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Disturbances Identification in Smart Distribution Grids

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الآراء الواردة في الرسالة الجامعية

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Dedications

To God, my late father (God rest his soul), my family, and my friends.

For their endless love, support and encouragement.

Mohammad.H.Al-Amaryeen

Acknowledgments

I would first like to thank Allah for the blessings and grace during this project and my whole life. I dedicate this project to the first and best teacher of all time the prophet Mohammed (Pease be upon him).

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Mohammad Al-Amareeyn

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List of Abbreviation

Acronyms		Full Form
AMI	:	Advanced Metering Infrastructure
ANN	:	Artificial Neural Network
CL	:	Classifier Learner
DG	:	Distributed generation
DS	:	Distribution Substation
EV	:	Electric Vehicle
FDR	:	False Discovery Rate
IEC	:	International Electro-technical Commission
IEEE	:	Institute of Electrical and Electronics Engineers
PCC	:	Point of Common Coupling
PPV	:	Positive Predictive Value
PQ	:	Power Quality
PQD	:	Power Quality Disturbances
PV	:	Photovoltaic
RVC	:	Rapid Voltage Change
SLD	:	Single Line Diagram
SDG	:	Smart Distribution Grid
THD	:	Total Harmonic Distortion
THDI	:	Current Total Harmonic Distortion
THDV	:	Voltage Total Harmonic Distortion

Abstract

Disturbances Identification in Smart Distribution Grid.

Mohammad Al-Amaryeen

Mutah University, 2023

Electric power distributors, as well as users, are increasingly concerned about the quality of the power and power interruptions. It is necessary to continue monitoring the power delivered to customer's sites in order to improve the quality of electricity. Identification of Power Quality Disturbances (PQD) and reliable PQD categorization are therefore particularly desirable. In addition, the detection and classification of the PQD in distribution systems are important tasks for protection of power distributed network. Most of the disturbances are non-stationary and transitory in nature hence it requires advanced tools and techniques for the analysis of PQD. In this thesis a monitoring of many Distribution Substations (DSs), which have different power systems, are used to compare the disturbances types occur on each substation, and because there are many applications in Smart Distribution Grid (SDG) have been developed to achieve consumer service and support the electrical network the monitoring of new modifications is also important. One of these applications is connect of renewable energy resources. This work build up to study the disturbances occurs on diffuses power systems and develop a new computer software to detect and classify disturbances signals. The study is divided into three main parts:

I. First part contain choosing and monitoring different power system connected to the Al-thaniah and Al-safi main substations. Residential, Commercial, photovoltaic (PV) system and Electric Vehicles (EV) charger are the four-power systems, which used to monitor the disturbances signal and capture a sample for the event signals.

II. Second part studies briefly the disturbance events appear on each DS and compares the number of occurred events at a specific time. Voltage sag and swell, transient, Rapid Voltage Change (RVC) and Total Harmonic Distortion (THD) are the main events described and captured by the measurement device. Recently, there are many attempts to create a computer software that capable of determining the time and type of disturbance occurs on power system, and many modern and old techniques were used for this purpose.

III. The third part of this thesis presents the use of disturbances data that extracted from the monitoring of the distribution transformers, mentioned earlier, to build a computer software capable of capturing, identifying and classifying the disturbance signals using the Artificial Neural Network (ANN) and Classifier Learner(CL) technique that built by using the MATLAB program.

الملخص

تحديد الاضطرابات في شبكة التوزيع الذكية.

محمد العميريين

جامعة مؤته، 2023

يشعر موزعو الطاقة الكهربائية، وكذلك المستخدمون، بقلق متزايد بشأن جودة الطاقة وانقطاعات الطاقة. لذا من الضروري المراقبة المستمرة للطاقة التي يتم توصيلها إلى مواقع العملاء من أجل تحسين جودة الكهرباء. وبالتالي، فإن تحديد اضطرابات PQ والتصنيف الموثوق به لـ PQD ضروري ومهم. بالإضافة إلى ذلك، يعد اكتشاف وتصنيف PQD في أنظمة التوزيع من الأعمال المهمة لحماية الشبكة الموزعة للطاقة. معظم الأحداث على الشبكة الكهربائية غير ثابتة وعابرة في طبيعتها ولذلك فهي تتطلب أدوات وتقنيات متقدمة لتحليل الحدث. في هذه الأطروحة، تم رصد العديد من محطات التوزيع الفرعية ذات أنظمة الطاقة المختلفة المستخدمة لمقارنة نوع الاضطرابات التي تحدث في كل محطة فرعية، ولأن هناك العديد من التطبيقات في شبكة التوزيع الذكية تم تطويرها لتحقيق خدمة المستهلك ودعم الشبكة الكهربائية فإن مراقبة التعديلات الجديدة مهم أيضًا. أحد هذه التطبيقات هو ربط موارد الطاقة المتجددة. تم بناء هذا العمل لدراسة الاضطرابات التي تحدث على أنظمة الطاقة المنتشرة وتطوير برنامج كمبيوتر جديد لاكتشاف إشارات الاضطرابات وتصنيفها. تنقسم الدراسة إلى ثلاثة أجزاء رئيسية:

I. يحتوي الجزء الأول على اختيار ومراقبة أنظمة الطاقة المختلفة المتصلة بمحطتي الثنية والصافي الرئيسيتين. النظام السكني والتجاري والكهروضوئي وشاحن المركبات الكهربائي هي أنظمة الطاقة الأربعة المستخدمة لمراقبة إشارة الاضطرابات والتقاط عينة لإشارات الحدث.

II. يدرس الجزء التالي بإيجاز حدث الاضطراب الذي يظهر في كل محطة توزيع فرعية ويقارن عدد الأحداث التي حدثت في وقت محدد. ترهل الجهد وتضخمه، وتغير الجهد السريع العابر (RVC) والتشوه التوافقي الكلي (THD) هي الأحداث الرئيسية الموصوفة والتي تم التقاطها من جهاز القياس. في الآونة الأخيرة، هناك محاولات عديدة لإنشاء برنامج كمبيوتر قادر على تحديد وقت ونوع الاضطراب الذي يحدث على نظام الطاقة، والعديد من التقنيات الحديثة والقديمة المستخدمة لهذا الغرض.

III. يعرض الجزء الثالث من هذه الرسالة استخدام بيانات الاضطرابات التي تم استخلاصها من مراقبة محولات التوزيع المذكورة سابقًا لبناء برنامج كمبيوتر قادر على التقاط إشارات الاضطراب وتحديدها وتصنيفها باستخدام تقنية ANN المبنية باستخدام برنامج MATLAB.

Chapter One
Overview

1.1 Introduction

The rise in power usage is a significant element that forces researchers to consider and plan carefully how much and what kind of energy we will consume in the future. Furthermore, rising consumption, in combination with serious issues such as global warming, resource shortages, and electricity costs, lead politicians and scientists around the world to discover solutions to these looming challenges. One of these challenges is the expanding use of semiconductors in modern life where the non-linear loads are a major danger to power quality (PQ) levels (Michalec Ł et al., 2021). The quality of electric power and disturbances occurred in power signal has become a major issue among the electric power suppliers and customers. Many disturbances like voltage swell, voltage sag, notch, transients, and harmonic distortions, so on effect on the power signal, and cause degradation in quality of power. PQ is the ability of a power grid to supply power to the consumers efficiently and it expresses the ability of an equipment to consume the power being supplied to it. In technical terms, disturbances need to monitor, measure, study and classified by analyzing the sinusoidal waveform at the rated voltage and frequency (IEEE Std., 2009). It can have a large detrimental effect on industrial processes and the commercial sector.

1.2 Problem Statement

Disturbances problems have increased significantly because of today's power supply, which is dependent on developing renewable sources such as solar, wind, and nuclear energy. PQD must be detected and identified correctly and precisely in order to preserve PQ and assure its reliability. In general, a smart distribution system is a complicated system that incorporates Distributed Generators (DGs) in terms of renewable energy resources, Information and Communication Technology (ICT), sensing and measurement, automation, electrical vehicles linked into the network, consumers, and connections (Colak, I et al., 2016). Such complexity in distribution networks makes the faults occurred due to either operation, damage in equipment, natural disasters, or malicious attacks, to name a few; leading to potentially cascading disturbances or even blackouts.

As a result, understanding disturbances is critical to the smart distribution grid's ability to provide electricity whenever and wherever it is needed. This thesis attempts to classify the effect of disturbances on the SDGand identify disturbance kinds in order to improve the electric power network's reliability by using a practical approach and computer software.

1.3 The scope of research

Recently, many applications in distribution grid have been employed to allow generate energy to the distribution grid and connecting modern load types. Such as applications have a bad impact on the distribution network, and cause a degradation in quality of power delivered for consumer. So monitoring of PQ is one of most important issues in distribution network, and nowadays monitoring can be achieved by Artificial Intelligent Technique (AIT), like ANN and Deep and Machine Learning. The degradation in quality of power comes from any disturbing phenomena that cause the mains voltage (or current) wave to depart from its nominal characteristics and called disturbances. This work is narrowed to achieve disturbances identification on real DSs by installing advance measurement devices and design a software that can precisely do the job.

1.4 Research Aim and Objectives

This research aim to identify disturbances and its impact on the distribution network that contains renewable energy resources and modern load types. In order to achieve this goal. Study, monitor and identify disturbances in power line requires, then design computer software able to monitor power signal event, the following objectives are made:

1. Comprehensive disturbance analysis in the distribution networks.
2. Disturbance identification, using a practical approach by detection capabilities into monitoring equipment so disturbances are identified, captured, and classified.
3. Using computer software to build up an identification system.

1.5 Research Methodology

To achieve the previous mention objectives, the research has been conducted as follows:

1. An overview the disturbances identification methods and techniques.
2. Develop Integrated Monitoring System of disturbances by installing advance measurement devices.
3. Using a MATLAB code environmental to design classification technique, by using ANN/ Classification Learner (CL).
4. Comprehensive disturbance analysis and classification.

1.6 Thesis Organization

A Disturbance Identification in SDG designed and simulated in this thesis. The thesis is divided into five chapters, as follows:

Chapter 1: Introduction, aim and objectives, methodology and scope of this work.
Chapter 2: Examine the definition of Smart Grids and their main components, overview the distribution grid disturbances, which is the thesis's focus, and present a literature review SDG disturbances and disturbances identification techniques done by researchers.
Chapter 3: Declaration the result of creating an integrated monitoring system by installing advanced measurement equipment on DS with comprehensive disturbances classification then discus the used technique to achieve disturbances identification by MATLB code environmental. Illustrate the result of disturbances identification used performance.
Chapter 4: Present a discussion, conclusion and future work**.**
References

Chapter 2
Theoretical Background and Literature Review

2.1 Introduction

This chapter presents an introduction to SDG, disturbances and some previous studies related to disturbances in SDG and techniques used to disturbances identification.

2.2 Smart Grid: An Overview

Using two-way communication technology, a smart grid delivered electrical power between suppliers and consumers (Zhou et al., 2013). It is used to construct intelligent consumer-side applications, like buildings that promote energy conservation. It is predicted that the smart grid will update the traditional electrical power network. It offers automatic optimization, protection, control, and monitoring of the interconnected elements' performance (Pramangioulis et al., 2019).

The U.S. Department of Energy (DOE) has offered the following description of a smart grid: “an automated system that incorporates a digital grid and allows for a two-way flow of information and electricity between users and the utility” (Vincenzo & Steven, 2012).

The National Electrical Manufacturers Association (NEMA) had also incorporated an important distinction between smart grids and traditional grids to their definition of the former. Demand-side management systems (DSM), distribution automation (DA), distributed generation (DG), renewable energy (solar, biomass, wind, etc.), metering, and other modern technologies into the grid are examples of smart grids (Agung & Handayani, 2020). Figure (2.1) shows smart grid applications and components (Refaat & Mohamed, 2019).

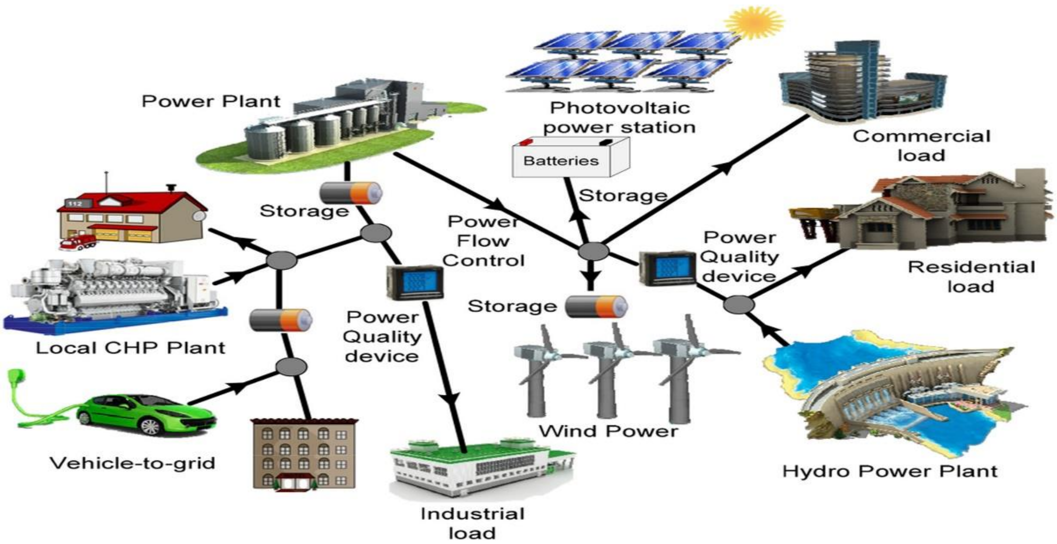


Figure 2.1: Smart Grid applications (Refaat & Mohamed, 2019).

2.2.1 Characteristics of Smart Grid

The smart grid (SG) is described differently by different competent authorities, but it may be simply defined as the outcome of utilizing communication, power electronics, and storage technologies to manage the power system and balance demand and supply.

The next generation of power systems, which enable the bidirectional movement of electricity and information, are referred to as smart electrical grids. Utilizing advanced communications to provide data flow between supplier and consumer, such as monitoring, controlling, and using renewable energy sources to enable the transformation from centralized generation power system to DG power system.

Researchers believe that the distribution system should be upgraded to accept more DGs and construct a more robust system, though, as a result of the advancement of society and technology. The grid's reality show that it is urgently necessary to update existing distribution grid by:

I- Meeting the Reliability and Quality Criteria:

The requirement of the public for power supply reliability and power quality (PQ) is increasingly high. “The event of “8.14” in 2003 made the US government realize the significance of a robust power system” (Dayu 2004).

II- The requirement of sustainable development:

The international economy has enjoyed successful growth over the last ten years, but this progress unavoidably comes with it issues for the environment. They have high rates of carbon emissions and per capita energy consumption, particularly in some developing nations, and low rates of renewable energy installations. The entire globe has come to the realization that we should rely less on fossil fuels and choose for a sustainable path. The science is clear: “To avoid the worst impacts of climate change, emissions need to be reduced by almost half by 2030 and reach net-zero by 2050” (Sun et al.,2019).

III- Accepting more DGs.

Many DGs like Wind power generation and PV power generation penetrate into the power system. However, the traditional distribution grids are not able to accept DG as many as possible for they are designed based on the one-way flow and have no potential to accept more. In other words, renewable power integration urges the old system to upgrade (Fallahzadeh-Abarghouei et al., 2018).

Obviously, all the problems mentioned above may be solved by SDG. The SDG is a distribution system, which incorporated with conventional and advanced distribution engineering technology, Advanced Metering Infrastructure (AMI) and communication technology etc. It can accommodate distributed electric source and supply safe, reliable and qualified power to the consumers. The advantages of SG over traditional grid can be clarified in the Table2.1 (Ourahou et al., 2020).

Smart grids are designed to enable high penetration of renewable energy generation into the electrical system, accomplish system security and stability, and maintain high service quality. Additionally, it offers increased flexibility for distribution system operation and maintenance through enhanced distribution asset management.

Table 2.1: Comparing SG with conventional grid.

Comparative	Conventional Grid	Smart Grid (SG)
Communication	One-directional	Bi-directional
Instrument	Electromechanical & Digital	Digital
Capacity	Large in central	DG with various capacities
Sensing	Limited number of sensors	Large number of sensors
Monitoring	Less self-monitoring	Complete self-monitoring
Restoration	Less automatic restoration	Complete automatic restoration or Self-healing
Adaptation	Less adaptable in case of failures and blackouts	Adaptive and allows islanding
Controllability	Less control	Unlimited control
flexibility	Limited choices for consumers	Wide variety of choices for consumers
Designing	Hierarchical structure	Network structure
Real time data	Less feedback network	The inherent and real-time control
Interruption & Blackout	Wide area interrupts at the time of fault.	Islanding & Filtering disconnection
Controllability	Network restriction control	Network comprehensive control
Services	subscriptions provided with limited services	subscriptions provided with various services
Structure	Radial Network	Dispersed Network
Response	Slower in response during emergencies	Quicker in response during emergencies
Data availability	Small volumes of data available	Large quantities of data available

2.2.2 Type of Power System in SDG

There are five primary power system types connected to SDG. Different electrical loads will be used by various power systems. “This has an impact on how an electrical engineer builds and keep system in the safe operation” (Koshy 2018). It will be seen why commercial electrical load calculations are different from those for industrial, domestic, agricultural, or other power systems.

The amount of electricity used and the peak hours for power utilization will vary greatly between different power systems, with considering the difference between the amount of energy needed in a home and, say, a factory. In general the types of load connected to the SDG can be divided into five categories are (Electrical workbook 2022):

I- Residential power systems:

Circuits found in a typical home are known as domestic (or residential) power systems. Lighting and appliances will be the primary elements in residential circuits.

The residence uses different amounts of power. Some appliances, such as the refrigerator and landline phone, will be left on all the time. Others, like a laptop, electrical vehicle or a radio, are only occasionally utilized. Additionally, there will be "peak hours" for electricity usage, such as after residents get house from school or work.

II- Commercial power systems:

For buildings like schools, supermarket, and movie theaters, commercial power systems are used. Lighting and air conditioning are two examples of commercial electrical loads. Commercial electrical loads are often active for longer periods than home electrical loads. Think about how most businesses keep their lights on throughout the day, yet most homes only turn them on when it becomes dark.

Calculating commercial electricity loads is essential for a profitable operation of the company.

III- Industrial power systems:

Compared to residential and commercial electrical loads, industrial electrical loads may be significantly more diverse. For instance, you may anticipate that a factory would have many inductive loads to power machines and specialized equipment. These processes frequently operate nonstop for a number of hours each day. As you may expect, the power consumption will be very different from that of a shop or home. The electrical circuit will be under much more pressure.

IV- Agricultural power systems:

Power systems used in agriculture can be very complicated. For instance, many agricultural settings will have far-flung structures and equipment dispersed over a large area of land. As a result, massive grids or generator connections may be required for electrical circuits. For the regulation of heating and cooling for animals and crops, resistive and inductive loads will be typical. Agricultural electrical loads can run continuously or for a long period of time, just like commercial and industrial power systems.

V- Traction, Electric Vehicle and Railways:

All modes of transportation connected to the electrical distribution grid is one of this type of loads. Examples include tram vehicles, rope cars, and trolley buses. The most prevalent load and one that is available worldwide are electrical vehicles.

Finally, in the distribution grid both natural and man-made events can cause power system disturbance. Therefore, it is important for operators to identify the specific causes and types of disturbance in the power system to make decisions and respond appropriately. Next section will introduce all disturbances may accrued in electrical distribution system.

2.3 Distribution Grid Disturbances

The purpose of a power system is to provide customers with electrical energy or power. This provided power's quality is disturbed by nonlinear loads, utility switching, and fault clearing. PQ refers to the standard of the voltage that is typically delivered to our houses, factories, etc. The degree to which the voltage and current waveforms deviate from the ideal, pure sinusoidal waveforms of fundamental frequency serves as the foundation for this. PQD are a collection of criteria that describe how the user receives the power supply under typical operating settings in terms of voltage continuity and voltage characteristics. PQ is described as follows in the IEEE 100 Authoritative Dictionary of IEEE Standard Terms: “The concept of powering and grounding electronic equipment in a manner that is suitable to the operation of that equipment and compatible with the premise wiring system and other connected equipment” (IEEE 100, seventh edition 2000). PQD problems are broadly classified as two categories (Athens Utilities Board, n.m):

1. Internal causes:

Around 80% of issues with PQD come from commercial buildings. That because of heavy machinery starting or stopping, poor grounding, overloaded circuits, or harmonics.

2. External causes:

The utility transmission and distribution system is the source of about 20% of PQ issues. As a result of lightning strikes, equipment malfunctions, bad weather, etc.

However, the disturbances can be divided into two basic categories:

1. Steady-state variations:

Small deviations from the desired voltage or current values, like:

I- Voltage Fluctuations (VF):

Due to variations of total load of a distribution system, action of transformer tap changers, switching of capacitor banks, etc. The performance of the apparatus may be impacted if the fluctuations are significant enough or fall within a specific critical frequency band (Chang et al., 2018).

II- Voltage Unbalance (VU):

Voltage variation in a three-phase system where the phase angle disparities or the three voltage magnitudes are not equal. Causes include heavy single-phase loads and an inefficient distribution of all single-phase loads throughout the three-phase system.

III- Harmonic Distortion (HD):

It is typical voltage and current variations brought on by alterations in the frequency of electrical distribution networks. Particularly, there are differences from the usual sinusoidal voltage or current changes. Nonlinear loads, such as those connected to power electronic converters and variable frequency drives (VFDs) installed for fans and pumps supporting building air conditioning systems, are the main source of harmonics. "The causes of harmonics distortion mainly is non-linear loads (power electronics equipment) as DC brush motors, converters, welding machines, electrical-arc-furnaces, and electric machines operating above the magnetic saturation point (knee of the magnetization curve) "(Grady 2012).

Total Harmonic Distortion (THD) is the most common index for voltage and current harmonic, which is also known as "distortion factor". It is determined by divide rms value of harmonic greater than fundamental and rms value of the fundamental.

Voltage total harmonic distortion THDv is equal to (Srndovic et al., 2016):

$$THDv(\%) = 100 \times \sqrt{\sum_{2}^{\infty} (\frac{V_n}{V_1})^2} \qquad (1)$$

Where:

v_n is the harmonic RMS voltage in order n.

v_1 is the fundamental RMS voltage.

n=2 to ∞.

In addition, current total harmonic distortion THDi is equal to:

$$THDi(\%) = 100 \times \sqrt{\sum_{n}^{\infty}(\frac{I_n}{I_1})^2} \qquad (2)$$

Where:
I_n is the harmonic RMS current.
I_1 is the fundamental RMS current.
n=2 to ∞.

Another harmonic index is Total demand distortion (TDD), that determine the harmonic distortion as a % of max. Demand load current (Shmilovitz 2005):

$$TDD(\%) = 100 \times \sqrt{\sum_{n}^{\infty}(\frac{I_n}{I_L})^2} \qquad (3)$$

Where:
I_n is the harmonic RMS current.
I_L is the Max. Demand current = Max current averaged over specific interval.
n=2 to ∞.

IV- High Frequency Voltage Noise:

Non-periodic high frequency components in supply voltage. Caused mainly due to arc welding or operation of electrical motor. Analysis needed only if it leads to some problem with power system or end user equipment.

2. Events:

Significant sudden deviations of voltage or current from the nominal or ideal wave shape, like:

I- Interruptions:

When the voltage at the supply terminals has become zero, supply interruption happens. Typically started by defects, which then set off protective measures. Interruptions are classified according to duration into (Bayliss 2007)

1. Sustained interruptions.
2. Temporary interruptions.
3. Momentary interruptions.

II- Voltage Sag:

Decrease in the RMS value of the voltage, ranging from a half cycle to few seconds (less than 1 minute).

Referred to as ‘under voltage’, if continues for longer duration. Causes:

1. Faults on the transmission or distribution networks.
2. Connection of heavy loads.

The consequences are:

1. Malfunction of microprocessor-based control systems.
2. Loss of efficiency in electrical rotating machines.

III- Voltage Swell:

Momentary increase of the voltage, at the power frequency, outside the normal tolerances with duration of more than 1 cycle, and typically less than 1 minute. Referred to as ‘over voltage', if continues for longer duration. Causes:

1. Heavy loads starting and stopping.
2. Poorly regulated transformers.

The consequences are:

1. Flickering.
2. Damage of equipment.

IV- Transients:

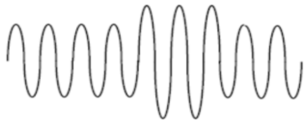
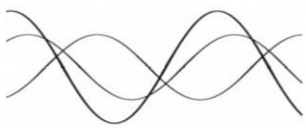
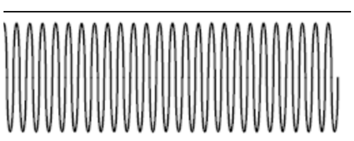
Sub cycle disturbances of very short duration that vary greatly in magnitude. Mainly subdivided into that:

1- Impulsive transient, where there is a large deviation of the waveform for a very short duration in one direction, followed possibly by a couple of smaller transients in both directions.

2- Oscillatory transient, where there is a ringing signal or oscillation following the initial transient.

Voltage sags, voltage swells, voltage unbalance, flickers, interruptions, transients, harmonics, supraharmonics and interharmonics are illustrated in Table 2.2 (Seymour 2001). Finally, the primary types of PQ disturbances and their negative effects to the consumers are described also in Table 2.2 with the details of underlying causes (Elphick et al., 2015) and (Fuchs & Masoum 2011).

Table 2.2: PQ disturbances Sources, Adverse effect and illustrated.

Disturbance	Sources	Adverse effect	Illustration
Voltage Sag	1. Voltage sags frequently accompany EPS problems. 2. Switching heavy loads or turning on big motors can potentially be the cause.	Sag can cause minor changes in the speed of induction machines and a negligible drop in the output of a capacitor bank.	
Voltage Swell	1. Although far less frequent than voltage sags, these are frequently linked to EPS failure scenarios. 2.Load switching (OFF condition) or capacitor switching may also be the cause (ON condition).	The equipment subject to the frequency of incidence may fail if the supply voltage to the EPS machinery is increased more than its nominal rating. In certain situations, electronic devices with variable speed drives, CPUs, and automated controllers may display instant breakdown modes.	
Voltage unbalance	Unbalanced loads are the main sources of VU. VU may also be the effect of capacitor bank.	VU more usually arises in discrete customer loads caused by phase load imbalances, particularly where heavy, one-phase power loads are handled	
transients	Transients is mainly a lighting. These transients are usually caused by switching events.	Measurement transformers, capacitors, cables, and relay. Moreover, it may prompt nuisance tripping of adaptable speed drives owing to the dc link OV protection electrical system.	
Interruptions	Faults.	Interrupt the service to the final customer also maybe caused a black out.	
Harmonics	Its existence owing to the nonlinear characteristics of electric equipment and loads on the EPS.	1. Overheating of rotational machines, static machines (for example, transformer), and current-carrying conductors. 2. Premature breakdown or action of protecting appliances (for example, fuses) and harmonic resonance situations on the customers' EPS..	
Interharmonics	The key resources of this type of waveform distortions are static frequency converters, cycloconverters, induction motors, and arcing devices.		

2.4 Photovoltaic system and Electric vehicle

2.4.1 Photovoltaic system

There are different renewable energy sources, including geothermal, hydroelectric, biomass, solar, wind, and others (Pearsall, 2017). The desire to be independent from conventional fuels and the use of renewable energy sources, however, is strengthened by the rise in electricity consumption and the effects of global warming.

By directly converting solar energy through the PV effect, a PV system can directly transform solar energy into electrical energy for a specific load. The proposed system is extremely adaptable. The main components are PV modules, which can be assembled into arrays to produce more electricity (Ramakumar & Bigger 1993). PV systems can be categorized into two main groups, that are, the standalone (off-grid) PV systems and the grid-connected (on-grid) PV systems (El Nozahya & Salama 2013) In order to convert energy into a usable form or store energy for later use, extra equipment is typically required. Therefore, the energy requirements (or loads) will decide the final system in a specific application. Generally grid- connected or on-grid PV system componants are:

1. Photovoltic (PV) Moudules:

A PV module's fundamental component that turns solar energy into electricity is the PV cell. The amount of energy incident on the cell's surface and the operating temperature of the PV cell will determine the power output. A single cell can power tiny loads like calculators or watches, but in order for these cells to be helpful for applications with substantial energy demands, they must be connected in series and parallel. An array of solar cells that have been assembled in a single mounting mold is known as a PV module. Therefore, the cells that make up the module itself determine the type of module (Vieira et al., 2020).

2. Inverter

These inverters must be able to generate nearly perfect sinusoidal voltages and currents because they are connected to the electrical distribution network and operate in that manner. Local utilities often decide on the operational specifications for these kinds of inverters; however, they frequently base their decisions on already-accepted norms. The minimum specifications that manufacturers must incorporate into inverter designs in order to prevent negative distribution impacts are included in these standards (Mirafzal & Adib 2020)

PV systems, which are highly prevalent in DGs and are responsible for the majority of their function, give power systems additional flexibility. Generally, DGs are widely used, which offers many advantages but also creates new security, stability, and reliability issues in power systems. For instance, even though decentralized control schemes, such as droop controllers, can address power-sharing between DG units, optimal energy management and economic dispatch between DGs cannot be achieved without a type of supervisory control scheme, which requires a specific form of communication between a utility operator and inverters (Arbab-Zavar et al., 2019). Figure 2.2 shows all PV system components (Clean Energy Reviews 2022).

Figure 2.2: PV system components (Clean Energy Reviews 2022)

2.4.2 Electric Vehicle (EV)

EVs are now playing a more and bigger role in our lives. Only a small amount of information provided to researchers who are independent of any one company, however, because firms retain patents and carefully defend their knowledge. EV or electric drive vehicle defined as a vehicle-based on one or more motors to ensure the propulsion, which nowadays include cars, buses, trucks, and even tractor-trailers that are partially powered by electricity. At the level of the Middle East, Jordan is regarded as a leader in the electrification of the transportation system. Until 2019, more than 18,000 private EVs were registered in Jordan, according to the country's statistics agency. In addition to creating the necessary infrastructure, Jordanian governments support enacting the necessary legislation for e-mobility. The consistency of power prices in Jordan compared to gasoline prices, which have an impact on the operating costs of conventional vehicles, is one of the key factors that support the ownership of EVs (Shalalfeh et al., 2021).

EV charging is expected to create problems for these networks by overloading transformers (Moses et al., 2012) and creating unacceptably low voltages (Geth et., 2012).

2.5 Machine and Deep Learning

One of the fields of researcher computing is machine learning. To make machines intelligent, a lot of study has been done. Learning is a natural human trait that has been incorporated into the design of machines. Numerous application fields have used machine learning methods (P.Shinde & Shah 2018). Researchers have worked very hard to increase the machine learning algorithms' accuracy. Another angle was considered, leading to the idea of deep learning.

2.5.1 Classifier Learner Toolbox

Deep Learning Toolbox provides a framework for designing and implementing deep neural networks with algorithms, pertained models, and apps. Convolutional neural networks (ConvNets, CNNs) and long short-term memory (LSTM) networks can be used to perform classification and regression on image, time-series, and text data. Apps and plots help to visualize activations, edit network architectures, and monitor training progress (Schütt et al., 2022).

In the Classification Leaner (CL) toolbox, the automated learning used to find the best model type, including decision trees, discriminant analysis, support vector machines (SVM), logistic regression, nearest neighbors, naive Bayes, kernel approximation, ensemble, and neural network classification.

2.5.2 Artificial Neural Network

A neural network is a computational model with layers of interconnected nodes whose structure is similar to the networked structure of neurons in the brain. A neural network can be trained to identify patterns, categorize data, and predict future events since it can learn from data (Demuth et al., 2014).

A neural network organizes the input into successively more abstraction layers. Similar to how the human brain accomplishes it, it may be trained over a large number of samples to detect patterns in voice or images, for instance. Its behavior is determined by the connections between its component parts and by the weights, or strengths, of those connections. During training, these weights are automatically modified in accordance with a given learning rule until the neural network successfully completes the target task. (Negnevitsky 2005).

A neural network, which uses straightforward components functioning in parallel and is modeled by biological brain systems, includes many processing layers. An input layer, one or more hidden layers, and an output layer make up this structure. Each layer uses the output of the layer preceding it as its input, and nodes, or neurons connect the layers.

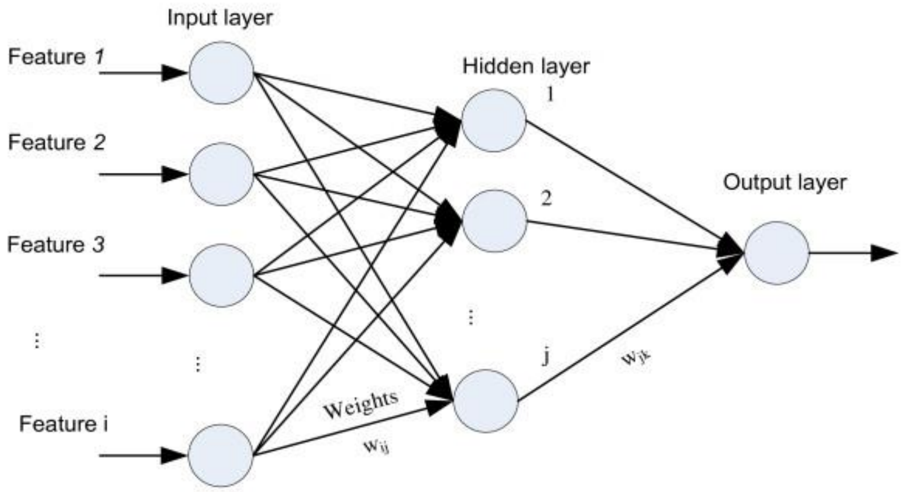


Figure 2.3: Backpropagation Neural Network (Negnevitsky 2005).

2.6 Literature review

This sction presents some previous studies related to disturbances in SDG and disturbances identification.

2.6.1 SDG Disturbances

Due to the urgent need to produce clean electricity in industrial, commercial and residential societies, there is still a need to study the effect of disturbances on the electrical grid and what poor power quality cause in electrical equipment is a topic of great importance. Initially, transformer is a basic component of power system and designed to work on all load types. Increase the harmonic distortion will cause on_load, eddy current and other stray losses increase that will decrease the capacity of transformer, overloading of transformer and reduction in useful life of transformer (Singh et al., 2017) and (Jaiswal et al., 2019). On the other hand, in industrial distribution system where a sensitive equipment operates, the poor quality of power will cause a tripe in some equipment to protect it against a fluctuation in voltage profile and because the equipment is interlinked to each other's the un-wanted monetary losses done due to shut down in some section (Behera et al., 2019).

However, with increasing the need of reliable electricity and expectation of service, developments in communication technologies opportunities are emerging and bi-directional power flow many utilities are moving toward modernization of distribution system. Smart distribution system for reliability combines technology advances in computing, communications, measurement, and control that to reduce the number and duration of electrical power interruption and/or to improve the efficiency of power delivery. Today, with emergence of the term

SDGwith connecting a renewable energy resource and entering a new load type on electrical grid, there is a need to redefine the main guides of smart distribution system (IEEE 2019).

Recently researchers expected that the clean energy penetration and the retirement of conventional fossil fuel plants, clean energies are expected to provide almost 50% of total electricity globally by 2050 (Sun et al., 2019). The numerous solar power policies in place in many nations throughout the world have thus been summarized by some study, and the barriers to the development of clean energy as well as the Indian government's pertinent policies to promote clean energy throughout India are introduced in (Solangi et al., 2011). It known the clean energy policies on electricity of some countries who are supportive of the promotion of clean energy, but most publications only concentrate on one country or one type of clean energy. Understanding global clean power policies requires a thorough analysis and comparison of diverse clean energy-supporting policies from various nations (Sun et al., 2020).

The management of energy production and delivery for all uses in Jordan is the responsibility of the energy sector. The sector is made up of government actors who are in charge of strategic planning, the energy regulation authority, and the utilities that control the distribution of power for a variety of uses, including industrial, commercial, and residential. The Cabinet of Ministers approved the report “A National Green Growth Plan for Jordan” (NGGP). The League of Arab States gave it special recognition as a best practice example to be replicated in the area. The NGGP evaluates Jordan's potential for green growth and develops a roadmap to achieve a transition to a green economy in Jordan through strategic direction and recommendations (Sandri et al., 2020) and (ENERGY SECTOR 2020).

Highly prevalent, in electrical distribution networks there are two important things can be decide the degradation of the PQ: Harmonics and Disturbances, Which accompany the transmission of energy in transmission lines. Whereas their existence makes it impossible to keep ideal sinusoidal waveforms of voltage or current. Also highly prevalent, power electronic interface for example PV panels, batteries, and D.C loads (e.g., EVs) are effective source of harmonics. In (Amaripadath et al., 2017), researchers adopted adding smart grid loads and source connections to study the contribution of it as a source of harmonics, and the effect of superharmonic emission on the communication infrastructure has been discussed by developing a measurement system to analyze the transferred energy. Also, in (Klaić et al., 2019) and (Karmaker et al., 2019) the impact of adding smart grid components have been individually clarified. Researchers have been devoted them effort in recent years to find the most robust and compelling finding to produce cheap electricity, Therefore, they have developed studies on the entering of renewable energy resources and connect them to the electric grid in general and in particular connecting the solar energy systems to the distribution network and the PQ cations that may accompany the connection, especially that the inverters are an essential component of solar energy systems (Klaić et al., 2019). On the other hand, the replacing of conventional vehicles with EVs is raising such that in 2010 only 17 000 electric cars were on the world's roads but by 2019 there were about 7.2 million electric cars most of them concentrated in China, Europe and US additionally the amount of Spending on electric cars increased significantly such that in 2019 it was USD 90 billion, a 13% increase from 2018 (Chiu 2017). So, with the globally changing on the shape of transportation and trend towards electric vehicles, some researchers go to study the effect of adding large number of electric vehicles charging station on the electric distribution system (Karmaker et al., 2019).

That and other reasons was guide the researchers to know more and more about disturbances and it is classification in electrical distribution system. So, researchers have worked to develop new techniques to detection and classification of disturbances in electrical distribution grid such as reactive power transients, large current, voltage fluctuations, sag, swell and harmonics…etc (Han et al., 2020).

2.6.2 DISTURBANCES IDENTIFICATION

Referring to IEEE 1159 standard, PQ refers to a wide range of electromagnetic phenomena that describe the voltage and current in a power system at a certain time and location. IEC provide several groups to classify these phenomena, all the PQ issues are comprised into following categories and all classification is shown in (Association 1995).

1. Transients.
2. Long-Duration Voltage Variations.
3. Short-Duration Voltage Variations.
4. Voltage Imbalance.
5. Waveform Distortion.
6. Voltage Fluctuation.
7. Power frequency variations.

As the disturbances and PQ issues directly affect the overall continuation of electric grid and distribution network, the uninterrupted monitoring of electric power systems (EPSs) has become highly necessary for the utility industry. Figure 1 shows the increase of disturbances detection field representing its popularity. The figure presents the numbers of articles reported in the Scopus database annually from 1990 to 2018 (ITEES 2019).

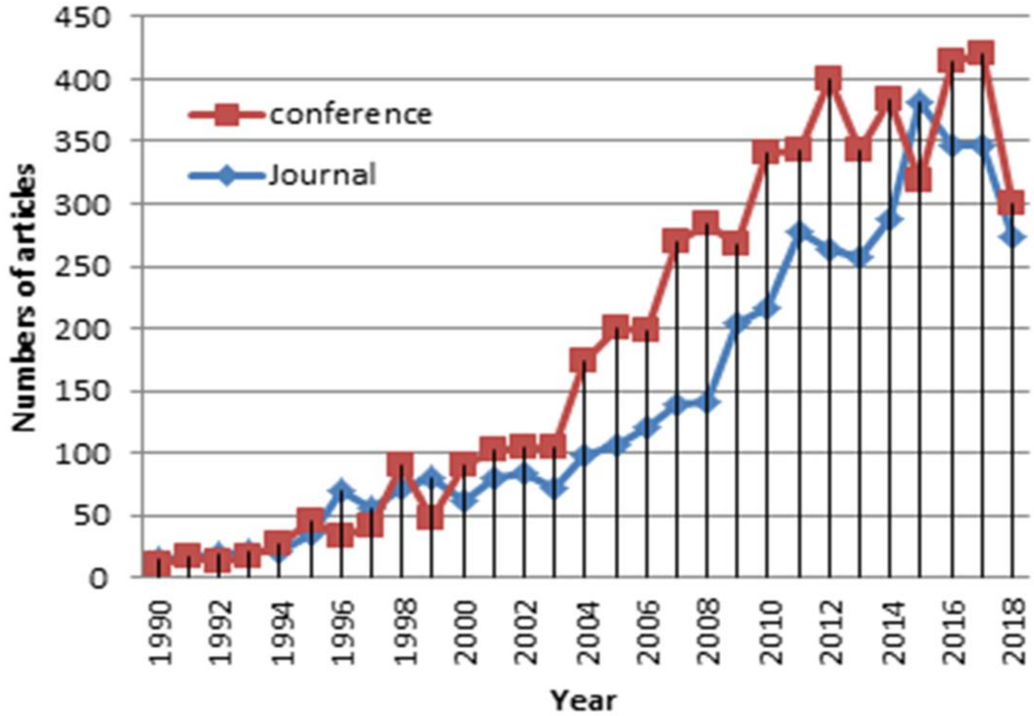


Figure2.4: Numbers of article published in year wise related to disturbances and PQ analysis (ITEES 2019).

Because the electric signal and disturbances can be represented as mathematical sinusoidal signals, the earliest techniques used to detect and classify the disturbances signal against real time signal are "Signal Processing Techniques" such as "Fourier Transform (FT)", "Hilbert-Hung Transform (HHT)", "Wavelet Transform (WT)" and "Stockwein Transform (Stockwein Transform (Stockwein Transform (WT)". Researcher in (V.Thiyagarajan & Subramaniam 2016) used developed discrete wavelet approach transforms to improve the accuracy of classification, the synthetic equations used for normal voltage and disturbances show in Table (2.3), and by using MATLAB power tool the effectiveness of given approach has been tested.

Table 2.3: synthetic equations for normal voltage and disturbances

Event	Synthetic Model	Parameters
Normal	$x(t) = sin(\omega t)$	
Swell	$x(t) = A(1 + \alpha(u(t - t1) - u(t - t2)))$ $sin(\omega t)$ $t1 < t2, u(t) = 1, t \geq 0, t < 0$	$0.1 \leq \alpha \leq 0.8,$ $T \leq t2 - t1 \leq 9T$
Sag	$x(t) = A(1 - \alpha(u(t - t1) - u(t - t2)))$ $sin(\omega t)$	$0.1 \leq \alpha \leq 0.9,$ $T \leq t2 - t1 \leq 9T$
Interruption	$x(t) = A(1 - (u(t2) - u(t1)))$ $cos(\ t)$	

Where: x(t)- PQ signal, A-Amplitude(constant), ωn-angular frequency, t-time, α -time duration of event occurrence (constant), T-time duration.

FT and its variants'-based methods are also the most widely used technique for frequency domain analysis. The input signal, which is selected for analysis, can be described as a sum of essential sinusoids of different frequencies. Three variants of FT such as Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), and Short-Time Fourier Transform (STFT) were generally used for PQ disturbance recognition by various researchers in the last two decades. DFT It is one of the most extensively used computation algorithm. DFT is generally considered for the steady-state analysis of the stationary signals (Szmajda et al., 2007). The outcome of FFT is like that of DFT, but faster execution time. It is extensively applied for harmonic study of PQD (Huang et al., 1999) and (Heydt et al., 1999). STFT is used to determine the frequency and phase information of the waveforms as they vary over time. Using a moving window, the relation between the time and frequency variation can be recognized. Ease implementation is the advantage of STFT (Dash et al., 2003).

The HHT method has been developed in the recent year to study nonstationary PQ disturbances. Generally, this technique is the amalgamation of two techniques such as empirical mode decomposition and Hilbert transform (Biswal et al., 2013).

The ST is the advancement of WT and STFT by its phase correction and a variable window, respectively. Like WT, it can offer an improved time and frequency representation of a signal. Moreover, the fixed modulating sinusoids respecting the time-axis plus the scalable and movable Gaussian window properties of the ST can be used for better recognition of PQ events. But the drawback of this technique does not suit well in practical application as the widths of the frequency windows in the ST are directly related to their central frequency, which causes an inappropriate measurement of harmonics (Dash, Panigrahi & Panda 2003) and (Lee & Dash 2003).

Comparing between some of mathematical techniques to select which one having the advantages over others is also now field of research. The compared techniques in (Wang Huihui & Wang Ping 2015) and (Ingale & Tawade 2013) confirmed the effectiveness of mathematical methods to detect the disturbances in micro-grid and power system with high accuracy.

PQ Disturbance (PQD) signals are classified into two or more categories based on their characteristics using Artificial Intelligence (AI)-based classification techniques. Defining and extracting high-quality features are crucial steps in determining the intensity of a disturbance. Optimization techniques such as Genetic Algorithm (GA), particle swarm and ant colony optimization and classification technique such as ANN and Support Vector Machine (SVM) are used individually or hybrid with each other's for PQDS classification (Khokhar et al., 2015). In addition, a combination of signal processing and AI techniques are used to classifier PQDs, in (Mishra et al., 2007) S-Transform based probabilistic neural network (PNN) classifier for recognition of PQDs. A lot of signal processing, optimization and intelligent techniques used to identify PQDs in conventional distribution system and now with increasing renewable energy resources, especially P.V penetration, the researcher in (Mahela & Shaik 2015) and (Prakash et al., 2020) used signal processing and AI respectively to identify the PQDs with high P.V penetrations.

One of the most common techniques used to identify PQDs is Fuzzy Logic (FL), the membership values for a specific sample are usually limited such that the total of all the membership values for that sample equals 1. To analyze PQ disruptions, knowledgebase needs expertise in the selection of the proper membership mechanism and, if applicable, the addition of new rules. Basic FL with Distribution Static Compensator (DSTATCOM) used to improve PQ of weak AC grid in the presence of various loads (Chawda & Shaik 2018). Other Fuzzy Expert System (FES) based classification algorithms include fuzzy reasoning approach with discussed the effect of noise on classification accuracy presented in (T.Zhu et al., 2004).

CHAPTER THREE
Power systems mentoring, Classifier Learner Predictions and Results

3.1 Introduction

In this chapter, developing integrated monitoring system of disturbances by installing advance measurement devices is the first step and using it to produce a real disturbances event with real voltage, current and frequency signals. After that CL used by MATLAB code environmental to design classification technique. Figure 3.1 shows the flowchart of these steps.

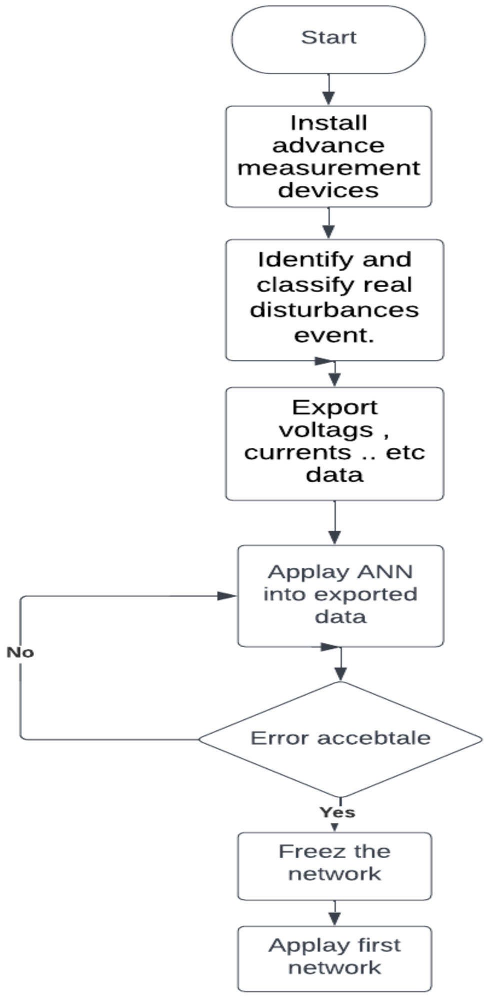


Figure 3.1: Flowchart of proposed steps.

3.2 Disturbances Identification in Distribution Substations

Develop integrated monitoring system of disturbances done by install Fluke 435- II power quality analyzer, it designed to help researchers minimize downtime, quickly troubleshoot PQ issues and easily discover the costs of wasted energy. Downtime is expensive and getting the data you need to solve to critical PQ problems quickly is key.

The Fluke 435 Three Phase PQ Analyzer complies with IEC/EN61010-1-2001, CAN/CSA C22.2 No 61010-1-04 (including cCSAus approval) and UL std No 61010-1(Fluke User Manual).

Fluke 435- II power quality analyzer installed at the low voltage side of the DSs, and the recording of voltage and current signals started with (3) second interval. Figure 3-1 shows the Fluke 435- II power quality analyzer and its installation at main distribution board.

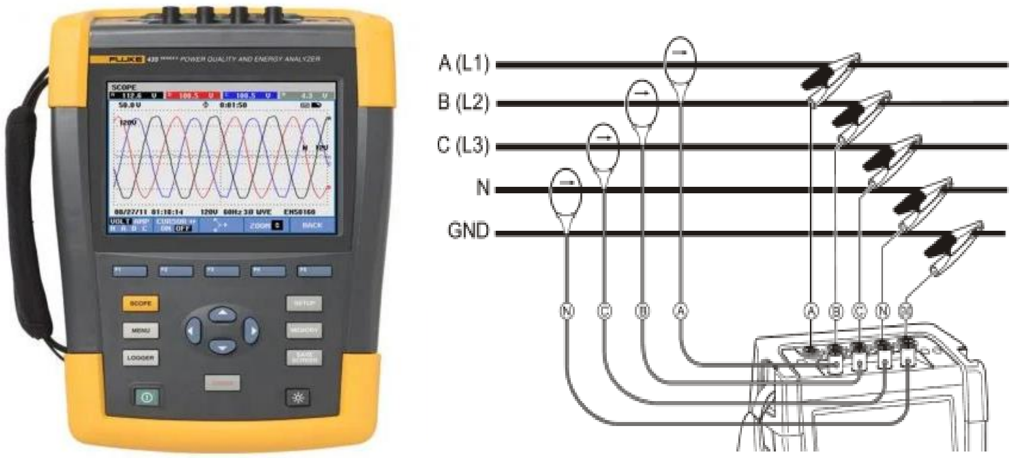


Figure 3.2: Fluke 435- II and Installation.

Four DSs in the city of AL-Kark were selected as a measurement site. Table 3.1 lists the substations that were selected, their transformation ratios, and the type of power system for each. In the appendices (A and B), there will be additional details about DSs and their placement on the Single Line Diagram (SLD).

Three-phase voltage and current signals are shown in figure 3.3, at each substation the magnitude and shape of current is changing response to the nature of connected loads and disturbances occurred.

Table 3.1: Distribution substations

Sub. Number	Sub. Name	Tran. Ratio K.V	Type of P.S
T.R1	Reaf Meroad	33/0.415	Resedantial.
T.R2	Al-Salahat	33/0.415	Commerical.
T.R3	Kahf "Loot"	33/0.415	Domstic with PV.
T.R4	Al-Msherfa Manaseer EVs charger	-	EV charger.

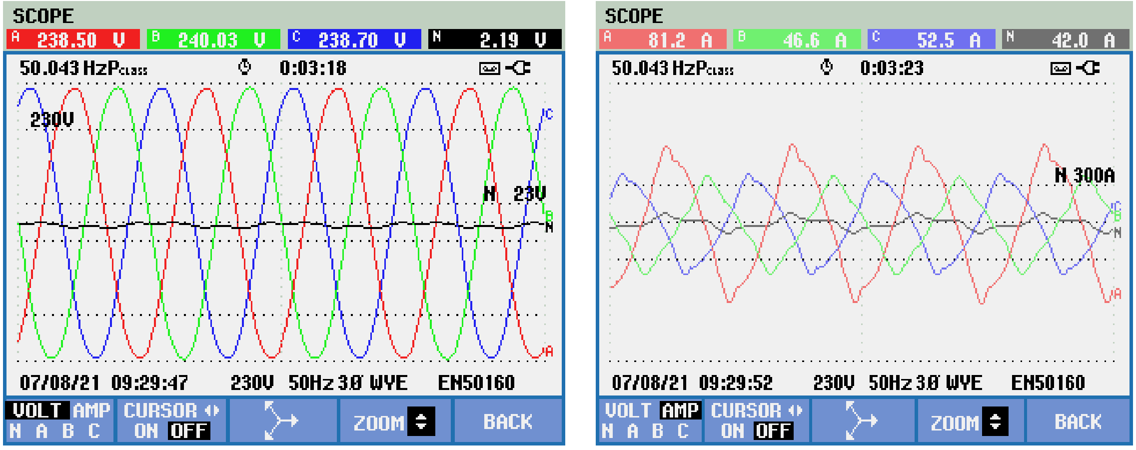


Figure 3.3: Three phase voltage and current signals.

This section of the chapter build up to allow an objective comparison of the disturbances experienced at each substation. In the first part of the comparison, which focuses on five hours of substation records during the day, common disturbances at each substation will be identified and recorded using thorough disturbance analysis. The install of AMD done during the summer of year (8/2021).

3.2.1 Disturbances Event in Distribution Substations:

To ensure a comprehensive comparison of the daytime loads of all substations, reference in comparison will be the type of disturbance that occurs. Disturbances event occurred on the substations:

I- Voltage sage and swell:

Voltage sage and swell decrease or increase in RMS value of the voltage percentage from nominal voltage value. Nominal voltage RMS value is 230 V and figures 3.4 and 3.5 shows swell and sage event respectively.

The "RMS" value calculated by simply multiplying the peak amplitude by 0.707 or:

$$RMS = \frac{\text{Peak}}{\sqrt{2}} \qquad (7)$$

In figure 3.4, from TR1 records, during the operation the current value dropped and the voltage response to that drop, the magnitude of voltage became 359 Vp (253.8 Vrms). On the other side, increasing load in figure 3.5, from TR4 records, dropping the voltage to become 280 Vp (197.9 Vrms).

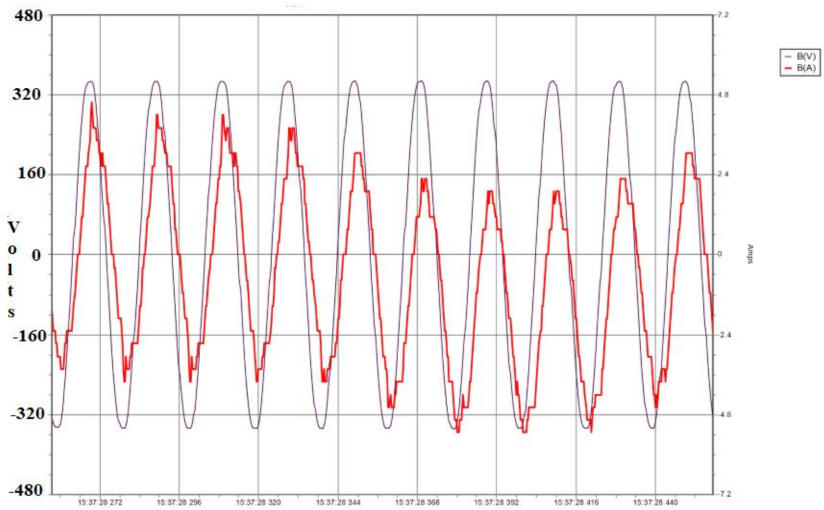


Figure 3.4: Voltage swell event on phase B.

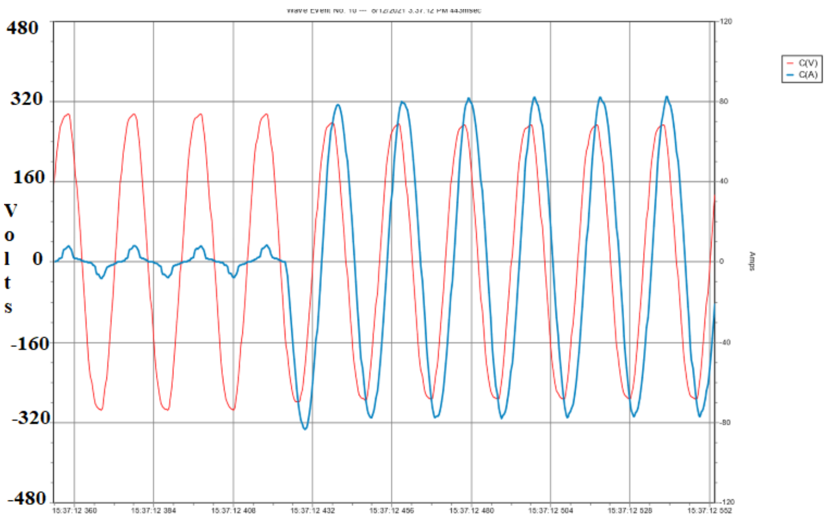


Figure 3.5: Voltage sag event on phase C.

II- Transient:

Short duration disturbances that vary greatly in magnitude. Figure 3.6, from TR1 records, shows transient event, transient in voltage was accompany by change in the current value.

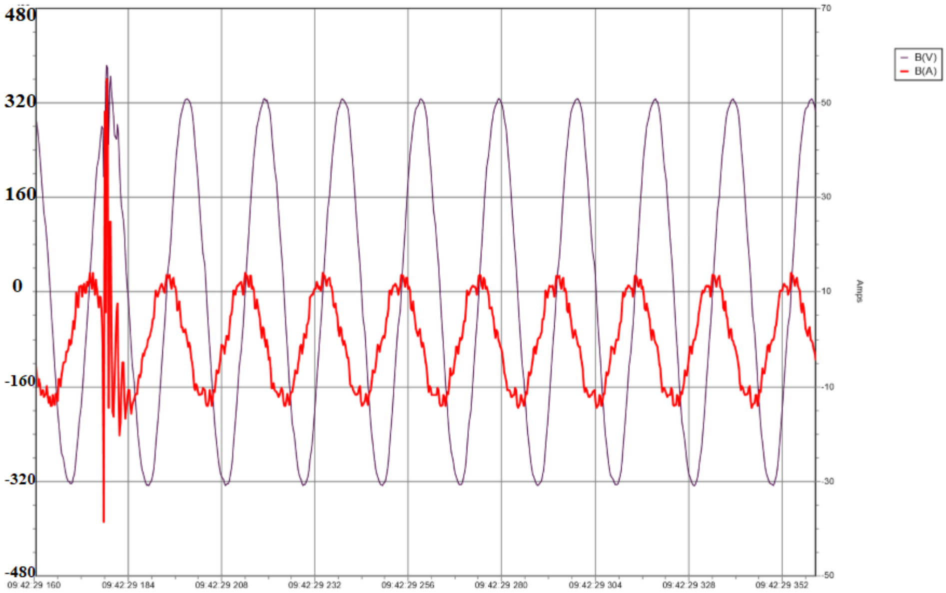


Figure 3.6: Transient event on phase B.

III- Rapid Voltage Change (RVC):

According to IEC 61000-4-30, RVC defined as "a quick transition in root means square (RMS) voltage occurring between two steady-state conditions, and during which the RMS voltage does not exceed the dip/swell thresholds" (Barros et al., 2017).

RVCs may generated during switching operations like as transformer tap-changer operations, load switching, capacitor bank on/off, and motor starting. Additionally, they may be drawn by sudden changes in the load or by disturbances in the power production of distributed energy sources like solar or wind power systems (Barros et al., 2016). Figure 3.7, from TR2 records, shows RVC event where the peak voltage dropped from 330 Vp (233 Vrms) to 320 Vp (226 Vrms) during 1 cycle due to increasing in ampere value.

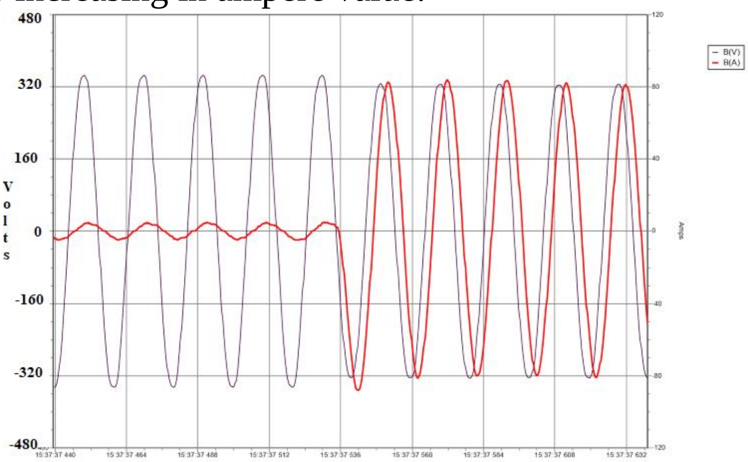


Figure 3.7: RVC event on phase B.

IV- Interruption:

Figure 3.8, from TR4 records, shows sustained interruption event occurred in one substation due to utility fault.

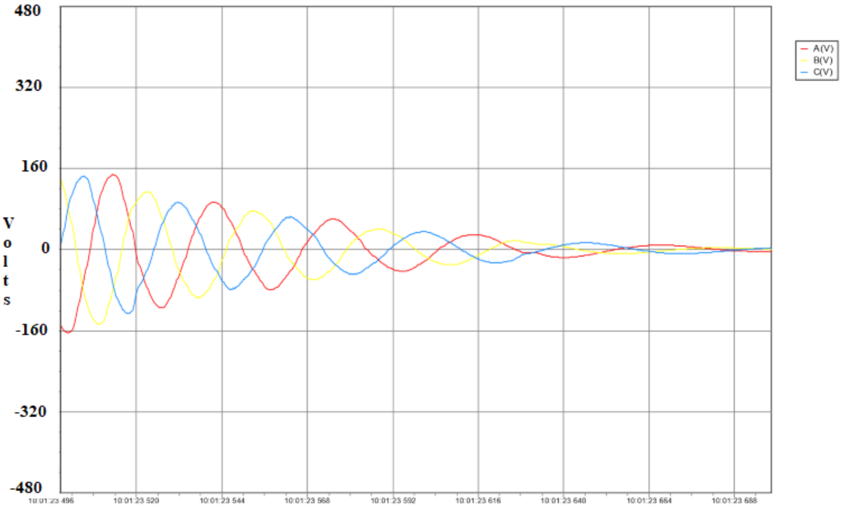


Figure 3.8: Sustained Interruption event on three phases.

Table 3.2 shows the disturbances occurred on each substation. Voltage sag/swell, transient, RVC, interruption and instantaneous flicker sensation (Pinst) occurred on three phase can be counted as an event.

Table 3.2: disturbances occurred on DSs.

Sub.No / **Disturbance**	TR1 (Resedantial)	TR2 (Commercial)	TR3 (Domestic with PV).	TR4 (EV charger)
V Sage	5	0	0	1
V Swell	0	0	0	1
Transient	443	16	6	6
RVC	14	6	2	8
Interruption	0	0	0	1
Flickr (Pinst)	3	3	0	3

V- Harmonic Distortion:

On the other hand, voltage and current harmonic distortion different from substation to another. Figure 3.9 shows both harmonics in TR1 (Residential). Voltage harmonic on three phase does not exceed 1.76% and it is almost same on each phase while the current harmonic different from phase to phase due to unbalance load.

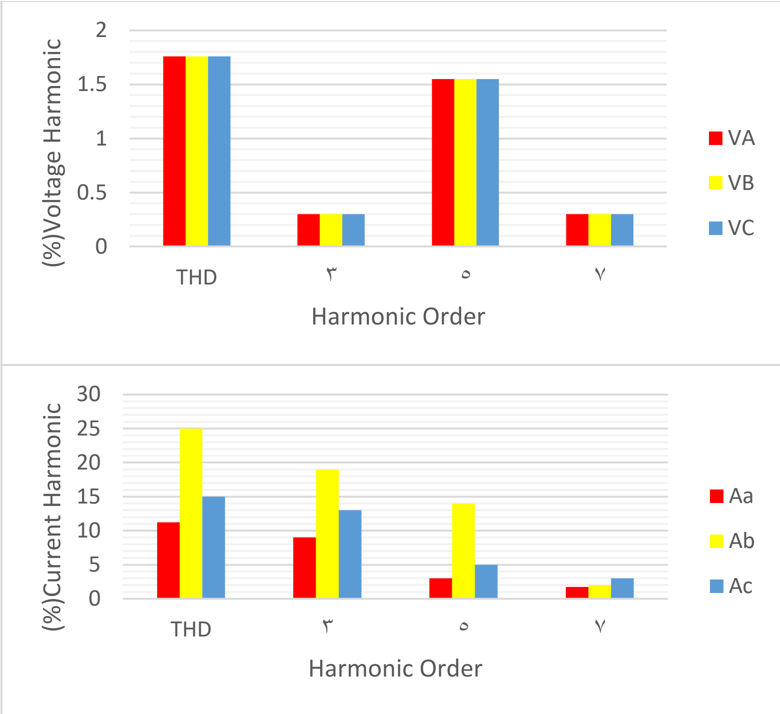


Figure 3.9: voltage and current harmonic on TR1.

Figure 3.10 shows voltage and current harmonic on commercial PS (TR2). Voltage harmonic on three phase is not the same value and not exceed 2.5% and same as TR1 the current harmonic different from phase to phase. Both voltage and current harmonics magnitude in commercial PS large than harmonics in residential.

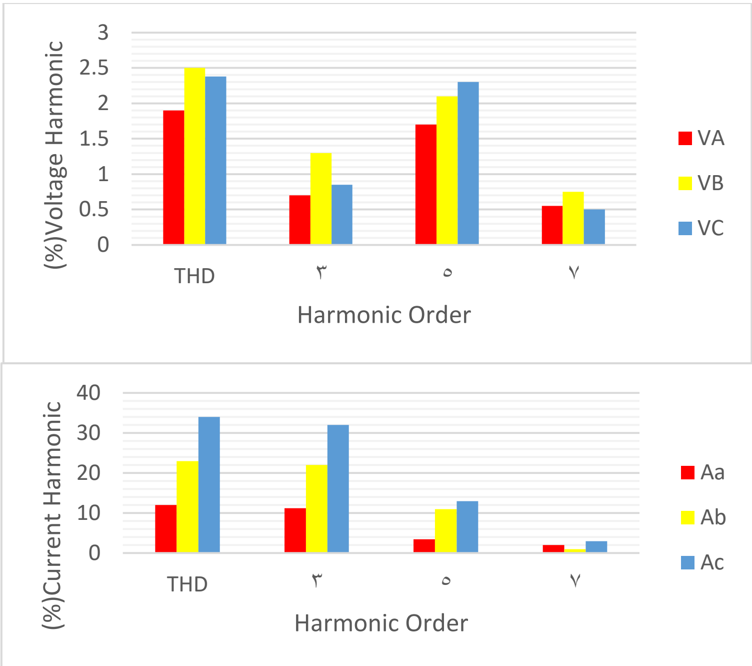


Figure 3.10: voltage and current harmonic on TR2.

In the daytime period harmonics for domestic loads with PV system shown in figure 3.11. It is clear that voltage harmonic during the penetration lager than THDv in both commercial and residential, but the current harmonics that depend on the load power factor, less than THDi on it. During penetration PF value modify from the inverter, while the PF value in commercial PS between 0.86- 0.92.

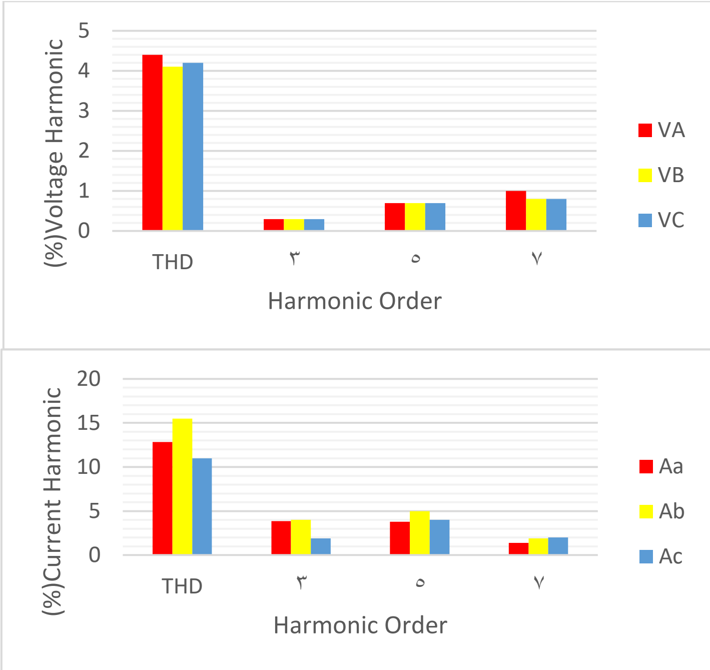


Figure 3.11: voltage and current harmonic on TR3.

Finally, the harmonics order on EV charger at the same period shown in figure 3.12. Voltage and current harmonics is relatively high compare with other substations, that because the interruption event occurred.

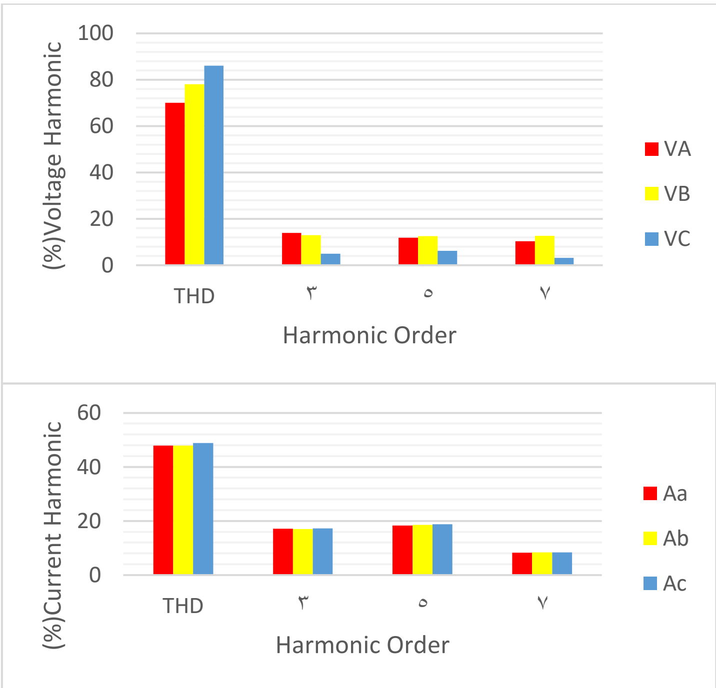


Figure 3.12: voltage and current harmonic on TR4.

3.3 Artificial Neural Network / Classifier Learner modules, Predictions, result and testing

3.3.1 Classifier Learner Training

In this work, feedforward ANN/CL is trained to identify and classify the disturbances occur on electrical power system. The training dataset is obtained using DS monitoring in section (3.2). The advantage of the proposed CL is its simple architecture because it requires only six inputs that are the three-phase voltages and frequencies. According to the measured three-phase parameters, the CL can identify and classify the disturbances event.

Neural Network Toolbox in MATLAB is used to train the ANN. Figure 5.2 shows the structure of the feedforward ANN used to identify disturbances. The simple ANN/CL shown in Figure 5.2 consists of an input layer, one hidden layer, and an output layer. The default activation functions used in the hidden layer and output layer are hyperbolic-tangent sigmoid (tensing) and linear (purlin) functions, respectively (Beale et al., 2017). This simple architecture reduces the response time of the ANN significantly, because the computational time of the ANN increases exponentially as the number of its hidden layers increases.

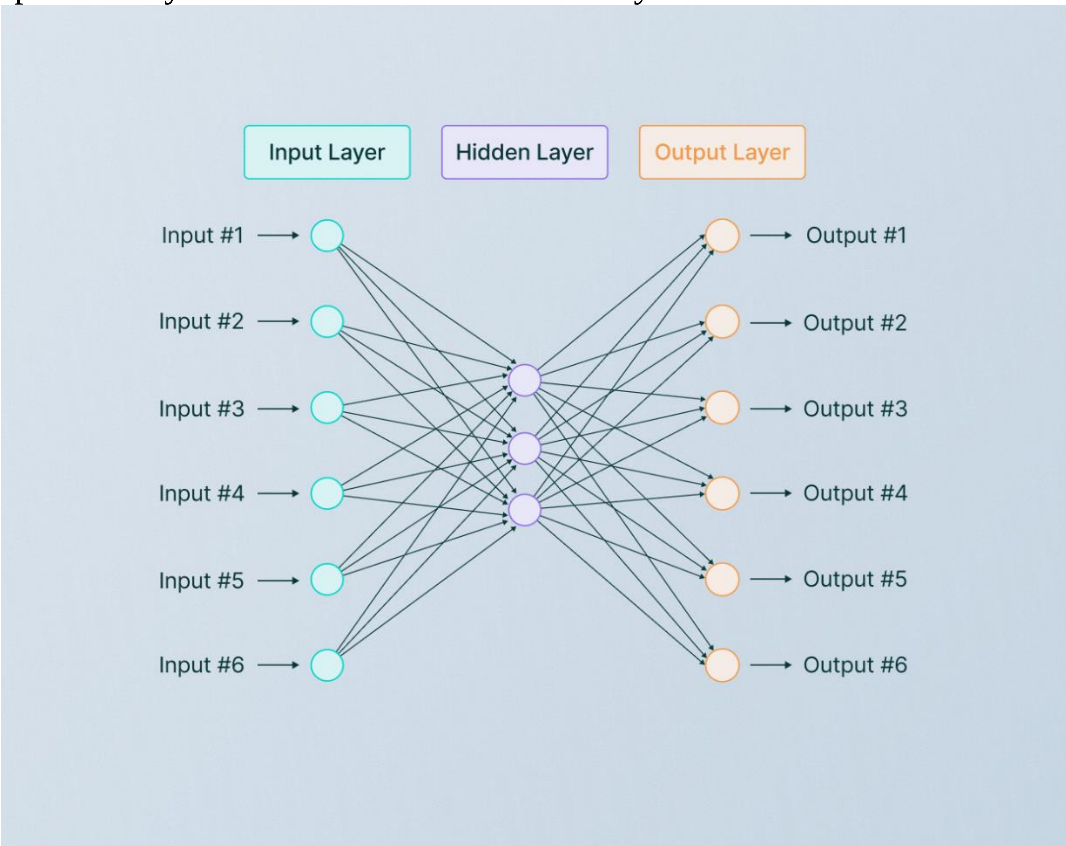


Figure 3.13: CL trained to identify disturbances.

3.3.2 Classifier Learner modules, Predictions

This section presented and discussed the obtained results from the ANN classification based on EDCO DSs data with the Matlab Classification learner toolbox. In order to forecast data, the Classification Learner tool trains Classifier models. The data have been browsed, was choosed features, defined validation procedures, trained models, and evaluate outcomes with this tool. The automated learning used to find the best model type, including decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbors, naive Bayes, kernel approximation, ensemble, and neural network classification.

The training data for the implemented forecasting models are shown in Table 3.3, with an emphasis on training time, prediction speed, and accuracy. It is worth noted that the (medium tee) algorithm obtained the lowest training time possible, clocking in at 0.4521 seconds, with the maximum expected speed (by 7200 obs/sec) and 100% accuracy. While the Ensemble subspace KNN method had the slowest training time (7.6963 seconds), it also had the slowest speed (330 obs/sec) when it was finished. The Ensemble boosted trees algorithm had the lowest accuracy rate of 31.4%.

The creation of a confusion matrix, which compares the expected results from the model with the actual results from the dataset, is one of the most popular approaches to evaluate the effectiveness of a classification model. Positive Predictive Value (PPV) and False Discovery Rate (FDR) are two metrics that we frequently pay attention to when analyzing a confusion matrix. The possibility that an observation with a positive anticipated outcome will in fact have a good outcome is known as PPV. The FDR is the percentage of times that features considered relevant are actually null, or the ratio of incorrect forecasts to all predictions multiplied by the anticipated data.

As stated in Table 3.4, there are six categories that need to be categorized. Fine tree, medium tree, and ensemble-bagged trees produced the best PPV with no errors for the first category. Whereas the majority of the model produced great outcomes for the second, third, fifth and sixth categories. The majority of Ensemble group models and the group of tree models both received the highest scores for the fourth category. The fine and medium trees were the best model to earn the best scores for all categories, but we prefer the medium tree due to its speed in addition to accuracy.

Table (3.3): The accuracy of the taught models and training timeframes.

Model type	Training time	Prediction speed	Accuracy
Fine tree	7.2894 sec	1400 obs/sec	100%
Medium tree	0.4521 sec	7200 obs/sec	100%
Coarse tree	0.4766 sec	6700 obs/sec	71.7%
Linear discriminant	2.3857 sec	3700 obs/sec	64.9%
Quadratic discriminant	0.9069 sec	3400 obs/sec	91.7%
Linear SVM	7.4284 sec	1100 obs/sec	64.9%
Quadratic SVM	4.1902 sec	1000 obs/sec	95.1%
Cubic SVM	4.1986 sec	1100 obs/sec	93.8%
Fine gaussian SVM	4.2712 sec	1200 obs/sec	93%
Medium gaussian SVM	3.1814 sec	1500 obs/sec	91.4%
Coarse gaussian SVM	3.2077 sec	1500 obs/sec	64.4%
Fine KNN	1.1571 sec	3700 obs/sec	87%
Medium KNN	0.47304 sec	5300 obs/sec	83.4%
Coarse KNN	0.6152 sec	3700 obs/sec	63.4%
Cosine KNN	0.7895 sec	3200 obs/sec	80.8%
Cubic KNN	0.6776 sec	3800 obs/sec	83.6%
Weighted KNN	0.5486 sec	5000 obs/sec	88.8%
Ensemble boosted trees	2.9468 sec	5900 obs/sec	31.4%
Ensemble bagged trees	6.4743 sec	720 obs/sec	100%
Ensemble subspace discriminant	6.3718 sec	440 obs/sec	61.8%
Ensemble subspace KNN	7.6963 sec	330 obs/sec	66%
Ensemble RUSboosted trees	1.3272 sec	5400 obs/sec	73.2%

Table (3.4): The trained model's Positive Predictive Value and False Discovery Rate for Classification category.

Model type	Classification category											
	1		2		3		4		5		6	
	PPV	FDR	PPV	FDR	PPV	FDR	PPV	FDR	PPV	FDR	PPV	FDR
Fine tree	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%
Medium tree	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%
Coarse tree	40%	60%	100%	0%	100%	0%	100%	0%	100%	0%	NA	NA
Linear discriminant	35%	65%	100%	0%	100%	0%	NA	NA	100%	0%	NA	NA
Quadratic discriminant	87%	13%	100%	0%	100%	0%	74%	26%	100%	0%	100%	0%
Linear SVM	35%	65%	100%	0%	100%	0%	NA	NA	100%	0%	NA	NA
Quadratic SVM	92%	8%	100%	0%	100%	0%	82%	18%	100%	0%	100%	0%
Cubic SVM	90%	10%	100%	0%	97%	3%	78%	22%	100%	0%	100%	0%
Fine gaussian SVM	86%	14%	100%	0%	100%	0%	79%	21%	100%	0%	100%	0%
Medium gaussian SVM	83%	17%	100%	0%	100%	0%	76%	24%	100%	0%	100%	0%
Coarse gaussian SVM	41%	59%	100%	0%	100%	0%	31%	69%	100%	0%	NA	NA
Fine KNN	74%	26%	91%	9%	94%	6%	83%	17%	100%	0%	75%	25%
Medium KNN	56%	44%	100%	0%	100%	0%	87%	13%	100%	0%	100%	0%
Coarse KNN	40%	60%	100%	0%	100%	0%	40%	60%	100%	0%	NA	NA
Cosine KNN	60%	40%	100%	0%	97%	3%	77%	23%	100%	0%	48%	52%
Cubic KNN	56%	44%	100%	0%	100%	0%	87%	13%	100%	0%	100%	0%
Weighted KNN	76%	24%	91%	9%	94%	6%	82%	18%	100%	0%	86%	14%
Ensemble boosted trees	NA	NA	NA	NA	NA	NA	NA	NA	31%	69%	NA	NA
Ensemble bagged trees	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%
Ensemble subspace discriminant	35%	65%	100%	0%	100%	0%	NA	NA	88%	12%	NA	NA
Ensemble subspace KNN	35%	65%	100%	0%	100%	0%	100%	0%	100%	0%	100%	0%
Ensemble RUSboosted trees	94%	6%	100%	0%	100%	0%	100%	0%	55%	45%	100%	0%

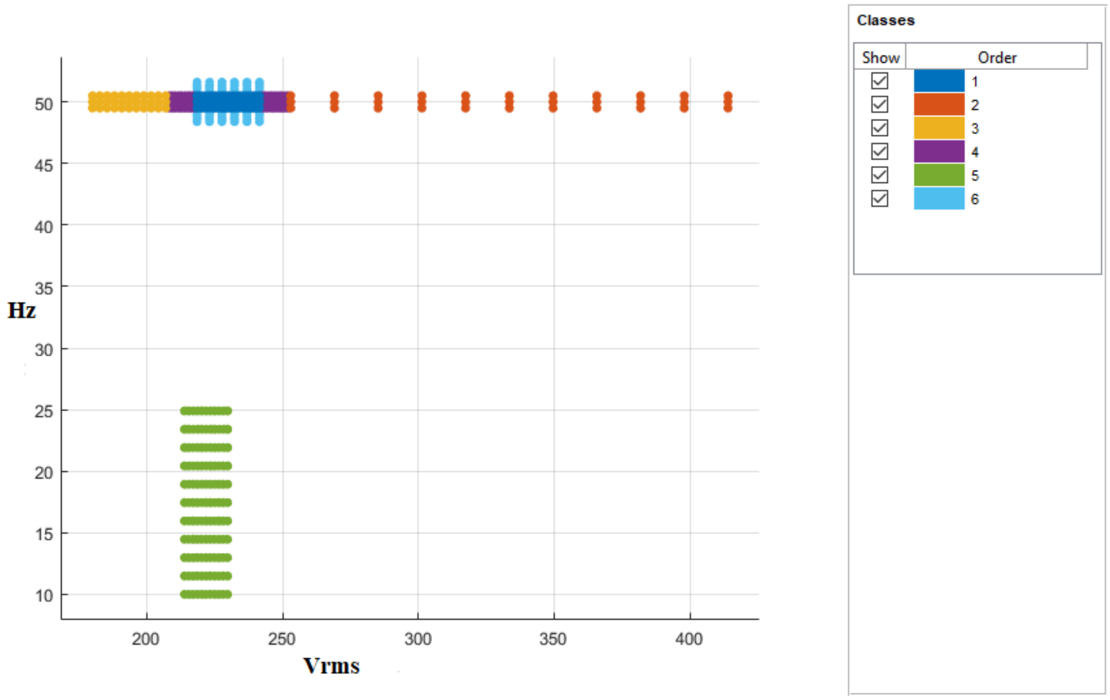


Figure 3.14: The classified categories in Matlab Application.

By giving the data classes a known set of input data (observations) and known responses, as shown in Figure 1, supervised machine learning was carried out. The information is used to train a model that forecasts how new data will behave. The categories that required classification were clearly shown in Figure 3.14. It should be remembered that the vertical axis denotes frequency, and the horizontal axis the voltage difference.

Additionally, it should be highlighted that each group adopted a certain position on the curve, which aids in a more accurate classification in accordance with each group's features and for all observations.

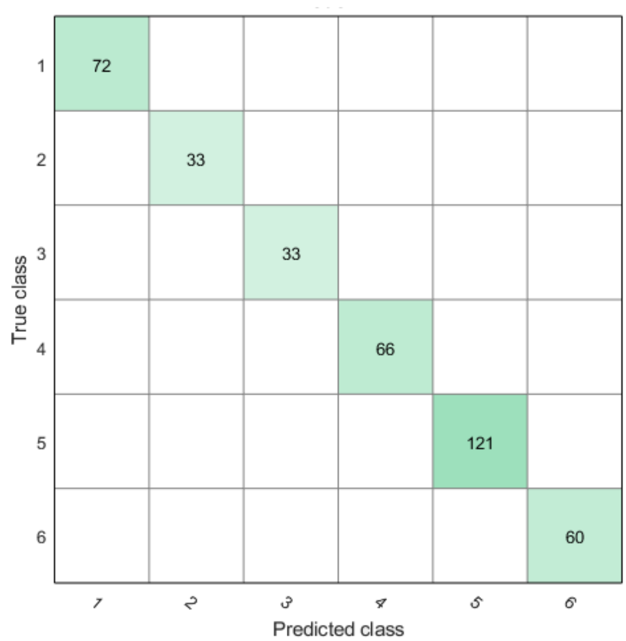


Figure 3.15: The confusion matrix of Fine tree, Medium tree and Ensemble bagged trees models.

A table called a confusion matrix is used to describe how well a classification system performs. Figure 3.15 demonstrated that all data were correctly classified across all categories using the Fine tree, Medium tree, and Ensemble bagged trees models.

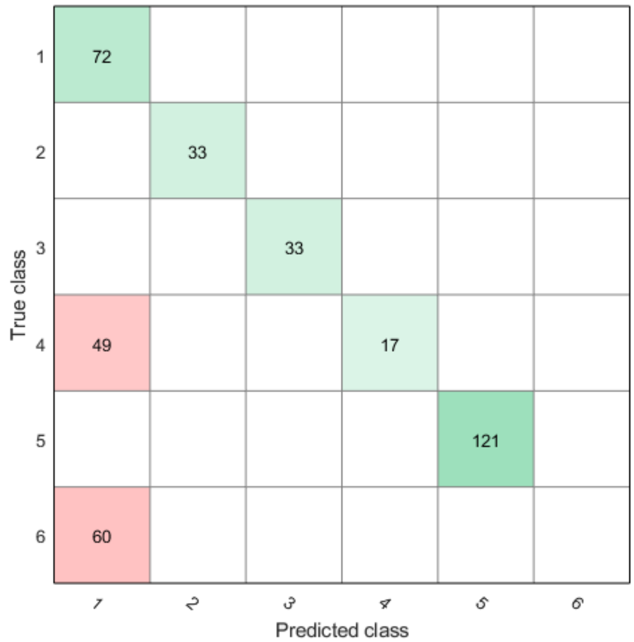


Figure 3.16: The confusion matrix of coarse tree model.

It can be seen from Figure 3.16 that, the fourth category, which had a 25.7% success rate, was completely misclassified by the coarse tree model, as was the sixth category as an entire.

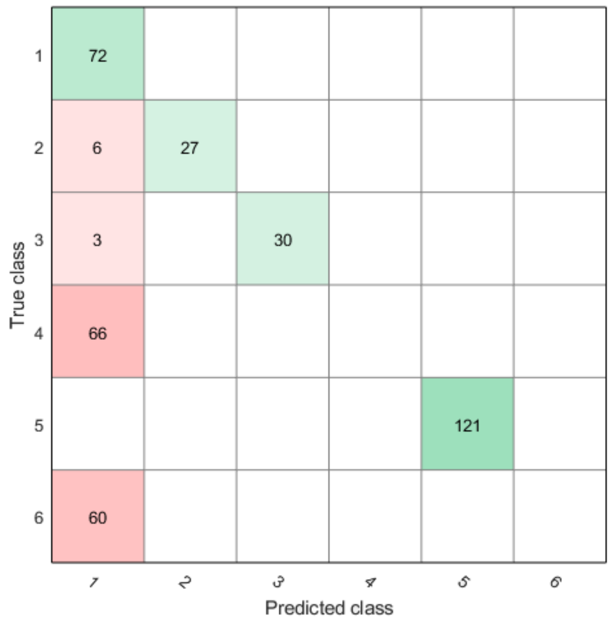


Figure 3.17: The confusion matrix of linear discriminant and linear SVM models.

In Figure 3.17, the second category with 6 observations, the third category with three observations, and the sixth category with all observations were incorrectly classified by the linear discriminant and linear SVM models.

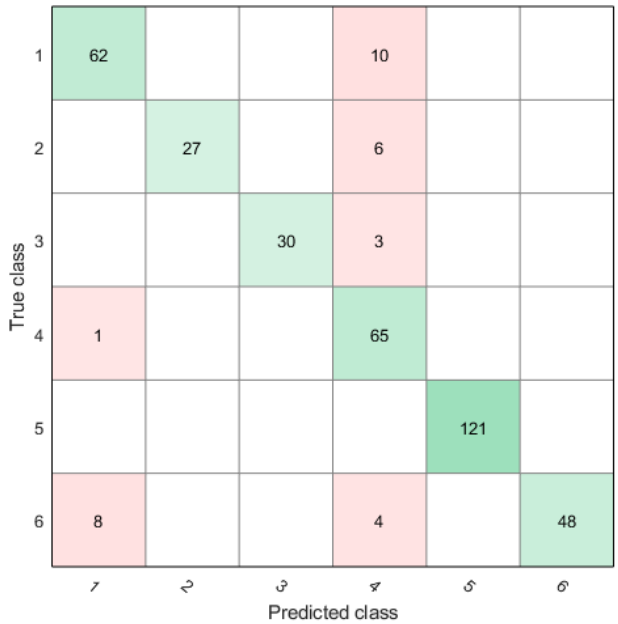


Figure 3.18: The confusion matrix of Quadratic discriminant model.

Figure 3.18 illustrates the classification success rates for each category for the quadratic discriminant model, which were 86.1%, 81.8%, 90.9%, 98.5%, 100%, and 80% for categories 1 to 6, respectively.

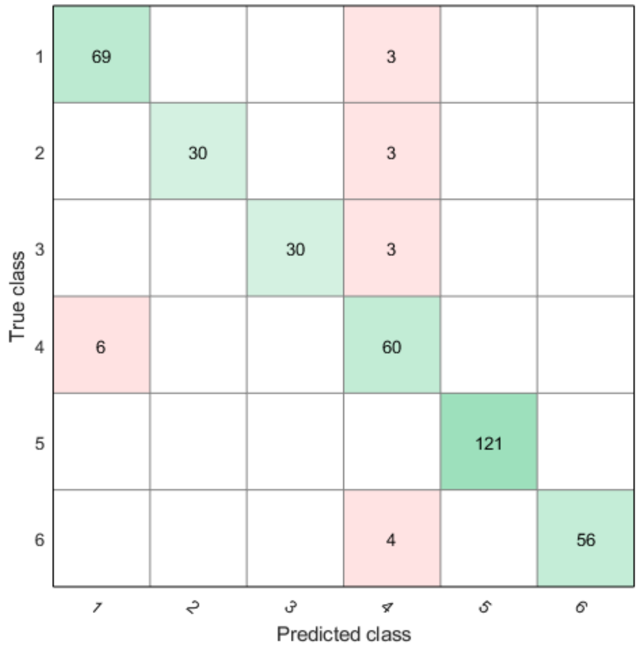


Figure 3.19: The confusion matrix of Quadratic SVM model.

For the quadratic SVM model, the classification success rates for categories 1 through 6 were 95.8%, 90.9%, 90.9%, 90.9%, 100%, and 93.3%, respectively as shown in Figure 3.19.

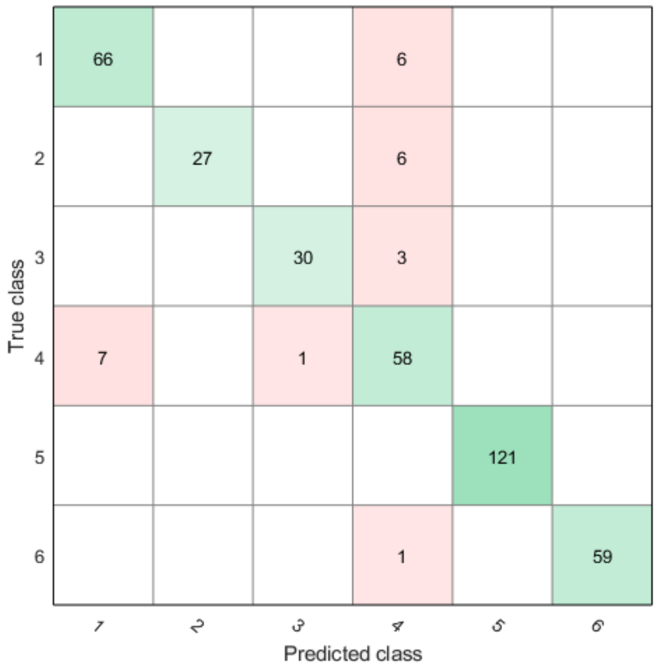


Figure 3.20: The confusion matrix of Cubic SVM model.

Figure 3.20 shows the classification success rates for categories 1 through 6 for the Cubic SVM model, which were 91.6%, 81.8%, 87.9%, 100%, and 98.3%, correspondingly.

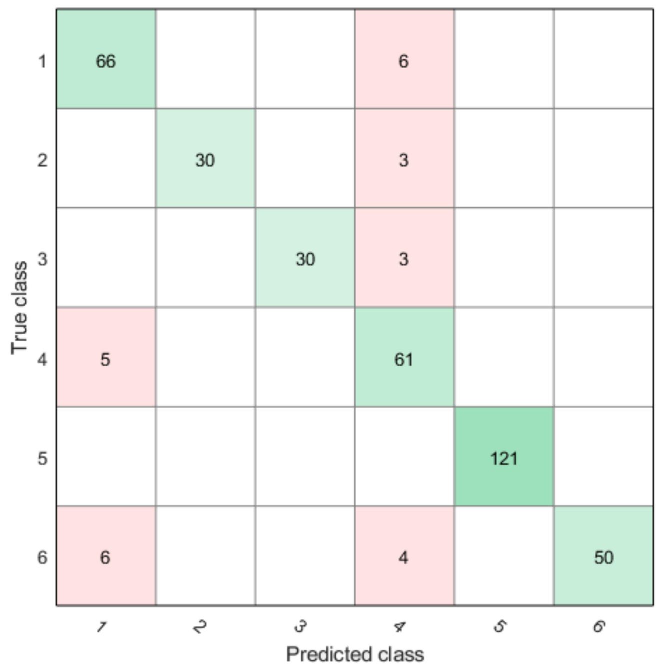


Figure 3.21: the confusion matrix of Fine gaussian SVM model.

Figure 3.21 illustrates the classification success rates for the Fine Gaussian SVM model for categories 1 to 6, which were 91.6%, 90.9%, 90.9%, 92.4%, 100%, and 75.8%, sequentially.

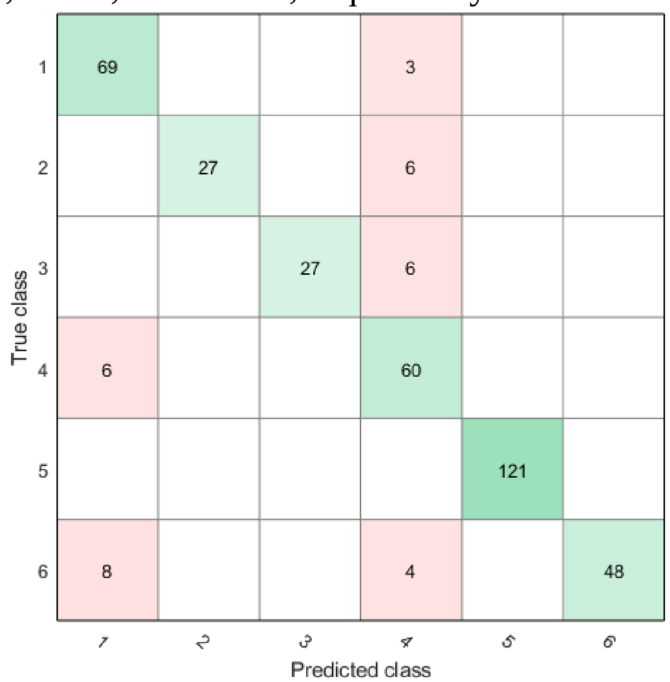


Figure 3.22: The confusion matrix of Medium gaussian SVM model.

As illustrated in figure 3.22, the medium gaussian SVM model achieved the following classification success rates for categories 1 through 6: 95.8%, 81.8%, 81.8%, 90.9%, 100%, and 72.7%.

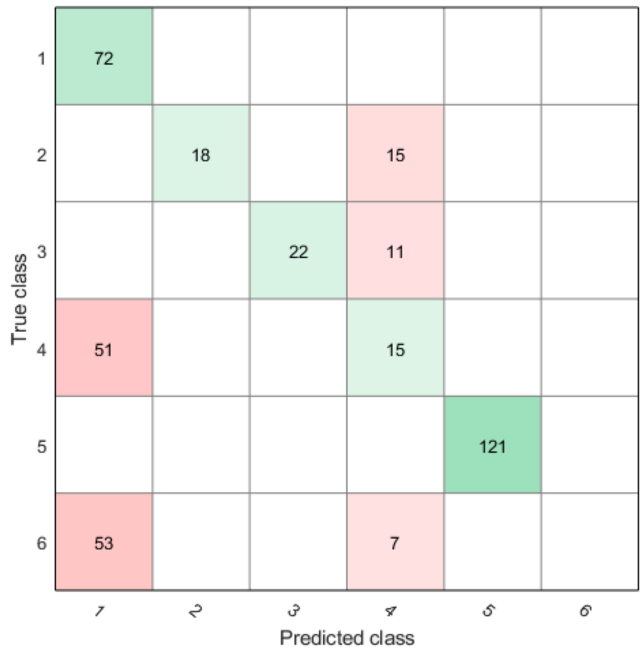


Figure 3.23: The confusion matrix of coarse gaussian SVM model.

Figure 3.23 shows the classification success rates for categories 1 to 6 according to the coarse gaussian SVM model: 100%, 54.5%, 66.6%, 22.7%, 100%, and 0%, accordingly.

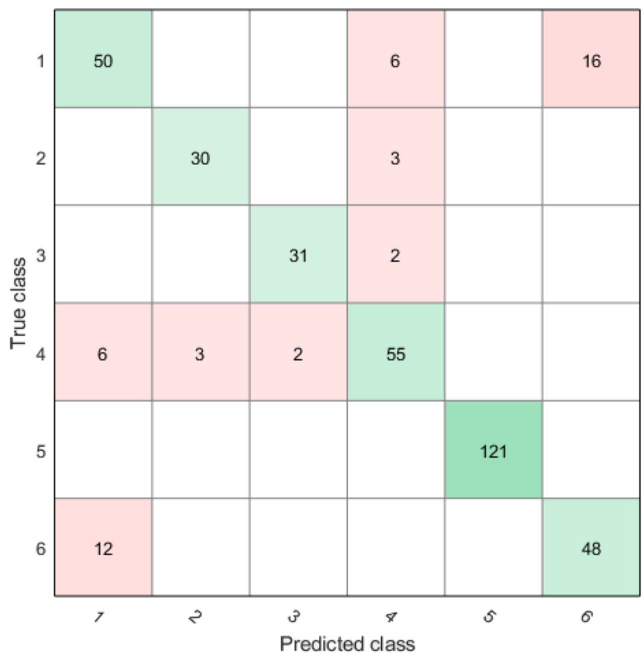


Figure 3.24: The confusion matrix of Fine KNN model.

The classification success rates achieved by the Fine KNN model for categories 1 through 6, were 69.4%, 90.9%, 93.4%, 83.3%, 100%, and 72.7%, respectively (see Figure 3.24).

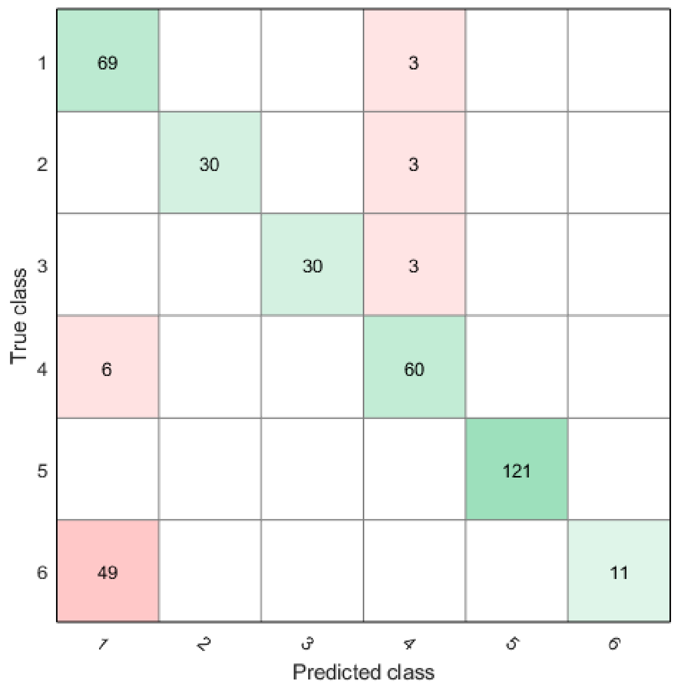


Figure 3.25: The confusion matrix of Medium KNN model.

Figure 3.25 exhibits the classification success rates for the medium KNN model for categories 1 to 6, which were 95.8%, 90.9%, 90.9%, 100%, and 16.7%, accordingly.

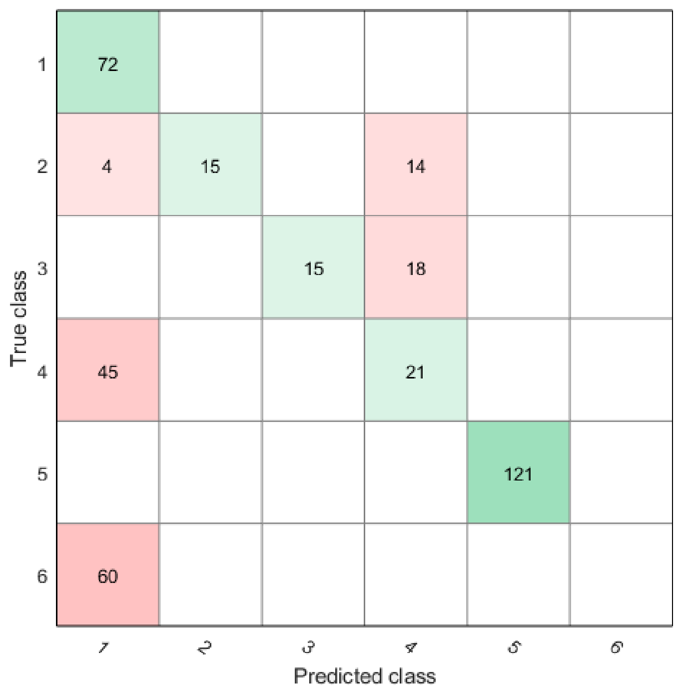


Figure 3.26: The confusion matrix of Coarse KNN model.

According to figure 3.26, the coarse KNN model had classification success rates of 100%, 45.5%, 31.8%, 100%, and 0% for categories 1 through 6.

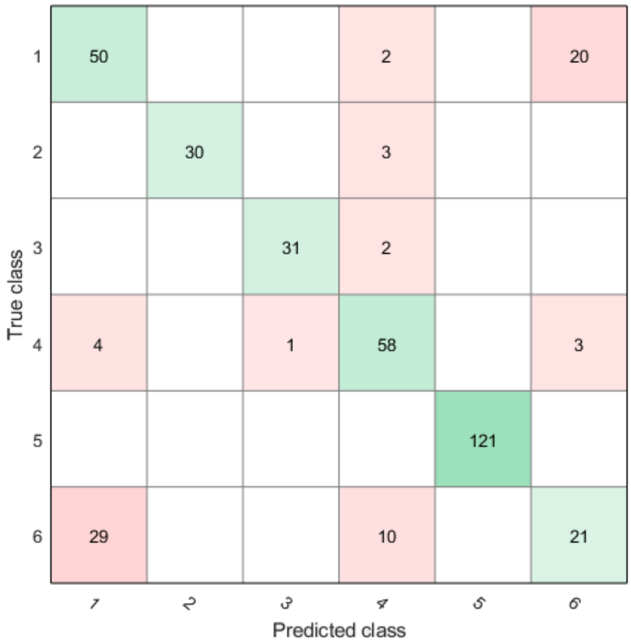


Figure 3.27: The confusion matrix of Cosine KNN model.

According to figure 3.27, the Cosine KNN model scored 69.4%, 90.9%, 93.9%, 87.9%, 100%, and 31.8% for each category 1 to 6 of classification success rates.

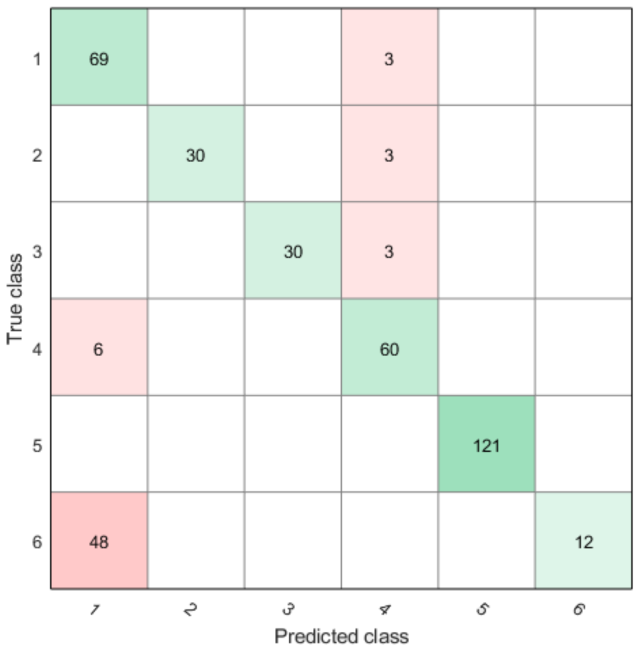


Figure 3.28: The confusion matrix of Cubic KNN model.

As illustrated in figure 3.28, the Cubic KNN model achieved classification success rates for categories 1 through 6 of 95.8%, 90.9%, 90.9%, 100%, and 18.2%, accordingly.

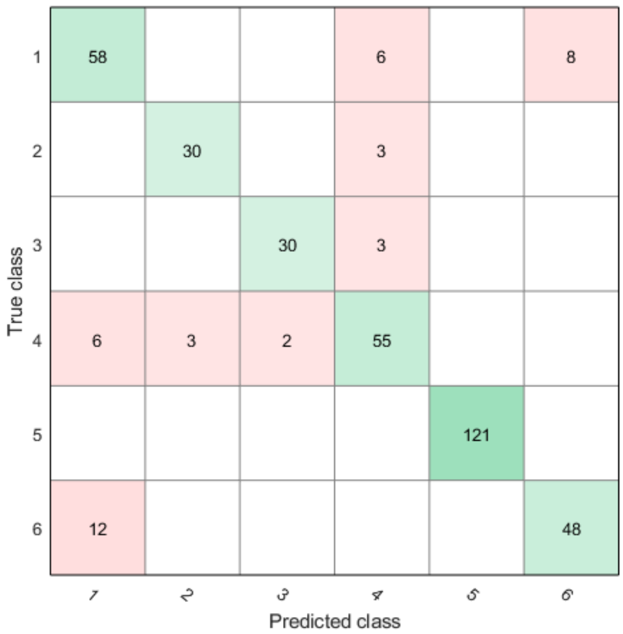


Figure 3.29: The confusion matrix of Weighted KNN model.

The weighted KNN model obtained the following classification success rates for categories 1 through 6: 80.6%, 90.9%, 90.9%, 83.3%, 100%, and 72.7%. As illustrated in Figure 3.29.

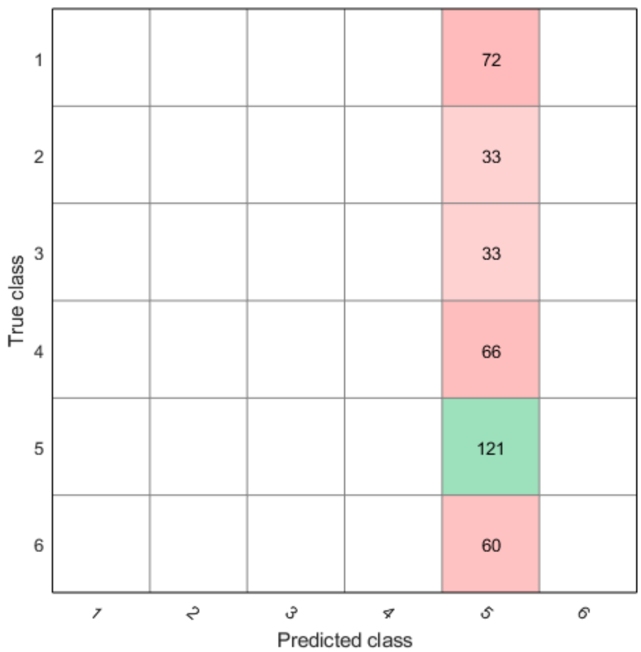


Figure 3.30: The confusion matrix of Ensemble boosted trees model.

According to Figure 3.30, the ensemble boosted trees model successfully classified every observation in Category 6 but failed to do so for the other categories.

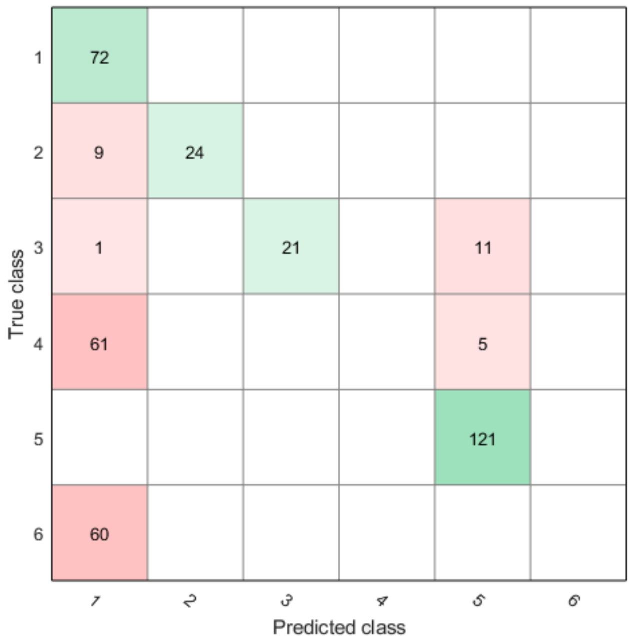


Figure 3.31: The confusion matrix of Ensemble subspace discriminant model.

All observations in categories 1 and 5 were successfully classified using an ensemble subspace discriminant model, while observations in categories 4 and 6 were not. As demonstrated in figure 3.31, it also successfully identified categories 2 and 3 with success rates of 72.7% and 63.6%, respectively.

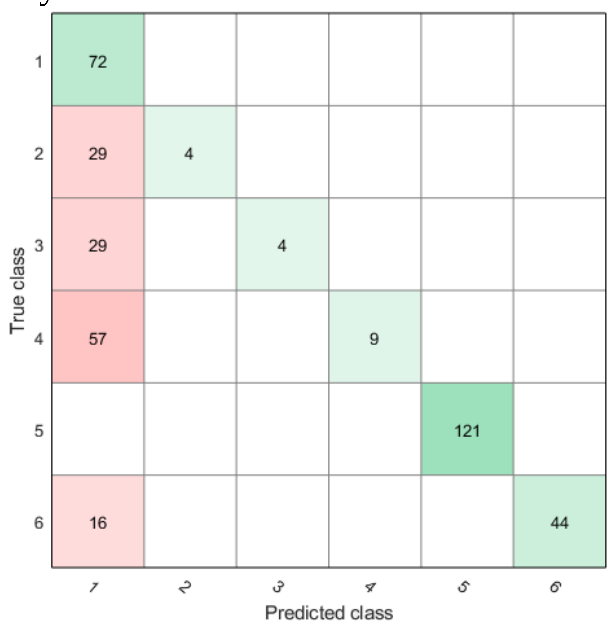


Figure 3.32: The confusion matrix of Ensemble subspace KNN model.

All observations from categories 1 and 5 were successfully classified using the ensemble subspace KNN model. Additionally, as shown in figure 3.32, it identified categories 2, 3, 4, and 6 with success rates of 87.9%, 87.9%, 86.4%, and 66.6%.

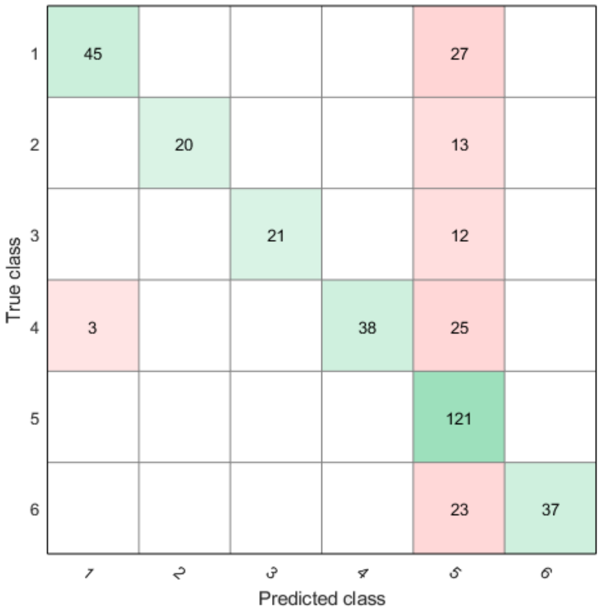


Figure 3.33: The confusion matrix of Ensemble RUS boosted trees model.

The following classification success rates for categories 1 through 6 were obtained using the ensemble RUS enhanced trees model: 62.5%, 60.6%, 63.6%, 57.6%, 100%, and 56.1%. According to Figure 3.33.

3.3.3 Testing results:

The best model was chosen once the training procedures for the various models were finished, and it was then used to various scenarios to guarantee the diversity of the six necessary categories. The network readings were given to the system, which was then activated to get the necessary classification status. The following cases were implemented:

Case one: normal conditions.

The prediction model in this case received the readings listed as follows:

Phase A voltage = 229 Volt   Phase B voltage = 220 Volt   Phase C voltage = 219 Volt

Phase A frequency = 49.9 Hz   Phase B frequency = 50.0 Hz   Phase C frequency = 50.1 Hz

The outcomes of the execution are shown in the following window.

```
Command Window
>> classifier_V1
Enter the three phase readings (V1-F1-V2-F2-V3-F3)=[229 49.9 220 50 219 50.1];
phase A is normal
phase B is normal
phase C is normal
>>
```

Case two: swell conditions.

The prediction model in this case received the readings listed as follows:

Phase A voltage = 270 Volt Phase B voltage = 220 Volt Phase C voltage = 219 Volt

Phase A frequency = 49.9 Hz Phase B frequency = 50.0 Hz Phase C frequency = 50.1 Hz

The outcomes of the execution are shown in the following window:

```
Command Window
>> classifier_V1
Enter the three phase readings (V1-F1-V2-F2-V3-F3)=[270 49.9 220 50 219 50.1];
phase B is normal
phase C is normal
Swell in phase A
Unbalance Condition
fx >>
```

Case three: sag conditions.

The prediction model in this case received the readings listed as follows:

Phase A voltage = 230 Volt Phase B voltage = 206 Volt Phase C voltage = 219 Volt

Phase A frequency = 49.9 Hz Phase B frequency = 50.0 Hz Phase C frequency = 50.1 Hz

The outcomes of the execution are shown in the following window:

```
Command Window
>> classifier_V1
Enter the three phase readings (V1-F1-V2-F2-V3-F3)=[230 49.9 206 50 219 50.1];
phase A is normal
phase C is normal
Sag in phase B
Unbalance Condition
fx >>
```

Case four: rapid voltage change conditions.

The prediction model in this case received the readings listed as follows:

Phase A voltage = 229 Volt Phase B voltage = 220 Volt Phase C voltage = 210 Volt

Phase A frequency = 49.9 Hz Phase B frequency = 50.0 Hz Phase C frequency = 50.1 Hz

The outcomes of the execution are shown in the following window:

```
Command Window
>> classifier_V1
Enter the three phase readings (V1-F1-V2-F2-V3-F3)=[229 49.9 220 50 210 50.1];
phase A is normal
phase B is normal
Rapid Voltage Change in phase C
Unbalance Condition
fx >>
```

Case five: flicker conditions.

The prediction model in this case received the readings listed as follows:

Phase A voltage = 214 Volt   Phase B voltage = 220 Volt   Phase C voltage = 210 Volt

Phase A frequency = 20.0 Hz   Phase B frequency = 50.0 Hz   Phase C frequency = 50.1 Hz

The outcomes of the execution are shown in the following window:

```
Command Window
>> classifier_V1
Enter the three phase readings (V1-F1-V2-F2-V3-F3)=[214 20 220 50 210 50.1];
phase B is normal
Rapid Voltage Change in phase C
Fliker in phase A
Unbalance Condition
>>
```

Case six: unbalanced conditions.

The prediction model in this case received the readings listed as follows:

Phase A voltage = 229 Volt   Phase B voltage = 220 Volt   Phase C voltage = 210 Volt

Phase A frequency = 49.9 Hz   Phase B frequency = 48.6 Hz   Phase C frequency = 50.1 Hz

The outcomes of the execution are shown in the following window:

```
Command Window
>> classifier_V1
Enter the three phase readings (V1-F1-V2-F2-V3-F3)=[229 49.9 220 48.6 210 50.1];
phase A is normal
Rapid Voltage Change in phase C
Frequency variation in phase B
Unbalance Condition
>>
```

Chapter Four
Conclusions and Future Work

4.1 Conclusion

The thesis effectively deals with electrical network events, and it achieved well by monitoring and analyzing the signal in several power systems. As a result, work was done to create models of the disturbances that appeared in the monitored systems and analyze them. Then, a computer software was constructed to monitor the signal, capture the emergence of disturbances, and accurately identify its type.

4.1.1 Disturbances Monitoring

1- It is recommended when choosing the substations for monitoring, considering the kind of electrical load as well as the location of substation on the SLD.

2- The effect of changing electrical load amount and type was observed on the shape of the voltage wave drawn. That can be predicted the disturbance on the DS is formed because of either the source changing (event on the source side) or the change in the electrical load on the substations, and since the study is based on monitoring the electrical load on the DS, disturbances occurred because changing on the load side can be noted.

3- The location of the substation on the SLD affects on the types of disturbances and the number of times it occur, as it has been observed that substation far from the main feeding source (the end of the feeder (TR1)) have a large number of transient and RVC disturbances other than those close to the feeding source.

4- The percentage of THDi is almost highly than THDv without interruption event occurs on the substation and both of THDi and THDv not the same on each phase.

5- Transient and RVC events require continued monitoring in order to be able to track them as they happen since the time it takes for them to occur and end is so short.

6- EV charger recorded highest percentage of THDv and THDi due to the nature of load and the THDi drops along with a rise in current, and vice versa that because the using of DC converter.

4.1.2 Artificial Neural Network modules, Predictions

1- The Ensemble subspace KNN method had the slowest training time (7.6963 seconds) and lowest accuracy rate of 31.4%. The Ensemble boosted trees algorithm had the fastest training time, clocking in at 0.4521 seconds with maximum expected speed (by 7200 obs/sec) and 100% accuracy.

2- Fine tree, medium tree, and ensemble-bagged trees produced the best PPV with no errors for the first category. Fine and medium trees were the best model to earn the best scores for all categories. The majority of Ensemble group models and the group of tree models earned the highest scores for the fourth category.
3- Confusion matrix tables shows the percentage success rate for each categories , some of categories have a high success rat in some order and others fail to reach a good success rate.
4- In part of section (3.3.3), normal operation and disturbances events tested by medium tree algorithm, and the results showed that the system succeeded in identifying the state of disturbances, and classifying its type. In addition, the appearance of more than one disturbance at the same time was tested, and it succeeded as the system as well.

4.2 Future Work

1- Monitoring the quality of power is one of the important issues, especially when there are sensitive loads in a facility, factory or others. Therefore, the installation of advance monitoring devices must continue increasingly on these loads and straighten the situation when the defect founded.
2- Examining the degree to which other power systems, those not included in the dissertation, have contributed to causing disturbances in the electrical network. The architecture of the electrical network and its components also should be studied because they have an impact in the emergence of different disturbances.
3- Developing some of the main elements in smart grid, such as smart meters (in costumers sits) and automatic reclosers (along the networke) for monitoring the quality of the power.
4- Using the ANN techniques to find the best module can calculate the THD.

The following table contain all mentioned transformers nameplates data:

Table 4.1: Distribution TRs nameplate data.

S.No.	Description of Data to be given	TR1	TR2	TR3
1.	Manufacturer's Name	ELICO	ELICO	LANKA
2.	Serial Number	F1513006	20189213	100030808
3.	Kind of Transformer	Power TR	Power TR	Power TR
4.	Year of Manufacture	2011	2016	2016
5.	Number of Phase	3	3	3
6.	Rated Power (KVA)	250	400	1000
7.	Rated Frequency	50	50	50
8.	Rated Voltages (HV/LV)(KV)	33/0.415	33/0.415	33/0.415
9.	Vector Group Symbol	Dyn11	Dyn11	Dyn11
10.	Types of Cooling	ONAN	ONAN	ONAN
11.	insulating Oil Weight	275	328	685
12.	Total Weight	1385	1630	3520
13.	Dilectric volume	310	364	-
14.	Details about Tap-Changer	5 taps	5 taps	5 taps
15.	Impedance Voltage %	4.55	4.671	5.45
16.	Rated current (HV/LV)(A)	4.3/347.4	7/556.48	17.5/1391
17.	Standerd	IEC60076	IEC60076	IEC60078:2000
18.	Ambiant Tempreature (C°)	50°	50°	50°

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APPENDIX I
MATLAB CLASSIFIER CODE

By using MATLB tool box the enterd data had been trained. And the out of box MATLB code used to classify distirbances is showen below:

```
% Classifier MATLAB code
%V1,2,3= Voltage at phase 1,2,3.
%F1,2,3= Frquncy at phase 1,2,3.
X = input('Enter the three phase readings (V1-F1-V2-F2-V3-F3)=');
X1 = [X(1) X(2)];
X2 = [X(3) X(4)];
X3 = [X(5) X(6)];
load('classifier_ensemble.mat')
y1 = classifier_ensemble.predictFcn(X1);
y2 = classifier_ensemble.predictFcn(X2);
y3 = classifier_ensemble.predictFcn(X3);
% load('classifier_SVM.mat')
% yfit1 = classifier_SVM.predictFcn(X1);
% yfit2 = classifier_SVM.predictFcn(X2);
% yfit3 = classifier_SVM.predictFcn(X3);
%--------------------------------------------------------------------
------
if y1 == 1
    disp('phase A is normal')
end
if y2 == 1
    disp('phase B is normal')
end
if y3 == 1
    disp('phase C is normal')
end
%--------------------------------------------------------------------
------
if y1 == 2
    disp('Swell in phase A')
end
if y2 == 2
    disp('Swell in phase B')
end
if y3 == 2
    disp('Swell in phase C')
end
%--------------------------------------------------------------------
------
if y1 == 3
    disp('Sag in phase A')
end
if y2 == 3
    disp('Sag in phase B')
end
if y3 == 3
    disp('Sag in phase C')
end
%--------------------------------------------------------------------
------
if y1 == 4
    disp('Rapid Voltage Change in phase A')
```

```
end
if y2 == 4
    disp('Rapid Voltage Change in phase B')
end
if y3 == 4
    disp('Rapid Voltage Change in phase C')
end
%-----------------------------------------------------------------------
------
if y1 == 5
    disp('Fliker in phase A')
end
if y2 == 5
    disp('Fliker in phase B')
end
if y3 == 5
    disp('Fliker in phase C')
end
%-----------------------------------------------------------------------
------
if y1 == 6
    disp('Frequency variation in phase A')
end
if y2 == 6
    disp('Frequency variation in phase B')
end
if y3 == 6
    disp('Frequency variation in phase C')
end
%-----------------------------------------------------------------------
------
if (y1 == 1)&&(y2 == 1)&&(y3 ~= 1)
    disp('Unbalance Condition')
end
if (y1 == 1)&&(y2 ~= 1)&&(y3 == 1)
    disp('Unbalance Condition')
end
if (y1 ~= 1)&&(y2 == 1)&&(y3 == 1)
    disp('Unbalance Condition')
end
if (y1 ~= 1)&&(y2 ~= 1)&&(y3 == 1)
    disp('Unbalance Condition')
end
if (y1 ~= 1)&&(y2 == 1)&&(y3 ~= 1)
    disp('Unbalance Condition')
end
if (y1 == 1)&&(y2 ~= 1)&&(y3 ~= 1)
    disp('Unbalance Condition')
end
if (y1 ~= 1)&&(y2 ~= 1)&&(y3 ~= 1)
    disp('Unbalance Condition')
end
```

APPENDIX II

Distribution Transformers Nameplate

The manufacturer and designer of transformers required minimum information and data to be hold on a transformer nameplate are as follows:

- Name of manufacturer
- Serial number
- year of manufacture
- Number of phases
- kVA or MVA rating
- Frequency
- Voltage ratings.
- Tap voltages.
- Connection diagram.
- Cooling class
- Rated temperature in °C
- Polarity (for Single Phase Transformers)
- Phasor or vector diagram (For Polyphase or Three Phase Transformers).
- % impedance.
- Approximate mass or weight of the transformer
- Type of insulating liquid.
- Conductor material of each winding.
- Oil volume (of each transformer Container/Compartment)
- Instruction for Installation and Operation

❖ Residatial TR (Reaf Meroad) nameplate shown in Figure 4.1:

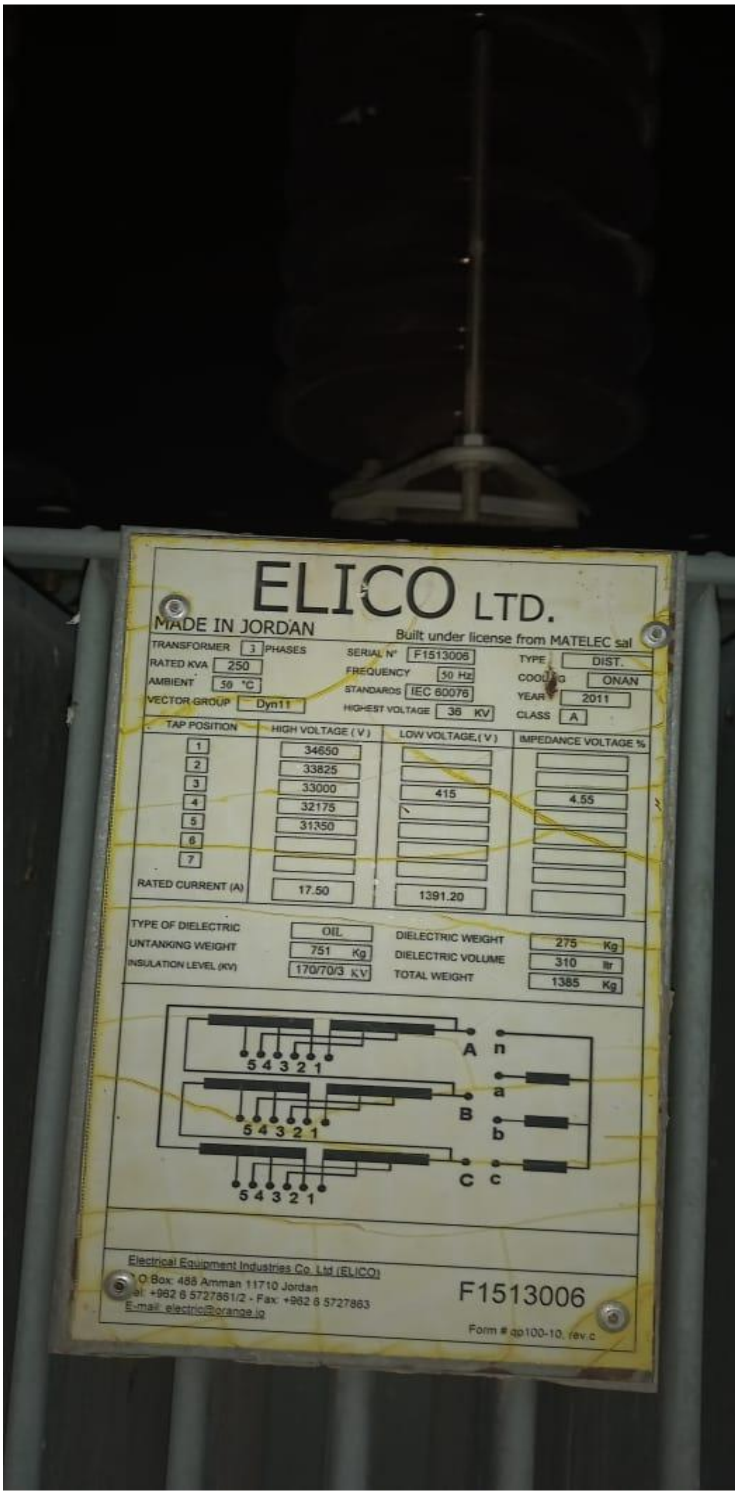


Figure 4.1: TR1 Nameplate.

❖ Commerical TR (Alsalhat) nameplate shown in Figure 4.2:

Figure 4.2: TR2 Nameplate.

❖ Domstic with PV TR3 ("Loot" Kahf) nameplate shown in Figure 4.3:

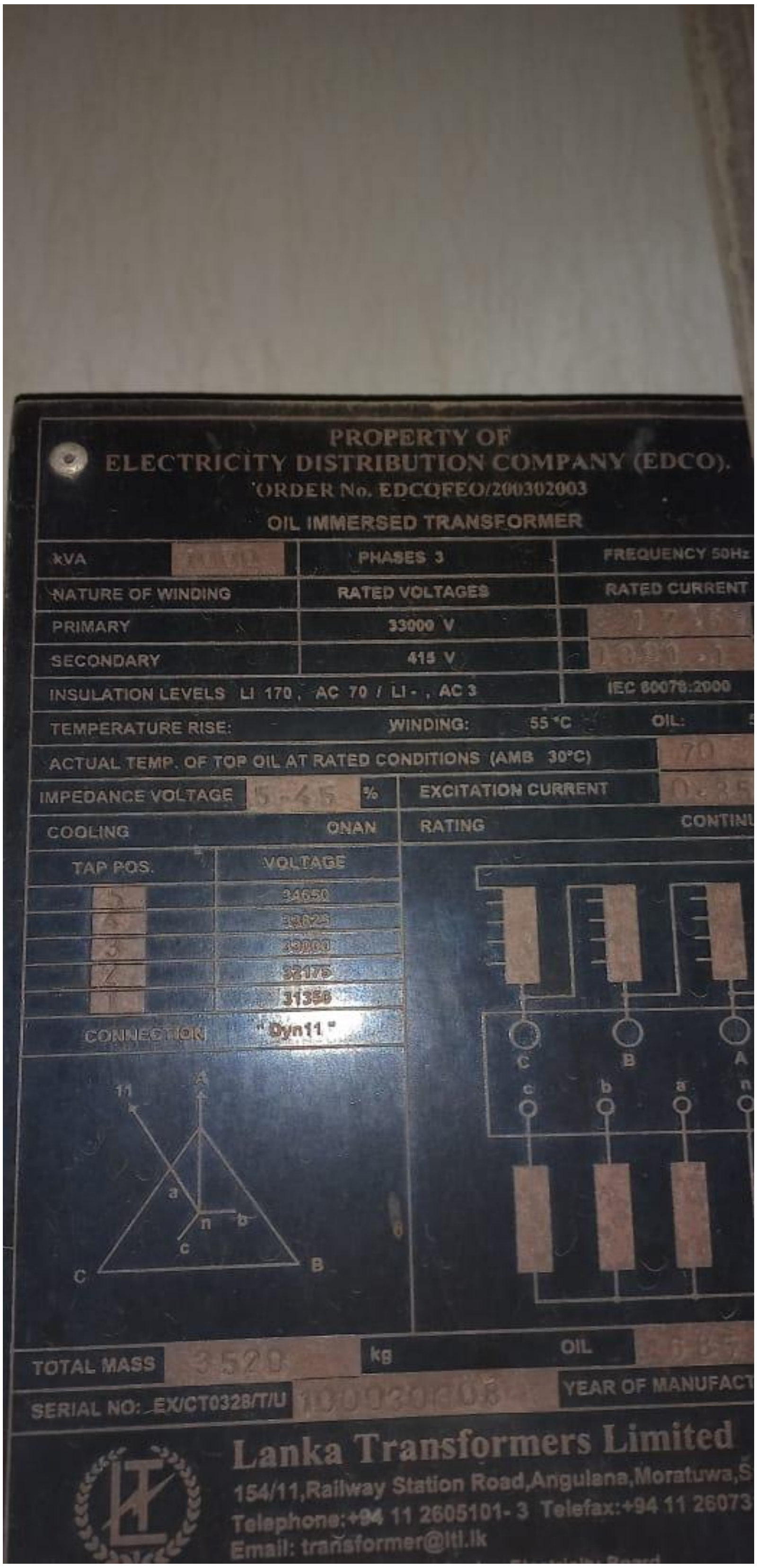


Figure 4.3: TR3 Nameplate.

APPENDIX III
Single Line Diagrams (SLDs)

In this appendex the SLD of power system and the location of DSs are shown. Reaf Meroad and Alsalhat substations shown in figure (4.4), both substations feed from new Athniah step-down substation shown in figure (4.5).

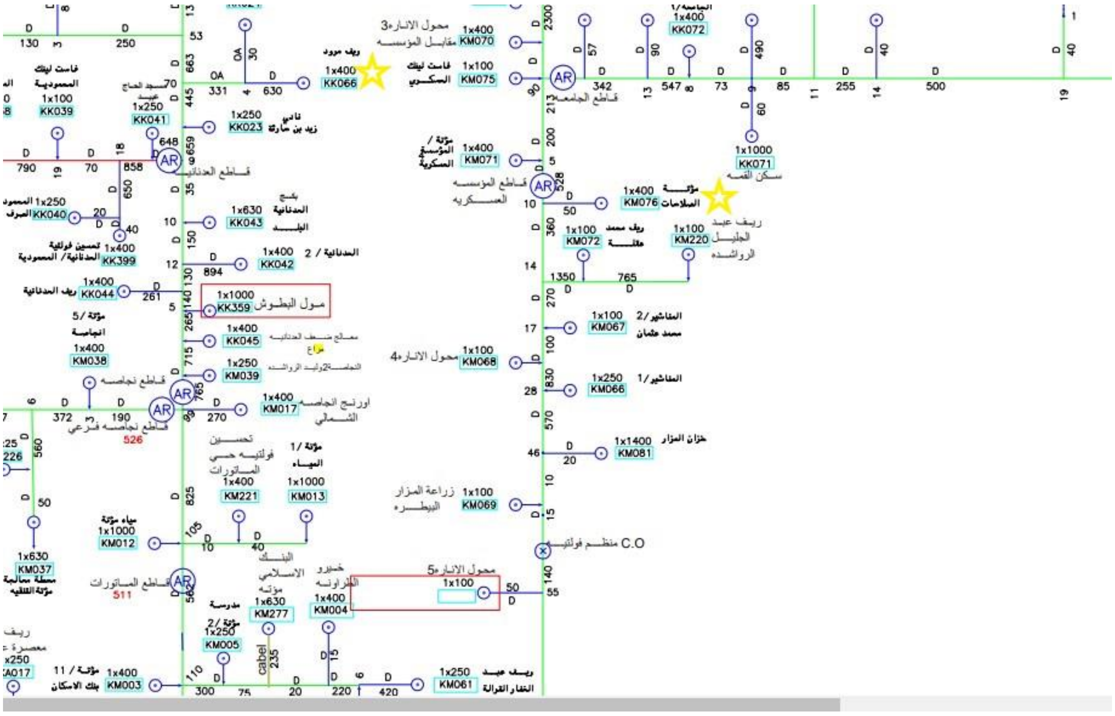
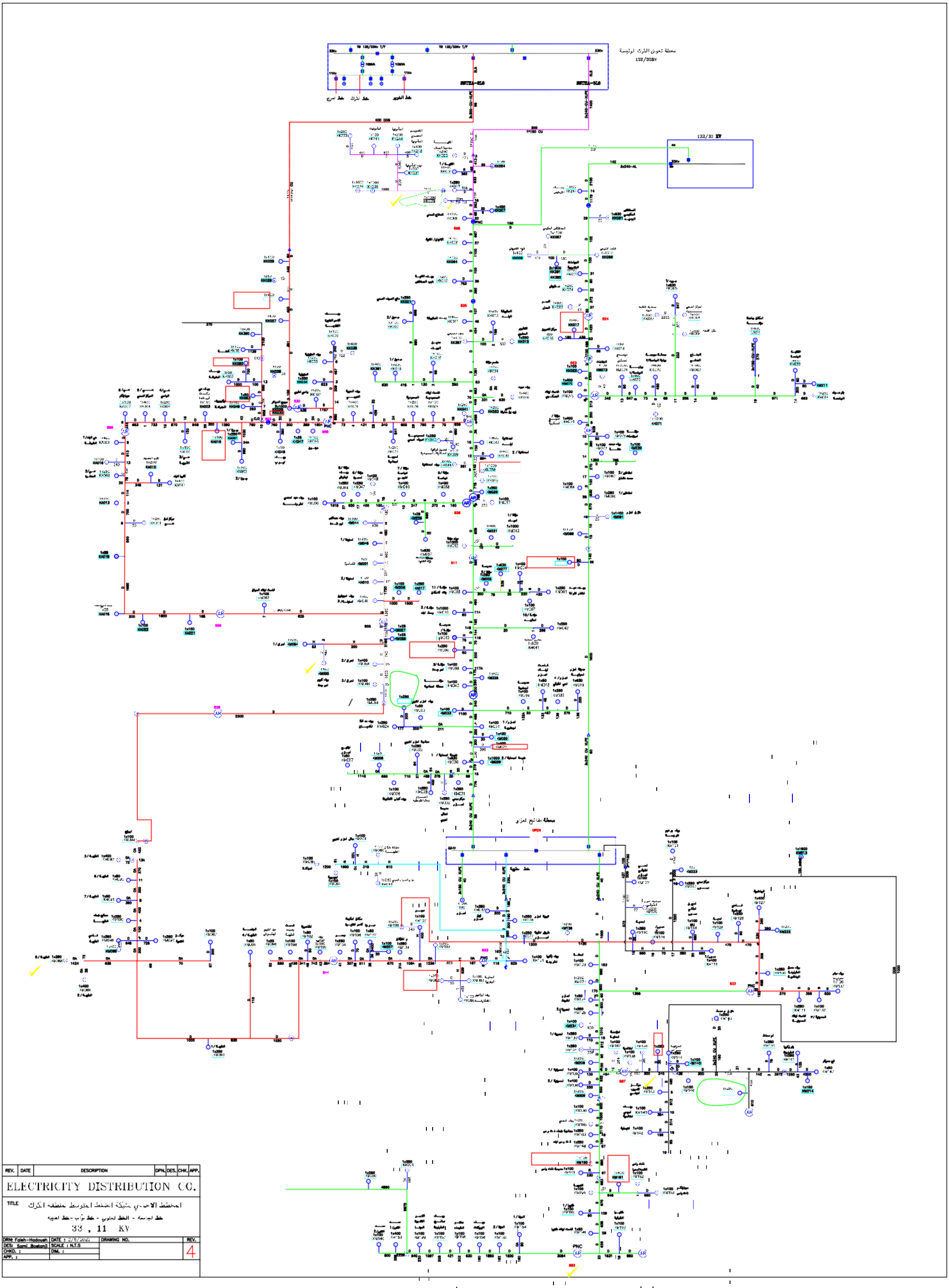


Figure 4.4: ☆ Reaf Meroad and ☆ Alsalhat substations.

TR3 (Kahf Loot) is feed from Alsafi step-down substation and the SLD shown in figure (4.6).



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TITLE
المخطط الاحادي لشبكة الضغط المتوسط لمنطقة الكرك
خط الجامعة - الخط الجلوبي - خط مؤاب - خط العليه
33 , 11 KV
DRN: Faleh-Hadoush
DATE : 2/8/2022
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SCALE : N.T.S
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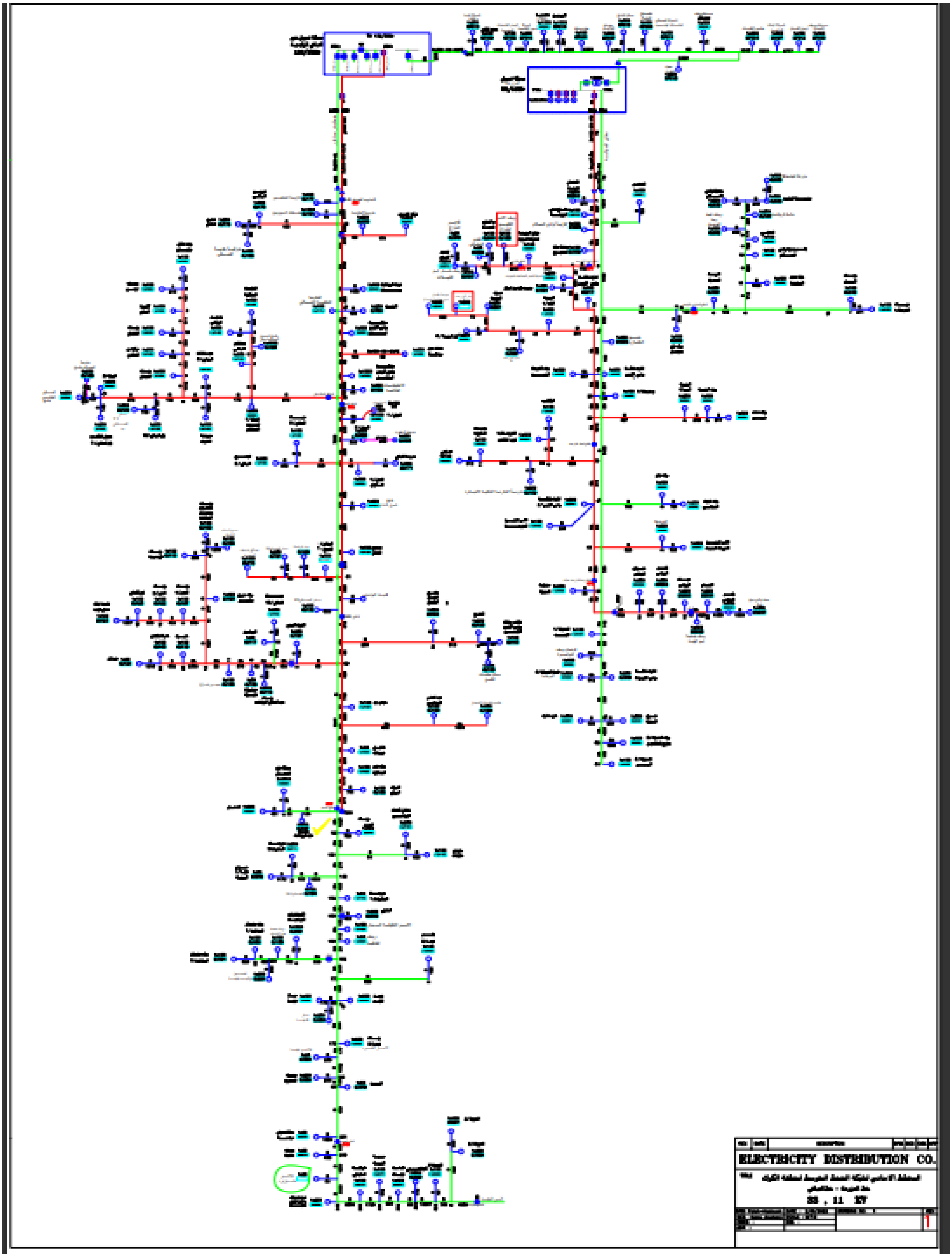

Figure 4.6: SLD for Alsafi main substations.

المعلومات الشخصية

الاسم: محمد حامد العميريين

الكلية: الهندسة

التخصص: الشبكات الذكية في أنظمة القوى الكهربائية

السنة: 2023