الجمهورية الجزائرية الدمقراطية الشعبية

Democratic and Popular Algerian Republic

وزارة التعليم العالي والبحث العلمي

Ministry of Higher Education and Scientific Research

Mohamed Chérif Messadia University
Souk-Ahras

جامعة محمد الشريف مساعدية
سوق أهراس

Faculty of Science and Technology

Department of Electrical Engineering

Theme

Presented this Theme to obtain a Master's degree

PV solar fault diagnosis based on feature selection and support vector machine

Specialty

Automation and Industrial Computing

by:

Mamine Sameh

Examination committee:

Lotfi Moussaoui	Chairman	MCA	U.SOUK-AHRAS
Ridha Rouaibia	Examiner	MCB	U.SOUK-AHRAS
Tawfik Thelaidjia	Supervisor	MCA	U.SOUK-AHRAS
Zouhir Boumous	Co-Supervisor	MCA	U.SOUK-AHRAS

Year **2023/2024**

بسم الله الرحمن الرحيم

Acknowledgements

First and foremost, I want to thank Allah Almighty for all the blessings He has bestowed upon me, and His facilitation throughout.

I would like to extend my deepest appreciation to my supervisors, Doctor **Tawfik Thelaidjia and Zouhir boumous**, for their invaluable guidance, unwavering support, and continuous encouragement throughout the course of this research. Their expertise, insightful feedback, and dedication have been instrumental in shaping this thesis.

My respectful thanks to all the members of the jury **Dr.Lotfi Moussaoui** and **Dr.Ridha Rouaibia** for their insightful comments, constructive criticism, and valuable suggestions for this work.

I also thank the faculty members of the Electrical Engineering Department at Mohammed Al-Sharif University, College of Science and Technology, for their assistance and encouragement.

Special thanks are due to my family for their unconditional love, patience, and understanding during the challenging phases of this journey. Their unwavering support has been my source of strength.

Lastly, I extend my appreciation to all those who directly or indirectly contributed to this work. Your contributions have been deeply appreciated and have played a significant role in the completion of this thesis.

Dedication

To my mother and father, who has always been a strong pillar in my life and a source of love and endless support. To my dear brother Sami, who played a significant role in encouraging and supporting me in every stage of my life. And to my beloved sisters, Amal, Namcha, Khaoula, Houda, and Maryam, who have been my backbone and motivation to move forward.

To my friends,You are the best. Thank you for being there.

[Sameh]

List of figures

List of table

List of Symbols and Acronyms

List of Symbols:

Voc: open circuit voltage.

Icc: short circuit current.

GHG: greenhouse gases.

MLP: Multilayer Perceptron.

MPPT: Maximum power point tracker.

Time: Actual measurement time in seconds.

Ipv: PV array current measurement.

Vpv: PV array voltage measurement.

Vdc: DC voltage measurement.u

ia: Phase_A current measurement.

ib: Phase_B current measurement.

ic: Phase_C current measurement.

va: Phase_A voltage measurement.

vb: Phase_B voltage measurement.

vc: Phase_C voltage measurement.

List of Acronyms:

GPV: Photovoltaic generator.

PV: Photovoltaic panels.

PVT: photovoltaic thermal.

SVM: Support vector machines.

BPSO: Binary Particle Swarm Optimization

ملخص

مراقبة وكشف الأعطال في أنظمة الطاقة المتجددة ضروريان لتعزيز عمر خدمتها وموثوقيتها. فإذا لم يتم تشخيص هذه الأعطال، قد تقلل بشكل كبير من قدرة إنتاج الطاقة لهذه الأنظمة. لا يوجد نظام صناعي مثالي، كأنظمة الطاقة الشمسية التي تعتمد على النظام الكهروضوئي ، لأن هذه الأنظمة، مثل جميع الأنظمة الصناعية الأخرى، قد تواجه الأعطال والفشل في التثبيت أو التشغيل. لذلك، يمكن أن تفشل أو تتدهور مع مرور الوقت، مما يتطلب تطوير نظام تشخيصي يهدف بشكل أساسي إلى كشف وتحديد الأعطال، وبالتالي الحفاظ على إنتاج الطاقة لنظام الطاقة الشمسية. في هذا البحث، تم تطبيق طريقة التعرف على الأنماط لتشخيص الأعطال في نظام الطاقة الشمسية. وتحتوي الطريقة المقترحة على خطوتين رئيسيتين، حيث يتم في الخطوة الأولى استخراج واختيار المعلمات الإحصائية من الملاحظات. الا ان المعلمات المستخرجة ليس لها نفس الحساسية في تمثيل مختلف النماط لهذا فقد تم استخدام تقنية ذكاء اصطناعي لاختيار احسن المعلمات.اما في الخطوة الثانية فقد تم استخدام الفواصل ذات الهوامش الواسعة من تصنيف عدة أنواع من الأعطال. وقد اظهرت النتائج المحصل عليها فعالية هذا النهج في تشخيص الأعطال بدقة وفعالية.

الكلمات المفتاحية: النظام الكهروضوئي، الفواصل ذات الهوامش الواسعة ، المعلمات الإحصائية، التعرف على الأنماط، تقنية ذكاء اصطناعي لاختيار احسن المعلمات، تشخيص الأعطال.

Résumé

La surveillance et la détection des défauts dans les systèmes d'énergie renouvelable sont essentielles pour améliorer leur durée de vie et leur fiabilité. Si ces défauts ne sont pas diagnostiqués, ils peuvent réduire significativement la capacité de production d'énergie de ces systèmes. Aucun système industriel n'est parfait, comme les systèmes d'énergie solaire qui reposent sur des systèmes photovoltaïques, car ces systèmes, tout comme tous les autres systèmes industriels, peuvent rencontrer des défauts et des défaillances lors de l'installation ou de l'exploitation. Par conséquent, ils peuvent échouer ou se détériorer avec le temps, ce qui nécessite le développement d'un système de diagnostic visant principalement à détecter et à identifier les défauts, et ainsi à maintenir la production d'énergie pour le système d'énergie solaire. Dans travail, une méthode de reconnaissance des formes a été appliquée pour diagnostiquer les défauts dans le système d'énergie solaire. La méthode proposée se compose de deux étapes principales : dans la première étape, des paramètres statistiques sont extraits à partir des observations, puis l'algorithme des essaims des particules binaires est utilisé pour la sélection des paramètres pertinents. Dans la deuxième étape, les séparateurs à vaste marges sont utilisés pour classer les différents types de défauts. Les résultats obtenus démontrent l'efficacité l'approche proposée pour le diagnostic précis et efficace des défauts dans système de panneau photovoltaïque.

Mots clés : Système photovoltaïque, Séparateur à vaste marge, Paramètres statistiques, Algorithme des essaims des particules binaires, Reconnaissance des formes, Diagnostic des défauts.

Abstract

Monitoring and fault detection in renewable energy systems are essential to enhance their service life and reliability. If these faults are not diagnosed, they can significantly reduce the energy production capacity of these systems. There is no perfect industrial system, such as solar energy systems that rely on photovoltaic system, because these systems, like all other industrial systems, may be affected by faults and failures during installation or operation. Therefore, the development of a diagnostic system to detect and identify faults is an industrial necessity. In this work, a pattern recognition method was applied for solar energy system faults diagnose. The proposed method consists of two main steps: in the first step, statistical parameters are extracted from observations, then binary particle swarm optimisation algorithm is applied for selecting relevant features. In the second step, support vector machine is used to classify the different types of faults. The obtained results demonstrate the effectiveness of this approach in accurately and efficiently for photovoltaic solar system fault diagnosis.

Keywords: Photovoltaic system; Support vector machine; Statistical parameters; Binary particle swarm optimisation; Patternrecognition; Fault diagnosis.

Table of contents

Chapter I: solar energy

Chapter II: Faults diagnosis based on Pattern recognition

Chapter III: Support vector machine (SVM)

Summary

Chapter IV: PV solar fault diagnosis based on dimensionality reduction and SVM.

General introduction

General introduction

Energy sources are among the blessings created by God on this planet (such as the sun, wind, water, oil, gas, and various minerals), and mankind must recognize their value and make good use of them to facilitate life. Energy is the foundation of social and economic progress in all countries. Energy demand is one of the major problems facing modern life on a daily basis and remains unresolved due to insufficient resource availability.

Traditional energy sources such as natural gas and oil are crucial in production. The only sustainable resources are renewable energies that will address many environmental issues associated with fossil and other fuels. Renewable resources such as wind, solar, and hydroelectric power, as well as wave and tidal energy, exist naturally and are already partially economically exploited. These renewable energy sources are permanent, safe, limitless, and constantly renewable even as fossil fuels are being used to maintain supplies and energy needs. Consequently, efforts must undertake to explore other energy sources and work on establishing many plants to increase their production.

Solar revenues are very significant in the general economic domain and in individual lives. This energy is one of the world's most innovative renewable energy sources for electricity production. Interest in the use of photovoltaic systems has rapidly multiplied over the years due to its numerous advantages: it is considered a universal energy source, pollution-free, noise-free, easy to install, and possible to convert for electronic and computer tool development or embedding.

Many countries around the world are currently aiming to promote clean electricity production as part of their efforts to enhance energy security and mitigate external shocks, a trend accentuated after the Russo-Ukrainian war. In this context, the global solar energy market has experienced significant growth in recent years, supported by increasing concerns about climate change, the growing need for renewable energy sources.

The value of the global solar energy market was estimated at $109 billion in 2022, and the market itself is expected to grow at a compound annual growth rate of 10.6% between 2023 and 2033, according to information accessed by the specialized energy platform **[1]**. The desert area in Algeria represents more than 80% of its total area, and it's an adequate area to attract investors to benefit from this type of resource. Therefore, our country has high potentials enabling it to export solar electrical energy worldwide and successfully sweep the energy market. The photovoltaic generator is the only direct converter capable of converting solar radiation into electrical energy through photovoltaic panels **[2],** and its ability to produce electricity directly from a renewable resource is widely available. Thus, developments are not very challenging from a supply standpoint.

During the operation of the photovoltaic installation, the cells are very sensitive to disturbances due to exposure to the external atmosphere such as air, rain, snow, dust, etc., or various internal faults that affect the efficiency. Faults diagnosis in the photovoltaic system can protect the system from downtime or serious damages, improve the efficiency of the photovoltaic system, ensure safe operation, and reduce electricity production costs. Therefore, a diagnostic method to detect faulty components of photovoltaic systems is particularly important and necessary due to the degree of expansion of photovoltaic systems and the need to improve their reliability and performance **[3].**

In this work, we will propose a photovoltaic system fault diagnostic method. The proposed method is based on three essential steps: the first step involves extracting statistical parameters from the three currents. After that a binary particle swarm optimisation algorithm is employed to select relevant features. While the last step is dedicated for classifying different types of faults based on support vector machines.

This thesis has been decorticated into four chapters as outlined below:

The **first chapter** provides an overview of solar energy and photovoltaic systems, photovoltaic construction and its effect as well as their operating principle.

The **second chapter** presents pattern recognition diagnostic methods.

The **third chapter** discusses the concept of support vector machine.

In the **fourth chapter**, the proposed method for photovoltaic system fault diagnosis will be presented. Numerical simulations will be conducted using MATLAB software to evaluate the performance of the proposed approach.

Chapter I:

Solar energy

I.1.Introduction

Renewable energy is produced by converting natural phenomena into useful forms of energy. These energy sources, such as sunlight and wind, are replenished at a rate greater than their consumption, unlike conventional resources like coal, oil, and gas, which take millions of years to form. Fossil fuels emit harmful greenhouse gases like carbon dioxide when burned for energy, whereas renewable energy production results in significantly lower emissions. Addressing the climate crisis necessitates a shift from fossil fuels, which are major contributors to emissions. Additionally, renewable energy has become increasingly cost-effective in many countries and generates more jobs than fossil fuels **[4].**

Human utilization of renewable energy sources dates back centuries, with water mills, windmills, firewood, animal traction, and sailing ships which were playing significant roles in human development.

Renewable energy sources offer several advantages compared to fossil fuels **[5], [6]:**

- They are generally less harmful to the environment, emitting no greenhouse gases and producing minimal waste.
- They are natural, abundant, and inexhaustible resources.
- They enable decentralized production tailored to local resources and needs.
- They provide significant energy independence.

This chapter provides a comprehensive overview of solar energy, its types, operation, and the operating principle of photovoltaic cells.

I.2.Solar energy

The sun, our ultimate source of energy and fuel, has been producing energy for billions of years from a distance of approximately 150 million kilometers ; it provides energy in the form of radiation. Its spectrum primarily consists of wavelengths ranging from 0.3 to 0.4 µm **[6]**, and this solar energy provides both heat and light.

For thousands of years, people have benefited from the sun's rays to heat and dry meat, fruits, and grains. Over time, technologies have been developed to collect solar thermal energy and convert it into electricity . These technologies include converting sunlight into electrical energy through photovoltaic solar panels or through mirrors that concentrate solar radiation.

Solar energy is the most abundant of all energy sources and can even be harnessed on cloudy days.

The manufacturing costs of solar panels have decreased significantly over the past decade, making them not only more affordable but often the cheapest option for electricity generation. Solar panels have an average lifespan of about 30 years and come in different colors depending on the materials used in their manufacturing **[4]**.

I.3.Types of solar energy exploitation

I.3.1. Photovoltaic solar

The term "photovoltaic" is derived from the Greek "photo", meaning light, and from the word "voltaic", derived from Alessandro Volta, the Italian physicist who significantly contributed to the discovery of electricity. The photovoltaic effect was discovered in 1839 by Becquerel, but it took almost a century before scientists further explored and utilized this physics phenomenon.

The use of solar cells began in the 1940s in space. Research conducted after the second international war led to significant improvements in their performance and size. However, significant investment in photovoltaic technology and its terrestrial applications did not occur until the energy crisis of the 1970s **[6].**

It's important to note that the solar cell conversion process does not rely on heat. In fact, cell efficiency decreases as their temperature rises **.**

Any solar installation requires three elements to ensure the capture of sunlight, its conversion into electricity, and its distribution **[4]**:

- Photovoltaic panels;
- An inverter to convert the obtained electricity into alternating current;
- A meter used to measure the quantity of current produced and distributed.

In practice, photovoltaic cells are connected in series not only to increase voltage but also to minimize exposure to environmental factors, forming a photovoltaic unit, as illustrated in **Figure I.1.**

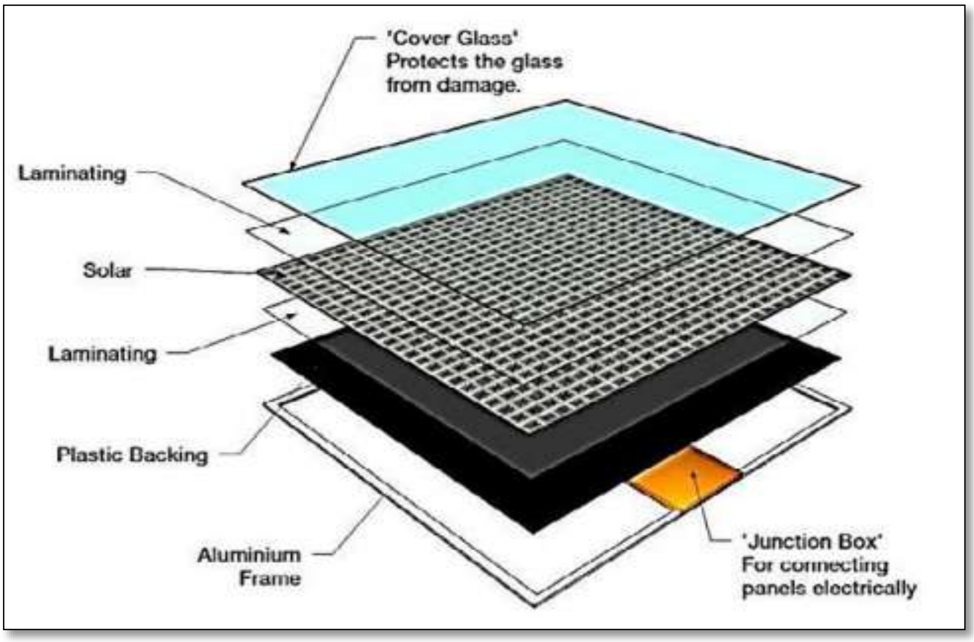


Figure I.1: Components of a PV module.

I.3.1.1. Photovoltaic cells

The PV solar cell is the basic element in a photovoltaic system. Additionally, the most technologically and industrially advanced sector is the production of silicon-based cells. Silicon is the most commonly used semiconductor element because it is found in very large quantities on Earth: it constitutes 28% of the earth's crust, in the form of silica, which is perfectly stable and non-toxic**.**

The photovoltaic effect phenomenon is defined by the conversion of solar energy (photon energy) into electrical energy usable by solar cells**.** Various types of photovoltaic cells exist, all using semiconductors to interact with photons from the sun to produce electricity. Photovoltaic cells are made of several layers of materials, each with a specific function. Specially processed semiconductor layers constitute the most important layers of photovoltaic cells. These are two distinct layers, one p-type and the other n-type, as shown in **Figure I.2.** This layer converts solar energy into usable electricity through the photovoltaic effect. Each of the two faces of the semiconductor includes a layer of conductive material to collect the generated electricity **[6].**

I.3.1.2. Electrical Characteristics of a PV Cell

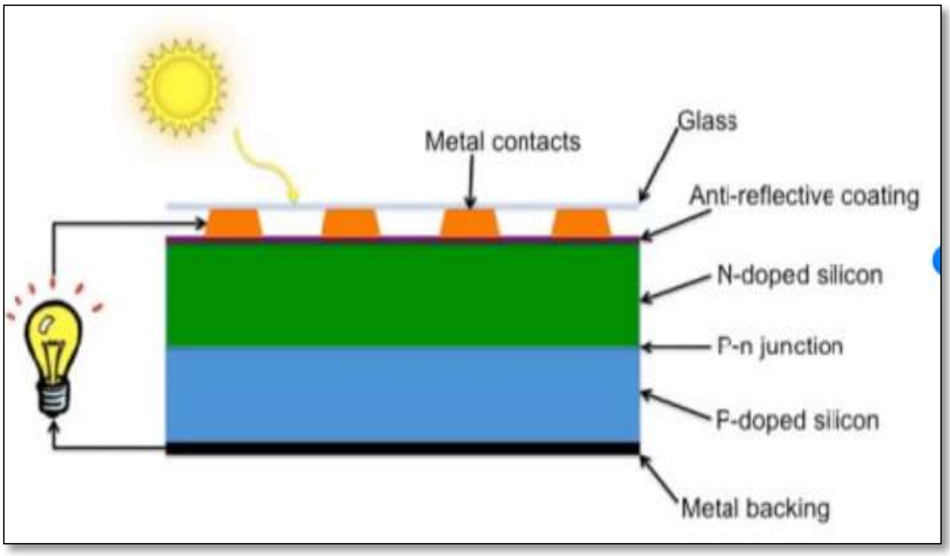


Figure I.2: Basic structure of a photovoltaic cell.

The operation of the photovoltaic cell is based on the properties of semiconductors, which, when struck by photons, set in motion a flow of electrons as illustrated in **figure 1.3**. Photons are elementary particles that carry solar energy at 300,000 km/s and were referred to by Albert Einstein in the 1920s as "grains of light." When they strike a semiconductor material like silicon, they dislodge electrons from its atoms. These electrons commence movement, initially in a disorderly manner, in search of other "holes» to occupy.

However, for an electric current to flow, these electron movements must all go in the same direction. To facilitate this, two types of silicon are combined. The side exposed to sunlight is "doped" with phosphorus atoms, which contain more electrons than silicon, while the opposite side is doped with boron atoms, which contain fewer electrons. This dual-sided structure becomes a sort of battery: the side with excess electrons becomes the negative terminal (N), while the side with fewer electrons becomes the positive terminal (P), creating an electric field between them.

When photons excite the electrons, they migrate towards the N zone due to the electric field, while the "holes" move towards the P zone. They are then collected by electrical contacts deposited on the surface of both zones before entering the external circuit as electrical energy. A direct current is created. An anti-reflection layer prevents excessive photon loss due to surface reflection.

Under normal operation, PV cells produce energy with an open circuit voltage (Voc) and a short circuit current (Icc). The last one is proportional to the surface area of the cell and depends on the intensity of absorbed light. Meanwhile, the open circuit voltage corresponds to the voltage across the cell when no current is flowing **[7]**.

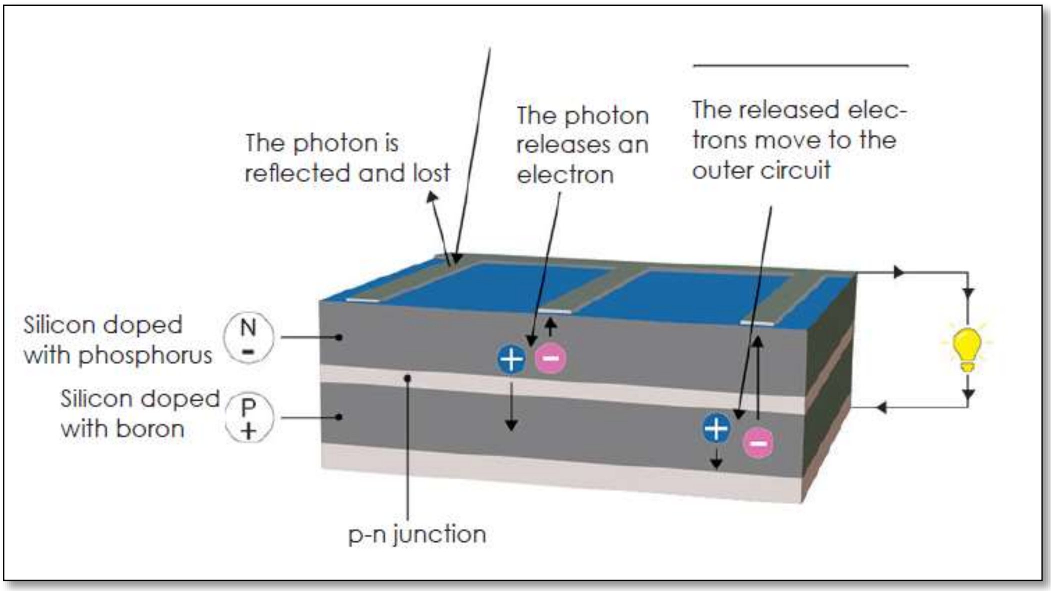


Figure I.3: Description of a photovoltaic cell.

I.3.1.3. The efficiency of a photovoltaic cell

The efficiency is the ratio between the electrical power produced and the light power falling on the cell. To define this, the cells, grouped into modules then into panels, are calibrated by being placed in front of a solar simulator, which reproduces the optimal conditions: sunshine of 1 000 W of light per square meter, an ambient temperature of 25° C. The electrical power created, called peak power, is a percentage of the solar power received. If a panel with a surface of 1 m^2 produces an electrical power of 200 W, its efficiency will be 20%. The efficiency of this type of cell cannot exceed a theoretical limit of approximately 33%, called the "Shockley-Queisser limit".

In real conditions, the quantity of electricity that the cell will produce, called the "Producible", will be calculated taking into account its yield, the average level of sunshine in the region over a year and the conditions of the installation.

Several much research is being carried out on photovoltaic cell technology to improve efficiency and reduce costs **[8]**.

I.3.1.4. The future of the Photovoltaic Panel

The future of solar energy is promising and bright. With advancements in technology, the production costs of solar panels are decreasing, making them more affordable for everyone. Additionally, the efficiency of solar panels is increased, allowing for greater electricity generation from the same amount of sunlight.

The use of solar energy is also becoming widespread, with governments around the world investing in this technology. This means that solar energy is becoming an increasingly viable option for powering homes, businesses and other applications **[4]**.

I.3.2. Solar thermal

Solar energy can be converted into heat through the use of solar collectors, making it suitable for heating homes and swimming pools, the production of hot water for sanitary needs, as well as drying of crops (e.g. animal feed, cereals and fruits). In other words, the question of solar energy arises more in terms of conversion than direct heating **[9].**

I.3.2.1 Thermal Solar collectors

The refrigerant, whether water with antifreeze or air, is used to recover heat. By circulating in the absorber located under the glass, the heat transfer fluid is heated by sunlight, while reducing infrared losses thanks to the greenhouse effect. Furthermore, glazing helps limit heat exchange with the atmosphere as shown in **Figure I.4 [6] [13].**

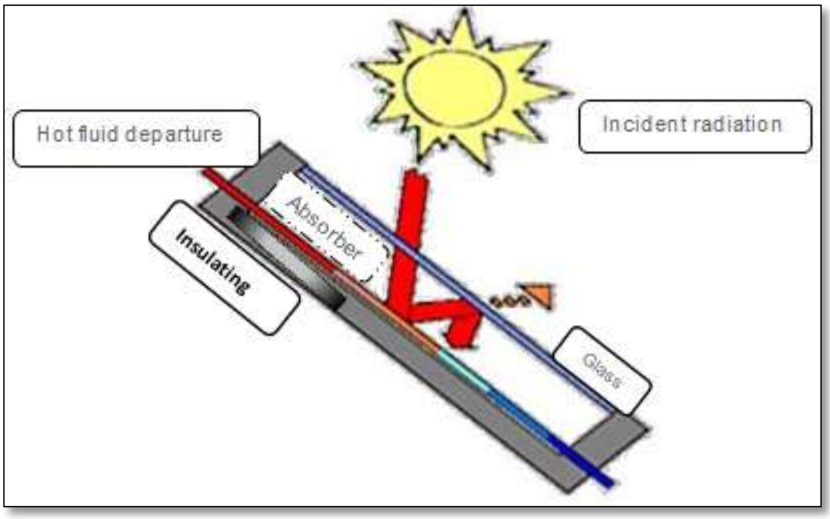


Figure I.4: Solar thermal collector.

Solar thermal collectors can be combined with photovoltaics (PV) to create a hybrid panel that produces both heat and electricity. These devices are called photovoltaic thermal (PVT) collectors. It has been shown that the energy produced by PVT is superior to that produced by the same area of conventional solar thermal and PV installed side by side as shown in **Figure I.5.**

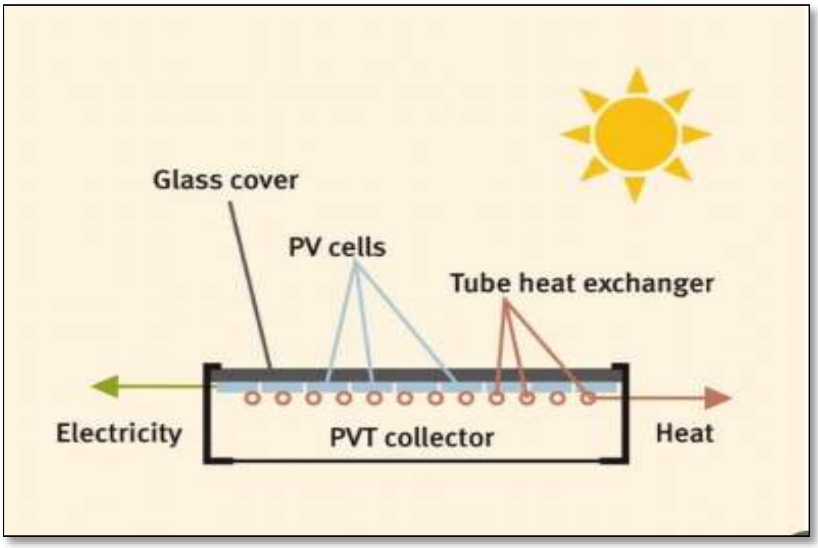


Figure I.5: Working principal of PVT collector.

I.3.2.2. Thermomechanical conversion process

Heat can be transformed into electrical energy by thermodynamic processes, in the same way as fossil fuels and nuclear energy. Several methods can be used to achieve this transformation, such as the use of a piston engine or a gas turbine.

The question of conversion remains an obstacle, because it is necessary to use heat, and the maximum efficiency of converting solar heat into electrical energy is determined by the Carnot efficiency **[8]**.

Generally, thermomechanical solar power plants require a water supply, which can constitute an obstacle to their establishment in arid regions.

I.3.3. Thermodynamic Solar

Thermodynamic solar energy is generated through concentrated solar power plants. These plants consist of an array of mirrors containing heat transfer fluids, connected to a solar electricity generator. Similar to thermal solar panels, these mirrors convert the energy captured from the sun's rays into heat. This heat reaches extremely high temperatures, much higher than the initial temperature at which it was absorbed. Depending on the specific technology utilized, temperatures can range from 250 to 800 degrees Celsius.

Subsequently, this heat is converted into electricity using a turbine and an alternator, similar to the process in a traditional thermal power station.

Despite its potential, this form of energy is not extensively utilized in France for example, where only one thermodynamic power station exists, known as Lio. This limited adoption may be attributed to France's temperate climate. Conversely, countries like Algeria, for instance, with more favorable conditions, tend to employ this technology more frequently **[4].**

I.4.Potential and benefits of solar energy

Despite significant advancements in solar energy harnessing techniques in recent years, there still remains immense untapped potential. Each day, the energy emitted by the sun is equivalent to 15,000 times the world's total energy consumption. By harnessing this energy more effectively, we could address a substantial portion of the pollution and energy supply challenges faced globally.

Solar energy has several advantages such as:

- Minimal greenhouse gas emissions (GES).
- A reliable and rechargeable energy source capable of providing electricity, water heating, sanitation, and other essential services.
- An abundant and silent energy source, suitable for various applications such as powering electrical appliances, lighting remote areas, and charging electronic devices.
- Solar energy offers economic advantages and helps mitigate reliance on traditional electrical grids.
- Solar installations and maintenance periods can provide long-term economic benefits, enhancing equipment functionality and reliability. This is particularly crucial in industries where machine uptime is critical for success.

Companies opting for solar energy can significantly reduce their energy expenses while also reducing their carbon footprint. This serves as a compelling marketing argument. **[10]**.

I.5. Disadvantages of Solar energy

We briefly outline the disadvantages associated with using solar energy:

- Solar photovoltaic technology is complex, expensive, and requires advanced technology for manufacturing and installation
- Solar panels have relatively low efficiencies (around 20%) and are best suited for low-energy projects.
- Batteries are necessary to store the electricity produced by an autonomous photovoltaic installation, but their cost is high and their storage poses problems.
- Electricity production from solar panels is unpredictable because it depends on sunlight and only takes place during the day.
- Photovoltaic installations have a lifespan of 20 to 30 years, and their efficiency decreases by 1% per year **[11].**
- The performance of solar panels is highly influenced by a number of environmental factors, especially sunlight intensity, cloudiness, and wind speed.

I.6. Conclusion

In this first chapter we presented a general overview of solar energy. We also saw the different types of solar energy exploitation, such as: photovoltaic solar, thermal solar and thermodynamic solar.

Chapter II:

Faults diagnosis based on Pattern recognition

II.1. Introduction

Many faults occur in industrial operations, these fault can lead to breakdowns and a drop in production if these defects are not repaired quickly. Therefore, it is in the economic interest to reduce the systems breakdowns and increase system reliability. Early detection of defects is therefore essential to facilitate repairs, avoid unwanted effects and reduce maintenance's time and effort. In this chapter, we will explain in detail the concept of systems surveillance and diagnostic. In addition, the technique of pattern recognition will be detailed.

In the first part of the chapter we will present the monitoring strategy that can be developed to meet industrial needs. In the second part we will introduce the concept of diagnosis and review the different existing diagnostic approaches, by situating them in relation to current scientific literature.

II.2. Architecture of a surveillance system

II.2.1. surveillance system

Surveillance systems are designed to efficiently track, monitor, and control automated processes. Our priority is to detect any possible flaws in the process **[12].**

When monitoring the system, it is essential to consider the following tasks:

- Detection and isolation of defects.
- Diagnosis of the causes of malfunctions and assessment of their impact on the component concerned as well as on the entire system.
- Reconfiguration and restoration of the normal operation of the system.

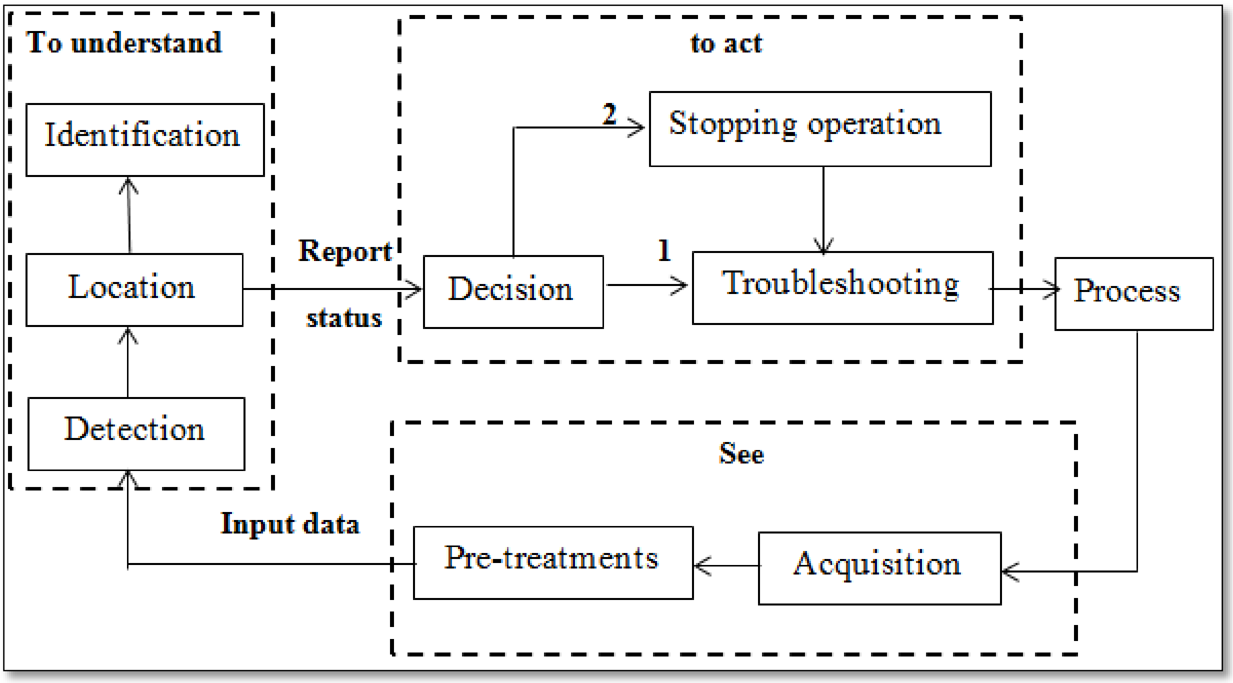


Figure II.1: the general architecture of a surveillance system.

Automatic monitoring is part of an overall management and supervision process. **Figure II.1** presents the general architecture of a surveillance system. We can find the three main functions - "See", "Understand" and "Act" - necessary for good monitoring as summarized in **[13].** The two essential tasks in diagnosis are therefore the observation of the symptoms of failure as well as the identification of the cause of failure using a logical reasoning based on observations acquired about the system. Based on the information available on its operating state, the objective is to detect, locate and identify failures which may affect its operational safety. In most cases, monitoring is based on alarm processing systems. Threshold values are defined beforehand by process experts according to safety criteria set by the operator. This alarm processing system is the basic tool to help the operator in his task of monitoring. However, it remains for the operator to analyze the situation and make an appropriate decision. Its effectiveness and performance in responding to an alarm depends on their experience. However, such a monitoring system does not make it possible to manage the evolving nature of a normal or abnormal state of the system. The use of a monitoring system based on more advanced techniques will make it possible to overcome these limitations. Recently, the monitoring and maintenance of industrial equipment has called for increasingly sophisticated diagnostic techniques. There are several diagnostic procedures [**14].** The choice of an approach is linked to the knowledge that one wishes to acquire about the system, but also to the complexity of this system. In this work we deal with the monitoring of components, the PV system, and we focus subsequently on the “See” and “Understand” components. We are therefore interested in the two elementary stages: perception and diagnosis, which will be described in the following paragraphs.

II.2.2. Perception

The perception phase constitutes the main source of information about the system. The perceptron includes two distinct phases. First, there is the data acquisition phase, during which the necessary hardware configuration is determined to capture the system signals. These acquired signals must provide relevant information to evaluate the operating state of the system. Then there is the signal conditioning phase, which includes operations such as filtering and denoising. The results of this perception phase provide preliminary information on the operation of the studied system and will be used by the diagnostic module **[15].**

II.2.3. Diagnosis

The definition given by national and international standardization organisations of the term diagnosis in the field of automatic is "the identification of the probable cause of the failure(s) using logical reasoning based on a set of information from an inspection, control or test"**[15].**

- Detection: it consists of identifying the mode of operation of the physical system. Based on prior knowledge of the normal and abnormal operating modes of the system, it makes it possible to decide whether it is in good or bad condition **[16];**

- Localization: it consists of determining in more depth the failing components or the probable cause of the failure;

- Identification: the purpose of defect identification is to determine the type (class, size, etc.) of a defect (classification). Generally speaking, providing a system diagnosis consists of making a comparison between the information measured, during the actual operation of the system, and the a priori knowledge of its operating modes. Based on the results obtained from this comparison, the user can intervene and implement the corrective actions necessary to return to normal condition. A good diagnostic approach should be able to detect small faults before they propagate throughout the system and cause failures. It must also avoid or reduce the frequency of false alarms which would cause unnecessary system shutdowns.

II.2.4. Some diagnosis approaches

Diagnostic techniques based on analytical models consist of monitoring the parameters and quantities of the machine using observation algorithms. On the other hand, model-free diagnostic methods are based on the extracting information from measurable signals such as Current, voltage, speed, vibrations or sound emissions which can provide useful information about faults **[17].**

The design of monitoring and diagnostic systems based on decision-making methods depends on the relevance selected fault indicators and the accuracy of measurement analysis. Pattern recognition methods are one of the well-known approaches.

II.3. Diagnostic system based on pattern recognition

Pattern recognition technology is used in big data analysis to find combinations of inherent patterns that often or rarely occur together. This information provides features of the data and helps predict unseen data**.**

Pattern recognition methods play an essential role in classification or identification of signatures (signals) associated with a normally functioning system or showing defects. Pattern recognition (RDM) is part of integral to artificial intelligence and makes it possible to interpret new observations (or patterns) based on a previously learned set of data or information. The known patterns are grouped into classes, thus creating prototypes to which new observations are compared in order to be identified. The algorithms used thus make it possible to classify observations whose properties differ compared to a standard observation model.

II.3.1. Pattern recognition approaches

Pattern recognition, which is an integral part of artificial intelligence, involves the interpretation of new observations using a set of previously learned data. This data is represented by observations grouped into classes, thus making it possible to assign a new observation to one of these classes. There pattern recognition is divided into two approaches:

- Syntactic, structural and form matching approaches (Template Matching): which use hypotheses about data distributions within classes. The classification procedures, in this case, are constructed using probabilistic hypotheses (e.g. Bayesian classification). They require significant calculation resources. As a result, this type of approach is not suitable for real-time applications.

- Statistical pattern recognition, unlike the previous one, relies on a digital representation of shapes based on parametric or non-parametric methods. Non-parametric methods make virtually no assumptions about the shape of the distributions (Ex K-nearest neighbors). Among the most used methods, we cite connectionist methods which constitute a subset of statistical methods **[18].** In our study, we focus on the second approach, focused on the study of digital forms**.**

II.3.2. Principle and formulation

A form corresponds to an observation made on the process, characterized by a set of parameters. It is represented by a point in a space of dimension ‘d’, defined by the different parameters (representation space).Since the parameters are usually real numbers, a form "i" can be represented by a vector: X_i=[x_{i1}, x_{i2}, ..., x_{id}] of R^d(See **Figure II.2**) **[19].**

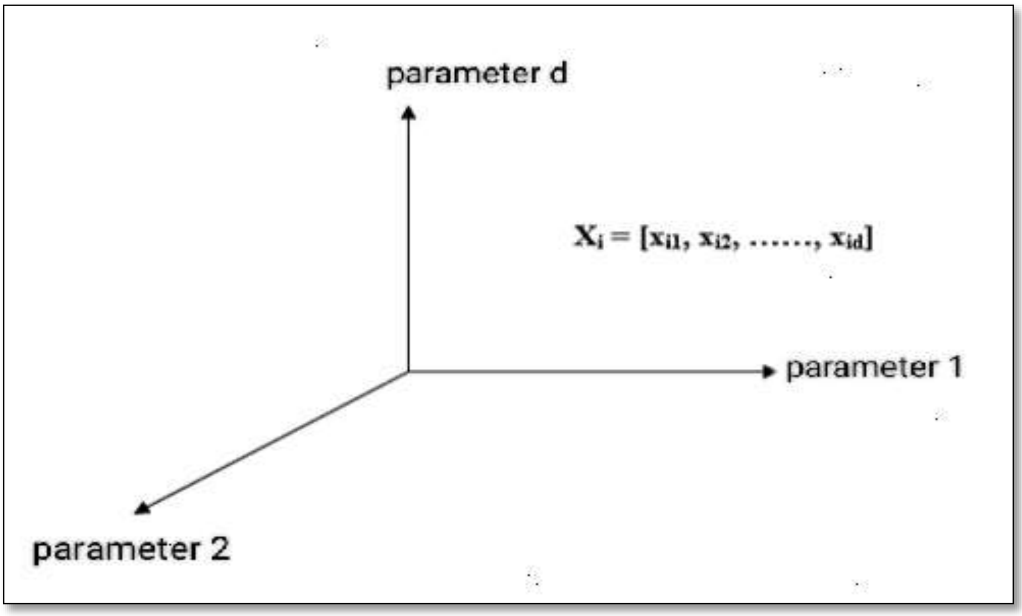


Figure II.2: Dimension space

The typical shapes, also called prototypes, are representative points of this space , and the challenge of recognition consists of associating an observed shape with one of the known typical forms. However, due to disturbances such as measurement noise and the precision of the sensors, a new observation will rarely be identical to one of the prototypes. In order to take into account the influence of noise, classes (n_1,n_2, n_c...n_M) are defined as zones in space, as illustrated in **Figure II.3.**

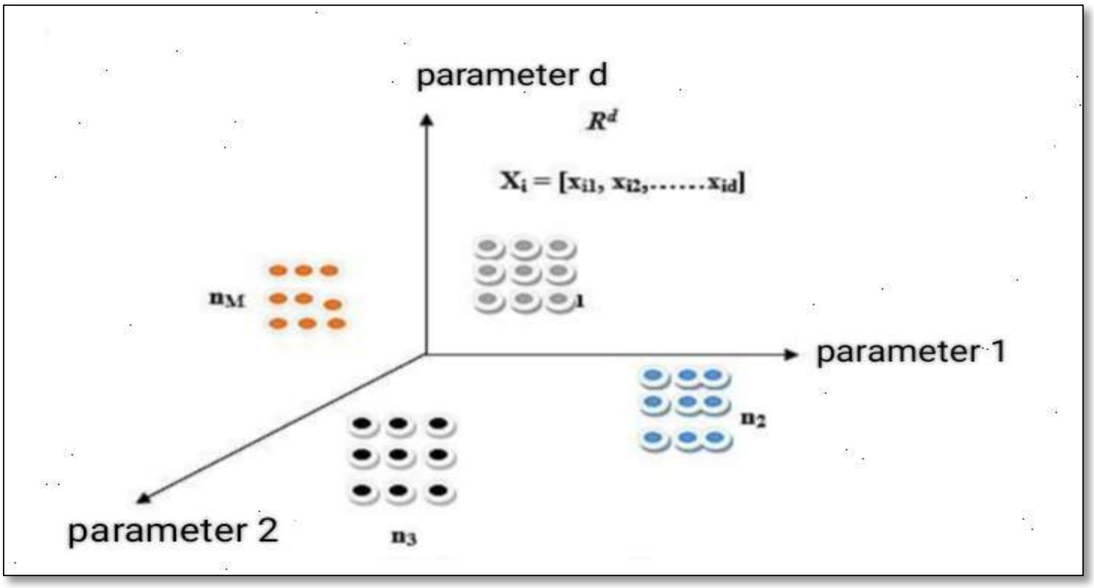


Figure II.3: Notions of classes in pattern recognition.

II.4. Construction of a pattern recognition system

A pattern recognition system is usually composed of five sequential steps , as illustrated in the following diagram:

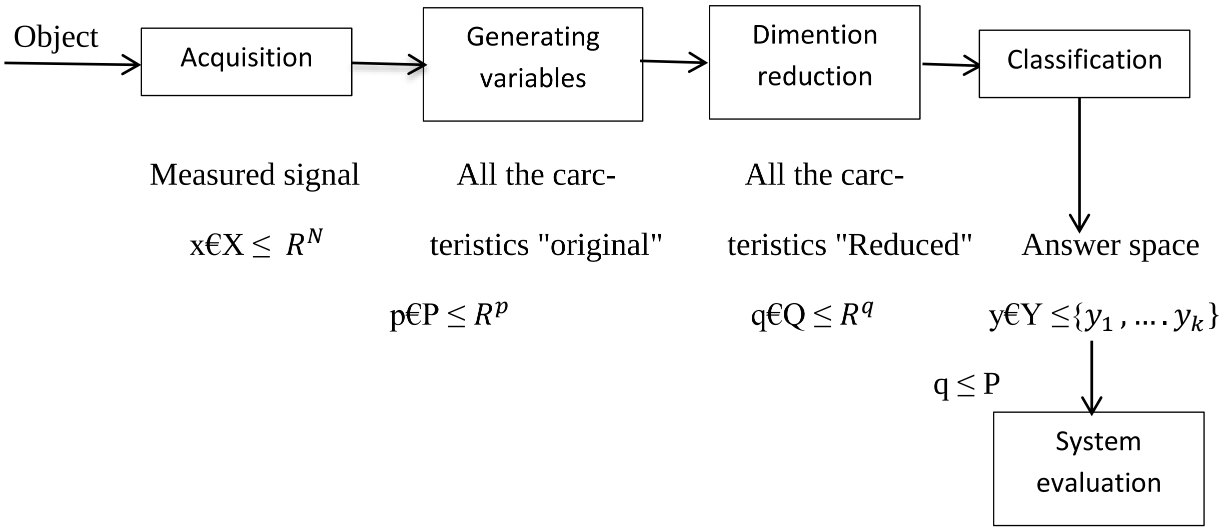


Figure II.4: Pattern recognition system.

These steps can be grouped into three main phases: the analysis phase, the selection of the decision method phase, and finally the exploitation phase.

II.4.1. Analysis phase

The main purpose of this phase is to examine the observations (information) coming from the sensors integrated into the system. In general, this information is presented in the form of signals that require a step of extracting digital values. **Figure II.5** summarizes this phase:

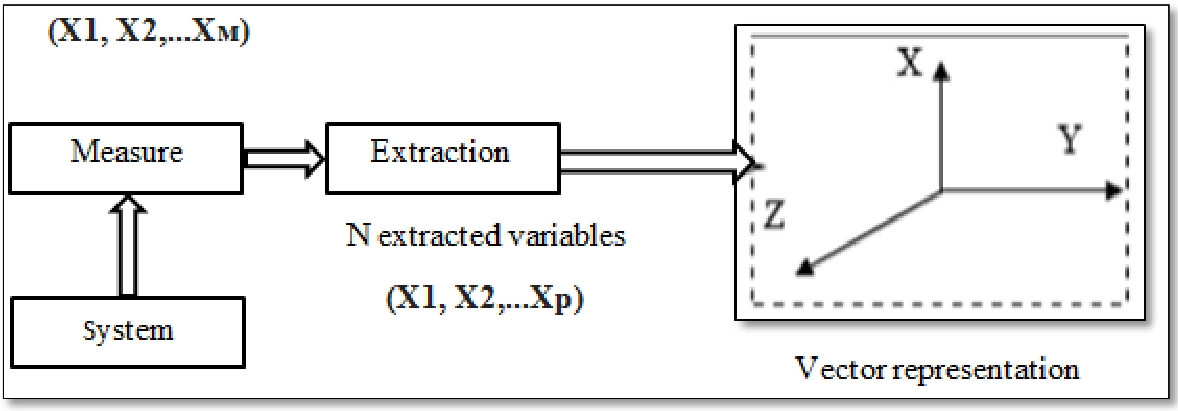


Figure II.5: Analysis phase to Constitution of the shape vector.

We must group the N available observations into M classes. The result of this grouping constitutes the learning set.

II.4.1.1. Determination of the representation space

It is about collecting data in the form of vectors that represent the measurements performed on a physical system or the information collected during the observation of phenomena. However, not all of these variables are equally informative. In order to obtain an initial coherent representation of these data, data analysis or signal processing methods are used to transform these vectors into a set of original parameters. Each observation is characterized by a set of p variables x = (x1, x2,..., xp), and the objective is to find the important information contained in the acquired signal. In the context of diagnosis, the characterization of the operating states consists in extracting a concise and stable representation of the collected measurements in order to determine the characteristics of the normal or abnormal operation of the system. This step is essential for the success of the diagnostic system based on pattern recognition.

II.4.1.2. Determination of the decision space

Pattern recognition consists of using a classification method to identify the class corresponding to an operating mode by associating a new observation at one of the classes. Classification methods are usually divided into supervised classification and unsupervised classification. If the original class of each observation is known, learning can be carried out in supervised mode by defining each class by geometric or statistical characteristics. The objective is to predict the class to which a new observation belongs by using a discriminator or classifier. In supervised mode, the decision space is perfectly determined if we have a learning set with the known original classes [**20]**. The purpose is to classify the news observations in such a way that the observations of the same class are similar and those of different classes are different**.**

II.4.1.3. Dimensionality reduction of the representation space

The reduction of the dimension of the shape vector aims to find a subset of parameters (d'<d) which maintains at best the separation of the classes of the initial learning set. This reduction in the representation space can be achieved either by parameter extraction methods, or by parameter selection methods. The selection of variables consists of retaining, among the set of p original variables, only the most relevant or the most informative, in the sense of a criterion of separability between classes and a criterion of condensation of the points of a same class. While the extractions approach, unlike the first, uses all the information from the initial variables by projecting them as best as possible into a smaller dimensional space. It is also important that meaningful properties present in the data are not lost during the transformation. This speeds up the decision phase. Principal Component Analysis (PCA) is one of the parameter extraction methods used **[12].** The objective of the parameter selection methods is to choose d parameters from the initial parameters, so as to obtain the best possible discrimination between the classes of the learning set. This makes it possible to reduce both the number of measurements to be performed and the size of the representation space, thus offering two advantages:

A reduction in calculation times and the elimination of redundant or irrelevant information. The parameters selected are those that allow the best combination according to a criterion of separability between the classes. Therefore, selection methods are often used to reduce the shape vector, while the extraction methods are reserved for the problems of visualization of the learning set.

II.4.2. Phase of choosing a decision method

During the phase of choosing a decision method, the objective is to establish clear boundaries between the different classes. The decision rules for classifying new observations into the different classes of the learning set are defined thanks to the used decision methods.

The evaluation of the performance of these methods is carried out by means of a performance index.

II.4.3. Exploitation Phase

II.4.3.1. Evaluation of the diagnostic system

By applying the decision rule that was developed in the previous step, the pattern recognition system allows each new observation collected on the system to be classified into one of the well-known categories. The definition of this class allows us to know the current operating state of the system by introducing the diagnosis; the idea is to apply a testing phase to estimate the true classification error (classification error rate). In practice, the sample S of size N is divided into two groups, a training group and a test group. According to the distribution between the two groups, there are several ways to estimate the classification error:

- **Re-substitution**: Both the training and test sets are identical and correspond to the entire sample set. If we denote 'n_e' as the number of errors made during the testing phase, then Error$= n_e/N$.

- **Holdout Method**: In this method, the sample S is divided into a training set and a test set. The distribution between the two sets must be random, typically in proportions of 1/2, 1/2 for each set, or 2/3 for the training set and 1/3 for the test set. If m is the size of the test set, then Error$= n_e/m$.

- **D- Cross-Validation:** The sample is partitioned into D parts of approximately equal sizes. Training is then performed on (D - 1)subsets, and testing on the remaining D^{me} subset. This process is repeated D times, leaving out one part each time for testing. If $n_e(d)$ represents the number of misclassifications made on the d^{th} subset, the estimation of the error is the arithmetic mean of $n_e(d)$, Error $= \frac{1}{N}\sum_{d=1}^{D} n_e(d)$.

- **Leave-one-out Method:** This technique is a special case of cross-validation where D = N. The classification procedure is repeated N times on (N - 1) instances, which makes it computationally expensive but recommended if the set E is small in size. Indeed, it leads to a minimum bias in the estimation of the error.

- **The resampling method (Bootstrap):** Given a sample E of size N, an ensemble of the same size N is drawn with replacement (an element of N may not belong to the training set or may appear multiple times), while the test set remains N. The error is then the average of the errors obtained for a certain number of iterations of the learning algorithm.

II.5. Conclusion

We have devoted this present chapter to the diagnostic approach based pattern recognition (RdF). After introducing the basic concepts of the pattern recognition approach, we presented the main steps in building a RdF diagnostic system. The acquisition module collects all the information on the process. Once the perception step has been carried out, the diagnostic process is triggered based on the whole recorded signals.

Chapter III:

Support vector machine (SVM)

III.1. Introduction

In this chapter, we will present the SVM method which is inspired of static theory of learning by Vladimir Vapnik .support vector machine (SVM) have been introduced in 1975 by Vapnik and Chervonenkis, who proposed the principle of risk structural and the VC dimension to evaluate the capacity of a learning machine. The SVM is a discriminant model that aims to limit learning errors and increase the distance between the data of different classes, which allows a regularization of the classifier by reducing its complexity**.** SVMs are learning techniques used to solve problems of discrimination or regression by deciding on the class of a sample or by predicting the value of a variable. SVMs have originally been used for classification purposes and their principles have been extended to the task of regression, clustering and feature selection. This method has experienced a great success thanks to its solid theoretical foundations which underlie it.

Indeed, there is a direct link between the theory of statistical learning and the learning algorithm of SVM. SVMs are particularly effective in treating very high-dimensional data such as texts, images and voice **[21].**

The theoretical aspects of the SVM method, their theoretical origins, their different forms, their fields of application as well as their advantages and disadvantages will be discussed in this chapter.

III.2. History

Support vector machine are based on two key concepts: the maximum margin and the kernel function. These two concepts had existed for several years before being combined to create the SVMs. The notion of a hyperplane with a maximum margin was studied as early as 1963 by Vladimir Vapnik and A. Lerner, as well as by Richard Duda and Peter Hart in 1973 in their book Classification of models. The theoretical bases of SVM have been explored by Vapnik and his collaborators in the 1970s with the development of the Vapnik-Chervonenkis theory.

The notion of kernel functions is not new either: Mercer's theorem dates back to 1909 and the usefulness of kernel functions in the context of artificial learning have been demonstrated as early as 1964 by Aizermann, Bravermann and Rozoener.

It was only in 1992 that these concepts were well understood and combined by Boser, Guyon and Vapnik in an article that is considered the founding article of support vector machine. The idea of springs variables, which allows solving some important practical limitations, was introduced in 1995.From this date and with the publication of Vapnik's book, SVMs have gained popularity and are used in many applications **[21].**

III.3. basic concepts

III.3.1. Hyperplan

Consider a binary classification situation where the examples to be classified are divided into two classes. The term "separator hyperplane" designates a hyperplane which separates the two classes appearing in **Figure III.1**, and more precisely, it separates the learning points of these classes. Since it is usually impossible to find one, we will rather look for a "discriminant hyperplane" which is an approximation according to a defined criterion (namely, maximizing the distance between the two classes) **[22, 23].** This hyperplane is defined by the vectors of the data points which are the nearest to the hyperplane, they are called support vectors.

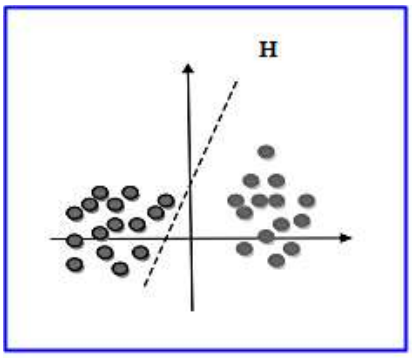


Figure III.1: The hyperplane H which separates the two sets of points.

III.3.2. Support vector machine

SVM are a type of classifier that works by the determination of the separable hyperplane, a method consists in using only the points closest to the border between the two classes of the data (called "support vectors", as indicated in **Figure III.2**) among the total set of training data **[22, 23].**

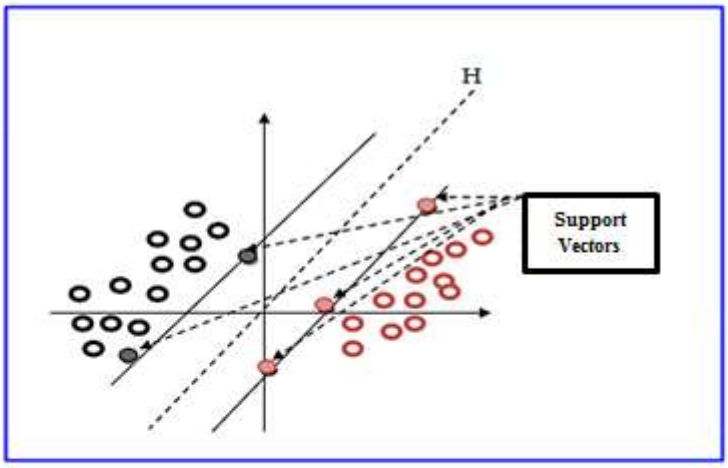


Figure III.2: The support vectors

III.3.3. Margin

It is possible to find an infinity of hyperplanes that are able to perfectly separate the two classes of examples. The principle of SVMs consists of selecting the hyperplane that maximizes the minimum distance between this hyperplane and the training examples (that is to say the distance between the hyperplane and the support vectors). This distance is called the "margin", as illustrated in **Figure III.3 [22, 23].**

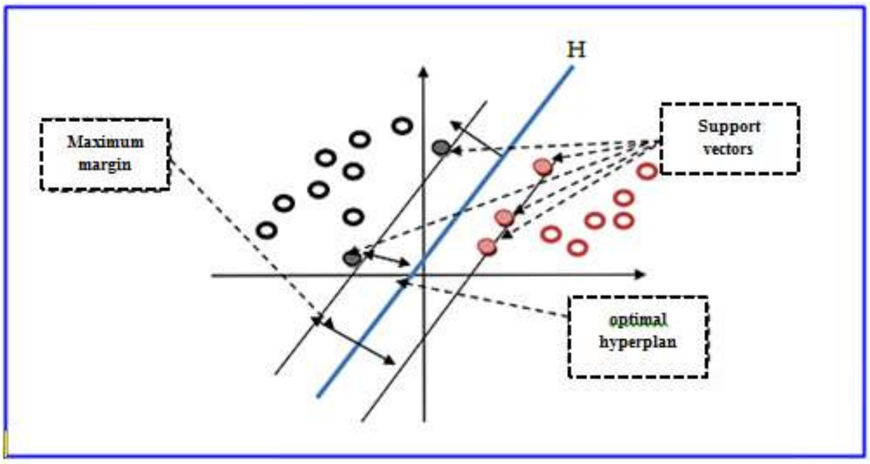


Figure III.3: Optimal hyperplane, support vectors and maximum margin.

III.4. Case of linearly separable data

When we have a database which contains several examples: A_n = {(x_1, y_1), (x_2, y_2)... (x_n, y_n)} Which represents a set of linearly separable data, where x_k corresponds to an observation and y_k represents the associated decision (assumed to belong to {-1, +1}), the objective of SVMs is to find the optimal hyperplane whose equation is:

$$\langle w; x \rangle - \lambda_0 = 0 \qquad \text{(III.1)}$$

With $\langle w; x \rangle$ is the dot product of the two vectors w and x.

When using Support Vector Machine, A hyperplane is considered optimal if it is able to separate the examples from the learning base A_n without error and if it is located at the maximum distance of the vectors x_k closest among those of A_n.

An hyperplane possessing these characteristics is called a "maximum margin hyperplane". There are a large number of possible solutions for such a problem. We can look for a canonical hyperplane where the parameters w and λ_0 satisfy the following equation **[9]:**

$$\min_{x \in A_n} | \langle w; x \rangle | - \lambda_0 = 1 \qquad \text{(III.2)}$$

As we will see later, this constraint is preferable to others because it simplifies the formulation of the problem. It is interesting to note that the distance between a point x_k in space and the hyperplane whose equation is $\langle w; x \rangle - \lambda_0 = 0$ is given by **[9]:**

$$\delta_k = \frac{|\langle w; x \rangle| - \lambda_0}{\|w\|} \quad \text{(III.3)}$$

From the equations (III.2) and (III.3), it is possible to conclude that the norm $\|w\|$ of w must be equal to the inverse of the distance between the closest observation and the hyperplane defined by $\langle w; x \rangle - \lambda_0 = 0$. On the other hand, the equation (III.2) results in the following two inequalities.

$$\langle w; x \rangle - \lambda_0 \geq +1, \text{ if } y_k = +1 \quad \text{(III.4)}$$

$$\langle w; x \rangle - \lambda_0 \leq +1, \text{ if } y_k = -1 \quad \text{(III.5)}$$

This can be summarized by a unified description of all the conditions:

$$y_k\,(\langle w; x \rangle - \lambda_0) \geq +1,\ \forall\ k \in \{1,\dots n\} \quad \text{(III.6)}$$

By combining the equations (III.3) and (III.6), we can deduce that the following inequality is verified for any x_k in A_n [**24, 25]:**

$$\delta_k > \frac{1}{\|w\|} \quad \text{(III.7)}$$

In addition, we can deduce from the equation (III.2) that the value of the margin, defined as the distance between the closest points of the hyperplane, is equal to $\frac{\mathbf{1}}{\|\mathbf{w}\|}$, as illustrated in **Figure III.4**. Therefore, the desired maximum margin hyperplane maximizes to $\frac{\mathbf{1}}{\|\mathbf{w}\|}$ or, equivalently, minimizes $\frac{\|w\|^2}{2}$ under the constraints (III.6) **[24-26].**

III.4.1. Search for the Solution

We are forced to look for a saddle point w^*, λ^* and α^* in the Lagrangian:

$$L(w,\lambda_0,\alpha) = \frac{\|w\|^2}{2} - \sum_{k=1}^{n} \alpha_k [y_k (\langle w;\ x\rangle - \lambda_0) - 1] \qquad (III.8)$$

Where $\alpha = (\alpha_1 \dots \alpha_n)$ denotes the n Lagrange multipliers ($\alpha_i \geq 0, \forall_i$). The relations verified by the optimal hyperplane can be deduced by canceling the partial derivatives of the lagrangian at the saddle point where the value of L: is minimum for $w = w^*$ and $\lambda_0 = \lambda_0^*$, and maximum for $\alpha = \alpha^*$ **[25, 26].**

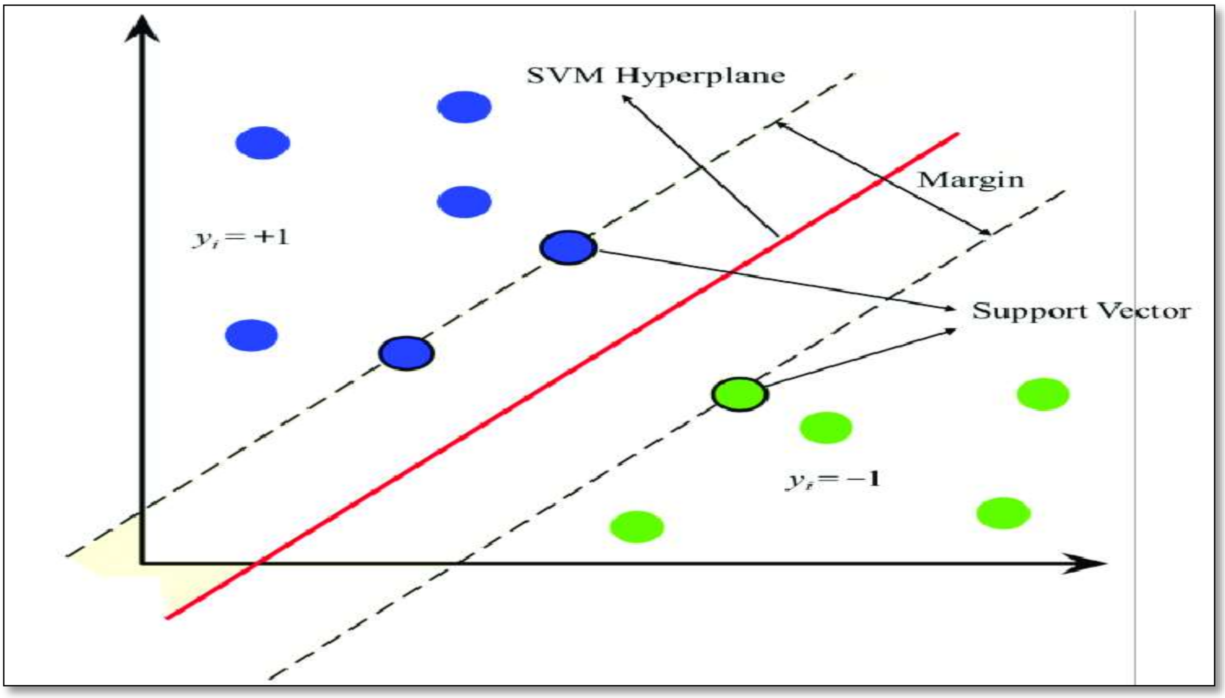


Figure III.4: Principle of SVMs in the case where the two classes are linearly separable.

The Support Vectors, indicated by arrows in **Figure III.4**, designate the samples closest to the separating hyperplane.

The cancellation conditions of the partial derivatives of the Lagrangian lead directly to the relations verified by the optimal hyperplane:

$$\begin{cases} \frac{\sigma L}{\sigma w} = 0 \Rightarrow w^* = \sum_{k=1}^{n} \alpha_k^* \, y_k \; x_k \,, \\ \frac{\sigma L}{\sigma \lambda} = 0 \Rightarrow \sum_{k=1}^{n} \alpha_k^* \, y_k = 0 \end{cases} \qquad \textbf{(III.9)}$$

It is possible to reformulate the initial problem using its dual, which consists of maximizing the following form of the Lagrangian with respect to α **[11].**

$$\begin{cases} W(\alpha) = \sum_{k=1}^{n} \alpha_k - \frac{1}{2} \sum_{k,k^F=1}^{n} \alpha_k \, \alpha_{k^F} y_k y_{k^F} \langle x_k ; x_{k^F} \rangle, \\ \text{under the constraints} \quad \sum_{k=1}^{n} \alpha_k \; y_k = 0 \; et \; \alpha_k \geq 0. \end{cases} \quad \textbf{(III.10)}$$

The matrix formulation of the optimization problem (III.10) can be presented as follows **[13]:**

$$\begin{cases} (\alpha) = 0.5 \, \alpha^T \, H\alpha - f^T \alpha, \\ \text{under the constraints} \quad y^T \alpha = 0 \text{ and } \alpha_k \geq 0, k = 1 \ldots n. \end{cases} \quad (III.11)$$

With α $=[\alpha_1, \alpha_2, \ldots, \alpha_n]^T$, H represents the Hessian matrix ($H_{ij} = y_i y_j x_i^T x_j$) and f is a vector of dimension (n, 1), f = $[1, 1, \ldots, 1]^T$.

To obtain α^*, we need to solve the quadratic optimization problem (III.11) to determine the values of α_k, k = 1, ..., n, and then calculate $\langle w^*; x \rangle = \sum_{k=1}^{n} \alpha_k^* \, y_k \, \langle xk; x \rangle$. The Kuhn-Tucker conditions (arising from solving the Lagrange problem) are as follows **[41]:**

$$\alpha_k^* \left[y_k \left(\langle w^*; x_k \rangle - \lambda_0^* \right) - 1 \right] = 0 \quad (III.12)$$

In this way, only the x_k points satisfying the following condition will be affected by the decision:

$$y_k \left(\langle w^*; x_k \rangle - \lambda_0^* \right) = 1 \quad (III.13)$$

Have non-zero Lagrange multipliers α_k^*.These points are named Support Vectors (SV). They are the closest points to the optimal hyperplane. We have in particular δ_k^* = 1. For the other observations, we have α_k^*= 0. In **Figure: III.4**, the x_{k-}^* and x_{k+}^* denote the support vectors associated with one or the other of the hypotheses in competition.

It is noted that from two Support Vectors x_{i-}^* and x_{j+}^* it is easy to calculate the threshold λ_0^* corresponding to the optimal hyperplane using the equation (III.13). Thus we have:

$$\lambda_0^* = \frac{1}{2}[\langle w^*;\ x_{i-}^*\rangle + \langle w^*;\ x_{j+}^*\rangle] \qquad \text{(III.14)}$$

By combining the equations (III.9) and (III.14), we can also express this as a function of the Lagrange multipliers:

$$\lambda_0^* = \frac{1}{2}\sum_{k=1}^{n} \alpha_k^*\, y_k\, [\langle w^*;\ x_{i-}^*\rangle + \langle w^*;\ x_{j+}^*\rangle] \qquad \text{(III.15)}$$

It is possible to calculate the threshold λ_0^* using all the Support Vectors that define the margin, which can improve the numerical robustness **[25].** Finally, the equation of the optimal hyperplane can be expressed as follows:

$$\langle w^*;\ x\rangle - \lambda_0^* = \sum_{k=1}^{n} \alpha_k^*\, y_k\, \langle x_k;\ x\rangle - \lambda_0^* \qquad \text{(III.16)}$$

We can determine λ_0^* using the equation (III.15). To classify a new observation x , it is enough to check the sign of the expression (III.16) to determine which side of the hyperplane the observation is on and make a decision accordingly.

The decision function is given by **[25]:**

$$D(x) = \sum_{k \epsilon s} \alpha_k^*\, y_k x_i^T x - \lambda_0^* \qquad \text{(III.17)}$$

Here S denote the support vectors indices. Thus, any new entry is classified in:

$$\begin{matrix} class\ 1 \text{ if } & D(x) > 0 \\ class\ 2 \text{ if } & D(x) < 0 \end{matrix} \qquad \text{(III.18)}$$

III.5. Soft margin Support Vector Machine

In practice, most problems involving data are not linearly separable, as shown in **Figure III.5**. Thus, it is necessary to modify the previous approach in order to take into account observations that may be incorrectly classified. To solve this problem, one solution consists in including a parameters ζ_k in the conditions (III.4) and (III.5) to make the constraints more flexible.

$$\langle w;\ x\rangle - \lambda_0 \geq +1 - \zeta_k, if\ y_k = +1 \quad \text{(III.19)}$$

$$\langle w;\ x\rangle - \lambda_0 \leq -1 + \zeta_k, if\ y_k = -1 \quad \text{(III.20)}$$

The method used to solve this problem is called "soft margin Support Vector Machine" **[26, 27],** where $\zeta_k \geq 0$. If ζ_k exceeds the value of 1, an error is committed on the observation x_k by the decision structure used. The function $\sum_{k=1}^{n} \zeta_k$ represents the cost of the error committed on the elements of the learning set. Thus, the optimization problem must be reformulated to minimize both the classification error of the decision structure and the maximization of the margin. In other words, it is necessary to minimize:

$$\frac{1}{2}\|\mathrm{w}\|^2 + \mathrm{C}\sum_{k=1}^{n} \zeta_k \quad \text{(III. 21)}$$

The real positive "C" is fixed by the user in order to control the compromise between the maximization of the margin and the minimization of the classification errors committed on the learning set, under the constraints (III.19) and (III.20). This type of classifier is called a "soft margin classifier". However, it is often preferable to tolerate certain errors, which makes it possible to obtain a larger margin. These errors can be caused by outliers or outlier observations that are not significant of the class with which they are associated. If the value of "C" is high, it means that errors are heavily penalized. The generalized optimal hyperplane is determined by the parameters that minimize (III.21) under the conditions (III.19) and (III.20).

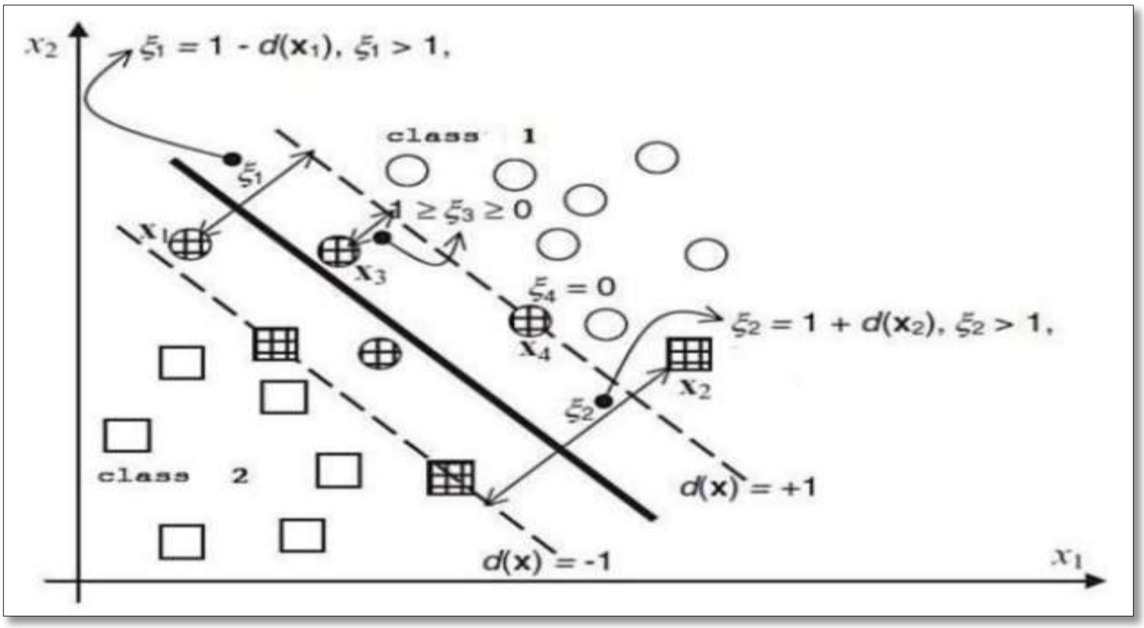


Figure III.5: Soft margin support vector machine

III.5.1. Search for the Solution

By applying the *Kuhn - Tucker* conditions, we are led to search for a saddle point w^*, λ^*, ζ^*, α^*, β^* of the lagrangian:

$$L(w, \lambda_0, \alpha) = \frac{1}{2}\|w\|^2 + C\sum_{k=1}^{n} \zeta_k - \sum_{k=1}^{n} \alpha_k[y_k(\langle w;\ x\rangle - \lambda_0) - 1 + \zeta_k] - \sum_{k=1}^{n} \beta_k\zeta_k \qquad (III.22)$$

Where $\alpha = (\alpha_1 \ldots \alpha_n)$ and $\beta = (\beta_1 \ldots \beta_n)$ denote the Lagrange multipliers ($\alpha_i \geq 0$ and $\beta_i \geq 0$, $\forall_i$). At the saddle point, the value of L: is minimum for $w = w^*$, $\zeta = \zeta^*$, $\lambda_0 = \lambda^*_0$ and the maximum for $\alpha = \alpha^*$ and $\beta = \beta^*$.

The *Kuhn - Tucker* conditions give:

$$\alpha_k\left[y_k(\langle w;\ x\rangle - \lambda_0) - 1 + \zeta_k\right] = 0 \ and\ \beta_k\zeta_k = (C - \alpha_k)\zeta_k = 0 \qquad (III.23)$$

The relations verified by the optimal hyperplane are obtained directly from the cancellation conditions of the partial derivatives of the lagrangian.

$$w^* = \sum_{k=1}^{n} \alpha_k^* \, y_k \, x_k \sum_{k=1}^{n} \alpha_k^* \, y_k = 0 \, , \alpha_k^* + \beta_k^* = C \qquad \text{(III.24)}$$

In order to obtain α^*, it is possible to formulate the initial problem in the dual form, which consists in maximizing the following form of the lagrangian.

$$W(\alpha) = \sum_{k=1}^{n} \alpha_k - \frac{1}{2} \sum_{k,k^F=1}^{n} \alpha_k \, \alpha_{k^F} \, y_k y_{k^F} \, \langle x_k ; x_{k^F} \rangle \qquad \text{(III.25)}$$

Under the constraints:

$$\sum_{k=1}^{n} \alpha_k y_k = 0 \text{ and } 0 \leq \alpha_k \leq C \qquad \text{(III.26)}$$

It should be noted that the dual forms (III.10) and (III.25) are identical. However, it is important to find the saddle point of (III.25) respecting an upper bound on the Lagrange multipliers α_k ($0 \leq \alpha_k \leq C$).

To obtain the equation of the optimal hyperplane as a function of the α_k^* , it suffices to substitute the proposed value of w^* by the first relation of (III.24).

Just as in the case of linearly separable data, the support vectors correspond to the observations closest to the optimal hyperplane, but which are also correctly classified by the decision structure. However, it is possible that there are incorrectly classified observations, which are also associated with non-zero Lagrange multipliers.

III.6. Elaboration of Non-linear support vector Machine

In order to allow SVMs to deal with complex classification problems, the initial algorithm presented above has been modified to develop non-linear detection structures, as indicated in **Figure. III.6**. To extend the algorithm to the nonlinear case, we use a transformation of each observation using a function φ, then a linear detector is applied **[28, 29],** as illustrated in **Figure III.7.** By applying the equation (III.25) in the space generated by φ, we obtain:

$$W(\alpha) = \sum_{k=1}^{n} \alpha_k - \frac{1}{2} \sum_{k,k^F=1}^{n} \alpha_k \, \alpha_{\mathrm{k}^{\mathrm{F}}} \, y_k y_{\mathrm{k}^{\mathrm{F}}} \, \langle \varphi_k ; \varphi_{\mathrm{k}^{\mathrm{F}}} \rangle \qquad (\mathrm{III.}\,27)$$

$$= \sum_{k=1}^{n} \alpha_k - \frac{1}{2} \sum_{k,k^F=1}^{n} \alpha_k \, \alpha_{\mathrm{k}^{\mathrm{F}}} \, y_k x_k \, \langle x_k ; x_{\mathrm{k}^{\mathrm{F}}} \rangle \qquad (\mathrm{III.}\,28)$$

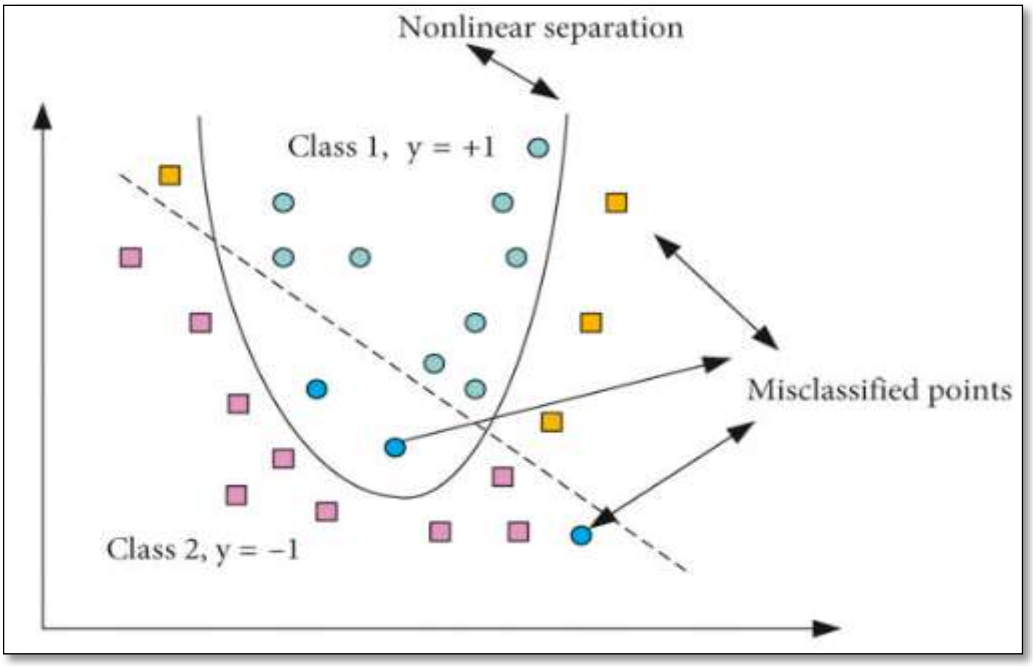


Figure III.6: Non-linear Support Vector machines.

The equation of the optimal hyperplane can be obtained by solving the optimization problem with the constraints $\sum_{k=1}^{n} \alpha_k y_k = 0$ and $0 \leq \alpha_k \leq C$, where κ is a reproducing kernel such that $\kappa\,(x_k;x_{k'}) = \langle \varphi_{\mathrm{k}};\varphi_{\mathrm{k}^{\mathrm{F}}} \rangle$. Thus, the equation of the optimal hyperplane is given by:

$$\mathrm{w}^{*}.\varphi(x) - \lambda_0^{*} = \sum_{k=1}^{n} \alpha_k^{*} y_k\, \kappa(x_k; x) - \lambda_0^{*} \qquad \text{(III.29)}$$

And

$$\lambda_0^{*} = \frac{1}{2}\sum_{k=1}^{n} \alpha_k^{*} y_k [k(x_k; x_{i-}^{*}) + \kappa(x_k; x_{i+}^{*})] \qquad \text{(III.30)}$$

The decision function is defined by the "Sign" of

$$\mathrm{D}(x) = \sum_{k \epsilon s} \alpha_k^{*}\, \mathrm{y}_k \kappa(x_k; x) - \lambda_0^{*} \qquad \text{(III.31)}$$

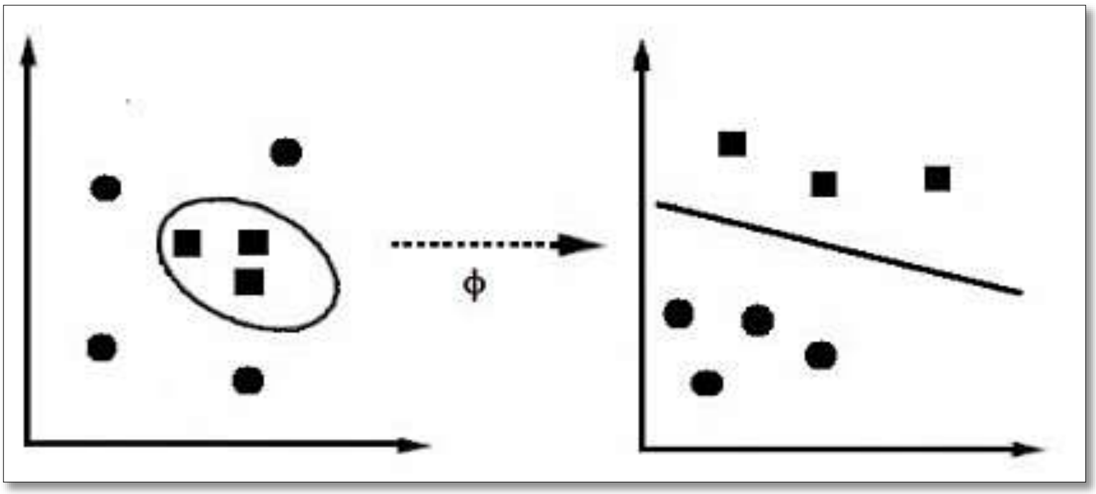


Figure III.7: Transformation of the observation by a kernel function reproducing.

III.7. Multi classification by wide margin separators

As mentioned earlier, Support Vector Machines are designed for two-class problems. However, since SVMs use direct decision functions, extending the problem to multi-class classification is not simple. We will discuss two types of SVMs that deal with multi-class problems:

- One against all support vector machines.
- One against one support vector machines.

The "one against all" method consists in converting a classification problem with n classes into ‘n’ binary classifiers, where for each binary classifier i, the class i is separated from the other classes **[25, 30].**

The "one against one" approach consists in transforming the n-class classification problem into n (n-1)/2 binary classifiers that cover all pairs of classes **[25, 30].**

III.7.1. One against all Multi classification approach

This section discusses the "one against all" approach for multi-class classification, using a discrete decision function.

For the "one against all" approach for an n-class classification problem, n decision functions are determined which separate each class from the other classes. The decision function i, which separates class i from the other classes with a maximum margin, is given by **[26]:**

$$\mathrm{D}_i(x) = \mathrm{w}_i^* \varphi(x) - \lambda_{0i}^* \qquad (\mathrm{III}.32)$$

In classification, if we have for an input vector x:

$$\mathrm{D}_i(x) > 0 \qquad (\mathrm{III}.33)$$

If the equation is satisfied for a single value of i, then x is classified in this class. As the decision only takes into account the sign of the function, it is therefore binary classification **[25].**

III.7.2. One-against-one Multi classification approach

In this section we discuss the” one against one” approach.

In the "one against one" approach, the decision functions are obtained from the combinations of two classes. To obtain a decision function for a pair of classes, the corresponding training data is used. Therefore, during each learning session, the number of training data is significantly reduced compared to the "one against all" approach of SVM, which uses all the learning data. However, the number of decision functions is n (n-1)/2, unlike n in the "one against all" approach of SVMs, where n is the number of classes. Thus, the decision function for class i against class j is given by **[25]:**

$$\mathrm{D}_{ij}(x) = \mathrm{w}^*_{ij}\varphi(x) - \lambda^*_{0ij} \qquad (\mathrm{III}.34)$$

And $\mathrm{D}_{ij} = -\mathrm{D}_{ji}$.

The regions:

$$R_i = \mathrm{D_i}(x) = \{x |\, D_{ij}(x) > 0, \mathrm{j} = 1, \dots, n, j \neq i\} \qquad (\mathrm{III}.35)$$

Do not overlap, and if $x \in R_i$, we classify x in class i **[25].**

III.8. The fields of application of SVM

SVM is a powerful classification method for solving a variety of problems. This method has shown its ability to be effective in many areas of application, such as image processing, speech or bioinformatics, and this, even on large data sets. The implementation of a learning program by SVM consists in solving an optimization problem involving a system to be solved in a large-dimensional space. To use these programs, it is essential to carefully choose a family of kernel functions and adjust the associated parameters. This selection is usually carried out via a cross-validation technique, which makes it possible to evaluate the performance of the system on data that has not been used during training **[21].**

III.9. Advantages and Disadvantages of Severe SVM

- **Advantages**

SVM is an interesting classification method due to its extensive scope of application. Among its advantages, we can mention:

- A high precision of classification and generalization compared to conventional methods.
- Less effort required to design the appropriate architecture (few parameters to adjust or estimate).
- The solution of the problem is translated into the resolution of a convex quadratic problem whose solution is unique and obtained by classical mathematical methods of quadratic programming.

- **Disadvantages**

- The major disadvantage of the SVM classifier is that it is designed for binary classification (the separation between two classes, one +1 and the other -1) **[31].**

III.10. Conclusion

SVM is a supervised learning algorithm which separates the data into different classes through the use of a hyperplane. The chosen hyperplane is one with the greatest margin between the hyperplane and all points, maximizing this margin is a regularization method that reduces the complexity of the classifier and produces a reduced set of data called support vectors, this allows us to obtain an accurate classification. The SVM automatically solves the problem of choosing the MLP parameters and offers a theoretical framework for processing data of various nature and complexity.

The efficiency and robustness of SVM have been demonstrated in many pattern recognition applications.

Chapter IV:

PV solar fault diagnosis based on dimensionality reduction and SVM.

IV.1. Introduction

In this chapter, we focus on various faults associated with photovoltaic systems. Subsequently, we delve into the proposed method for diagnosing faults in photovoltaic systems based dimensionality reduction and support vector machine. The digital processing is conducted using MATLAB software to evaluate the performance of the proposed approach. The obtained results will be then analyzed and discussed.

IV.2. Database

The data provided on the faults of the grid-connected PV system (GPVS-Faults) are collected from laboratory experiments of the faults in a PV micro-grid application; there are 8 data files, each file corresponding to an experiment scenario **[32].**

In this work, the grid-connected PV system is shown in **Figure: IV.1** The PV array output is generated through the programmable Chroma 62150H-1000S solar array emulator that allows varying effects of environmental conditions (*G* and *T*). The programmable AC source Chroma 61,511 is used as a grid emulator. The control algorithm was implemented on a DSpace 1104 environment, which is also used for data acquisition.

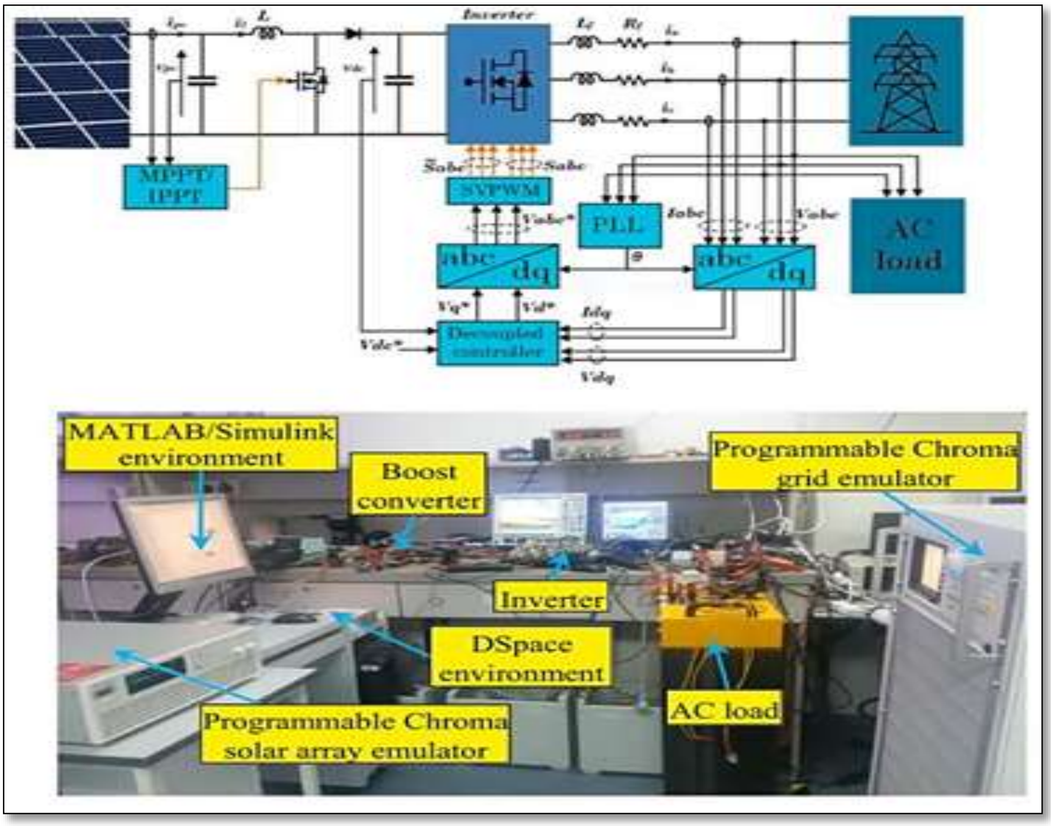


Figure IV.1: Overview of the PV system connected to the network.

The different types of defects are shown in **Table IV.1**

Table IV.1: Realistic injected fault in the GPV system.

Fault	Type	Description
F0	Without defects	/
F1	Inverter fault	Complete failure in one of the six IGBTs
F2	Feedback Sensor fault	One phase sensor fault 20%
F3	Grid anomaly	Intermittent voltage sags
F4	PV array mismatch	10 to 20% nonhomogeneous partial shading
F5	PV array mismatch	15% open circuit in PV array
F6	MPPT/IPPT controller fault	-20% gain parameter of PI controller in MPPT/ IPPT controller of the boost converter
F7	Boost converter controller fault	+ 20% in time constant parameter of PI controller in MPPT/IPPT controller of the boost converter

Each data file includes the following columns:

- Time: Time of real measurement in seconds. The average sampling is $T! = 9.9989\ \mu s$.
- Ipv: PV array current measurement.
- Vpv: PV array voltage measurement.
- Vdc: DC voltage measurement.
- ia: Phase_A current measurement.
- ib: Phase_B current measurement.
- ic: Phase_C current measurement.
- va: Phase_A voltage measurement.
- vb: Phase_B voltage measurement.
- vc: Phase_C voltage measurement.
- Iabc: Positive-sequence estimated current magnitude.
- If: Positive-sequence estimated current frequency.

- Vabc: Positive-sequence estimated voltage magnitude.
- Vf: Positive-sequence estimated vurrent frequency.

In this work we are interested in the use of the three currents: Ia, Ib and Ic. The database contains 400 samples, 50 samples for each class. The database is divided into two parts: the first part which contains 70% of the signals will be used for training. The second contains 30% of the samples will be used for test.

IV.3. Proposed method for the diagnosis of defects in solar panels

Figures IV.2 illustrates the proposed method for PV system fault diagnosis:

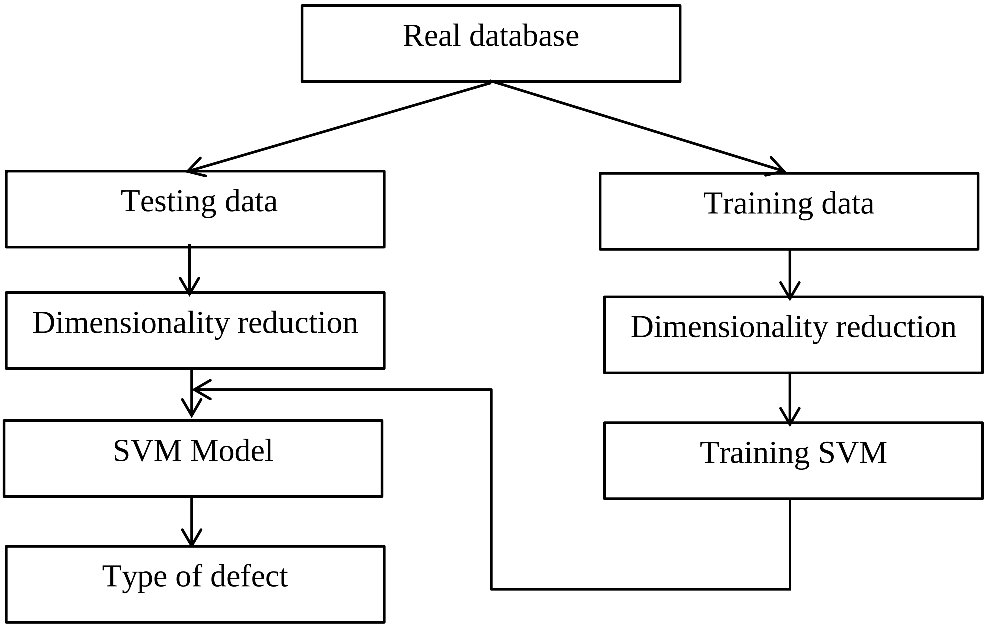


Figure IV.2: Proposed method for fault diagnosis.

The diagnostic procedure consists of six essential steps, described as follows:

1. Preparation of samples of measurements obtained from the PV system ;
2. Measurement of Ia, Ib and Ic currents;
3. Extraction of statistical parameters from the three currents;
4. Feature selection based on BPSO
5. Division of the data into two matrices: 70% for learning and 30% for testing;
6. Classification of defects based on support vector machine.

Figure IV.3 illustrates the detailed flowchart of the suggested method**.**

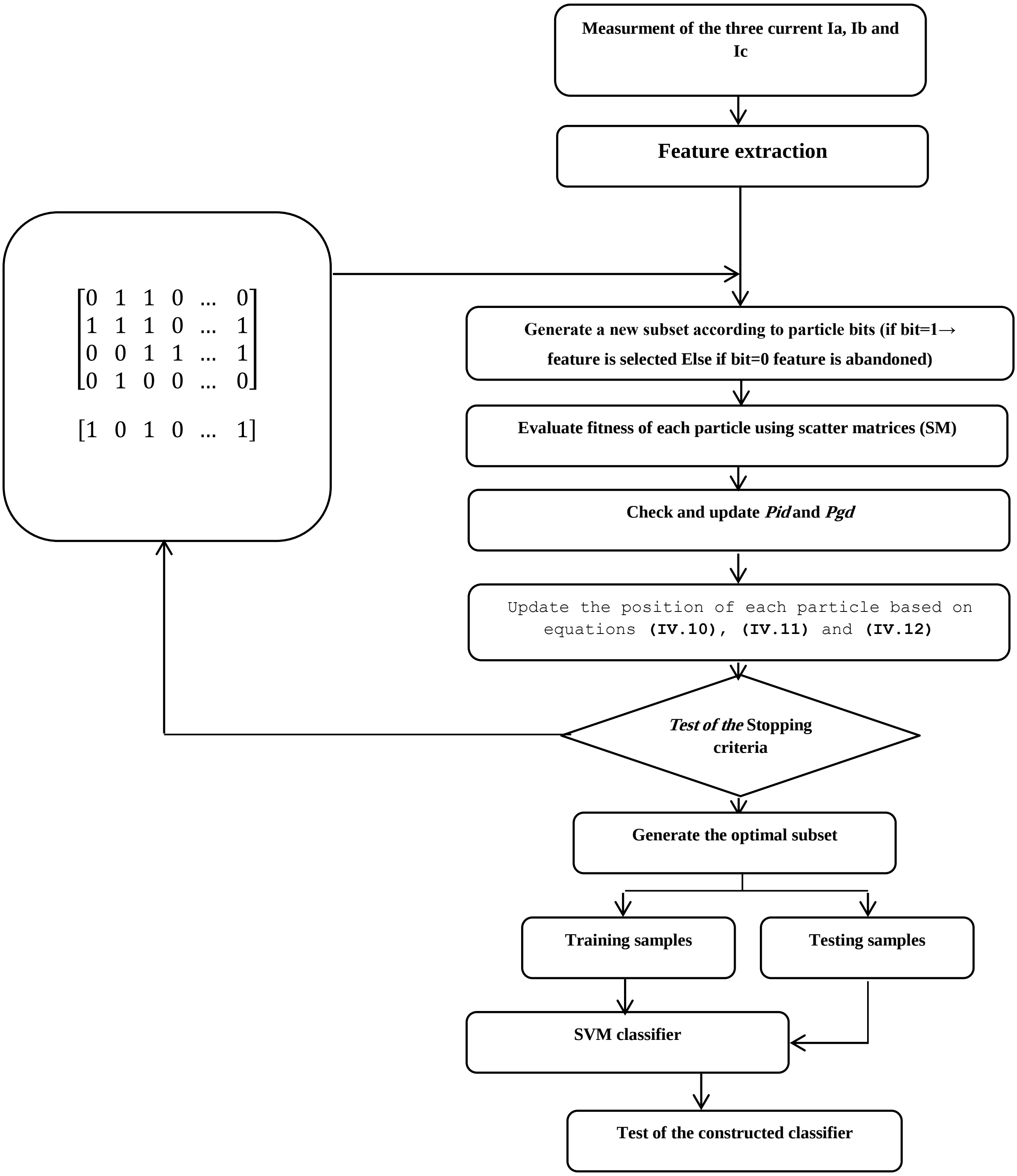


Figure IV.3: Scheme of the suggested methodology for PV system fault diagnosis

IV.3.1. Feature extraction based on statistical parameters

The feature extraction is an essential step in pattern recognition. We have extracted the following eight parameters (the MIN value, the MEAN value, the MAX value, the KURTOSIS value and the SKEWNESS value, the VARIANCE value, the RMS value, the MEDIAN value, the MODE value and the RANGE value). These parameters are defined by the following equations:

$$\boldsymbol{Min} = \min (\boldsymbol{x}) \quad \textbf{(IV.1)}$$

$$\text{Mean} = \frac{\sum_{i=1}^{N}(x(i))}{N} \quad \textbf{(IV.2)}$$

$$\boldsymbol{Max} = \boldsymbol{max}\,(\boldsymbol{x}) \quad \textbf{(IV.3)}$$

$$\boldsymbol{Kurtosis} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x(i)-\bar{x})^4}{\left[\ \frac{1}{N}\sum_{i=1}^{N}(x(i)-\bar{x})^2\ \right]^2} \quad \textbf{(IV.4)}$$

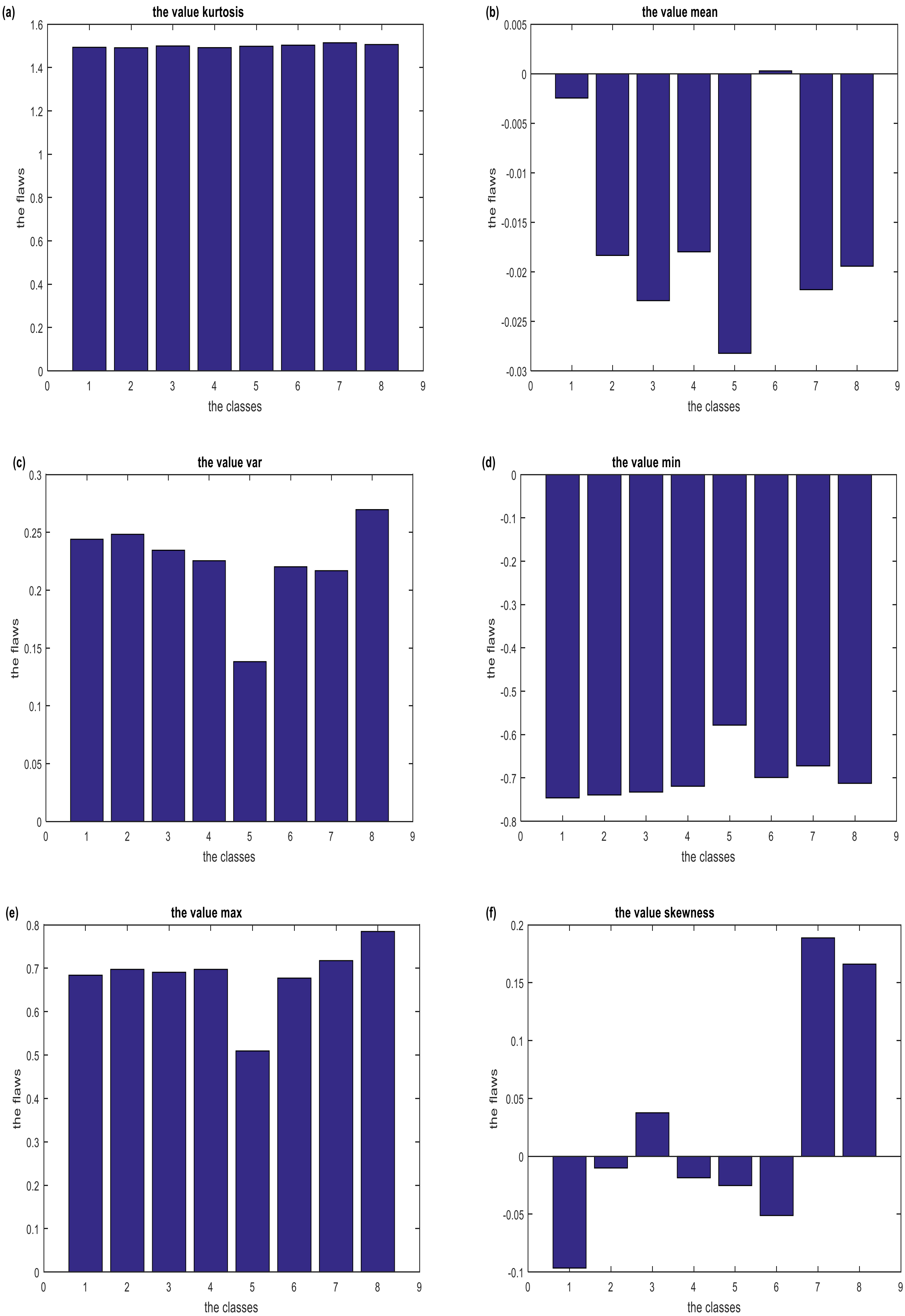
$$\boldsymbol{Skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x(i)-\bar{x})^3}{\left(\sqrt{\left[\ \frac{1}{N}\sum_{i=1}^{N}(x(i)-\bar{x})^2\ \right]}\right)^3} \quad \textbf{(IV.5)}$$

$$\text{Variance} = \frac{\sum_{i=1}^{N}(x(i)-\bar{x})^2}{N} \quad \textbf{(IV.6)}$$

$$\text{Median} = \frac{(N+1)^{th}}{2} \quad \textbf{(IV.7)}$$

$$\text{Range} = \max - \min \quad \textbf{(IV.8)}$$

The **Figures IV.4, IV.5, IV.6** illustrates the eight extracted statistical parameters from the currents Ia, Ib, Ic according to different types of faults.


(a)
the value kurtosis
the flaws
the classes
(b)
the value mean
the flaws
the classes
(c)
the value var
the flaws
the classes
(d)
the value min
the flaws
the classes
(e)
the value max
the flaws
the classes
(f)
the value skewness
the flaws
the classes

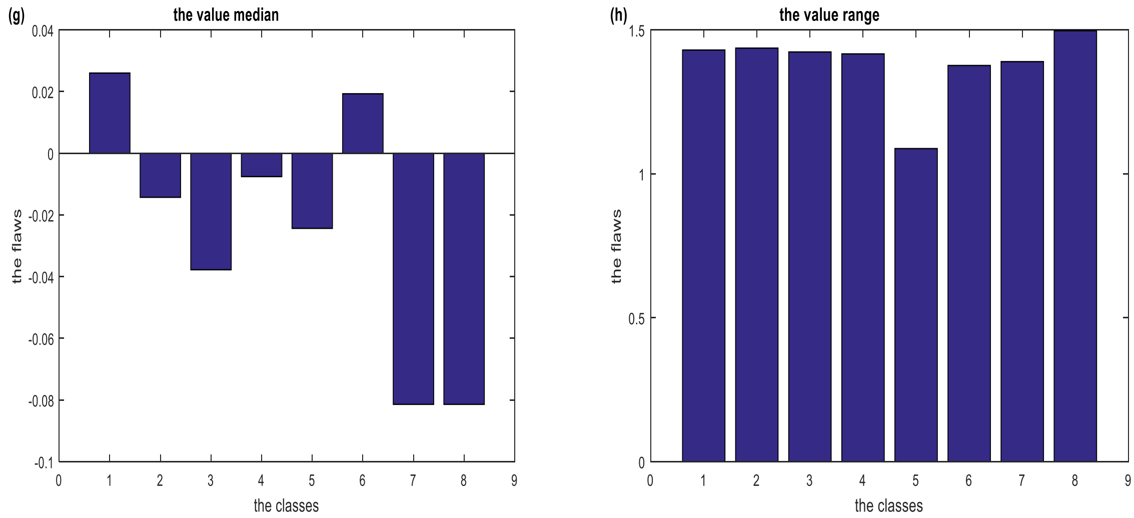
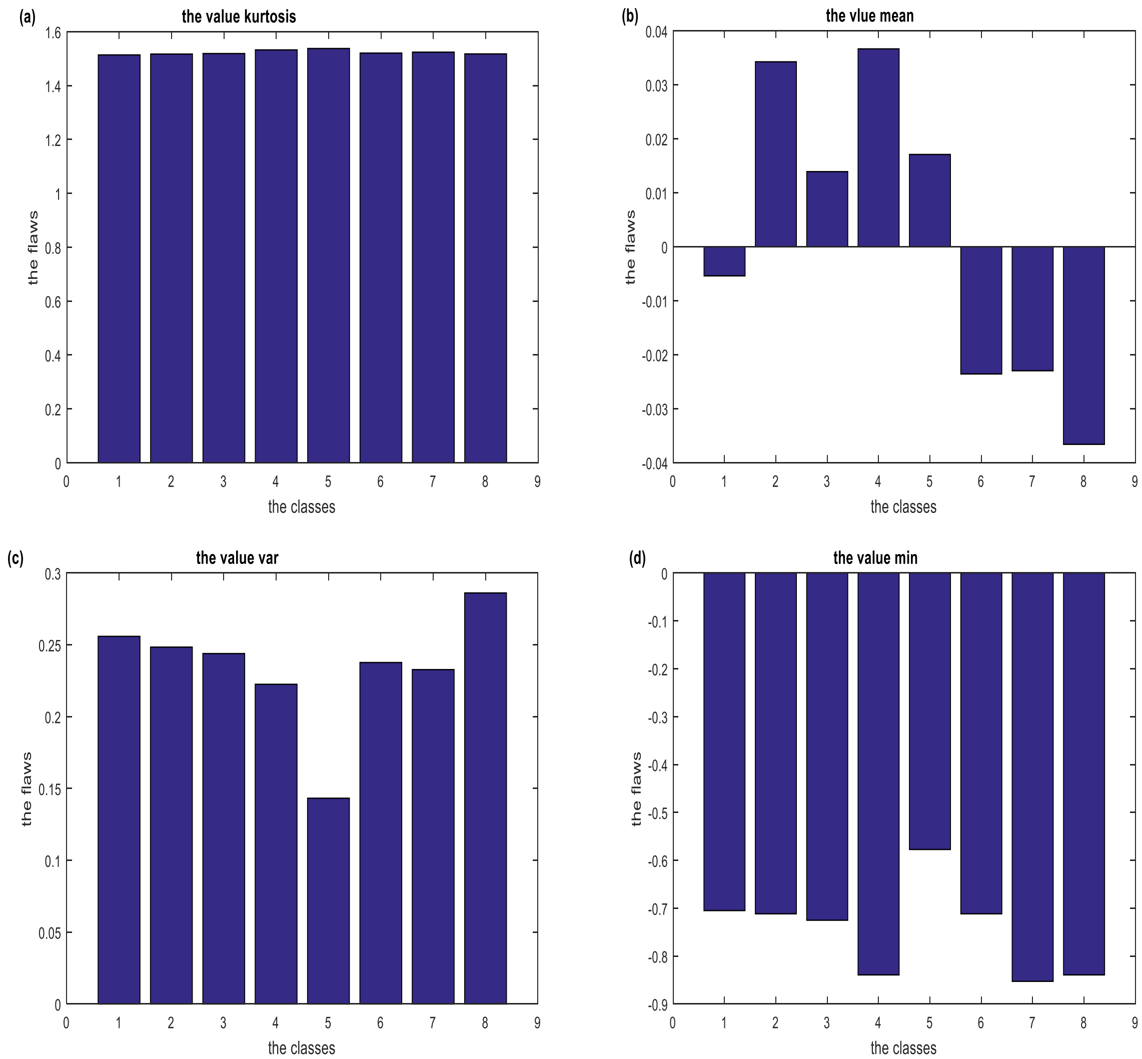


Figure IV.4: Extracted statistical parameters from current Ia according to different types of faults (a: KURTOSIS value, b: MAEN value, c: VAR value, d: MIN value, and e: MAX value, and f: SKEWNESS value and g: MEDIAN value, and h: RANGE value)



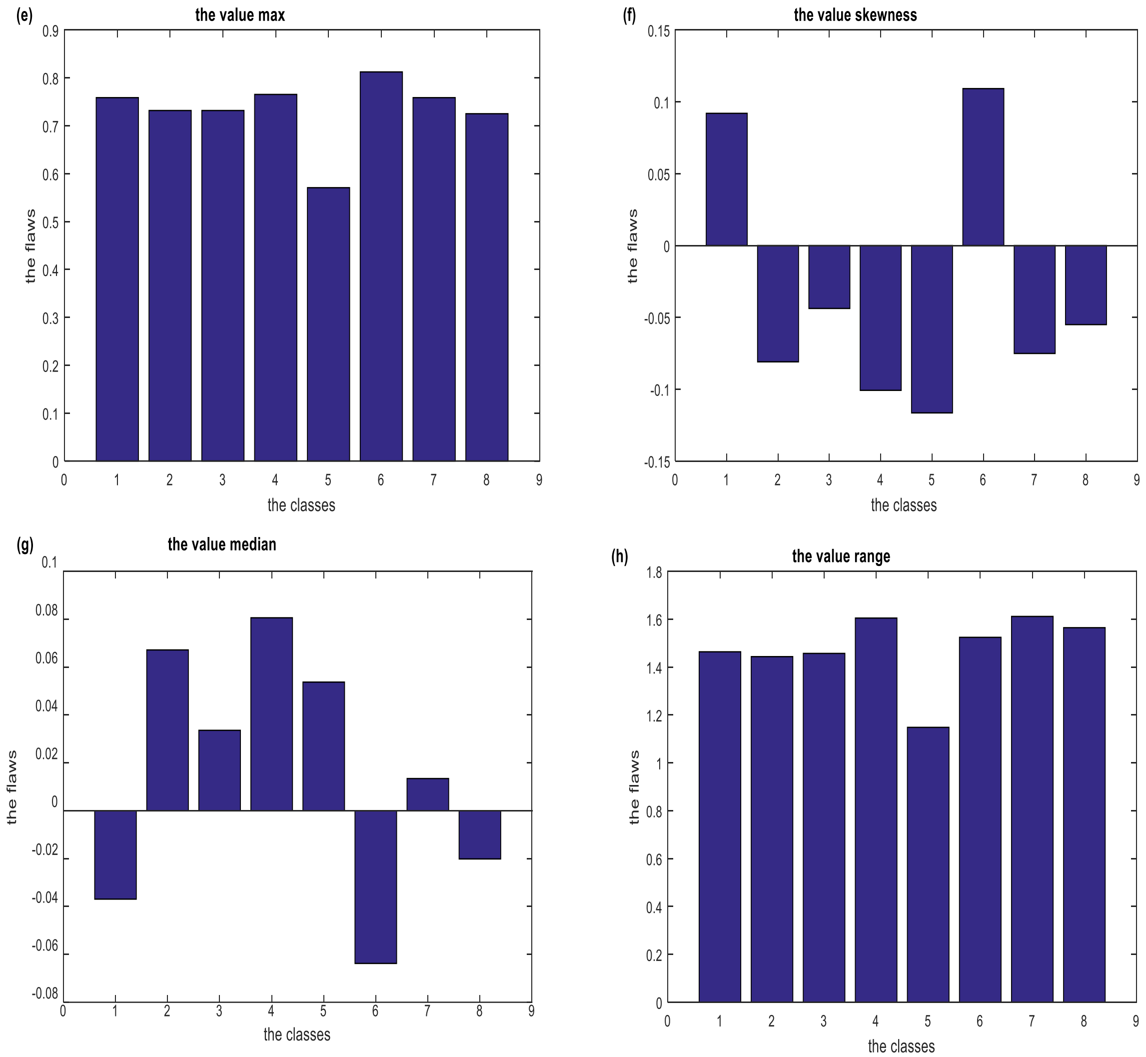
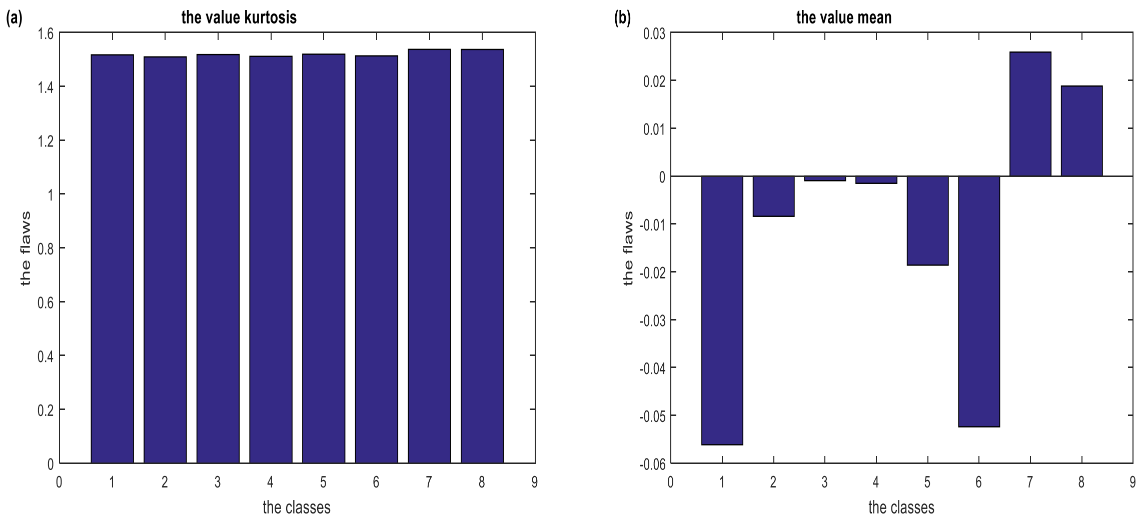


Figure IV.5: Extracted statistical parameters from current Ib according to different types of faults (a: KURTOSIS value, b: MAEN value, c: VAR value, d: MIN value, and e: MAX value, and f: SKEWNESS value and g: MEDIAN value, and h: RANGE value)



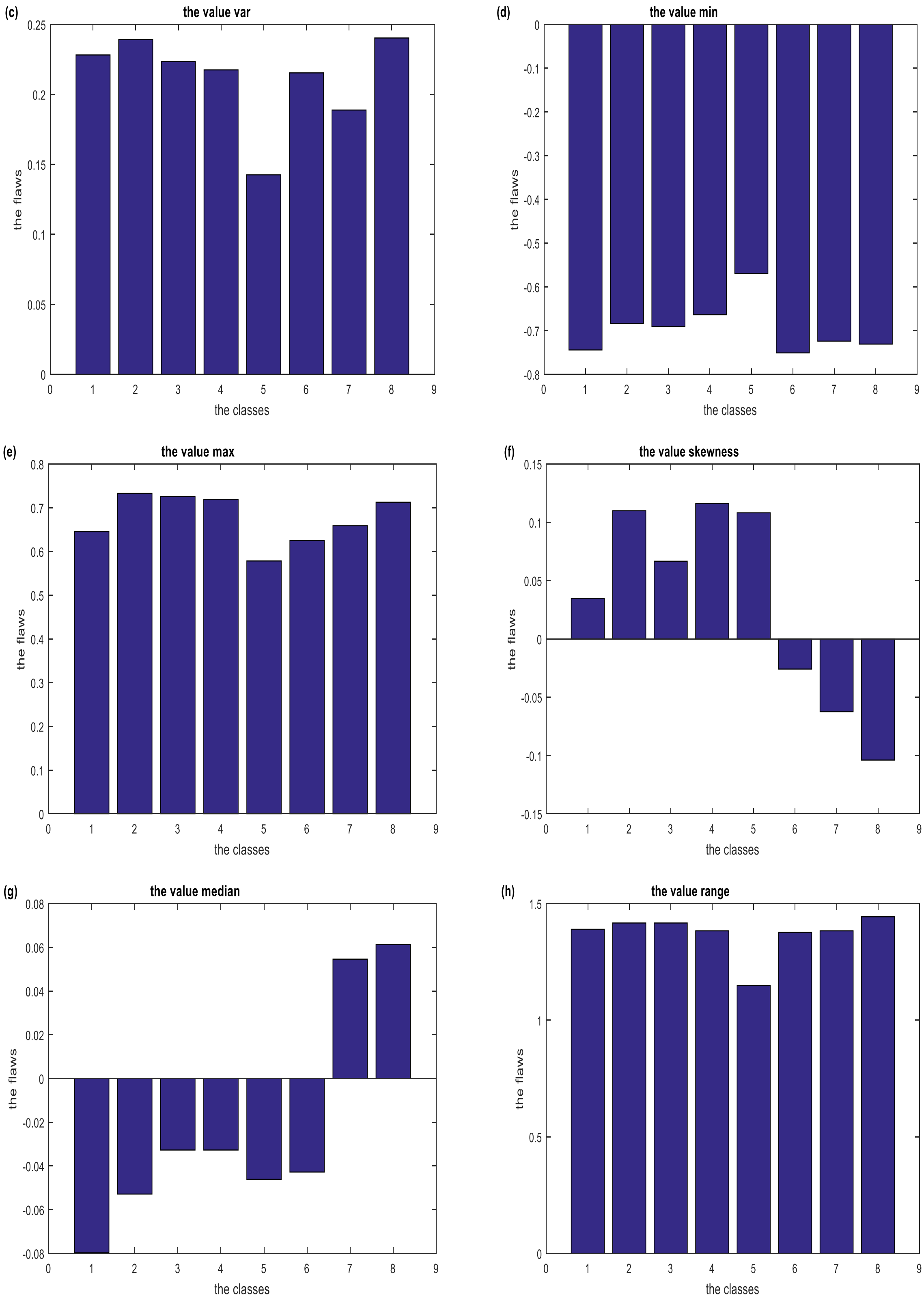


Figure IV.6: Extracted statistical parameters from current Ic according to different type of faults (a: KURTOSIS value, b: MAEN value, c: VAR value, d: MIN value, and e: MAX value, and f: SKEWNESS value and g: MEDIAN value, and h: RANGE value)

From **Figures IV.4**, **IV.5, IV.6,** it can be observed that all statistical parameters vary depending on the type of fault. However, they have not the same sensitivty. For this reason a second phase is introduced to select the relevant parameters which will be used as input of the support vector machine classifier.

IV.3.2 Feature selection

Feature selection is an important process in data analysis and machine learning. The primary goal of feature selection is to identify and choose a set of effective and distinctive features from a large feature vector, in order to improve the performance of the classification model.

IV.3.2.1. The BPSO (Binary Particle Swarm Optimization)

BPSO algorithm can be used in the feature selection process in machine learning and data analysis applications. BPSO improves the feature selection process by identifying and enhancing the most beneficial set of features from a large pool of features. With its ability to handle complex data and improve performance, BPSO is considered an effective tool for enhancing the accuracy of machine learning models and simplifying data analysis.

PSO is an evolutionary algorithm which performs searches using a population of individuals. Each particle, is characterized by its current position (Z_{id}^{k-1}), its velocity (V_{id}^{k-1}) and its best position (P_{id}), it tries to modify its position using its best previous position (P_{id}) and the best position among all the particles (P_{Gd}).

The velocity and the position of each particle can be updated by the following equations **[33]:**

$$Z_{id}^{k} = Z_{id}^{k-1} + V_{id}^{k} \qquad \textbf{(IV.9)}$$

Where:

$$\mathrm{V_{id}^{k}} = \mathrm{w.V_{id}^{k-1}} + \mathrm{c_1.d_1.}\left(\mathrm{P_{id}} - \mathrm{Z_{id}^{k-1}}\right) + \mathrm{c_2.d_2.}\left(\mathrm{P_{Gd}} - \mathrm{Z_{id}^{k-1}}\right) \quad \textbf{(IV.10)}$$

Here:

$\mathrm{P_{Gd}}$: is the best position in the group, $\mathrm{P_{id}}$: is the best position of the i[th] particle, Z_{id}^{k} : the position of the i[th] particle at the k[th] iteration, $\mathrm{V_{id}^{k}}$: the velocity of the i[th] particle at the k[th] iteration, $\mathrm{c_1}, \mathrm{c_2}$: are positive constants, w: is the inertia weight and d_1,d_2 are random numbers in the range [0,1].

In the BPSO algorithm, each particle position is expressed as a binary bit vector composed of zeros and ones. Each position is updated based on the velocity value which is converted to probability values using the following function **[34]:**

$$\mathrm{F(V_{id}^{k})} = 2 * \left|\left(Sigmoid\left(V_{id}^{k}\right) - 0.5\right)\right| \quad \textbf{(IV.11)}$$

After mapping velocities to probability values using **(IV.11)**, the new binary particle position is determined as follow **[34]:**

$$\text{If rand()} < F(V_{\mathrm{id}}^{\mathrm{k}}) \text{ then } Z_{id}^{k} = exchange\left(Z_{id}^{k-1}\right) \; else \; Z_{id}^{k} = Z_{id}^{k-1} \quad \textbf{(IV.12)}$$

IV.3.2.2. Class separability measure based on scatter matrices

In the present work, we suggest a new fitness function that quantifies the class-discriminatory power of a *D*-dimensional feature space using scatter matrices (SM). The proposed objective function defined by **(IV.13)** is employed to choose those features which have the larger the value of this objective function **[35].**

$$J = trace\{S_w^{-1} S_b\} \quad \textbf{(IV.13)}$$

Here, S_w and S_b: represent the between-class scatter matrix and the within-class scatter matrix, respectively. They are given as follow:

$$S_w = \sum_{i=1}^{c} S_i \quad \textbf{(IV.14)}$$

$$S_b = \sum_{i=1}^{c} N_i(m_i - m_0)(m_i - m_0)^t \tag{IV.15}$$

Where, $S_i = \sum_{x \in D_i} N_i(x - m_i)(x - m_i)^t$ denotes the within-class scatter matrix of class $i = 1, 2, \dots, c$ and $m_0 = \sum_{i=1}^{c} N_i m_i$ is the global mean vector.

$'c'$ Represents the number of classes, m_i and N_i denote the mean vector and number of samples of class i, respectively.

Large value of '*J*' indicates that data points in the respective feature space have small within-class variance and large between-class distance. Hence, as 'J' increases the 'C' conditions separate.

After the application of the BPSO an optimal feature vector is obtained.

Figure IV.7 represents the convergence of the objective function according to the number of iterations

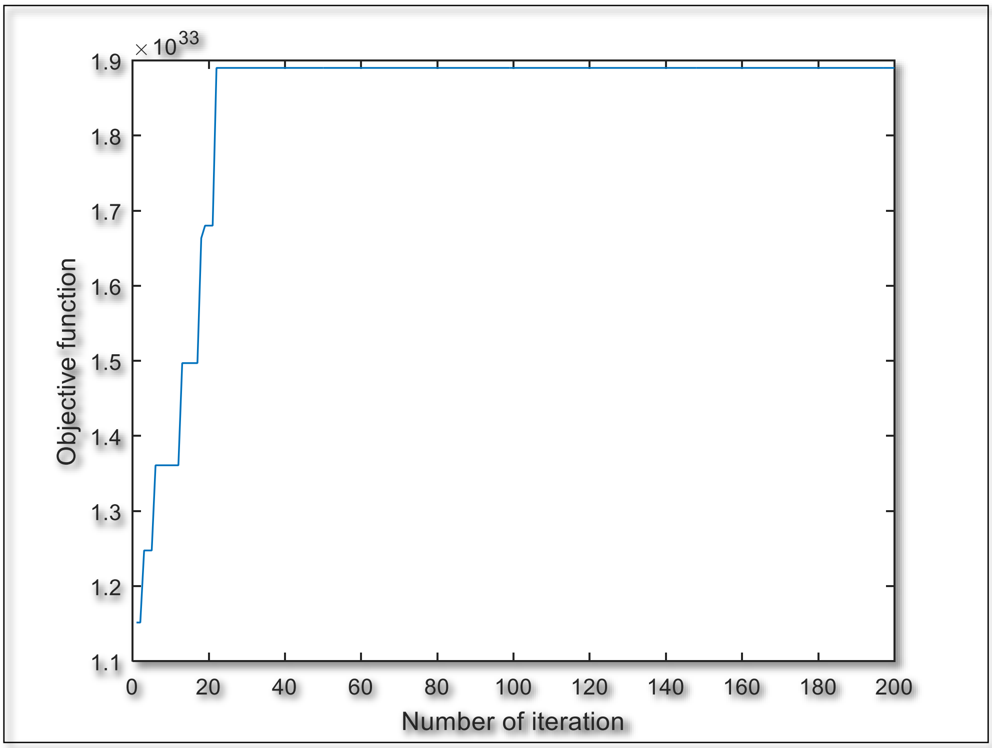


Figure IV.7: the convergence of the objective function according to the number of iterations.

From figure **IV.7** it can be seen that the BPSO converges to the optimal solution after a small number of iteration.

It should be noted that the only eight (08) features have been selected as presented in **Table IV.2**.

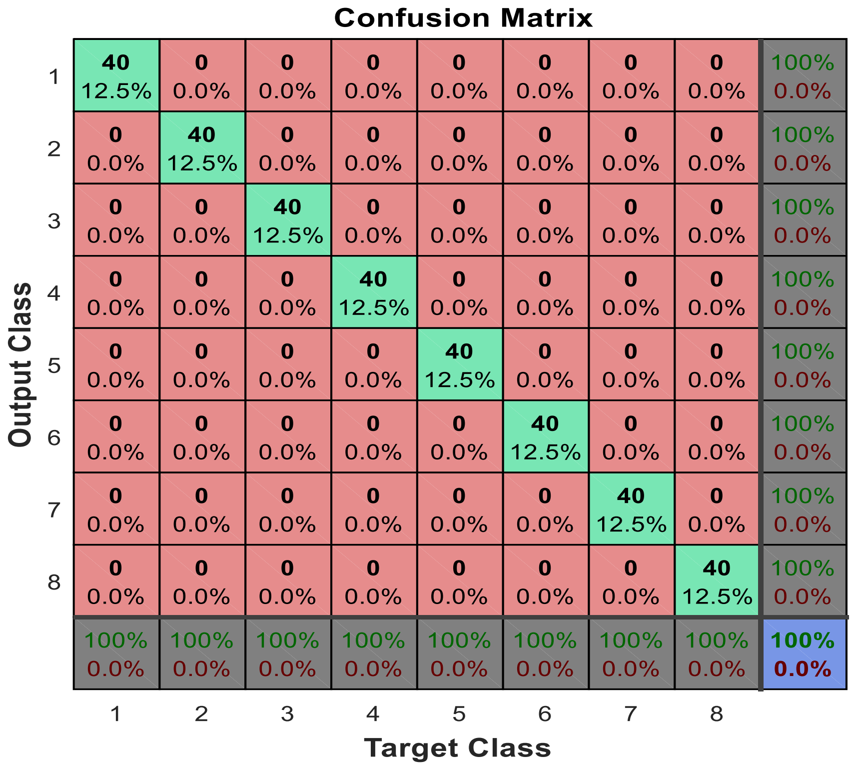
Table IV.2: selected the eight (08) features only

Features / Currents	**Kurtosis p1**	**Mean p2**	**Var p3**	**Min p4**	**Max p5**	**Skewness p6**	**Median p7**	**Range p8**
Ia	0	1	0	1	.0	1	0	0
Ib	0	1	1	0	0	0	0	0
Ic	0	0	1	1	0	1	0	0

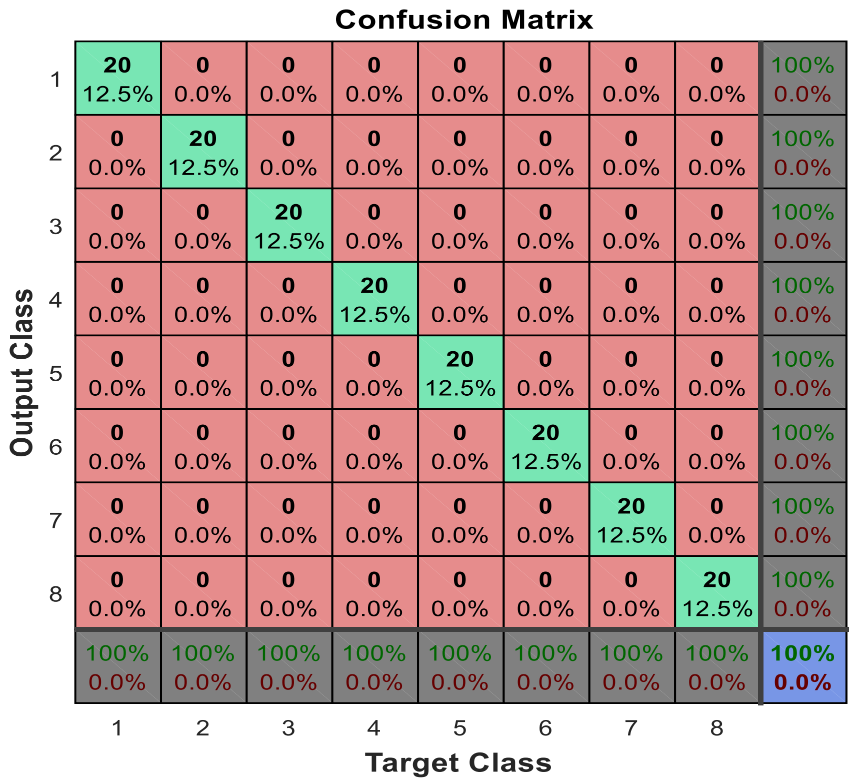
IV.3.3. Classification

In this phase, the obtained feature vector through the application of BPSO will be employed as input of a one against all support vector machine. .

presented selected feature **Figures IV.8** and **IV.9** represent the training and testing confusion matrices, respectively



Figures IV.8: Training confusion matrix.



Figures IV.9: Testing confusion matrix.

The diagonal of a confusion matrix represents the correctly classified samples, while the off-diagonal elements represent misclassified observations. This matrix is a valuable tool for evaluating the performance of a classification algorithm.

From **Figures IV.6** and **IV.7** it can be seen that all samples are correctly classified, as a result a test classification of 100% is obtained.

IV.4. Conclusion

In this Chapter, the suggested approach for PV system fault diagnosis is discussed. The chapter began by explaining the used database and the considered types of defects. After that the essential steps of the proposed method are detailed. The suggested methods consist of three main steps. Firstly, statistical parameters are extracted from the currenets. As a result a feature vector which contains 24 parameters is obtained. Secondly, a feature selection algorithm based on BPSO is adopted to select the relevant features. Finally, a one against all support vector machine is employed to classify the different kind of faults.

The obtained results show that the BPSO algorithm based on scatter matrix as a fitness function can effectively select the relevant features. In addition, the 100% testing accuracy show the high generalisation capacity of SVMs.

General conclusion

General conclusion

This thesis discusses the importance of diagnosing faults in industrial processes and the necessity of fault detection to ensure production continuity and reduce unplanned downtime. It focuses on pattern recognition as a fundamental tool for detecting faults, noting that pattern recognition methods are cornerstone in effectively identifying and repairing faults. One of the key of pattern recognition is dimensionality reduction which aims to improve diagnostic efficiency and reduce computational consumption.

This thesis focuses on diagnosing faults in photovoltaic (PV) systems using dimensionality reduction and support vector machine (SVM). The proposed approach consists of three steps viz: feature extraction, feature selection based on Binary Particle Swarm Optimization (BPSO), and classification using SVM.

In the feature extraction step, statistical parameters such as mean, variance, kurtosis and skewness are calculated from current measurements. This step is followed by the application of BPSO to select the most relevant features and enhance the classification performances. The BPSO algorithm employed scatter matrices as an objective function to maximize class separability.

Finally, the obtained feature vector is employed as an input of SVM classifier.

The obtained results demonstrate the effectiveness of the proposed approach for PV system fault diagnosis.

Bibliographic references

Bibliographic references

[1] Almasoud, A. H., & Gandayh, H. M. (2015). Future of solar energy in Saudi Arabia. Journal of King Saud University-Engineering Sciences, 27(2), 153-157.

[2] Shahsavari, A., & Akbari, M. (2018). Potential of solar energy in developing countries for reducing energy-related emissions. Renewable and Sustainable Energy Reviews, 90, 275-291.

[3] Poggi, F., Firmino, A., & Amado, M. (2018). Planning renewable energy in rural areas: Impacts on occupation and land use. Energy, 155, 630-640.

[4] https://www2.gnb.ca/content/gnb/fr/ministeres/der/energie/content/renewable.html.

[5] Maradin, Dario (2021). Advantages and disadvantages of renewable energy sources utilization. In: International Journal of Energy Economics and Policy 11 (3), S. 176 - 183. https://www.econjournals.com/index.php/ijeep/article/download/11027/5802.

[6] Lahiani, M. (2022). Intégration d'une centrale d'énergies renouvelables aux édifices publics de la municipalité d'Esprit-Saint au Bas-Saint-Laurent (Doctoral dissertation, Université du Québec à Rimouski).

[7] Boutabba, T. (2018). Contribution à la modélisation et à la commande d’un système de génération hybride Solaire-Eolien (Doctoral dissertation, Université de Batna 2).

[8] A. Martin,G. Keith Emery,Y. Hishikawa,W. Warta,D. Ewan, Dunlop.Solar cell efficiency tables, Progress in Photovoltaics: Research and Applications, Vol. 21(5), pp. 827–837,2013.

[9] Rodot, M., & Benallou, A. (1993). Electricité solaire au service du développement rural.

[10] https://opera-energie.com/energie-solaire/.

[11] Bouzidi, A. (2016). Diagnostic et contrôle des systèmes de conditionnement de l’énergie photovoltaïque. Cas d’un système connecte au réseau électrique (Doctoral dissertation, Université de Batna 2).

[12] Gaouaoui, M. (2012). Diagnostic par reconnaissance des formes : Application à la machine asynchrone (Doctoral dissertation, Université Mouloud Mammeri).

[13] Basseville, M., & Cordier, M. O. (1996). Surveillance et diagnostic de systèmes dynamiques : approches complémentaires du traitement de signal et de l'intelligence artificielle (Doctoral dissertation, INRIA).

[14] G. Zwingelstein. Diagnostic des défaillances : Théorie et pratique pour les systèmes industriels, traité des nouvelles technologies. Série Diagnostic et Maintenance. Hermès (1995).

[15] Mamar, Z. H. (2008). Analyse temps-échelle et reconnaissance des formes pour le diagnostic du système de guidage d'un tramway sur pneumatiques. Université blaise.

[16] J. N. Chatain. Diagnostic par système expert, traité des nouvelles technologies, série diagnostic et maintenance. Hermès (1993).

[17] Thelaidjia, T. (2013). La modélisation autorégressive et les séparateurs a vaste marge pour le diagnostic des défauts des roulements à billes (Doctoral dissertation, Université Larbi Tébessi. Tebessa).

[18] Belmiloud, D. (2019). Contribution à l'étude de l'endommagement des matériaux, constituants de machines tournantes, en fonction des paramètres température et fréquence de rotation. Applications aux roulements (Doctoral dissertation, Reims).

[19] Benzahioul S., (2019), Surveillance et Diagnostic de Défauts Dans les Systèmes Electriques. Thèse de Doctorat Sciences, Université du 20 Août 1955 Skikda.

[20] Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN COMPUT. SCI.* **2**, 160 (2021). https://doi.org/10.1007/s42979-021-00592-x.

[21] Boukhechem, F. (2021). Sélection des paramètres et séparateur a vaste marge pour le diagnostic des défauts dans les roulements à billes.

[22] Hasan, M., & Boris, F. (2006). Svm : Machines à vecteurs de support ou séparateurs à vastes marges. Rapport technique, Versailles St Quentin, France. Cité, 64.

[23] Senoussaoui, M. (2007). Application des modèles de Markov caches les machines à vecteurs de support pour la reconnaissance des caractères isoles d'écriture en ligne. Mémoire de magister, Université des Sciences et de la Technologie d'Oran USTO- MB, SIMPA.

[24] Kecman, V. (2001). Learning and soft computing: support vector machines, neural networks, and fuzzy logic models. MIT press.

[25] Abe, S. (2005). Support vector machines for pattern classification (Vol. 2, p. 44).London: Springer.

[26] Wang, L. (Ed.). (2005). Support vector machines: theory and applications (Vol.177).Springer Science & Business Media.

[27] Vapnik, V. N., & Vapnik, V. (1998). Statistical Learning Theory, vol. 1. Hoboken.

[28] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20,273-297.

[29] Schölkopf, B., Smola, A. J., Williamson, R. C., & Bartlett, P. L. (2000). New support vector algorithms. Neural computation, 12(5), 1207-1245.

[30] Hamel, L. (2009). Knowledge Discovery With Support Vector Machines, A JohnWiley & Sons. Inc., Hoboken, New Jersey, 246.

[31] Duda, R. O., Hart, P. E., & Stork, D. G. (2001). Pattern Classification. Jone Wiley &Son. Inc, New Work.

[32] Guichi, A., Talha, A., Berkouk, E. M., Mekhilef, S., & Gassab, S. (2018). A new method for intermediate power point tracking for PV generator under partially shaded conditions in hybrid system. Solar Energy, 170, 974-987.

[33] Kennedy, J. and Eberhart, R.C. (1995) 'Particle swarm optimization', *IEEE 1995 International Conference on Neural Networks*', Perth, Western Australia, 27 November–1 December,pp.1942–1948.

[34] Nezamabadi-Pour, H., Rostami-shahrbabaki, M. and Farsangi, M.M. (2008) 'Binary particle swarm optimization: challenges and new solutions', *The Journal of Computer Society of Iran (CSI) On Computer Science and Engineering (JCSE)*, Vol. 6, No. 1, pp.21–32.

[35] Theodoridis, S. and Koutroumbas, K. (2009) *Pattern Recognition*, 4th ed., Academic Press,California, USA.