when the goal function provides to find optimum loss function value (prediction error), limited function adjusts trade off overfitting-underfitting stability. Meanwhile, after retraining the training values that caused the error, the predicted values are added to the previously predicted part ($f_t(x_i)$). Respectively, (t) , l, Ω , n, T are defined iterative number, loss function (gradient descend), penalty parameter (tradeoff overfitting and underfitting), number of samples and number of leaves [61].

$$L(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{5.10}$$

$$\Omega(f) = \gamma T + \frac{1}{2}\sqrt{\lambda}\|\omega\|^2 \tag{5.11}$$

$$L^{(t)} = \sum_{i=1}^{n} l\left(y, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{5.12}$$

One of the differences between bagging and boosting is that in bagging, base learners are trained independently and in parallel. For estimation problems, the average of the estimation performances resulting from each model is taken. In boosting, the models can be considered as a series, that is, they are sequentially and iteratively progresses until the estimated error is minimized.

In general, it is more appropriate to use bagging to reduce overfitting, while boosting can be preferred in case of underfitting.

5.3.3. Stack ensemble method

In stack ensemble learning, the aim is to obtain a new data set from the prediction results of the first ensemble model and to find the data with low prediction success and obtain a second prediction result by retraining. There are two stages of training and estimation. The first stage of training and prediction is expressed as level 0, and the second as level 1. The methods used in the training phase of the data for the second time are called meta learner, the processing is called meta learning [62].

As can be seen, the biggest advantages of ensemble learning methods are minimizing errors compared to optimization. With randomly selected different data sets, it maintains the targeted low variance and bias in machine learning, that is, overfitting and bias balance. Most importantly, it can create more robust and generalizable algorithms by bringing together different or same multiple base learners.

5.4. Prediction Metrics

R^2 defines the difference between the expected value and the predicted values of the model parameters. If the value is close to 1, the model parameters are said to be close to the real values and well modeled.

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y})^2}{\Sigma(y_i - \bar{y})^2} \tag{5.13}$$

The mean squared error (MSE) is the mean of the squared differences between the expected and predicted values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{5.14}$$

The mean absolute error (MAE) is the average of the absolute values of the difference between the expected and the predicted results.

$$MAE = \frac{1}{N}\sum_{i=1}|y_i - \hat{y}| \tag{5.15}$$

Root mean squared error (RMSE) is the square root of the MSE estimation metric, as seen in equation (5.16), regardless of purpose.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{5.16}$$

y_i : expected value

$\hat{y}$: predicted value

$\bar{y}$: mean value

N : number of observation value

6.PREDICTION OF POWER DISTURBANCES BY ARTIFICIAL INTELLIGENCE METHODS

In this study, when there is a short-term failure in the power system with a balanced power quality, the power quality deteriorates and voltage sag disturbances occur on all buses. How long ago, how and with which methods the magnitude estimation of the disorder will be optimally estimated requires examining the system as a whole. Therefore, first of all, load flow analysis is performed to observe the situation before the power quality deteriorates in order to provide power balance in the IEEE9 bus system used for the target. After the system is suitable for the short circuit fault to be applied, the status of the targeted fault for all busbars in the power grid is checked. The approach and simulation of using appropriate data is presented and appropriate algorithms are selected for the data structure and the target. In this section, how these stages take place is explained in order. The high performance of the estimation results in this context and how these stages are realized are explained in order in this section.

6.1. Load Flow Analysis for Balanced IEEE 9 Bus Power System

Load flow analysis is needed to observe power parameters during working stable on the power system. It is important for providing of sustainable power quality. Measured voltage signal and other power signals are pure sinusoidal waveform during nonfault or having balanced load flow. When short circuit fault occurs between at 1 and 1.1 seconds on the system, since stability of active and reactive power of the system is broken down, voltage sag phenomena occurs. According to the load balance state of the system is known, it can be calculated and observed how much voltage sag is in which busbar from MATLAB/Simulink interface. Therefore, first of all, load flow analysis of the 9 bus test system should be performed before the fault is created.

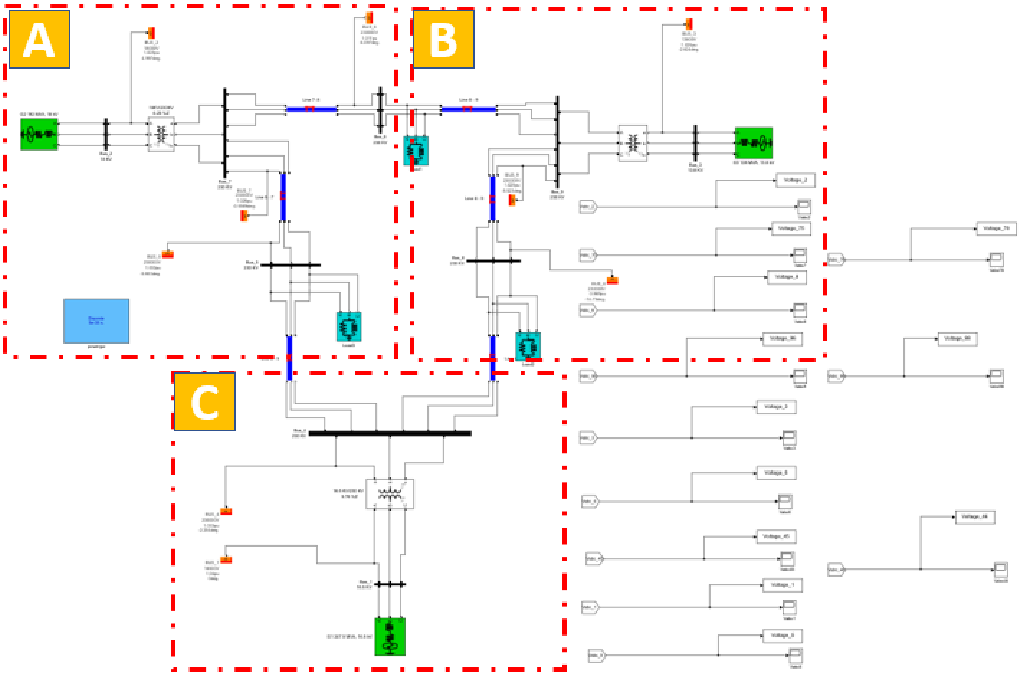

Figure 6.1. *IEEE 9 bus test system*

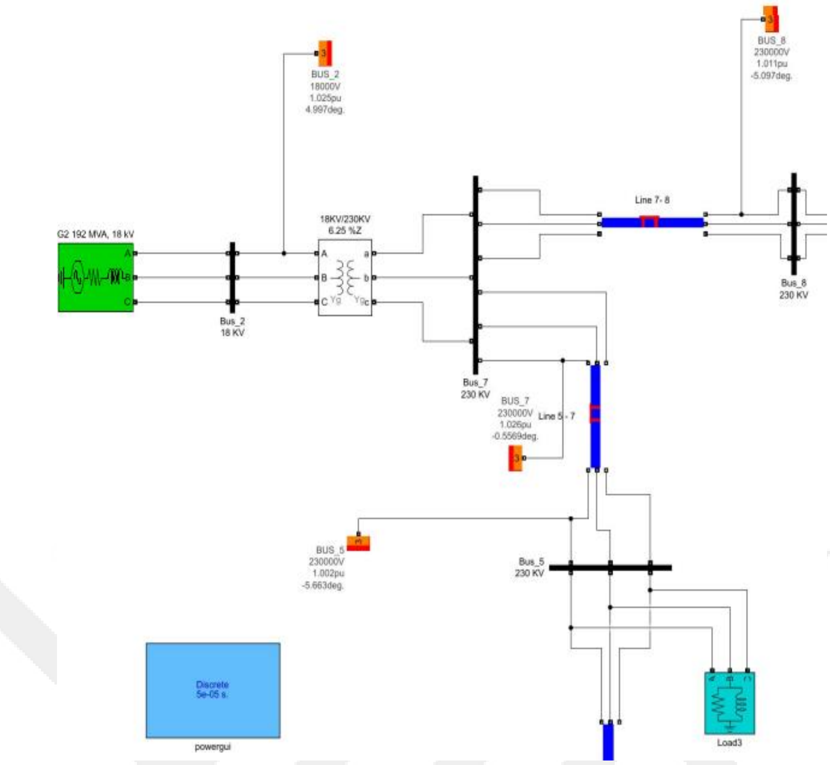

Figure 6.2. A Part of the power system

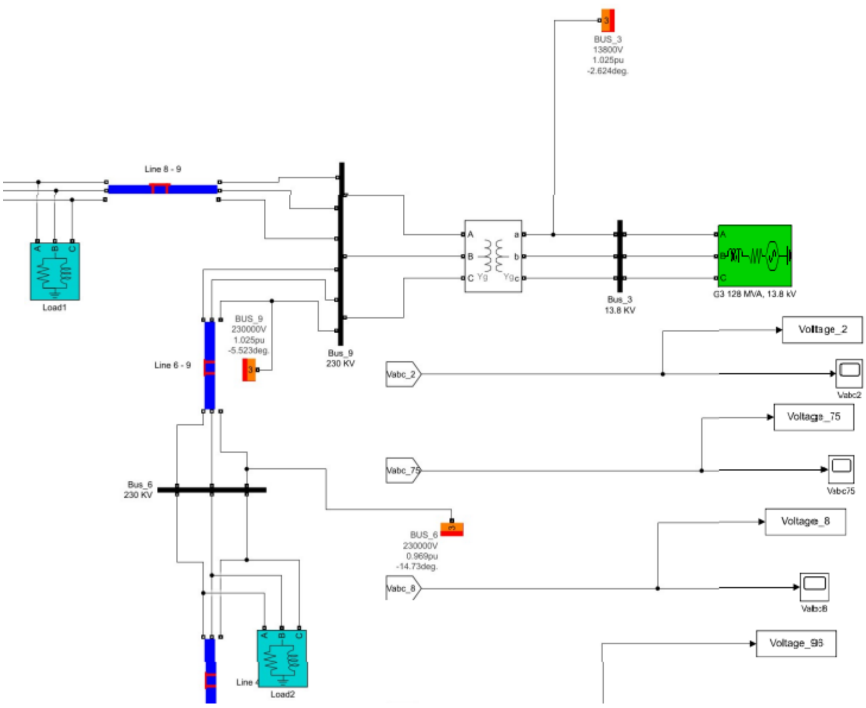

Figure 6.3. *B Part of the power system*

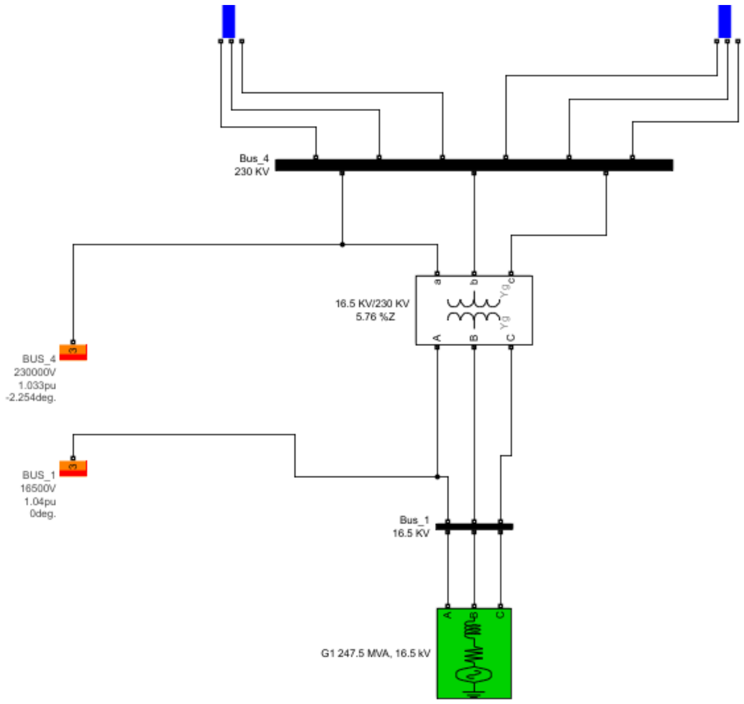

Figure 6.4. *C Part of the power system*

As it is seen, IEEE9 bus test system was separated three pieces (A, B and C). The power system is 100MVA three phase positive sequence(stable) system and the power units connected to the second, third and first buses are made with AC power producing, generators of 192 MVA, 128 MVA and 247.5 MVA respectively. There are three step-up transformers that convert the medium voltage from the generators to high voltage. 18kV in the second bus, 13.8kv in the third bus and 16.5kv in the first bus are converted into 230kv high voltage, and energy is transmitted from generators to the transmission line. There are six medium pi-section (medium length) transmission lines specifying the length of the transmission line and three fixed PQ loads connected to them.

The input data of the power parameters to be used for load flow analysis are defined in the MATLAB/Simulink program below. The parameters are active and reactive powers (Pgen, Qgen) transmitted from generators to lines and loads, and fixed (Pl, Ql) loads drawn by PQ loads, voltages (p.u), phase angles and limited reactive power values.

Table 6.1. *Input data for load flow analysis*

Bus No	V (p.u)	Theta	Pgen (MW)	Qgen (MVAR)	Pload (MW)	Qload (MVAR)	Qmax	Qmin
1	1.04	0	0	0	0	0	inf	-inf
2	1.025	0	163	0	0	0	-inf	-inf
3	1.025	0	85	0	0	0	0	0
4	1.000	0	0	0	0	0	0	0
5	1.000	0	0	0	125	50	0	0
6	1.070	0	0	0	90	30	0	0
7	1.000	0	0	0	0	0	0	0
8	1.090	0	0	18.24	100	35	0	0
9	1.000	0	0	0	0	0	0	0

Before passing load flow analysis, bus types are certained on the power system While Slack bus is defined as first bus, second and third bus are defined PV (voltage controlled) and kind of other buses are load bus. Slack bus parameters include constant voltage and angle $(V = 1\angle 0)$ as a reference bus. Active power and voltage values are defined according to table for PV buses. Active and reactive power values are constant for load buses. The Newton Raphson model is an iterative solution is explained in Chapter 4. The load flow analysis of the IEEE 9 Bus system is calculated in the powergui - preferences interface, which is used for power simulations in Matlab/Simulink in Figure 6.5. As can be seen, the iteration number is defined as 100 (maximum value) and the tolerance value is defined as 1e-4. Tolerance value is defined power mismatches (ΔP, ΔQ) and iteration continues untill the convergence of tolerance value. After finding angle value for PV bus at state of providing tolerance value, reactive power is calculated. Unknown voltage and angle magnitude parameters are computed for PQ buses and then net active and reactive power are found for slack bus as in equations (4.33) and (4.34).

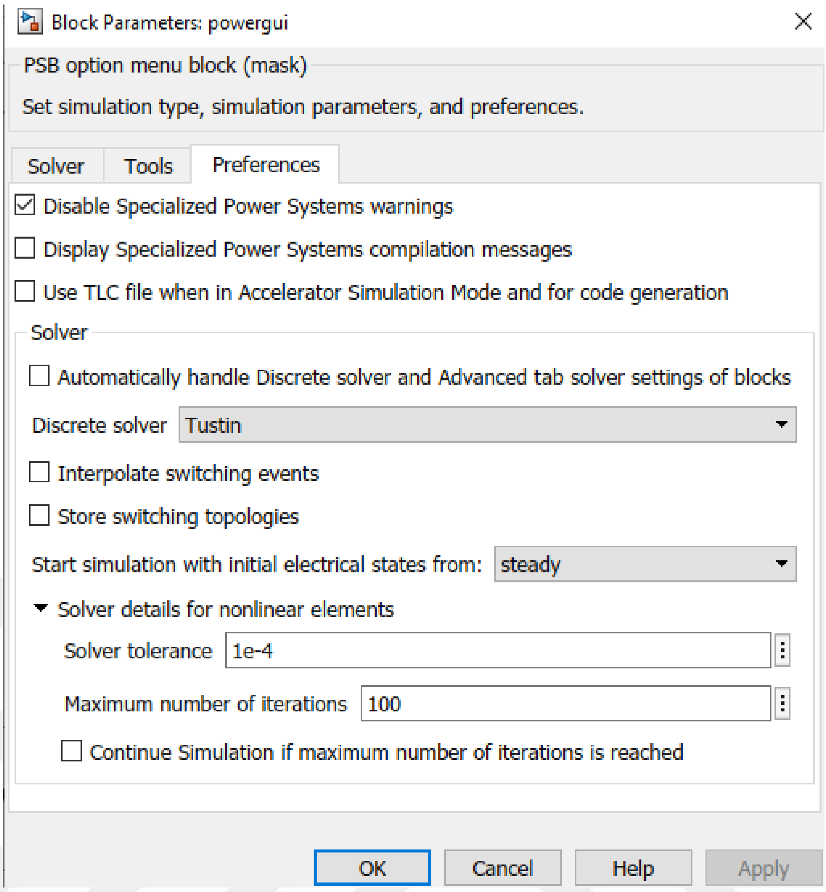

Figure 6.5. *Applied Newton Raphson method on IEEE 9 bus simulink model*

According to load flow solutions in Figure 6.6, it converges to finding of unknown parameters in 3 iterations. Voltage magnitude and angle is constant for slack generator bus. Then, active and reactive power are computed as 73.1393MW and 15.1759 MVAR respectively. Voltage controlled bus (for second bus) voltage angle and reactive power are computed as 5.1118 degree and 8.7535MVAR. Calculated of reactive power for other PV bus (third bus) is 5.5334 MVAR and voltage angle is-2.3303 degree. According to load buses P (active power) and Q (reactive power) are constant. When voltage magnitude and voltage angle are computed, voltage magnitude is 1.0105 p.u and voltage angle is -4.6468 degree for bus eight. In the same way, voltage magnitude is 1.0027 p.u and voltage angle is -5.38.58 degree for bus five. Then, voltage magnitude is 0.9707 and voltage angle is-13.4889 degree for bus six. Hence, stability of active and reactive power are balanced. In other expression, produced and transmitted active and reactive power are nearly equal.

		Block type	Bus type	Bus ID	Vbase (kV)	Vref (pu)	Vangle (deg)	P (MW)	Q (Mvar)	Qmin (Mvar)	Qmax (Mvar)	V_LF (pu)	Vangle_LF (deg)	P_LF (MW)	Q_LF (MVA)
1		Vsrc	swing	BUS_1	16.5000	1.0400	0	0	0	-Inf	Inf	1.0400	0	73.1913	15.1759
2		Bus	-	BUS_7	230.0000	1.0000	0	0	0	0	0	1.0246	-0.4476	0	0
3		Vsrc	PV	BUS_3	13.8000	1.0250	0	85.0000	0	-Inf	Inf	1.0250	-2.3303	85.0000	5.5334
4		Vsrc	PV	BUS_2	18.0000	1.0250	0	163.0000	0	-Inf	Inf	1.0250	5.1118	163.0000	8.7535
5	ad	RLC load	PQ	BUS_8	230.0000	1.0900	0	100.0000	35.0000	-Inf	Inf	1.0105	-4.6468	100.0000	35.0000
6		Bus	-	BUS_9	230.0000	1.0900	0	0	0	0	0	1.0231	-5.0460	0	0
7	ad	RLC load	PQ	BUS_5	230.0000	1.0000	0	125.0000	50.0000	-Inf	Inf	1.0027	-5.3858	125.0000	50.0000
8	d	RLC load	PQ	BUS_6	230.0000	1.0700	0	90.0000	30.0000	-Inf	Inf	0.9707	-13.4889	90.0000	30.0000
9		Bus	-	BUS_4	230.0000	1.0000	0	0	0	0	0	1.0325	-2.2434	0	0

Figure 6.6. *Report of load flow solution*

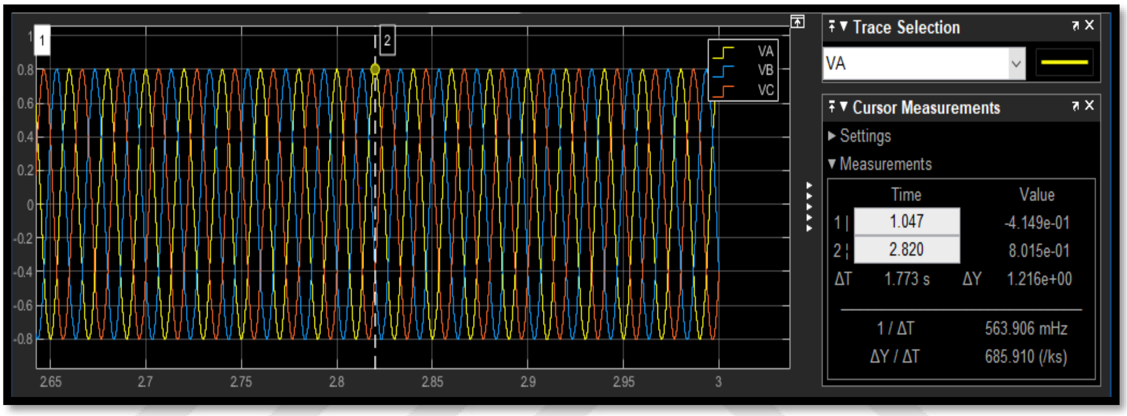

Figure 6.7. *Nonfault AC voltage*

After providing of the load flow, the 9 bus system continues to work in balance as long as there is not malfunction. In this case, the voltage of the system is shown in Figure 6.7. has also been expressed. The power system is obtained at a fundamental frequency of 50 Hz, in pure sinusoidal form with a voltage magnitude of about 0.8015p.u.

6.2. Behavior of Power System and Effect of Symmetrical Component Analysis for Chosen Data

As mentioned before, short circuit fault is the type of fault that causes power quality disturbances in a balanced system and the most common fault is single phase short circuit fault. In this context, in order to obtain voltage sag in the 9 Bus test system, a phase fault was applied in MATLAB/Simulink program between 1 second and 1.1 seconds, that is, a total of 14 scenarios.

Table 6.2. *Fault variations*

	Scripts	Fault Types	During Fault Time (1.0-1.1seconds)	Fault Buses								
1												
2				1	2	3	4	5	6	7	8	9
3	1	a phase ground	0.1		x							
4	2	a phase ground	0.1				x			x		
5	3	a phase ground	0.1	x								
6	4	a phase ground	0.1	x	x							
7	5	a phase ground	0.1	x				x				
8	6	a phase ground	0.1						x			
9	7	a phase ground	0.1									x
10	8	a phase ground	0.1					x	x			
11	9	a phase ground	0.1								x	
12	10	a phase ground	0.1			x		x				
13	11	a phase ground	0.1		x	x						
14	12	a phase ground	0.1		x						x	
15	13	a phase ground	0.1				x					
16	14	a phase ground	0.1							x		

As it is seen on Table.6.2., there are 14 type of a phase ground fault. The fault duration is certained time (0.1s) and sign "x" is faulted buses. The buses with single faults (7 ones) in the specified time interval are 1st, 3rd, 6th, 7th,9th, 13th and 14th scripts, while dual synchronous faults (other 7 ones) are happened 2nd,4th,5th and 8th, 10th, 11th and 12th scripts. When the fault is applied with defined fault variations, voltage sags events having different magnitudes at all buses and at same fault time frame.

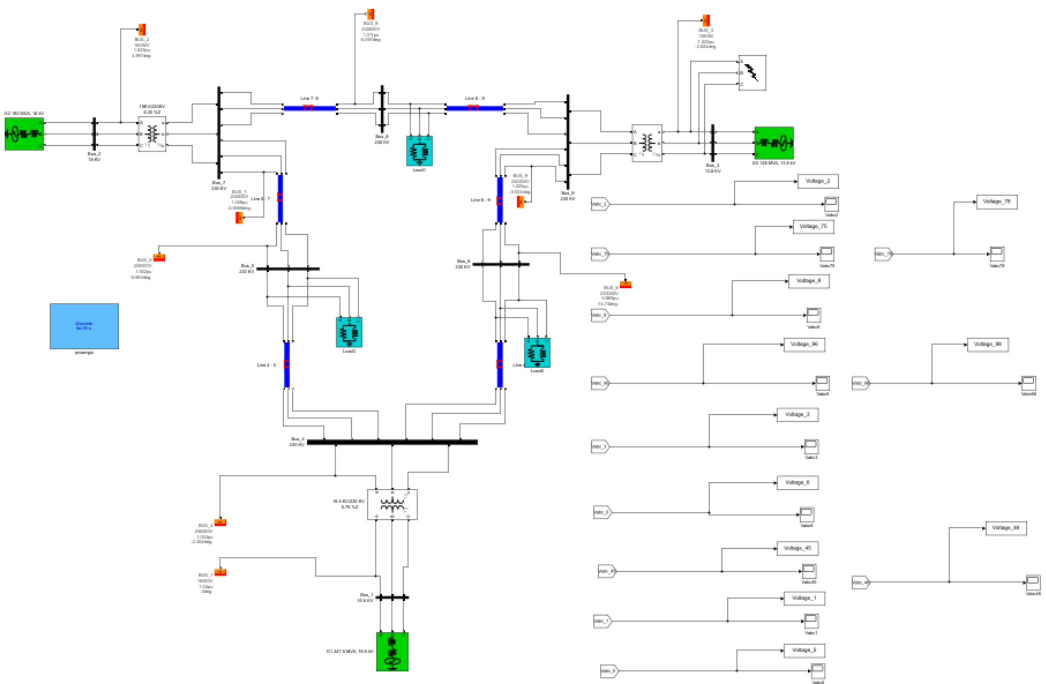

Figure 6.8. Faulted bus3

In the third chapter, while the short circuit analysis was explained, short circuit faults are observed on 3rd and 6th buses by faulted 6th bus. As a continuation of this section, a phase short-circuit fault is given to the 3rd bus at the specified time intervals and fault resistance of the three phase circuit breaker is 0.001ohm (Ω). Therefore, the magnitude of the voltage sag in the other buses is observed in the four below figures.

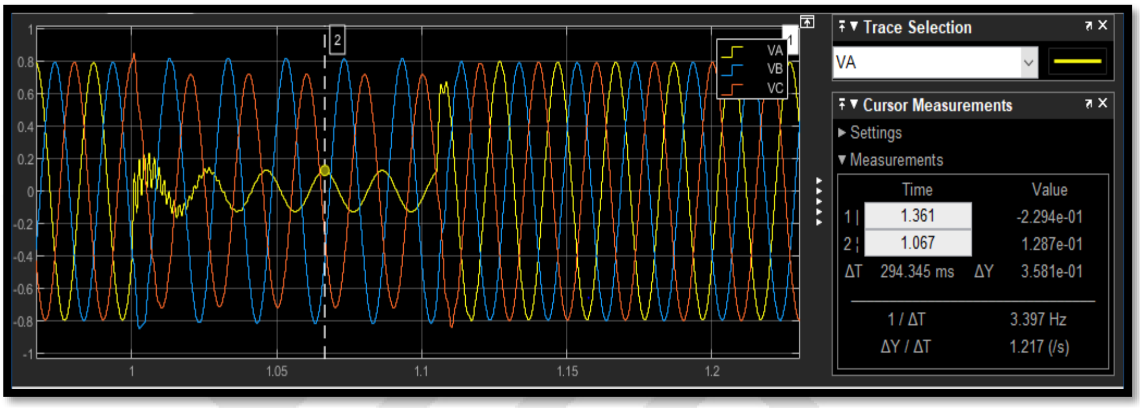

Figure 6.9. *Observation of LGF on bus 9*

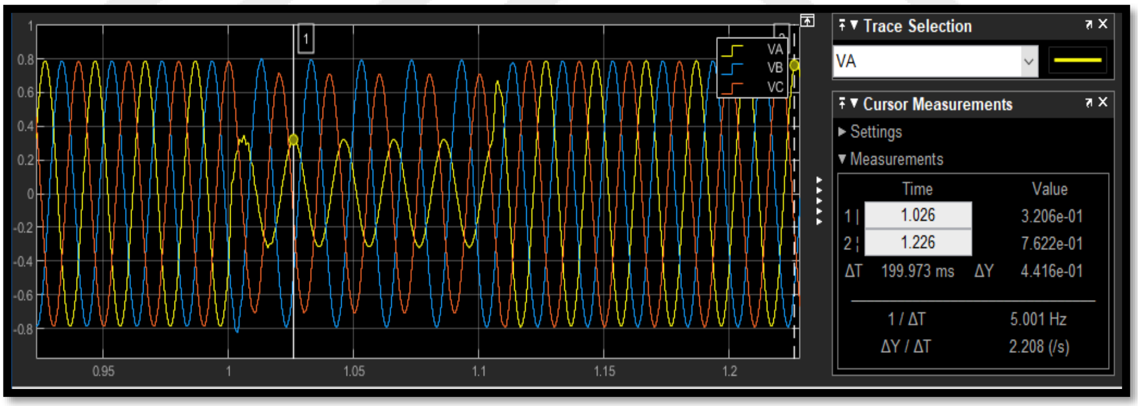

Figure 6.10. *Observation of LGF on bus 8*

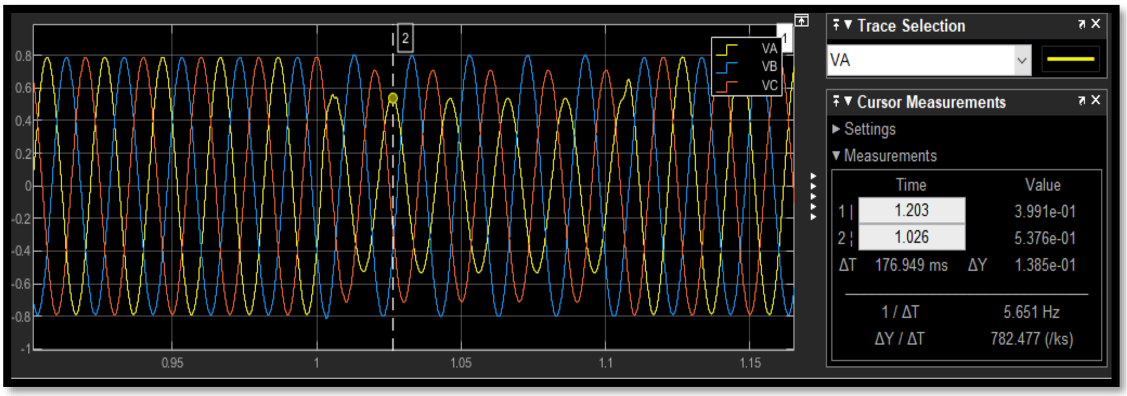

Figure 6.11. *Observation of LGF on bus 5*

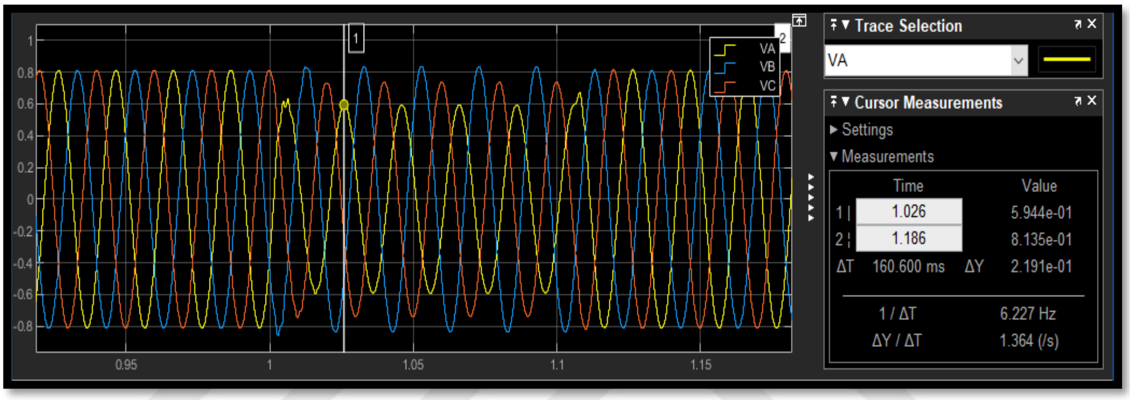

Figure 6.12. *Observation of LGF on bus 4*

When the discrete signal received with 20kHz sampling frequency for three seconds is examined, the voltage sag disturbances are periodic in the fault time frame and their magnitudes changes according to distances far from fault location and the line and transformer impedances in the power system. Additionally, the magnitude and behavior of the disturbance depends on combination of fault buses. Voltage sag increases that close to faulted bus or buses. On the other hand, it decreases that far from them. In normally, according to symmetrical component analysis on the unbalanced system, when a phase short circuit fault is given to power system, short circuit current effects on only a phase current. However, it changes amount of c phase voltage. Reason of the situation can be that the power system feeds with different three AC three phase sources and has three step up transformers. Transformers and line impedances can be affected due to system dynamics.

As experiments, to verify the above information, when a short-circuit fault is given to a phase of the 3rd bus, the amount of voltage sag decreases towards the 9th, 8th,5th and 4th buses respectively, as the distance increases.

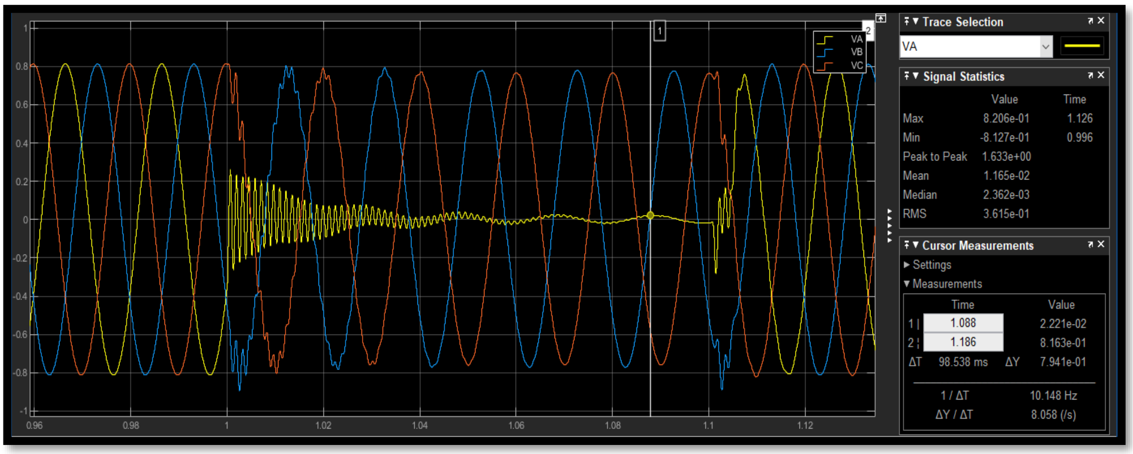

Figure 6.13. *Observation of LGF (1-5) on bus 4*

Differently, when the 1st and 5th buses are faulted, oscillation occurs in the 4th bus and as stated in the previous section, the given faulted buses have interruption phenomena in Fig.6.13. As seen in Figure 6.9, oscillation transients are seen in the first second interval at the 9th busbar. In some buses, this disturbance occurs instantly, but voltage sag event observes on all buses in fault range time without faulted bus or buses. If the behavior of the power system is investigated in generally, when, given short circuit fault on the buses according to fault scripts, the faulted buses have interruption on a phase voltage and other buses have voltage sags on a phase voltage. However, only b and c phase voltage of 2nd bus and connected at between 7th and 5th buses voltage drops during that time, when a phase fault is given to the buses.

When a single-phase short-circuit fault is given to the system, as the short-circuit current rises in phase a, the power system becomes unstable and the voltage phasors are not sequence, so magnitudes and angles from each other as mentioned before. With symmetric components analysis, the unbalanced quantities are calculated by dividing them into positive, negative and zero components. When a single-phase fault occurs, in the three-phase voltages ($V_a, V_b\ , V_c$) observed above, the voltage magnitude in phase a drop on the fault time and the balance is lost in the phases. Therefore, as can be understood from the matrix equations stated in the third section, all components are present in a single-phase fault, with "a" constant unit phasor. Since all components (V_0,V_1, V_2) are included in the phase voltages, which is considered important for the estimation of the voltage sag magnitude, it is important how it affects the voltage phasors ($V_a, V_b\ , V_c$) in all busbars when the system is faulted. Therefore, with a total of 14 fault scenarios, the number of buses to be observed is 9, and when calculated for each 3-phase voltage, 14x9x3 is equal to 378 features. Voltage phasors are nonstationary signals that occur in the time axis. The main purpose of this study is to predict the magnitude of the voltage sag in the specified time interval in which bus with defined the optimum time can be calculated using training and test data. In this context, a total of 379 features (columns) will be obtained, together with time series data which 20kHz frequency sampling for three seconds.

The reason for giving a double fault to the system will be to enable it to better learn the magnitude of the voltage sag and its positional effect that occur in the buses without faults.

6.3. Data Preprocessing

Occurring a relationship between the data is required in order to predict before defined time horizon how much the voltage sag is at which bus at faulty time range. Before the modeling and estimation step, data preprocessing must be made. When the data obtained is not in the required range, size, number and type, since a correct pattern cannot be established between the values, the model will also be wrong and an accurate prediction will not be made. The purpose of data preprocessing is to ensure that the necessary arrangements are made for the data to be functional in building a successful model.

The data obtained by malfunctioning in the MATLAB / Simulink were edited in the Excel program and transferred to the Anaconda /Jupyter Notebook application environment to process it. As seen in the table below, the data set is defined in a total of 379 columns that express the voltage magnitude values together with the time series. While specifying the attributes, it is understood how much magnitude of the voltages in which buses the faulty bus creates. For example, when the phase voltage of Van2_1-2_a is explain, given to the phase a of the 1st and 2nd busbars, we observe the magnitude values of the phase voltage of the 2nd bus. For Vbn3_1-2_a, when phase a of the 1st and 2nd buses fails, we observe the magnitude values of the phase voltage b in the 3rd bus. Therefore, it is understood that the data is labeled. Since the voltage sag signal is produced in short-term event and nonstationary signal, it becomes difficult to identify the signal in the sample taken for three seconds. For this reason, a total of 60000 voltage data were obtained with 20kHz sampling. If it is defined with the matrix expression, it is expressed as [379x60000].

Table 6.3. *Data structure (before preprocessing)*

	Van1_1-2_a	Vbn1_1-2_a	Vcn_1-2_a	Van2_1-2_a	Vbn2_1-2_a	Vcn2_1-2_a	Van3_1-2_a	Vbn3_1-2_a	Vcn3_1-2_a	Van4_1-2_a	...
count	6.000100e+04	6.000100e+04	60001.000000	60001.000000	60001.000000	6.000100e+04	6.000100e+04	6.000100e+04	60001.000000	6.000100e+04	...
mean	-3.067449e+05	-1.004983e+05	-0.000140	-0.000079	-0.000012	-1.683305e+04	1.166647e+03	2.761121e+05	0.000015	3.299945e+05	...
std	7.215325e+07	2.461717e+07	0.580601	0.563185	0.569864	4.123273e+06	2.266190e+07	7.974868e+07	0.560656	7.733407e+07	...
min	-8.040000e+09	-6.030000e+09	-0.832247	-0.808289	-0.805877	-1.010000e+09	-3.890000e+09	-9.280000e+09	-0.796313	-9.300000e+09	...
25%	-5.644026e-01	-5.802910e-01	-0.577882	-0.553448	-0.574078	-5.529754e-01	-5.466468e-01	-5.620217e-01	-0.558637	-5.571564e-01	...
50%	2.282789e-03	-1.289351e-03	0.004479	0.002448	-0.005992	1.493952e-03	3.837136e-03	-3.228300e-04	0.002613	8.661180e-04	...
75%	5.644235e-01	5.798524e-01	0.578423	0.551574	0.565604	5.529521e-01	5.466607e-01	5.618714e-01	0.558615	5.571775e-01	...
max	8.620000e+09	8.213270e-01	0.821523	0.808843	0.805877	8.058971e-01	3.960000e+09	9.730000e+09	0.796308	9.110000e+09	...

8 rows × 368 columns

The above table shows data characteristics. They are statistical measurement unit like machine learning metrics that used for prediction performance. If described characteristics are expressed briefly, count means total number of data, mean represents close value to total data distribution. It calculates with the sum of the data values divided by the number of data. Standard deviation measures spread of data. When it is low, data distribution closes to center, otherwise, data spreads wide range [52].

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} \quad \textbf{(6.1)}$$

$$\sigma = \sqrt{\frac{(\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}} \quad \textbf{(6.2)}$$

$\bar{x}$: Mean

x_i: i^{th} attribute value

N: Number of data

σ : Standard deviation

Max and min values defines maximum and minimum value of data respectively. Percentiles show the percentage distribution of the data. 25% means point of first quantile, 50% is median (middle value of data) value, 75% certains last quartile value.

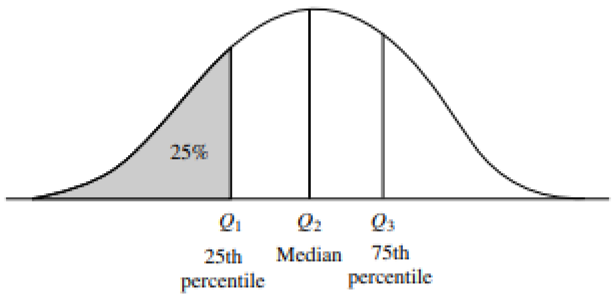

Figure 6.14. *Quartile data distribution* [52]

Counts are 60001 with attribute headers. While the total number of features are 379 with time series, it is 368 as shown in the table. The reason is that the values in 11 attributes are defined as objects. Therefore, these values will be converted to floats. Similarly, when we examine other descriptive features, we see that the data is not distributed in the range that should be in all columns. The maximum and minimum values should be about 0.85 and-0.85 p.u for voltage data. However, as can be seen, expressing these values as very large and very small causes the data distribution to be wide. As a result of the situation, both of standard deviation and mean value have unexpected output. When the problems obtained in the application (Jupyter Notebook) table were examined in excel, it was understood that the reason was 3 separate problems.

Problem 1: Some values of the voltage data during the fault of the bus with a single-phase short-circuit fault should be very close to zero, but very large or very small numbers are encountered. For example, values of Van8_2-8_a close to "-9.97e+9" at between 1.014250 and 1.006450 with seconds.

Problem2: The region approaching zero in the sine signal is the transition region where the sign change will take place. In these regions, the values of some features are very large or very small. For example, attribute values of Vbn8_7_a consists "9.57e+9" at between 1.2184501 and 1.218550 seconds.

Problem3: The peak values after failure should be 0.85 maximum and minimum values-0.85. For example, values between 1.103300 and 1.103700 seconds in the Vbn9_7_a attribute appear similarly to "-100.088.229.281.367". Value of Vcn9_7_a are observed as positive "100.417.775.896.674" at between between 1.101650 and 1.101750 seconds. When these errors are evaluated on a time basis, they occur instantly.

Solution: Since the same conditions must be met in all data in the solution of the problems, these conditions are assigned to the df=fix_df(df) function by algorithm. Assignment zero for Problem1 and Problem2 would be helpful. In the "check1dot" function defined for Problem 3, when converting the values read as strings to float, if 2 digits in decimal value are provided after the dot, the value will be read and if the peak point exceeds-0.85 for negative values, -0.85 will be assigned, and if 0.85 for the positive side is exceeded, 0.85 will be assigned.

AC three-phase voltage signals are dynamic and non-linear signals. In addition, since the voltage sag caused by the fault is a short-term signal, increasing the sampling rate of 20kHz collecting the data.

In the ongoing data preprocessing stage, when the time series data is examined separately from the voltage data, we observe that the values are incorrectly separated after a certain value as punctuation. For this reason, it was rewritten in the application after increasing the sample time by 5e-5 starting from the first index. Finally, it was observed that there was no missing, redundant and repetitive data and it was checked again that the data type was float.

Table 6.4. *Data structure (after preprocessing)*

	Time	Van1_1-2_a	Vbn1_1-2_a	Vcn_1-2_a	Van2_1-2_a	Vbn2_1-2_a	Vcn2_1-2_a	Van3_1-2_a	Vbn3_1-2_a	Vcn3_1-2_a	...
count	60001.000000	60001.000000	60001.000000	60001.000000	60001.000000	60001.000000	60001.000000	60001.000000	60001.000000	60001.000000	...
mean	1.500000	-0.000288	-0.000163	-0.000140	-0.000079	-0.000012	0.000092	-0.000009	0.000198	0.000015	...
std	0.866047	0.570499	0.580572	0.580601	0.563185	0.569864	0.563336	0.552654	0.562044	0.560656	...
min	0.000000	-0.823923	-0.823242	-0.832247	-0.808289	-0.805877	-0.809185	-0.794773	-0.849221	-0.796313	...
25%	0.750000	-0.564402	-0.580251	-0.577882	-0.553448	-0.574078	-0.552975	-0.546646	-0.562014	-0.558637	...
50%	1.500000	0.002209	-0.001289	0.004479	0.002448	-0.005992	0.001494	0.003837	0.000000	0.002613	...
75%	2.250000	0.564423	0.579852	0.578423	0.551574	0.565604	0.552952	0.546661	0.561773	0.558615	...
max	3.000000	0.824503	0.821327	0.821523	0.808843	0.805877	0.805897	0.797113	0.818431	0.796308	...

8 rows × 379 columns

As it is like above table, all of values are float and attribute values are arranged depending on self-feature of the voltage signals After providing a reliable range of data as a result of preprocessing, modeling and estimation stages can be easily passed to use the obtained data.

6.4. Model Building with Ensemble Machine Learning Methods

Homogeneous and heterogeneous machine learning algorithms are kinds of ensemble learning methods. Ensemble machine learning uses more than one base(weak) learners. Base learners are individual Support Vector Machine (SVM), k-nearest neighbors (k-nn), Multiple Layer Artificial Neural Network (MLANN), Linear Regression (LR), Classification and Regression Decision Tree (CART) and other artificial intelligence algorithms. Reason of used the ensemble (more than one base learners) methods is increasing generalization for prediction performance with collective learning. While homogeneous learning includes only one kind of base learner, heterogeneous learning includes more than one kind of base learners. In this study, decision trees were be used for the homogeneous ensemble learning model (Random Forest-RF), while SVM, CART and k-nn were be used for the heterogeneous ensemble learning model. One of the most important reasons for using these algorithms is that the magnitude of the voltage sag changes according to depending on distance of the targeted estimation (voltage sag magnitude in any buses) to the faulty (faulted bus) region and existence of fractal pattern according to the difference of distances, in other words, if a phase fault is given to the bus or buses, while interruption phenomena occurs on the buses, other all buses have voltage sag with different magnitudes depending on location of faulted buses.

10 different voltage sag scripts were shown instantaneously for a total of 0.1 seconds between the 1st and 1.1st seconds as experiments.

Respectively, 5 scripts of the 10 experiments are magnitude of the voltage sag at the 3rd bus of the fault occurring in 6 bus (Van3_6_a), the magnitude of the voltage sag at the 2nd bus of the fault formed in the 1st bus (Van2_1_a), the magnitude of the voltage sag at the 6th bus of the fault formed in the 2nd bus (Van6_2_a), the magnitude of the voltage sag at the 1st bus of the fault formed in the 9th bus (Van1_9_a), and the magnitude of the voltage sag at the 5th busbar of the fault created at the 4th busbar (Van5_4_a) instantly estimated 100ms before the optimum, using training and test data. As they are seen in below figures, difference amount of voltage sag magnitudes is shown in the fault range. Predictive aim is that estimating the magnitude of the voltage sag event between the selected dataset interval and the optimum time interval by recognizing the fault. As seen in the failure scenario for each input(attributes), the amount of the fault in which bus is labeled. Therefore, the magnitude of the voltage sag can be estimated at the desired location.

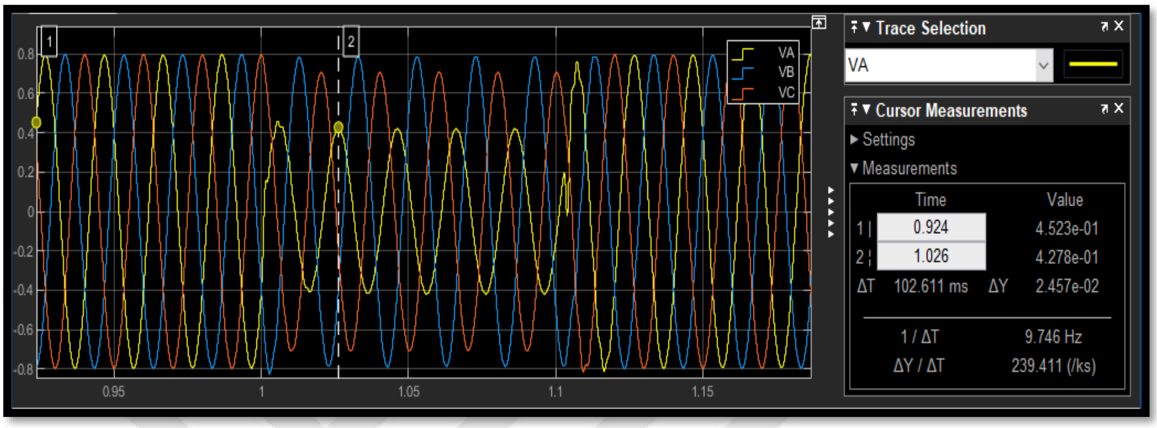

Figure 6.15. *Observation on Van3_6_a*

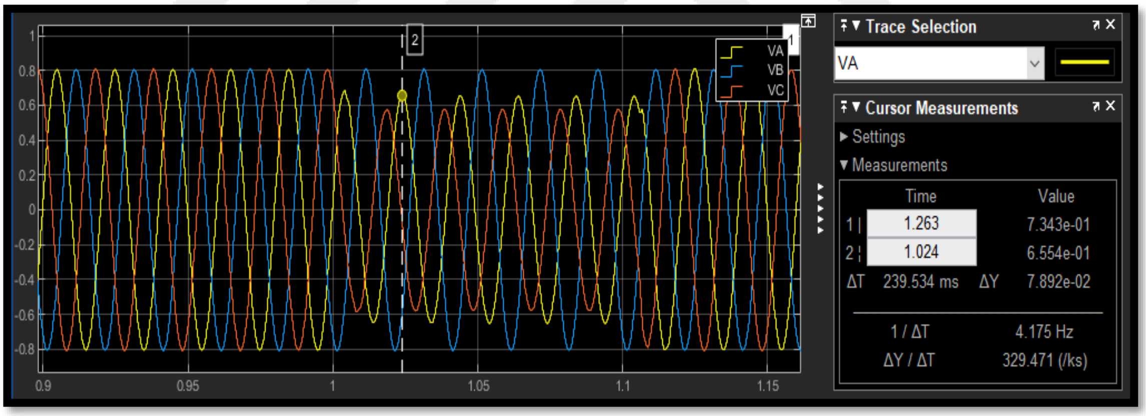

Figure 6.16. *Observation on Van2_1_a*

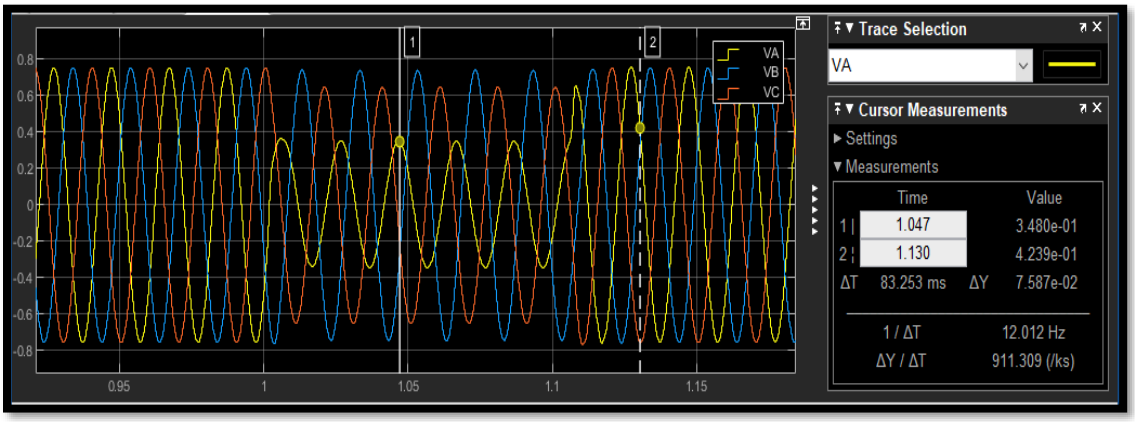

Figure 6.17. *Observation on Van6_2_a*

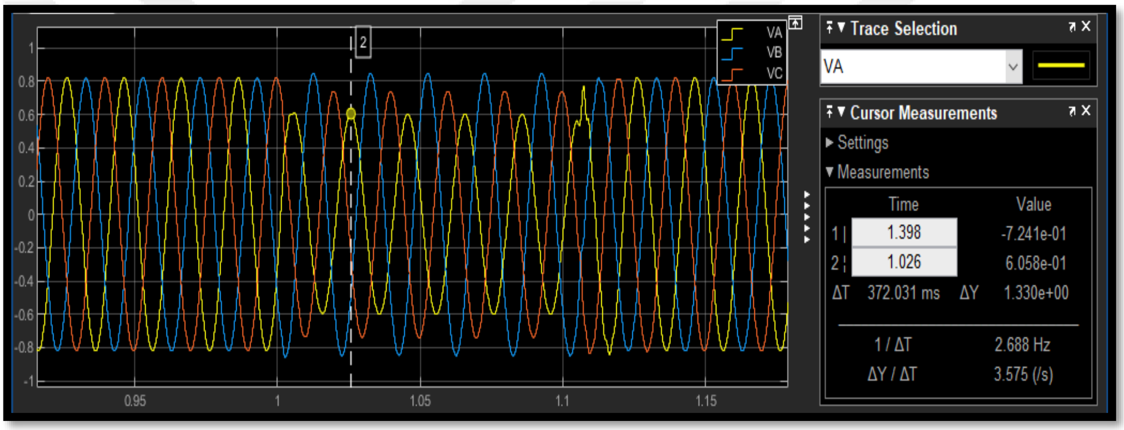

Figure 6.18. *Observation on Van1_9_a*

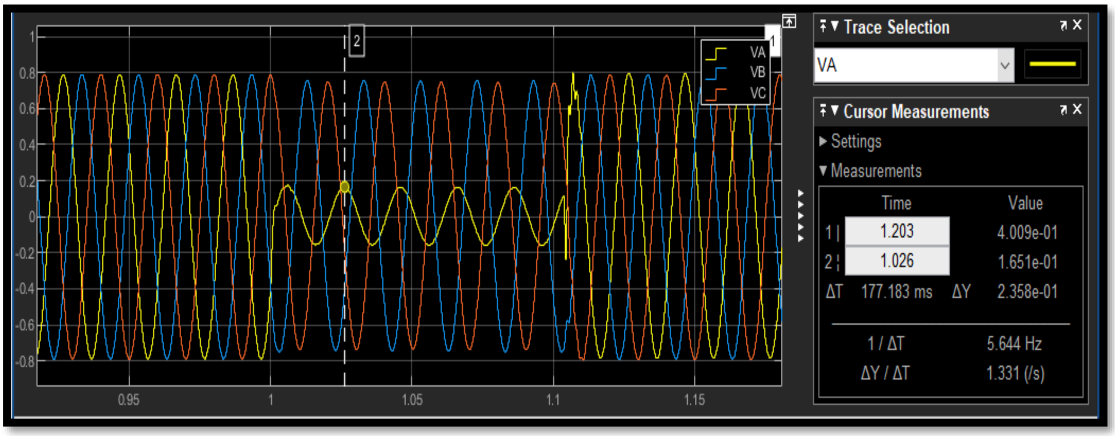

Figure 6.19. *Observation on Van5_4_a*

Firstly, for the voltage sag event detection, approximately two periods after the fault given time (until the signal is fully recovered) and accordingly, the optimum time interval before the fault starts is determined according to the amount of training and test data. The dataset range is between the 0.35. second (7000.index) and 1. 13995.second (22800.index).

Since the magnitude of the voltage sag signal, which behaves continuously and periodically in a certain time interval, is estimated, the data are not shuffled (shuffle=False) and therefore random_state is specified as "0". Then, 70% percent of data are chosen as training and 30% percent of them is defined as test data to reach the predictive aim.

Secondly, train data is splitted by K number equally with using of K-Fold Cross Validation method. The method is providing results about whether data structure and used methods are suitable for prediction before passing the test data. If result of validation is close to 1, it means that obtained data and the methods verifies to predict the test data.

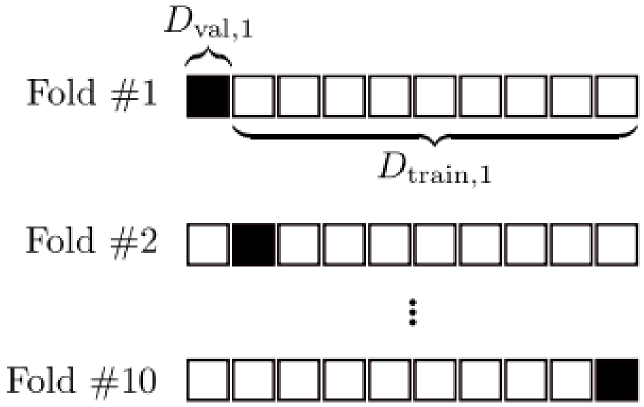

Figure 6.20. *K-Fold cross validation* [53]

Additionally, it is useful method to find out overfitting or underfitting during training. When the predictive performance metrics are compared with validation results, if the metrics show low performance, overfitting can be occurred. If cross validation results show low performance (distance far from 1), underfitting can be happened. Overfitting means that memorizing trained data, so it cannot make prediction for new values. Also, underfitting means that trained data cannot learn during training step. Reasons of that are data structure or methods or both cannot be suitable for prediction like mentioned about that.

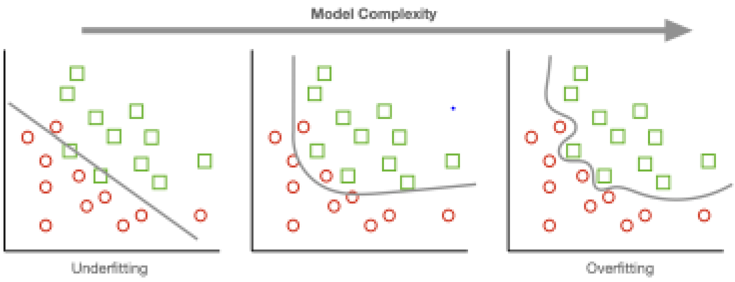

Figure 6.21. *Overfitting and underfitting* [54]

As it is seen in Fig.6.21, while data cannot be enough separated from each other for underfitting, data are separated but it memorizes in overfitting, so middle graph show better performance during training step.

When heterogeneous model is built with SVR, DecisionTreeRegressor and k-nn machine learning algorithms, hyperparameters need to be opimize for effective training performance. “GridSearchCV” structure is used for optimization of SVR, decision tree and random forest regressor (homogeneous) hyperparameters. If SVR is started to adjust them, radial based kernel function is chosen because, trained data can be applied on nonlinear multidimensional timeseries data during model building. C (penalty coefficient) and gamma values adjust trade of overfitting and underfitting with regularizing of decision boundary of estimator. After GridSearchCV tuning results, 10 and 0.0001 are chosen for C and gamma parameters respectively. Also, decision tree hyperparameters are occurred for optimum model building. Number of maximum depth(max_depth) paramter is maximum number of splitting until to reach maximum purity (all of leaves), so max_depth is defined as 7; minimum samples split defines number of sample to split of nodes, so it is defined as 3. Number of minimum sample leaf explains needed minimum samples on a leaf, so it is defined as 1 and last minimum hyperparameter is max_features, it is defined as “auto”. Auto equals number of total features, the model is decided to used number of features selfly. Then, n-neighbors hyperparameter is defined as 5. It expresses that according to based on five nearest vector of the all features, eucledian distance is calculated. Total result of the computes, then, it is devided to chosen “k” number for predicted values. The parameters that max_depth equals 7, min_samples_leaf is 1, max_features is defined as “auto” and n_estimators (number of decision tree) is 180 found for homogeneous (RF) model. The aim of hyperparameter tuning is obtaining low bias and low variance model, therefore, the hyperparameters are regulated to trade off underfitting and overfitting. After suitable hyperparameters are found, model buildings are happened and they are trained by heterogeneous and homogeneous machine learning algorithms to predict voltage sag magnitude that in which bus before defined time horizon in same training data frame. Other 5 different fault types are used as experiments in Figure 6.22, Figure 6.23, Figure 6.24, Figure 6.25, Figure 6.26.

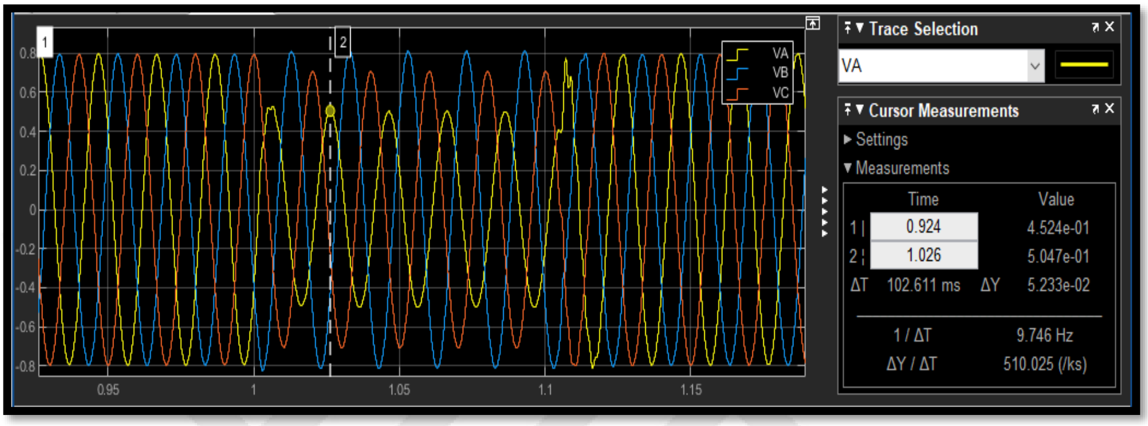

Figure 6.22. *Observation on Van3_4_a*

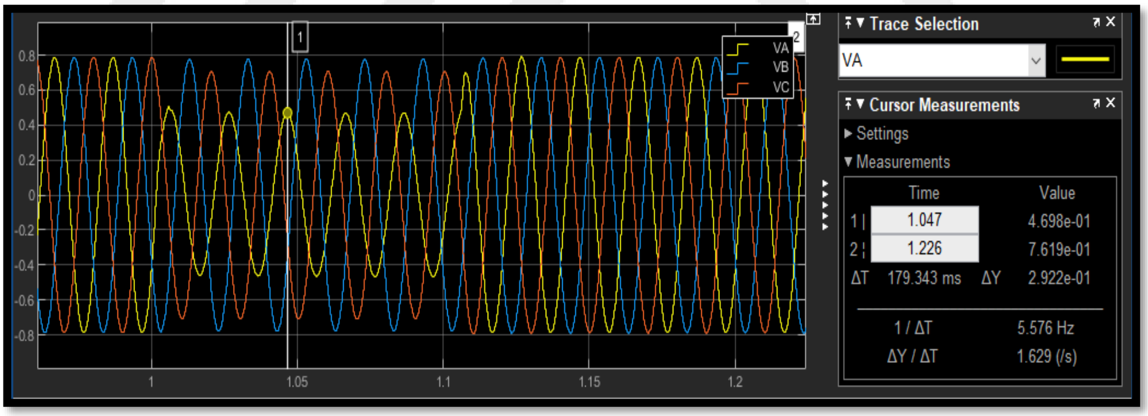

Figure 6.23. *Observation on Van8_1_a*

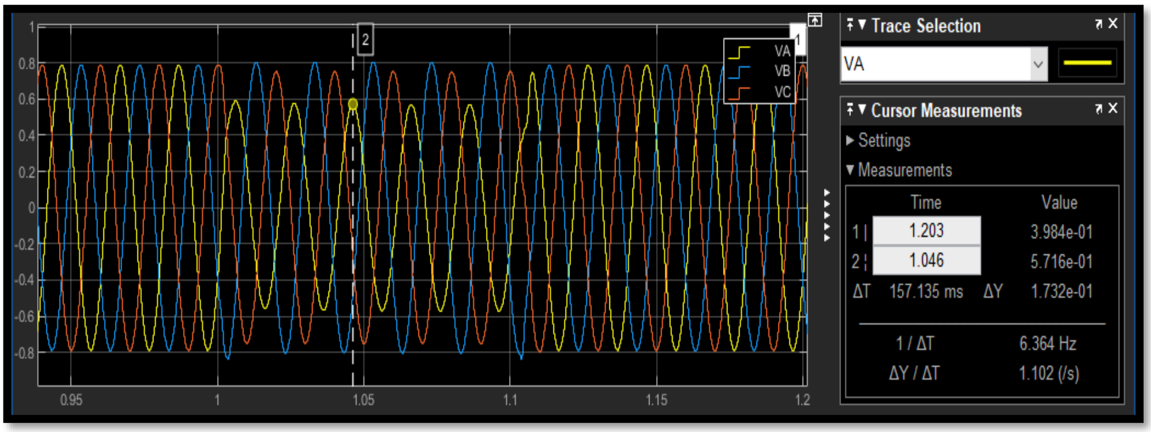

Figure 6.24 Observation on Van5_6_a

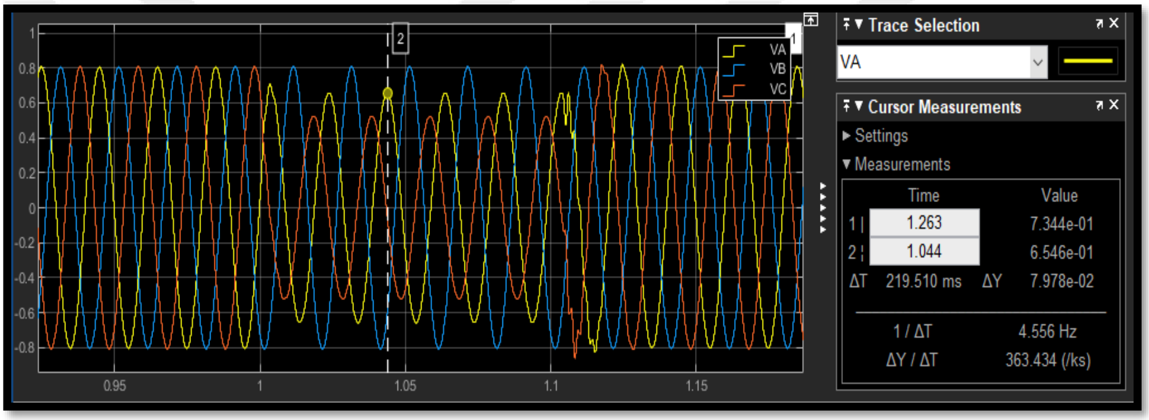

Figure 6.25. Observation on Van2_9_a

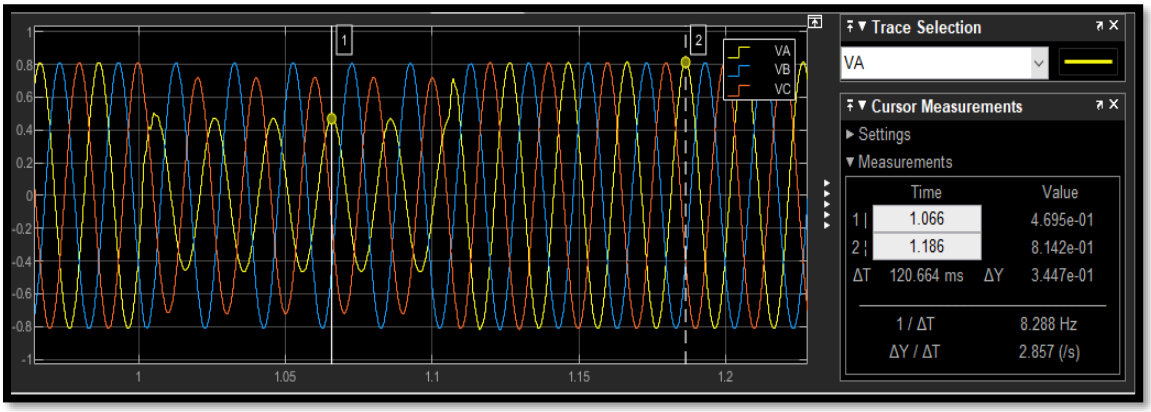

Figure 6.26. *Observation on Van_4_2_a*

They are read as the magnitude of the voltage sag at the 3th bus of the fault occurring in 4th bus (Van3_4_a), the magnitude of the voltage sag at the 8th bus of the fault occurring in the 1st bus (Van8_1_a), the magnitude of the voltage sag at the 5th bus of the fault occurring in the 6th bus(Van5_6_a), the magnitude of the voltage sag at the 2nd bus of the fault occurring in 9th bus (Van2_9_a) and the magnitude of the voltage sag at the 4th bus of the fault occurring in 2nd bus (Van4_2_a) respectively.

6.5. Prediction Results

In this work, 2 (homogeneous and heterogeneous) models belong to single phase fault prediction model. K-fold cross validation (CV=5) is used for defined homogeneous and heterogeneous model. Whether the model is overfitting or not can be better decided when the results from the cross-validation and prediction metrics are evaluated together. In homogeneous and heterogeneous training models, both cross validation scores and prediction metrics produce successful results, so the models have low bias and low variance. In other words, the generalization performance of the system can be said to be high when overfitting and underfitting are in balance. If the models are evaluated as speed performance, although, especially in, n_jobs equals to -1(using all performance of operating system), 1 hour pass to find optimum parameters for RF model, but for heterogeneous model, the operation lasts about 2 seconds.

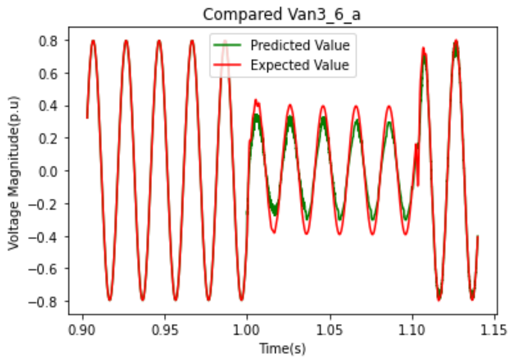

Figure 6.27. *Homogeneous model on bus3*

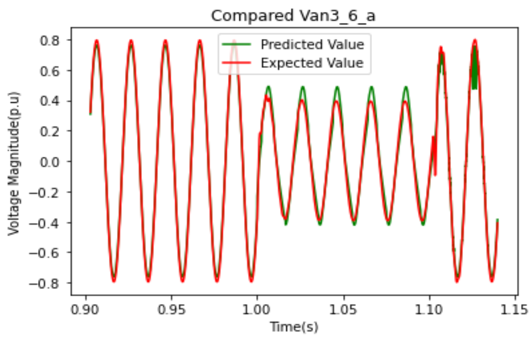

Figure 6.28. *Heterogeneous model on bus3*

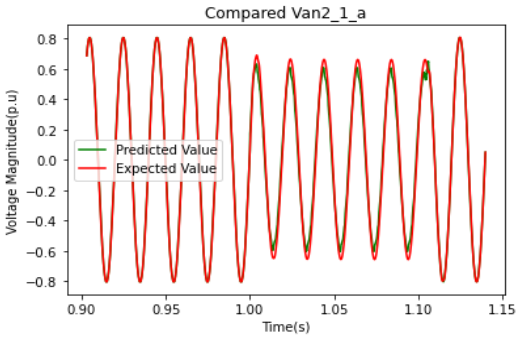

Figure 6.29. *Homogeneous model on bus2*

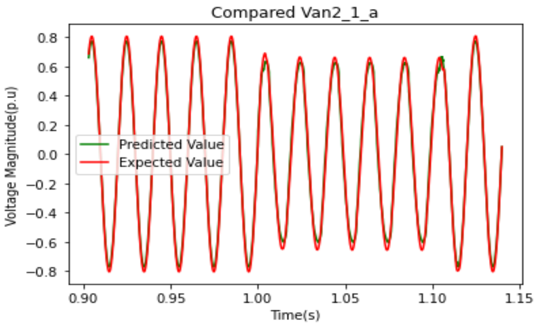

Figure 6.30. *Heterogeneous model on bus2*

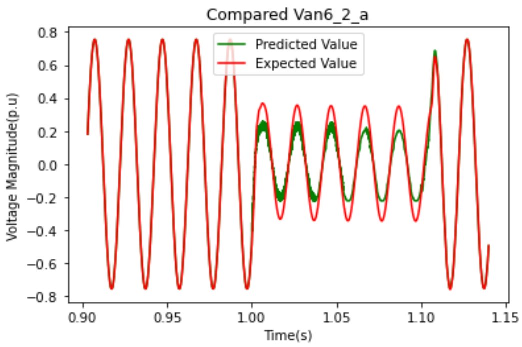

Figure 6.31. *Homogeneous model on bus6*

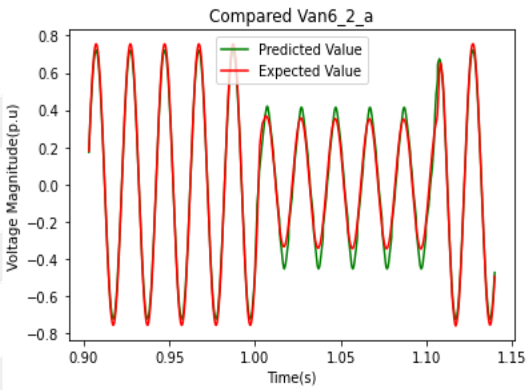

Figure 6.32. *Heterogeneous model on bus6*

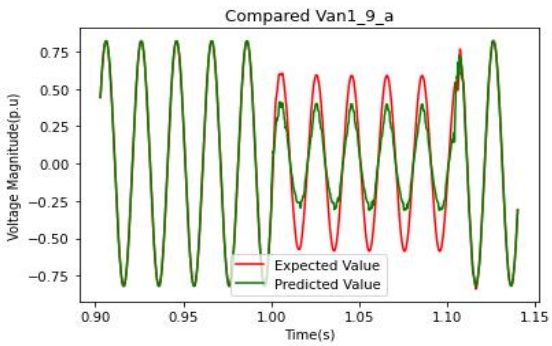

Figure 6.33. *Homogeneous model on bus1*

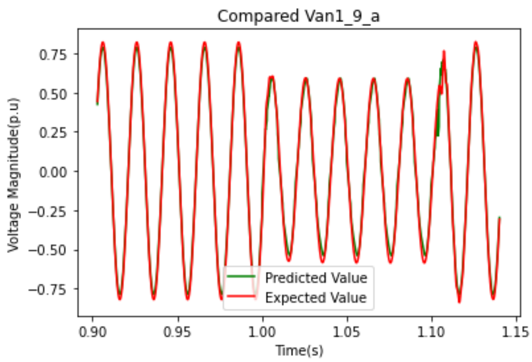

Figure 6.34. *Heterogeneous model on bus1*

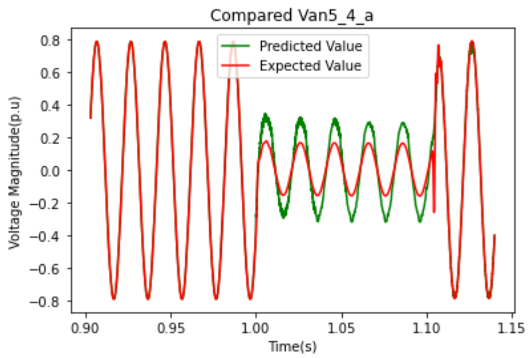

Figure 6.35. *Homogeneous model on bus5*

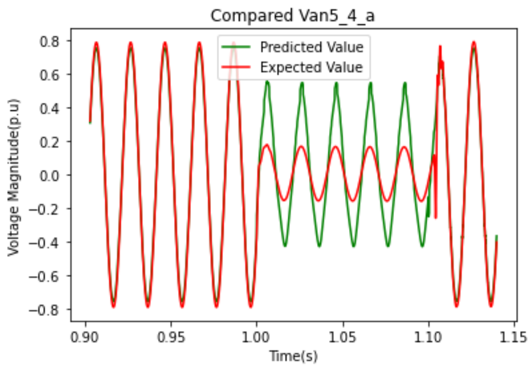

Figure 6.36. *Heterogeneous model on bus5*

If the prediction performances are compared between homogeneous and heterogeneous models, according to fault scenarios, prediction performances changes. Both of two model are better performance when predicting Van2_1_a sag magnitude. The performance decreases in both of models for prediction of Van5_4_a sag magnitude. When Van3_6_a, Van6_2_a and Van1_9_a sag magnitudes are predicted, heterogeneous model performance outperforms. Additionally, when the user chooses the hyperparameter setting selfly, the process takes seconds, but it is important to set the hyperparameter for the model to make the optimum estimation. However, hyperparameter tuning that made with GridSearchCV sometimes cannot give desired prediction results.

Table 6.5. *Prediction results(homogeneous)*

Homogeneous model performance					
	Van3_6_a	Van2_1_a	Van6_2_a	Van1_9_a	Van5_4_a
R2_score	0.98370	0.99263	0.97833	0.92906	0.97370
MSE	0.00321	0.00190	0.003751	0.01534	0.00517
MAE	0.03524	0.02690	0.03753	0.07586	0.04314
RMSE	0.05666	0.04360	0.06125	0.12386	0.07191

Table 6.6. *Prediction results(heterogeneous)*

Heterogeneous model performance					
	Van3_6_a	Van2_1_a	Van6_2_a	Van1_9_a	Van5_4_a
R2_score	0.98842	0.99509	0.98895	0.99346	0.90720
MSE	0.00234	0.00125	0.00203	0.00158	0.01919
MAE	0.03621	0.03006	0.03566	0.03016	0.09078
RMSE	0.04837	0.03539	0.04510	0.03987	0.13853

Table 6.7. *Difference voltage sag magnitude(homogeneous)*

Voltage(p.u)	Voltage sag peak magnitude difference(p.u)	Expected voltage sag peak magnitude(p.u)	Predicted voltage sag peak magnitude(p.u)
Van3_6_a	0.07346	0.40212	0.32865
Van2_1_a	0.05569	0.66395	0.60825
Van6_2_a	0.10511	0.35685	0.25173
Van1_9_a	0.19138	0.59325	0.40187
Van5_4_a	-0.15345	0.16895	0.32240

Table 6.8. *Difference voltage sag magnitude(heterogeneous)*

Voltage(p.u)	Voltage sag peak magnitude difference(p.u)	Expected voltage sag peak magnitude(p.u)	Predicted voltage sag peak magnitude(p.u)
Van3_6_a	-0.08646	0.48859	0.40212
Van2_1_a	0.03695	0.66395	0.62699
Van6_2_a	-0.05761	0.35685	0.41446
Van1_9_a	0.00296	0.59325	0.59029
Van5_4_a	-0.38000	0.16895	0.54895

According to R2_scores of homogeneous and heterogeneous models, especially in, performance of the heterogeneous model is quite low for prediction of Van5_4_a sag magnitude. Although MSE, MAE and RMSE metrics demonstrate low differences about between expected and predicted voltage sag magnitudes, amount of sag magnitude differences is-0.38000 for heterogeneous model. The question should be that although the forecast performance is high at this point, the difference between the estimated value and the actual value is large. When overfitting is evaluated, both CV score and estimation metric are at the desired level and hyperparameters are C = 10 and gamma = 0.0001 for all models. As a solution, C and gamma parameters can be changed in SVR or hyperparameters of other methods can be changed. Particularly, heterogeneous model outperforms for Van6_2_a and Van1_9_a predictions, when looking for predictive performance metrics.

When evaluated in general, as can be seen from the figures, metric results and magnitude differences of expected and predicted peak voltage sag, there is little difference and its actual(expected) value on fault time. Additionally, prediction of the sag magnitude which bus is it in is occurred before 100ms as an optimal time duration ,according to adjusted ratio of train and test set.

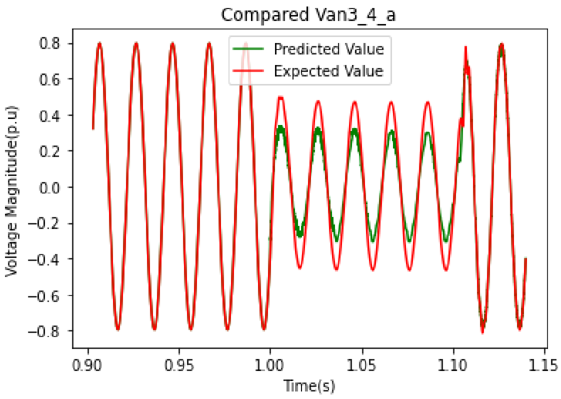

Figure 6.37. *Homogeneous model on bus3*

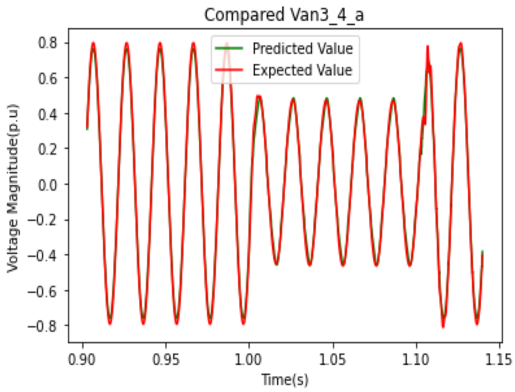

Figure 6.38. *Heterogeneous model on bus3*

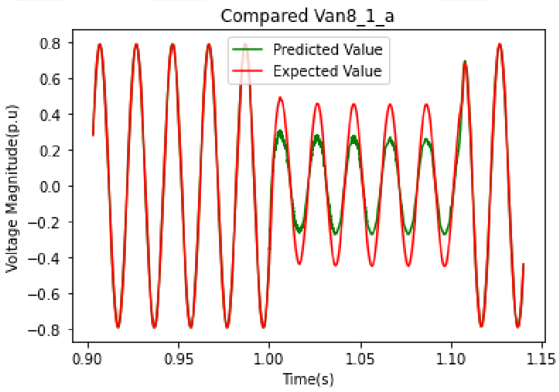

Figure 6.39. *Homogeneous model on bus8*

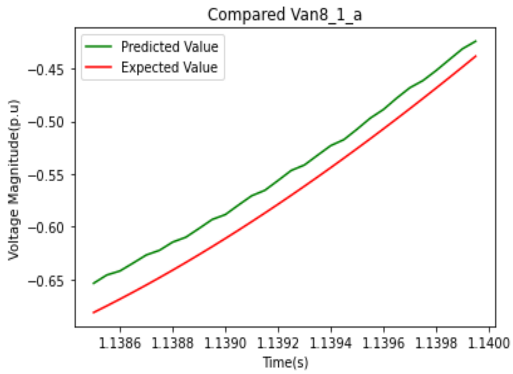

Figure 6.40. *Heterogeneous model on bus*8

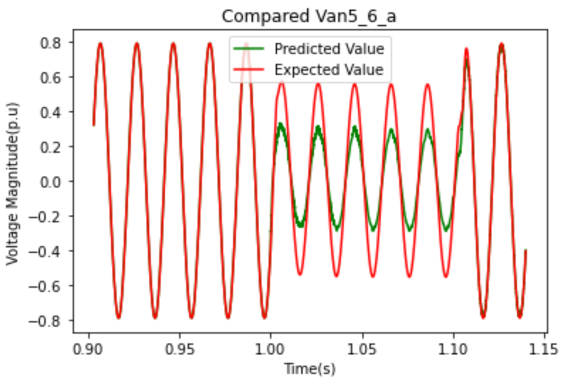

Figure 6.41. *Homogeneous model on bus*5

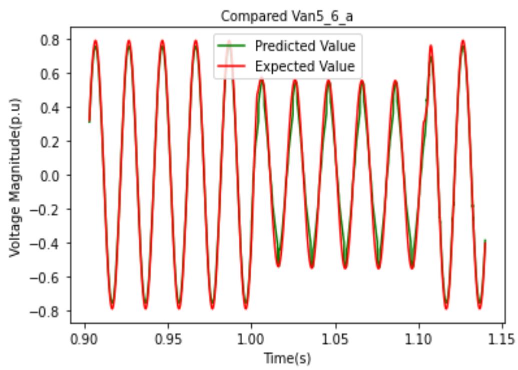

Figure 6.42. Heterogeneous *model on bus*5

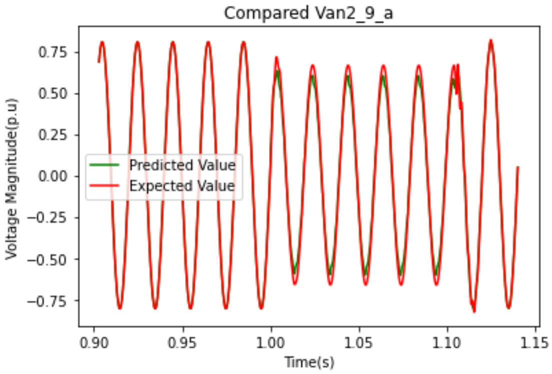

Figure 6.43. *Homogeneous model on bus2*

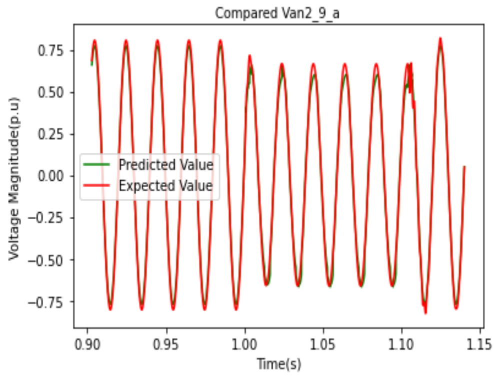

Figure 6. 44. *Heterogeneous model on bus2*

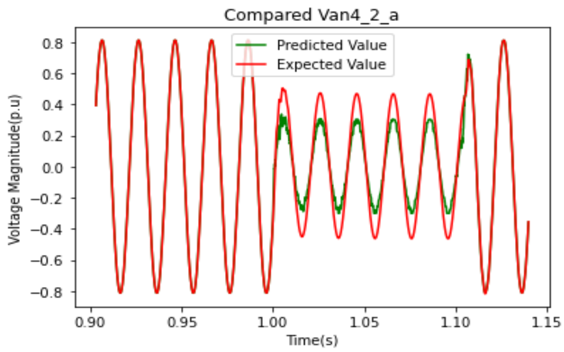

Figure 6.45. *Homogeneous model on bus4*

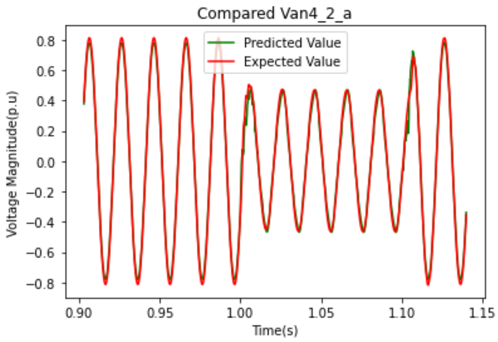

Figure 6.46. *Heterogeneous model on bus4*

The heterogeneous model is better in estimating for Van3_4_a, Van5_6_a and Van4_2_a sag magnitudes. While estimating Van8_1_a with predictive metrics at a certain performance, the heterogeneous model predicted Van8_1_a linearly and an incorrect result was obtained. Both models performed very well in estimating Van2_9_a. Model generalization is better for heterogeneous machine learning algorithms. One of the important reason can be that include more than one kind of base machine learning algorithms due to structure of focusing on optimization of ensemble learning algorithms. For higher-performance voltage sag magnitude estimation, the optimal 100 ms was set according to the proportions of the training and test dataset. As a criterion, the data interval from a certain starting point before the system fails until the system recovers for a certain time after the failure was preferred. According to this setup, the prediction of the voltage sag magnitude in the faulted interval 100 ms before the power system is generally accurate, as can be seen from the prediction metrics tables and visualizations.

Table 6.9. *Prediction results(homogeneous)*

Homogeneous model performance					
	Van3_4_a	Van8_1_a	Van5_6_a	Van2_9_a	Van4_2_a
R2_score	0.96522	0.96373	0.91964	0.99415	0.96617
MSE	0.00690	0.00700	0.01564	0.00150	0.00699
MAE	0.05233	0.05044	0.07630	0.02453	0.05096
RMSE	0.08307	0.08372	0.12507	0.03884	0.08361

Table 6.10. *Prediction results(heterogeneous)*

Heterogeneous model performance					
	Van3_4_a	Van8_1_a	Van5_6_a	Van2_9_a	Van4_2_a
R2_score	0.99566	0.89459	0.98246	0.99470	0.99436
MSE	0.00091	0.00050	0.00366	0.00136	0.00121
MAE	0.02329	0.02208	0.04422	0.02864	0.02670
RMSE	0.03018	0.02245	0.06055	0.03700	0.03485

Table 6.11. *Difference voltage sag magnitude(homogeneous)*

Voltage(p.u)	Voltage sag peak magnitude difference(p.u)	Expected voltage sag peak magnitude(p.u)	Predicted voltage sag peak magnitude(p.u)
Van3_4_a	0.15042	0.32238	0.47280
Van8_1_a	0.18031	0.45775	0.27744
Van5_6_a	0.24690	0.55971	0.31281
Van2_9_a	0.06346	0.66638	0.60291
Van4_2_a	0.16539	0.47334	0.30794

Table 6.12. *Difference voltage sag magnitude(heterogeneous)*

Voltage(p.u)	Voltage sag peak magnitude difference(p.u)	Expected voltage sag peak magnitude(p.u)	Predicted voltage sag peak magnitude(p.u)
Van3_4_a	-0.0098	0.47280	0.48263
Van8_1_a	-0.01420	-0.43816	-0.4239
Van5_6_a	0.01556	0.54415	0.54415
Van2_9_a	0.01695	0.66638	0.64942
Van4_2_a	0.00305	0.47334	0.47029

The same problem here is that although the prediction performance is high, the homogeneous model is a bit more inadequate in reflecting the magnitude of the voltage sag. Since the R2_score, MSE, MAE and RMSE metrics give average results when evaluated outside of the hyperparameter setting, a result close to one hundred percent is obtained for the data frame received before the fault time in the entire signal. It may be the nonfault signal in this range that raises the average value. In general, the prediction performance of the heterogeneous model outperforms.

7. DISCUSSION AND FUTURE WORKS

The basic and general question at the beginning of the study is, is it possible to predict when power quality disturbances will occur at other buses when a failure occurs at any bus in a power system early? Since it is a predictive approach, a meaningful pattern can be provided when training past fault data sets with artificial intelligence and the prediction of how much voltage sags will occur at which bus can be answered with time data. In this context, it is important to label individual features (e.g., Van2_9_a) for the purpose of the study. In a real-life dynamic, non-stationary power grid, power quality disturbances can occur in the system for different reasons at different time intervals, as well as multiple power quality disturbances can occur simultaneously in the grid and one power quality disturbance can trigger another power quality disturbance. In these systems, the real-time evaluation of power quality disturbance data stored by power quality analyzers and the establishment of an algorithm to predict the disturbance, which is the aim of this study, can provide many benefits in the transformation from traditional grids to smart grids and grid structures such as microgrids supporting renewable energy.

Forecasting increases the capacity of the grids to continue to operate safely by ensuring that necessary measures are taken in a timely manner. Therefore, a significant portion of the grid failures can be prevented in the future, and energy efficiency (production - consumption balance) can be increased, resulting in lower energy bills and maintenance costs, longer life of electrical appliances, and uninterrupted continuation of industrial production. With the increase in the use of electric vehicles and the integration of renewable energy with an intermittent nature, the grids are more loaded and the need for efficient use of energy increases. At this point, it is important to ensure the continuity of power quality for a balanced production and consumption. Modeling predictive compensation systems will be one of the effective solutions in this context [12]. As mentioned earlier in the literature review, the best estimate so far was a study for voltage sag, rapid voltage changes and interruption events on a power grid in Norway 10 minutes ago as an “Early Warn Project” [8].

One of the reasons for choosing the IEEE9 bus system is to easily follow the dynamics the power system at the time of fault and to express the effect of the voltage sag on the other buses of the fault given to a bus or buses while labeling, and to initially ensure the accuracy of the hypothesis. As can be seen in the evaluation metrics (R2_score, MSE, MAE and RMSE) and graphic outputs, the voltage sag problem can be expressed correctly in the selected features with the symmetric component analysis and the artificial intelligence algorithms used while choosing the combination of decision tree, SVR, k-nn and random forest as an indicator. When the power system is considered as a whole, and the effect on all buses is the voltage sag with different magnitudes depending on distance of fault locations in general, so pattern of input samples and target samples can be found successfully.

In the IEEE9 bus system, the targeted estimation was realized before 100ms, by using the improvement-oriented ensemble learning method, which is stronger as an algorithm and has high generalizability in estimation.

The realization of the prediction of power quality disturbances occurring at different time intervals in the grids that support a more realistic and renewable energy structure, much earlier than the time, will make significant contributions to the achievement of the study's goal and to the understanding of the "early warning system”.

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CURRICULUM VITAE

ORCID ID: 0000-0001-7626-2443

Objective: For a sustainable future and developable world, I want to contribute technology and production with a benefit-oriented and multidisciplinary understanding of ideas that are open to innovation in the light of science, believe in universality.

The impact degree of results depends on the process, so I think it is important to manage the process in a systemic and organized manner with interconnected stages.

Education

September (2012-2017) B.Sc., Eskişehir Osmangazi University, Electrical and Electronics Engineering (Eng.) / ESKİŞEHİR

- Increasing Hot Water Comfort in Thermosiphon Products with Electronic Control / Capstone Project (September 2016 – January 2017)

Scientific Publications and Activities

- Prediction of Power Quality Disturbances with Artificial Intelligence Methods / 8th International Congrees on Engineering and Technology Management (Verbal Presentation – Online), 08-10 December 2022, pp.99-106
- Power Quality Problems in Microgrids / ESTÜ – Seminar (June 2020)

Work Experience

October 2017- May 2018 Control Engineer, Güma İnşaat SAN. TİC. LTD. ŞTİ, ESKİŞEHİR

- Controlling the Electricle Projects for Kızılay Blood Building

Voluntary Works

- Eskişehir Chamber of Electrical Engineers (EMO/Board of Directors) (February 2022-) / Member (January 2018 -)
- School Support Association (ODD - Math Volunteer) (September 2020- 2021)
- Turkish Foundation for Combating Erosion, Afforestation and Conservation of Natural Assets (TEMA) (Member)
- Educational Volunteers Foundation of Turkey (TEGV-English Volunteer) (September- November 2019)

- IEEE Power and Energy Society- Electric Vehicles (November 2014 - March 2015)
- Eskişehir Osmangazi University Folklore Research Center (HAMER)- Rhythm Club (December 2012- April 2013/Playing Frame Drum)

Seminars

- Future Trends and Metaverse / TUGIAD Eskişehir (March 2022)
- Motion Simulation Platform Education / ESTÜ Innovation Industry (March 2022)
- Motion Capture Education / ESTÜ Innovation Industry (March 2022)
- Electric Vehicles Summit / ITU Electrical Engineering Club (March 2021)
- The Near Future of Solar Energy / Solar Baba (December 2020)
- Microgrids / Chamber of Electrical and Electronics Engineering (November 2020)
- Electric Vehicles and Charging Stations / Chamber of Electrical Engineers (September 2020)
- Innovation Schneider Electric / Eskişehir Organized Industry (October 2019)