People's Democratic Republic of Algeria

Ministry of Higher Education and Scientific research

University of Kasdi Merbah Ouargla

Faculty of Applied Sciences

Department of Mechanical Engineering

Field: Mechanical Engineering

Specialty: Energy engineering

Theme:

Prediction of cooling energy consumption in building using machine learning techniques

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University year: 2022/2023

Acknowledgment

First and foremost, we give Allah praise for providing us the perseverance, strength, and guidance throughout our life to get to this point and be able to carry out this humble Work.

DEDICATION

The first thing I want to say is praise to Allah for providing me the strength and endurance to get through all the roughest and most challenging times in order to complete this effort. I dedicate this work to my dear Father mercy be upon his soul for his guidance and the precious experiences which made the great man I am now, my mother, The veins of my beating heart for her love and support is what kept me motivated despite the struggles I have encountered. Last but not least I am grateful for my beloved family members because they shaped who I am now, and without them, I would not be where I am today.

Contents :

Abstract:

The objective of this study is to diagnose and quantify cooling energy consumptions of a typical residential building,

Our aim was to increase the energy efficiency of a solar cooling system by utilizing an innovative combination of optimized solar cooling, storage techniques, and absorption chillers with the use of the highly developed machine learning techniques such as the Artificial neural networks. This was done with the intention of meeting as much of the world's energy demand as possible with high renewable energy fractions.

Introduction:

This thesis focuses on the critical issue of energy consumption in Algeria, with a specific focus on the impact of energy demands for cooling in the southern regions. As Algeria experiences high temperatures and prolonged hot seasons, the need for cooling systems in buildings has significantly increased in recent years. The excessive energy consumption for cooling purposes poses challenges in terms of energy supply, environmental sustainability, and economic implications. Therefore, this research aims to shed light to the potential of integrating solar cooling systems to address the rising energy demands for cooling especially in southern Algeria and explores the utilization of machine learning techniques to train a predictive model to prognosticate a building's cooling energy Consumption.

Algeria, located in North Africa, faces a unique energy landscape with a heavy reliance on fossil fuels for electricity generation. However, the increasing demand for cooling in the country, particularly in the southern regions characterized by arid and desert climates, has necessitated a closer examination of energy consumption patterns and sustainable alternatives. Cooling systems, such as air conditioning, consume a significant portion of the energy supply, placing strain on the already limited resources.

To address this issue, this study explores the concept of simulating a solar cooling system. Solar cooling utilizes renewable energy from the sun to power cooling systems, reducing the dependence on conventional energy sources and mitigating the environmental impact associated with cooling demands. The simulation of such a system allows for an in-depth analysis of its feasibility, performance, and potential benefits in meeting the cooling needs of buildings in southern Algeria.

Additionally, this thesis explores the integration of machine learning techniques to train a model capable of predicting the outputs of a building's cooling energy. By leveraging historical data on energy consumption, weather conditions, and building attributes, machine learning algorithms can be employed to develop a predictive model that accurately forecasts cooling energy requirements. This predictive model holds immense potential for informing decision-making processes related to energy management, system design, and policy interventions aimed at reducing energy consumption and optimizing cooling efficiency.

Through an in-depth analysis of energy consumption patterns, the impact of energy demands for cooling, and the application of machine learning techniques, this research contributes to a comprehensive understanding of the energy landscape in Algeria. The findings and recommendations of this study can inform policymakers, energy experts, and stakeholders in developing sustainable strategies for managing energy consumption, reducing environmental impacts, and improving energy efficiency in the residential sector, particularly in the context of cooling systems.

By addressing the pressing issue of energy consumption in Algeria and specifically focusing on the significant energy demands for home conditioning in southern regions, this thesis endeavors to provide valuable insights, foster sustainable practices, and contribute to the overall energy transition of the country.

CHAPTER I

Introduction

I Global Energy situation:

The world's energy consumption has been increasing rapidly over the past few decades, and it is expected to continue to grow in the future. Fossil fuels such as coal, oil, and natural gas have been the primary sources of energy for many years, but their use has led to environmental problems such as air pollution and climate change.

Renewable energy sources such as solar, wind, hydro, and geothermal power have gained popularity in recent years due to their clean and sustainable nature. According to the International Energy Agency (IEA), renewable energy sources accounted for 26% of global electricity generation in 2018, and this share is expected to increase to 30% by 2024. [1] However, despite the growth of renewable energy, fossil fuels still dominate the global energy mix. According to the IEA, coal, oil, and natural gas accounted for 81% of global energy consumption in 2018. (Figure.1) This highlights the need for a transition to cleaner and more sustainable energy sources.

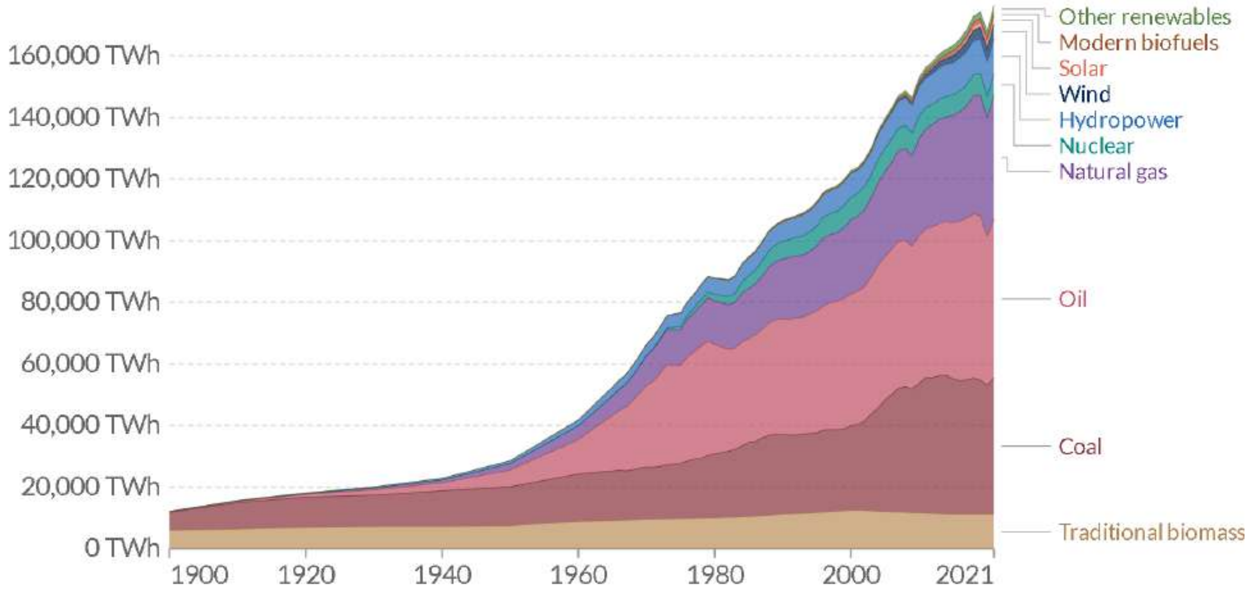
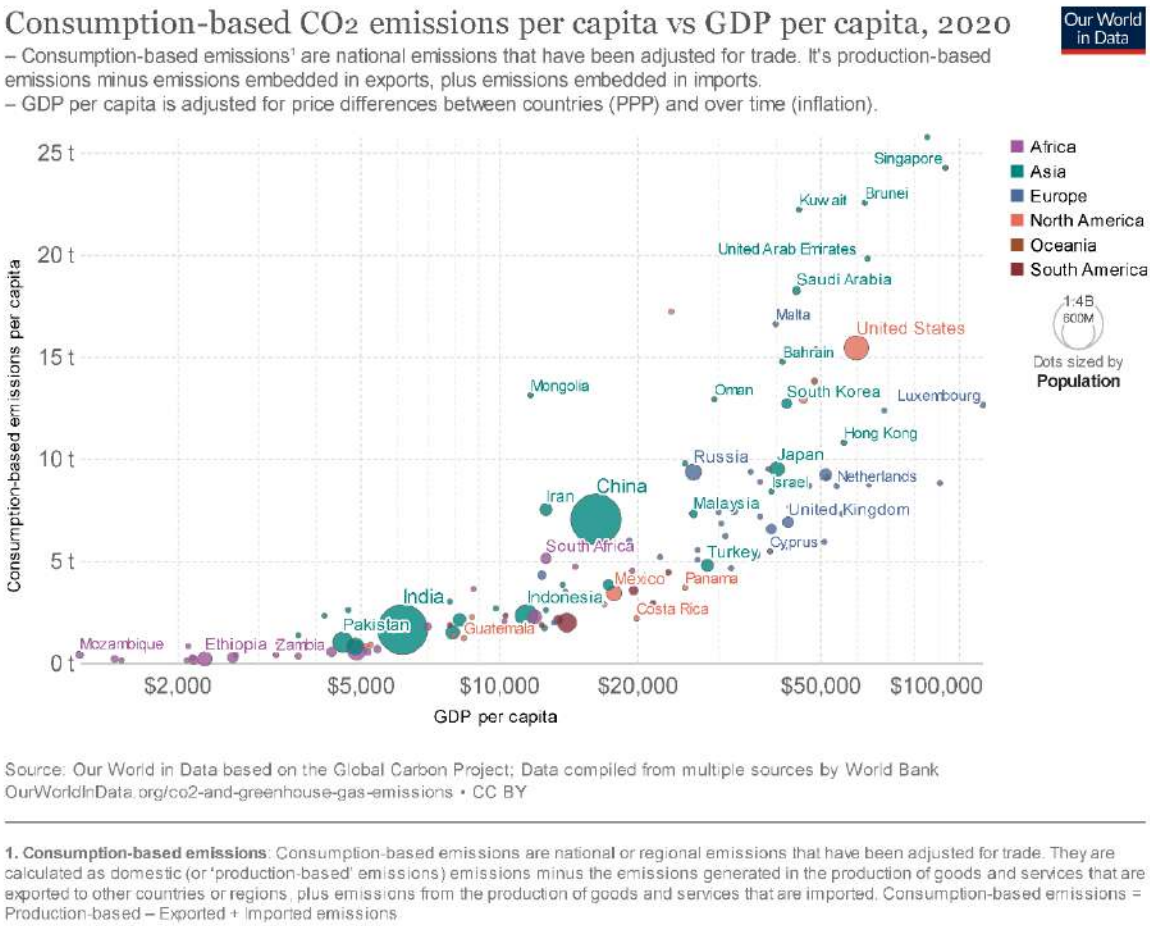


Figure.I.1 Global primary energy consumption by source

Governments around the world have recognized the importance of renewable energy and have implemented policies and incentives to promote its use. For example, the European Union has set a target of producing 32% of its energy from renewable sources by 2030, while China has become the world's largest producer of solar energy.

Greenhouse Gas Emissions Greenhouse gas emissions from energy production are responsible for 87% of global emissions [1]. The wealthiest countries have the highest emissions, with the richest 1% in the EU emitting nine times the global average. The world needs to reduce greenhouse gas emissions towards net-zero to combat climate change effectively. Figure 1 shows the per capita CO2 emissions of different countries.

Figure.I.2 Consumption-based CO_2 emissions per capita vs GDP per capita, 2020.



In conclusion, the global energy situation is complex and multifaceted, with a mix of fossil fuels and renewable energy sources. While renewable energy is growing in popularity, there is still a long way to go before it can replace fossil fuels as the primary source of energy. Governments and individuals must work together to promote the use of renewable energy and reduce our dependence on fossil fuels.

I.1 Overview of Energy Consumption in Algeria:

As a developing country with a growing population and economy, Algeria's energy demand has been increasing rapidly over the years. The energy sector is a vital part of the country's economy, accounting for about 97% of its export earnings and 60% of its budget revenues.

Algeria is the largest country in Africa, covering an area of 2.38 million square kilometers, with a population of over 44 million people. The country's energy consumption has been increasing rapidly over the years due to its growing population, urbanization, and industrialization. According to the International Energy Agency (IEA), Algeria's primary energy consumption reached 63.4 million tonnes of oil equivalent (Mtoe) in 2019, making it the second-largest energy consumer in Africa, after South Africa.

Algeria's energy consumption has long been heavily reliant on fossil fuels, particularly natural gas and oil as showcased in Figure3. The country boasts abundant reserves of these resources, which have traditionally served as the backbone of its economy. However, this heavy reliance on fossil fuels presents challenges in terms of energy diversification and environmental sustainability. It is imperative for Algeria to reduce its dependence on fossil fuels and embrace cleaner alternatives.

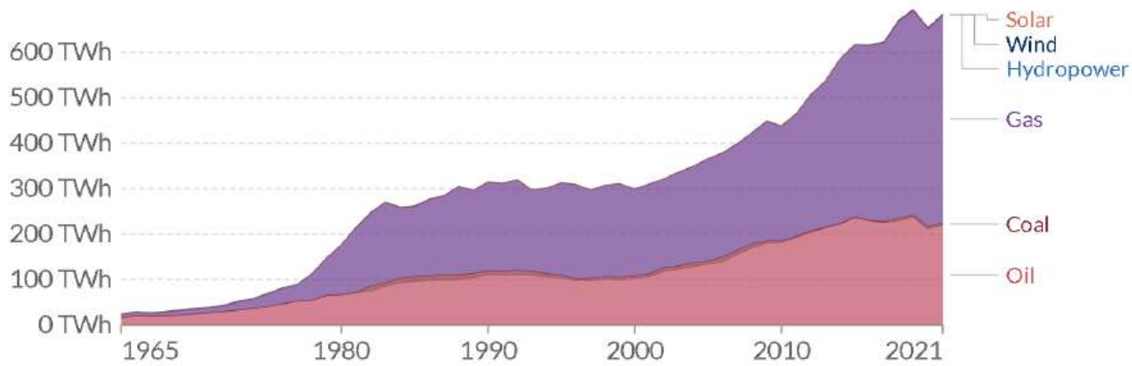


Figure.I.3 Energy consumption by source, Algeria

I.2 Breakdown of Energy Consumption by Sectors:

Energy consumption in Algeria can be broken down into various sectors, including residential, commercial, transport, and industry. According to the IEA, the residential sector is the largest energy consumer in Algeria, accounting for 44% of the total energy consumption in 2019, followed by the industry sector, which accounted for 37%. The commercial sector accounted for 12%, and the transport sector accounted for 7%.

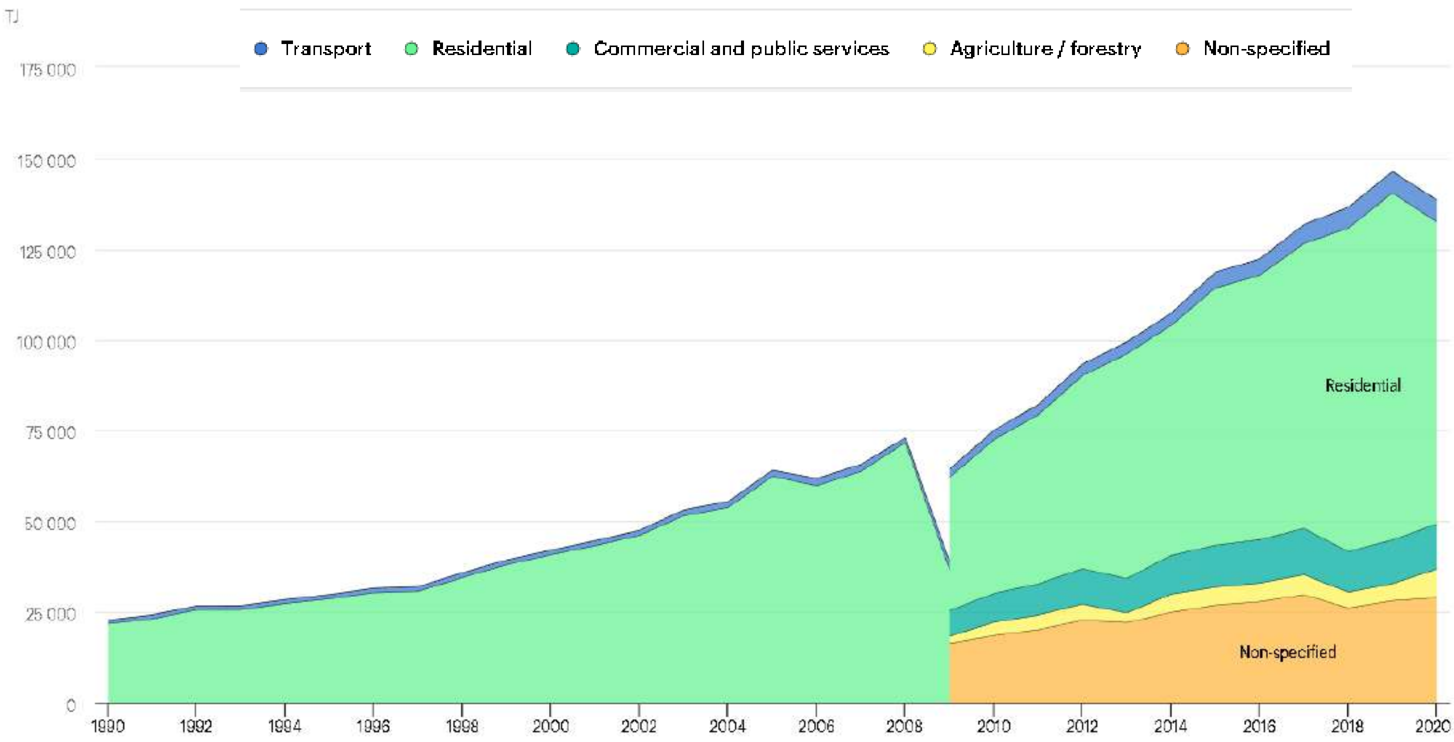


Figure.I.4 Electricity consumption by sector, Algeria 1990-2020

I.3 Dominance of the Residential Sector in Energy Consumption:

The dominance of the residential sector in energy consumption in Algeria (Figure.4), is primarily due to the country's high demand for heating and cooling. Algeria has a hot and dry climate, with temperatures reaching up to 50°C in summer and dropping to 0°C in winter. As a result, many households in Algeria rely on air conditioning units and electric heaters to regulate indoor temperature. The use of these appliances contributes significantly to the country's energy demand.

I.4 Understanding the Substantial Portion of Energy Consumption from Home Conditioning:

HVAC (heating, ventilation, and air conditioning) electricity consumption in Algeria is one of the major contributors to the country's energy consumption. According to the IEA, HVAC electricity consumption in Algeria has been increasing rapidly, with a growth rate of 9.6% per year from 2005 to 2019. The use of air conditioning units and electric heaters accounts for a substantial portion of HVAC electricity consumption in Algeria. [2]

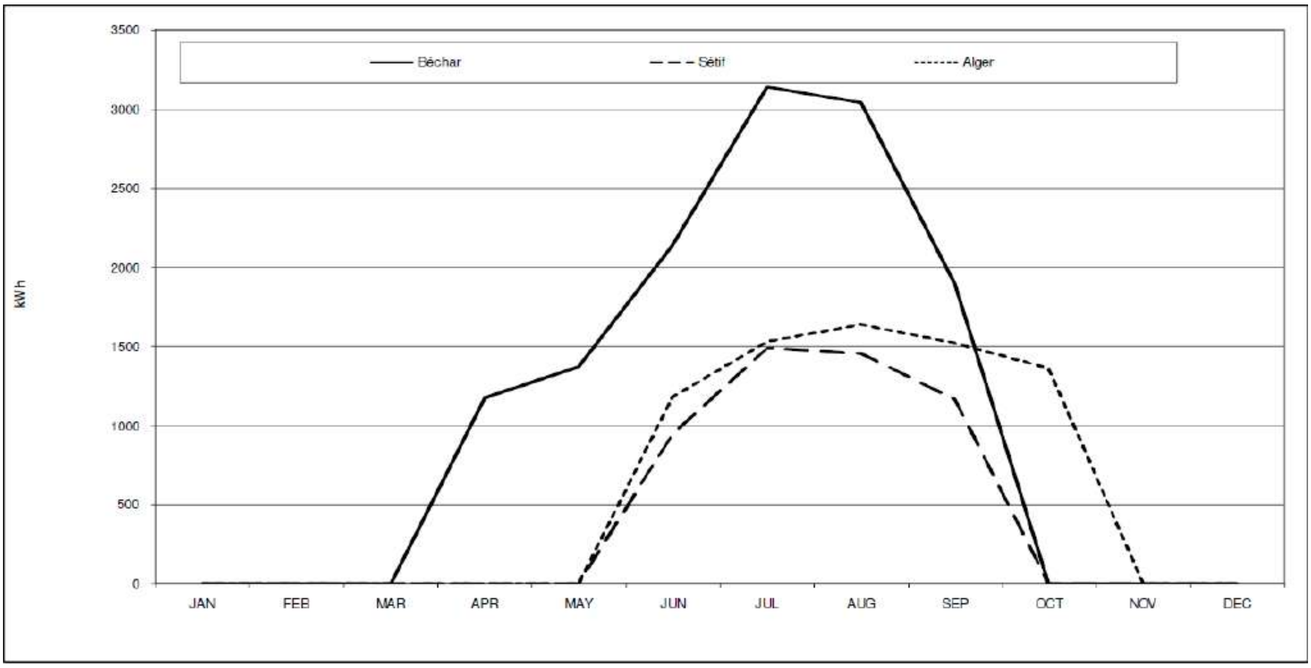


Figure.I.5. Cooling Net requirements for a standard house of 313 m³ in 3 different cities in Algeria

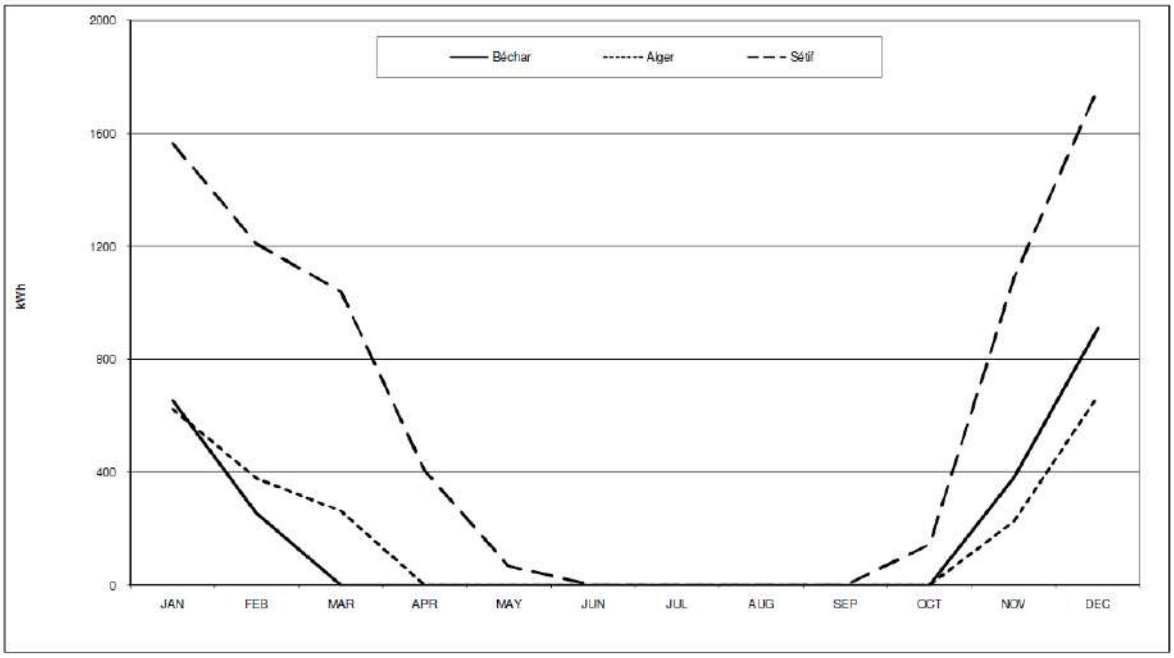


Figure.I.6. Heating Net requirements for a standard house of 313 m³ in 3 different cities in Algeria

I.5 The Impact of Energy Demands for Heating and Cooling Purposes:

The high energy demand for heating and cooling purposes in Algeria has several impacts on the country's economy and environment. Firstly, it puts a strain on the country's energy infrastructure, which can lead to power shortages and blackouts. Secondly, it increases the country's reliance on fossil fuels, which are not only expensive but also contribute to greenhouse gas emissions, leading to climate change and environmental degradation. Thirdly, it increases the cost of living for households, especially those with low-income, who may struggle to pay their electricity bills during peak seasons.

I.6 Government Policies and Initiatives to Address Energy Consumption in Algeria:

To address energy consumption and advance sustainable development, Algeria has established a number of government policies and initiatives. These initiatives attempt to encourage the use of renewable energy sources, boost energy efficiency, and lessen dependency on fossil fuels. Here are some of Algeria's most important legislation and initiatives:

- National Renewable Energy and Energy Efficiency Program (NREEEP): Promote renewable energy sources and energy efficiency.
- Renewable Energy Development Plan (REDP): Set targets for increasing renewable energy capacity by 2030.
- Feed-in Tariffs: Provide incentives for private investment in renewable energy projects.
- Energy Efficiency Measures: Implement energy-saving practices across sectors.
- National Energy Transition Fund: Finance renewable energy projects and energy efficiency initiatives.
- Energy Conservation and Awareness Campaigns: Educate the public on energy conservation.
- Research and Development: Invest in renewable energy technology research and development.
- International Cooperation: Collaborate with international organizations for knowledge sharing and technical assistance.

II The Physical Phenomena of Heat Transfer in Buildings:

Heat transfer is a fundamental physical phenomenon that plays a crucial role in maintaining comfortable indoor environments in buildings. Understanding the different modes of heat transfer is essential for designing energy-efficient buildings and implementing effective heating and cooling systems. In this section we will explore the three primary modes of heat transfer in buildings: conduction, convection, and radiation.

II.1 **Conduction:**

Conduction is the transfer of heat through direct contact between materials. In buildings, conduction occurs primarily through the building envelope, which includes walls, floors, and roofs. When there is a temperature difference between two adjacent materials, heat flows from the warmer material to the cooler one.

For example, during winter, heat from the interior of a building conducts through the walls to the colder exterior environment. Insulation materials, such as fiberglass or foam, are used to minimize heat conduction by providing a barrier with low thermal conductivity. Insulating the building envelope helps to reduce heat loss in cold climates and heat gain in hot climates.

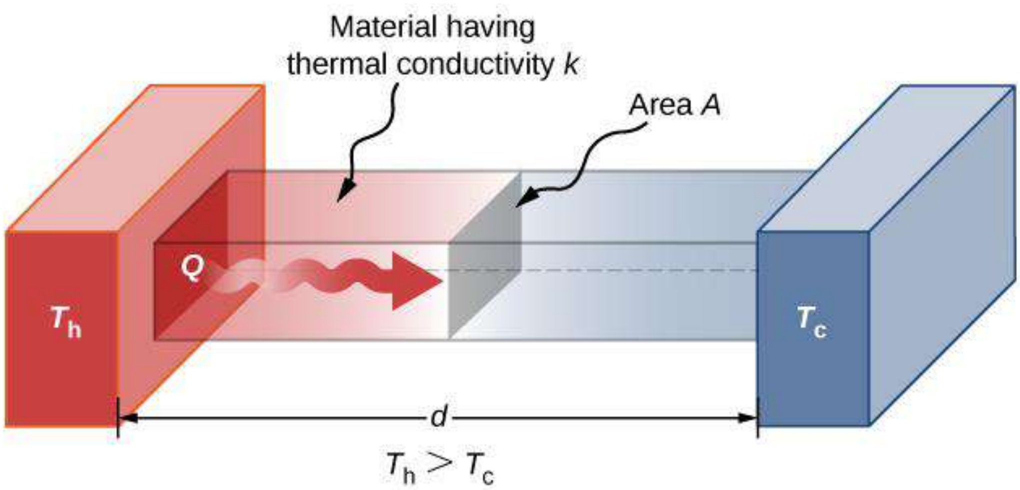


Figure.II.1 Heat conduction occurs through any material, represented here by a rectangular bar, whether window glass or walrus blubber.

Fourier's Law of Heat Conduction:

The mathematical theory of heat conduction was developed early in the nineteenth century by Joseph Fourier [1]. The theory was based on the results of experiments similar to that illustrated in Figure 1.1 in which one side of a rectangular solid is held at temperature T_1, while the opposite side is held at a lower temperature, T_2. The other four sides are insulated so that heat can flow only in the x-direction. For a given material, it is found that the rate, q_x, at which heat (thermal energy) is transferred from the hot side to the cold side is proportional to the cross-sectional area, A, across which the heat flows ; the temperature difference, $T_1 \quad T_2$; and inversely proportional to the thickness, B, of the material. That is:

$$q_x = \frac{k A \,(T_1 - T_2)}{B} \qquad ..(1)$$

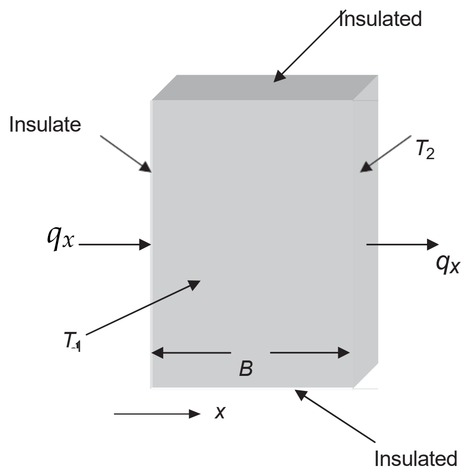


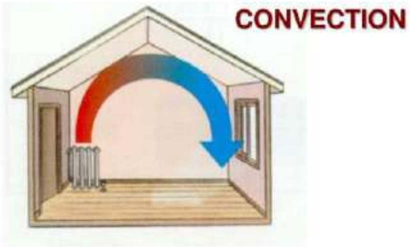
Figure II.2 One-dimensional heat conduction in a solid.

II.2 **Convection:**

Convection is the transfer of heat through the movement of fluids, either liquids or gases. In buildings, convection occurs through the circulation of air or water. There are two types of convection: natural convection and forced convection.

Natural convection occurs when warmer air or fluid rises due to buoyancy forces, while cooler air or fluid sinks. This circulation creates a natural airflow within a building. For example, when a radiator heats the air in a room, the warm air rises, creating a convective loop that circulates the heat.

Forced convection involves the use of mechanical systems such as fans or pumps to actively move air or fluid. Air conditioning systems and ventilation systems utilize forced convection to distribute cooled or heated air throughout a building. The forced airflow enhances heat transfer by increasing the contact between the fluid and surfaces.



Heated air rises, cools, then falls. Air near heater is replaced by cooler air, and the cycle repeats.

he equation for convection can be expressed as:

$$q = h_c A\, dT \qquad .... \ (2)$$

where:

q = *heat transferred per unit time (W, Btu/hr)*

A = *heat transfer area of the surface (m^2, ft^2)*

h_c = *convective heat transfer coefficient of the process (W/ (m^2 °C, Btu/ (ft^2 h °F))*

dT = *temperature difference between the surface and the bulk fluid (°C, F)*

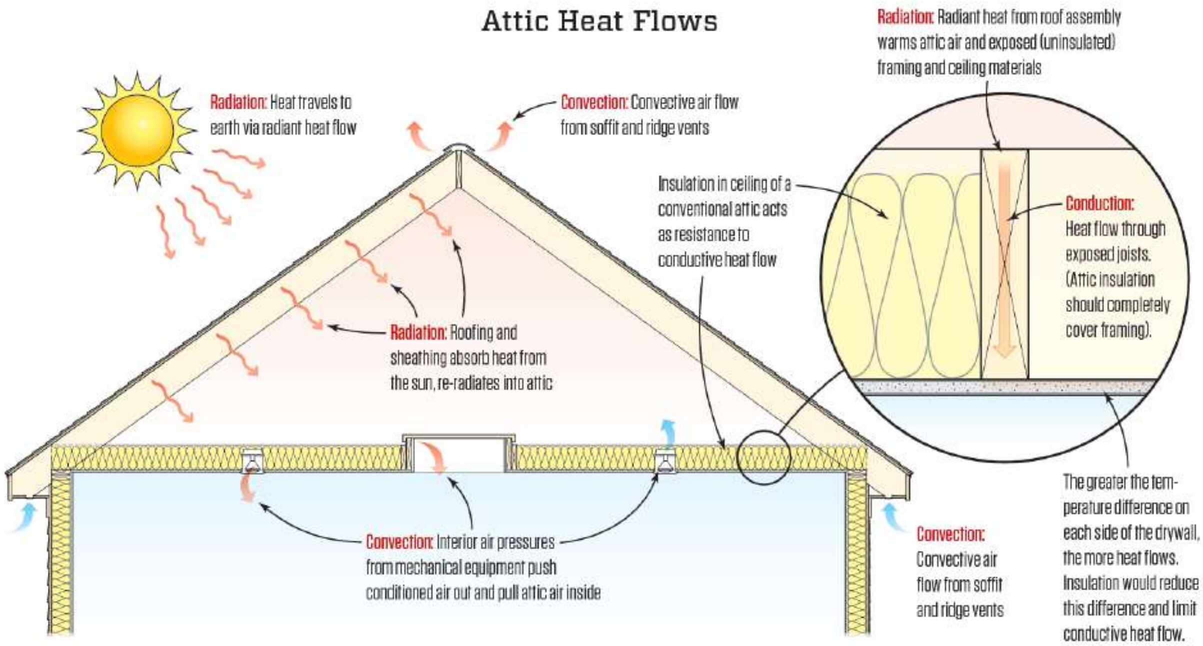
II.3 **Radiation:**

Radiation is the transfer of heat through electromagnetic waves. Unlike conduction and convection, radiation does not require a medium to propagate. In buildings, radiation occurs primarily through the exchange of thermal radiation between surfaces at different temperatures.

The sun radiates heat onto building surfaces, such as walls and windows. The absorbed heat warms these surfaces, which, in turn, radiate heat to cooler surfaces or to the surrounding environment. Reflective or low-emissivity coatings on windows and surfaces can minimize the absorption and emission of thermal radiation, reducing heat gain or loss.

II.4 Examples of Heat Transfer Through Buildings:

Heat moves through building assemblies primarily in three ways: by conduction, by convection, and by radiation. Here are some examples of how heat is transferred through buildings:



FigureII.3 an attic section Illustrating all 3 heat transfer methods

All three heat transfer methods are illustrated in this attic section. Roofing materials absorb radiant energy from the sun. As those materials heat up, they re-radiate heat into the attic, warming the attic air and exposed framing. Insulation limits heat flow by conduction across the ceiling; the more insulation, the more resistance to conductive heat flow. Convection helps cool the attic by moving air through soffit and ridge vents, while interior air pressures move air through holes in the ceiling[3]

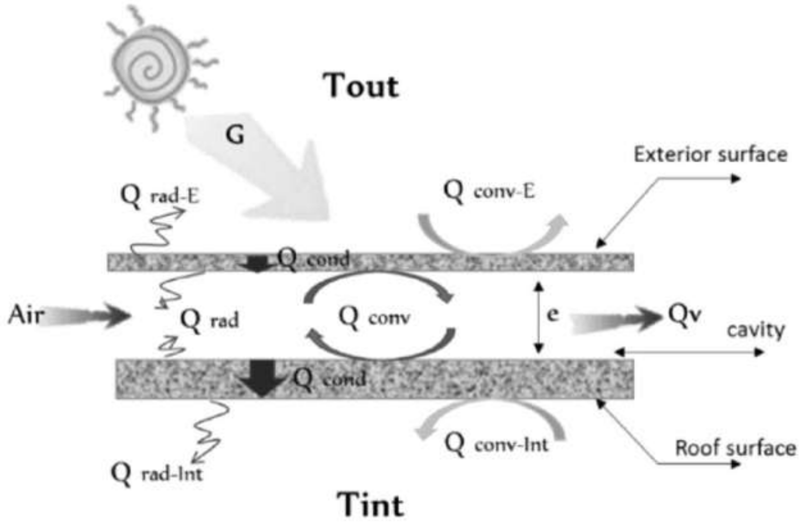


Figure.II.4. Mechanism of heat transfer in a ventilated roof

By comprehending the dynamics of heat transfer in buildings and integrating energy-efficient design principles, we can create indoor environments that are comfortable, sustainable, and energy-efficient. Implementing effective insulation, ventilation, and shading strategies can minimize energy consumption, reduce carbon footprint, and promote a healthier built environment for occupants and the planet as a whole.

CHAPTER II

Sustainable Cooling Systems and the Simulation of the Absorption refrigeration Technology

I Modern Sustainable Cooling Systems:

The increasing global population, urbanization, and climate change contribute to a surge in cooling demand, particularly in regions with hot climates. Like southern Algeria It is imperative to address this demand sustainably to avoid excessive energy consumption and associated environmental consequences.

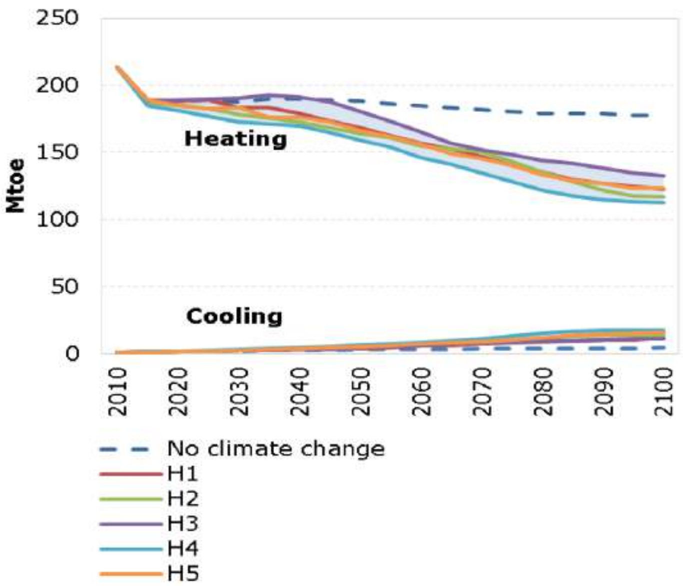


Figure 1. Annual energy demand (Mtoe1) for heating and cooling across the EU, assuming no adaptation, under a high warming scenario. H1- -5 is the demand according to using five different climate models. Also shown is a "no climate change" scenario with some reduction in residential heating needs thanks to efficiency improvements (particularly insulation). [4]

Traditional cooling systems heavily rely on fossil fuels and synthetic refrigerants, contributing to greenhouse gas emissions, air pollution, and ozone depletion. Sustainable cooling systems offer a way to mitigate these environmental impacts through energy-efficient technologies, environmentally friendly refrigerants and most importantly and the one we going to focus on in this study is the integration of renewable energy through solar cooling systems.

I.1 Energy-Efficient Cooling Technologies:

Variable Refrigerant Flow (VRF) Systems:

VRF systems optimize cooling capacity by adjusting the refrigerant flow rate based on the cooling requirements of individual zones. These systems offer precise temperature control, reduced energy consumption, and improved comfort levels compared to traditional fixed-speed systems.

High-Efficiency Air Conditioning Units:

Modern air conditioning units incorporate advanced technologies such as inverter compressors, improved heat exchangers, and intelligent controls. These features enhance energy efficiency, reduce operating costs, and minimize environmental impact.

Evaporative Cooling:

Evaporative cooling systems utilize the principle of water evaporation to provide cooling. These systems are highly energy-efficient, as they require less electricity compared to conventional air conditioners. They are particularly effective in dry climates and can be combined with other cooling technologies for hybrid solutions.

I.2 Sustainable Refrigerants:

Natural Refrigerants:

Natural refrigerants, including carbon dioxide (CO2), ammonia (NH3), and hydrocarbons (HCs), have low or zero global warming potential and ozone depletion potential. These refrigerants offer an environmentally friendly alternative to synthetic refrigerants, reducing the impact on climate change.

Hydrofluoroolefin (HFO) Refrigerants:

HFO refrigerants are a new generation of synthetic refrigerants designed to replace hydrofluorocarbons (HFCs) with high global warming potential. HFOs have significantly lower global warming potential and comply with environmental regulations, making them a sustainable choice for cooling systems.

I.3 Building Design and Passive Cooling Techniques:

Building Insulation:

Proper insulation minimizes heat transfer through walls, roofs, and windows, reducing the need for mechanical cooling. Well-insulated buildings improve energy efficiency and provide better thermal comfort for occupants.

Natural Ventilation:

Utilizing natural airflow and ventilation strategies can enhance cooling and reduce reliance on mechanical cooling systems. Techniques such as cross-ventilation, stack effect, and night flushing maximize the use of natural air movement to maintain comfortable indoor environments.

Green Roofs and Living Walls:

Green roofs and living walls provide natural insulation, reduce heat absorption, and improve air quality. These features contribute to passive cooling by reducing the heat island effect and enhancing thermal comfort in buildings.

I.4 Smart Building Management Systems:

Building Energy Management Systems (BEMS):

BEMS integrate various building systems, including cooling, lighting, and ventilation, to optimize energy consumption and occupant comfort. By monitoring and controlling energy usage, BEMS ensure efficient operation of cooling systems and reduce unnecessary energy waste.

Internet of Things (IoT) Integration:

IoT technology enables smart devices and sensors to collect and analyze data for intelligent cooling system operation. This integration allows for real-time monitoring, predictive maintenance, and energy optimization, resulting in more sustainable and efficient cooling solutions.

I.5 Renewable Energy Integration:

I.5.1 Solar Cooling Systems:

Solar cooling systems utilize solar energy to power the cooling process. They employ solar thermal collectors or photovoltaic panels to generate heat or electricity, which drives the cooling cycle. Solar cooling systems reduce reliance on grid electricity and contribute to a sustainable energy mix.

I.5.2 Geothermal Cooling Systems:

Geothermal cooling systems utilize the stable ground temperature as a heat sink for cooling. They circulate a refrigerant through underground pipes, harnessing the earth's natural heat sink properties. Geothermal cooling systems offer high energy efficiency and are suitable for both residential and commercial applications.

In Summary: To meet the rising cooling demand while reducing environmental effect, modern sustainable cooling systems are crucial. using technology that is energy-efficient.

The adoption of solar energy systems will be the major emphasis, as was already indicated.

II Solar Cooling Systems:

Solar cooling systems harness the power of the sun to provide cooling in residential, commercial, and industrial buildings, offering a sustainable alternative to traditional cooling methods. By utilizing renewable solar energy, these systems not only reduce electricity consumption but also contribute to mitigating climate change and promoting a greener future.

In this section, we will delve into the concept of solar cooling systems, exploring their significance, working principles, and potential benefits. We will examine how these systems leverage solar energy to drive the cooling process and discuss their role in promoting energy efficiency, reducing greenhouse gas emissions, and enhancing sustainability in the built environment.

III Classification of Solar Cooling Systems:

The solar cooling systems under research include several cooling methods, categories based on their working principles and components, which predominantly comprise of solar thermal cooling and solar photovoltaic cooling techniques. In this part of the thesis, we will delve into the concept of solar cooling systems: [5]

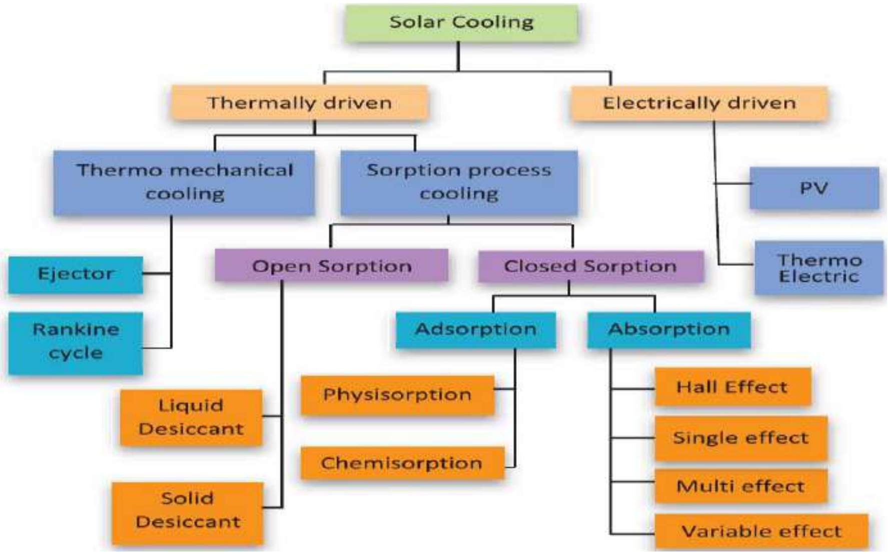


Figure 1: Classification of Solar Cooling Systems

III.1 Thermally Driven Systems:

Thermally driven solar cooling systems, also known as solar thermal cooling systems, are innovative technologies that harness solar energy to provide cooling and air conditioning in a sustainable and energy-efficient manner. These systems utilize the heat from the sun to drive a thermodynamic cycle that produces cooling effects, thereby reducing the reliance on conventional electricity-powered cooling systems. Let's delve deeper into thermally driven solar cooling systems and explore their various used techniques.

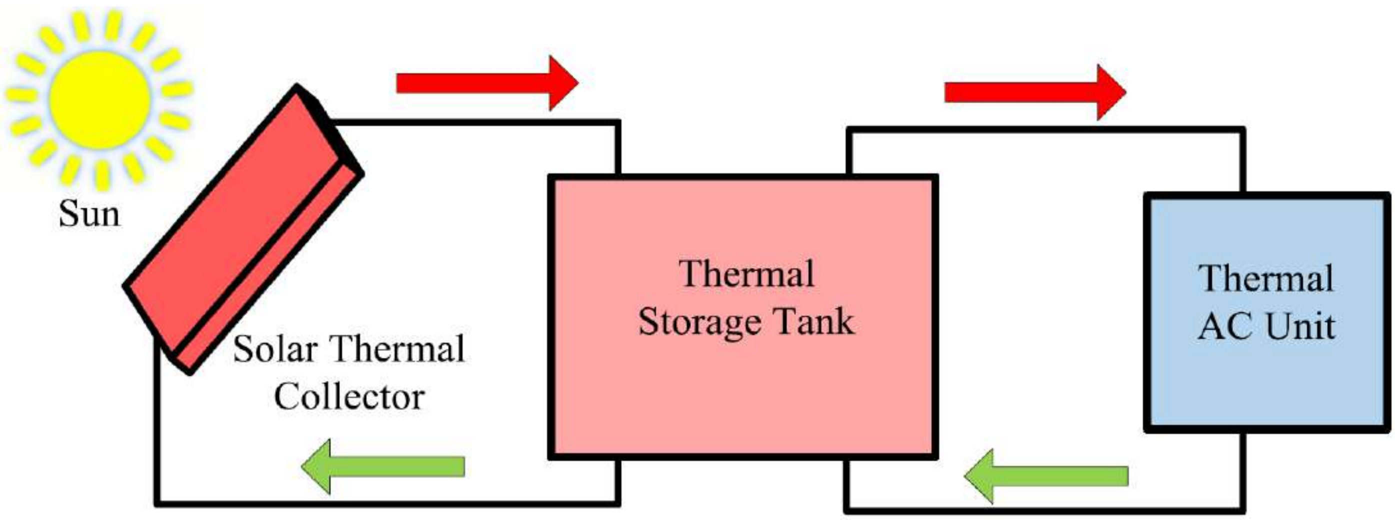


Fig. 5. Schematic diagram of Solar thermal cooling system

III.1.1 1. Solar Absorption Cooling Systems:

Solar absorption cooling systems operate on the principle of absorption refrigeration. They consist of solar thermal collectors, absorption chillers, heat exchangers, and cooling distribution systems. Solar collectors capture solar radiation, which heats a solution known as the absorbent. This thermal energy drives the absorption chiller, resulting in cooling. Absorption chillers typically use refrigerant-absorbent pairs, such as water-lithium bromide, to produce chilled water for cooling purposes.

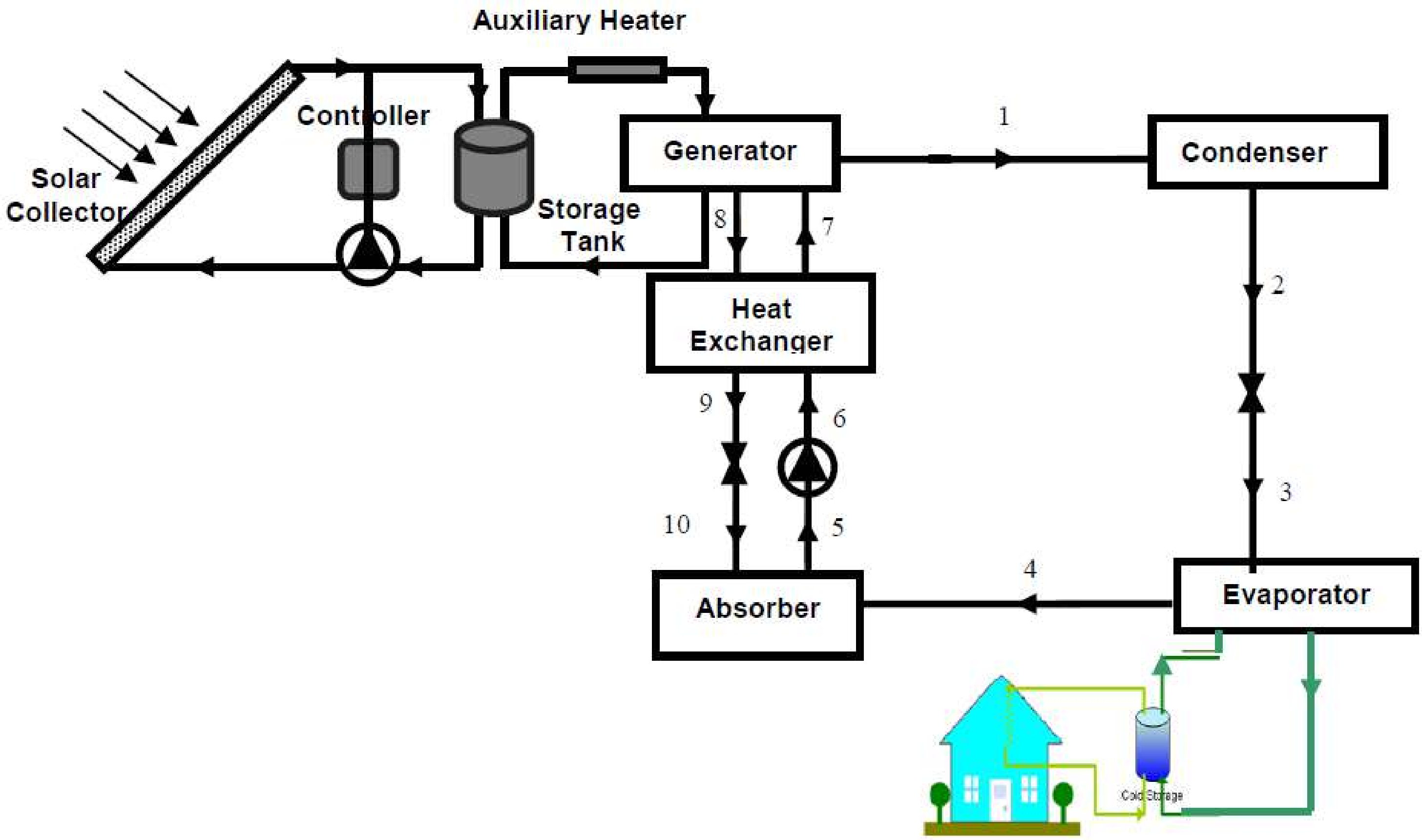


Fig. 1. The schematic illustration of the solar absorption refrigeration system

III.1.2 2. Solar Adsorption Cooling Systems:

Solar adsorption cooling systems also utilize solar thermal energy for cooling, but they employ adsorbent materials instead of refrigerant-absorbent pairs.

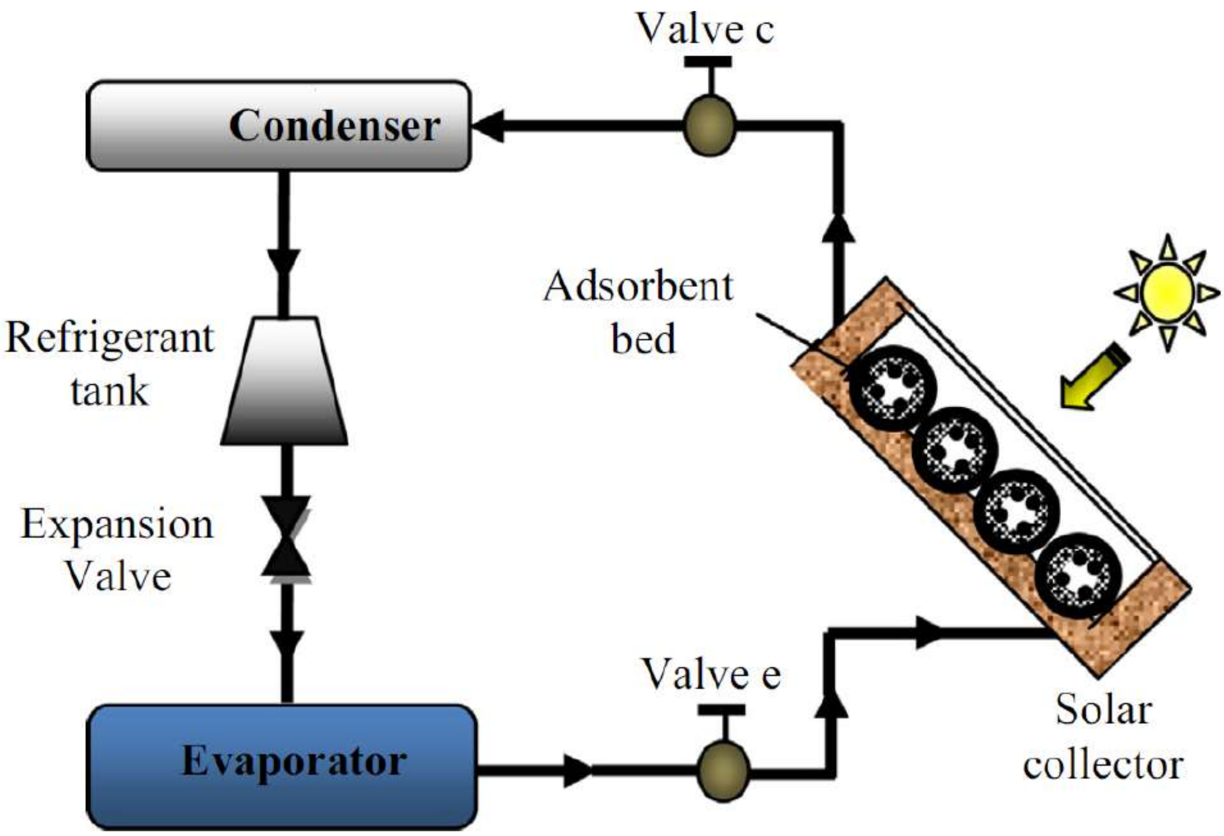


Fig. 1. Schematic Diagram of Solar Adsorption Refrigeration System

These systems typically use adsorbent materials such as silica gel or activated carbon, which have a high affinity for water. Solar collectors heat the adsorbent material, allowing it to adsorb water vapor. The desorption process, where the adsorbed water vapor is released, produces cooling. Solar adsorption cooling systems are suitable for smaller-scale applications and offer energy-efficient cooling solutions.

III.1.3 3. Solar Desiccant Cooling Systems:

Solar desiccant cooling systems focus on dehumidification as a means of providing cooling. These systems employ desiccant materials, such as silica gel or zeolite, to remove moisture from the air.

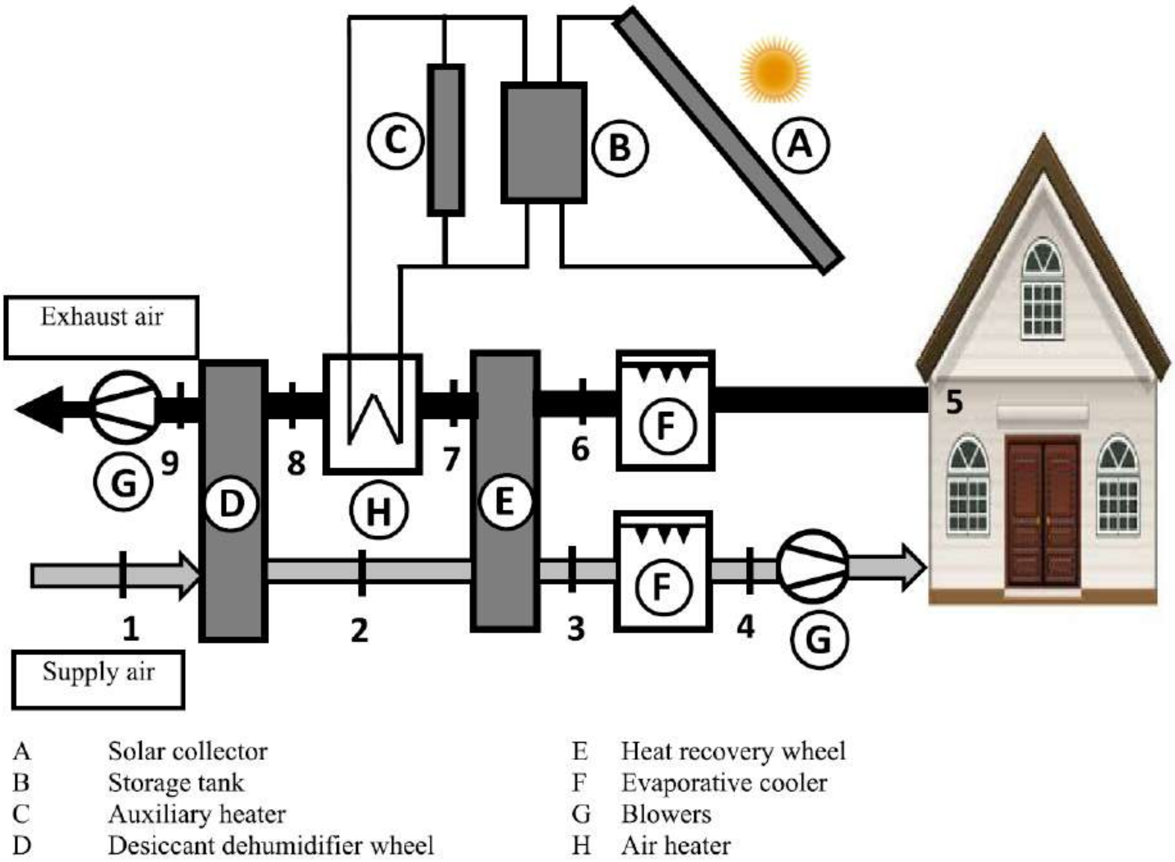


Figure. 7 The schematic diagram for the Solar Desiccant Cooling Systems with a solid desiccant wheel.

Solar thermal collectors capture solar energy, which is then used to regenerate the desiccant material by driving the desorption process. The dehumidified air is further cooled through a separate cooling system, such as an evaporative cooler or a conventional air conditioning unit. Solar desiccant cooling systems are particularly effective in humid climates, where humidity control is essential. [6]

III.2 Electrically Driven Systems:

III.2.1 Photovoltaic (PV)-Driven Cooling Systems:

PV-driven cooling systems utilize solar photovoltaic panels to convert sunlight directly into electricity. This electricity powers conventional electric air conditioning systems or cooling equipment. This type of solar cooling system is relatively straightforward to implement, as it requires the installation of PV panels to generate the necessary electrical power. PV-driven cooling systems are commonly used in residential and small-scale applications.

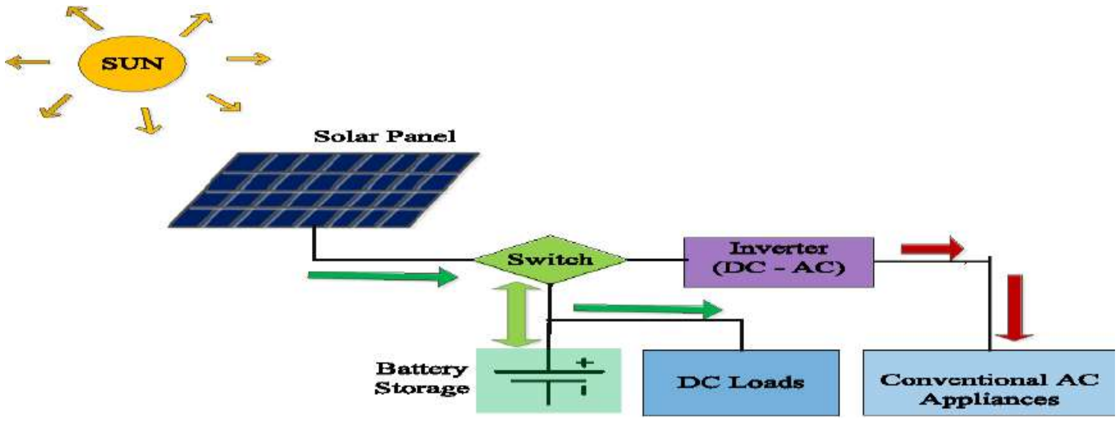


Figure 2: Solar Photovoltaic Cooling System

IV Advantages of Solar Cooling Systems:

Solar cooling systems offer several advantages that make them an attractive and sustainable choice for cooling needs:

1. Renewable Energy Source:

By utilizing solar energy, these systems rely on a renewable and abundant energy source, reducing dependence on fossil fuels and contributing to a greener energy mix.

2. Reduced Environmental Impact:

Solar cooling systems minimize greenhouse gas emissions and air pollution, helping to mitigate climate change and improve air quality.

3. Energy Efficiency:

Solar cooling systems are highly energy-efficient, leading to reduced energy consumption and lower operating costs compared to traditional cooling.

V. Modelling, Transient Simulation of Solar Thermal Based Air Conditioning System Using TRNSYS:

According to what we previously discussed, there are several solar thermal air conditioning systems. But for this specific case we chose the wide used technology of the absorption refrigeration cycle, to generate the performance of a household cooling system located in Hassi Messaoud, Ouargla Province, south of Algeria.

In order to obtain reliable simulation results we have decided to use TRNSYS software for this task.

V.1 Overview of TRNSYS simulation Program:

Designing an efficient and optimized system can be a daunting task for engineers and renewable energy experts. This is where TRNSYS simulation program comes in handy. TRNSYS simulation program is a software tool that helps professionals design and optimize renewable energy systems such as solar thermal systems, photovoltaic systems, low-energy buildings, and HVAC systems among others.

TRNSYS is an extremely flexible graphically based software environment used to simulate the model of transient systems. While the vast majority of simulations are focused on assessing the performance of thermal and electrical energy systems, TRNSYS can equally well be used to model other dynamic systems such as traffic flow, or biological processes.

TRNSYS allows engineers and researchers to simulate the functioning of complex energy systems. It can be used to model renewable energy systems, low-energy buildings, HVAC systems, and many other types of energy systems.

TRNSYS program is a state-of-the-art simulation tool that includes a wide range of components and libraries that can be used to model various types of energy systems. These components include solar thermal collectors, photovoltaic panels, wind turbines, heat pumps, boilers, chillers, and many others.

The TRNSYS simulation program provides an easy-to-use graphical interface for building models of energy systems. Users can drag-and-drop components onto a workspace and connect them together using wires. The program also includes tools for running simulations and analysing results. In addition to its user-friendly interface, TRNSYS has powerful scripting capabilities that allow users to customize their simulations and automate repetitive tasks.

TRNSYS is made up of two parts. The first is an engine (called the kernel) that reads and processes the input file, iteratively solves the system, determines convergence, and plots system variables. The kernel also provides utilities that (among other things) determine thermophysical properties, invert matrices, perform linear regressions, and interpolate external data files. The second part of TRNSYS is an extensive library of components, each of which models the performance of one part of the system. The standard library includes approximately 150 models ranging from pumps to multizone buildings, wind turbines to electrolysers, weather data processors to economics routines, and basic HVAC equipment to cutting edge emerging technologies. Models are constructed in such a way that users can modify existing components or write their own, extending the capabilities of the environment.

V.2 The perks of TRNSYS simulation for engineering and renewable energy:

TRNSYS simulation is an incredibly useful tool for engineering and renewable energy projects. It allows engineers and designers to virtually test different scenarios without physically building the systems, leading to cost savings, increased efficiency, and improved accuracy, also:

- Versatility and flexibility for modelling a wide range of energy systems
- Accurate simulation engine for precise predictions of system performance
- Extensive library of pre-built components for easy system modelling
- Integration of external models and user-defined components for enhanced adaptability
- Parametric analysis for optimization and efficient system configurations
- Visualization and reporting tools for effective analysis and communication

- ➢ Active user community for support, knowledge sharing, and collaboration opportunities
- ➢ Reliable tool for energy system modelling and simulation in designing sustainable systems

TRNSYS simulation program is a powerful tool for optimizing renewable energy systems and building energy efficiency. Its flexibility and extensive library of components make it an ideal choice for engineers and researchers alike. By using TRNSYS simulation, we can design buildings that are not only environmentally friendly but also cost-effective in the long run. As the world shifts towards renewable energy sources, TRNSYS simulation will undoubtedly play a crucial role in creating sustainable communities and helping us achieve our climate goals.

V.3 System Modelling:

The objective is to develop a TRNSYS model of a solar absorption cooling system for a building located in Hassi Messaoud.

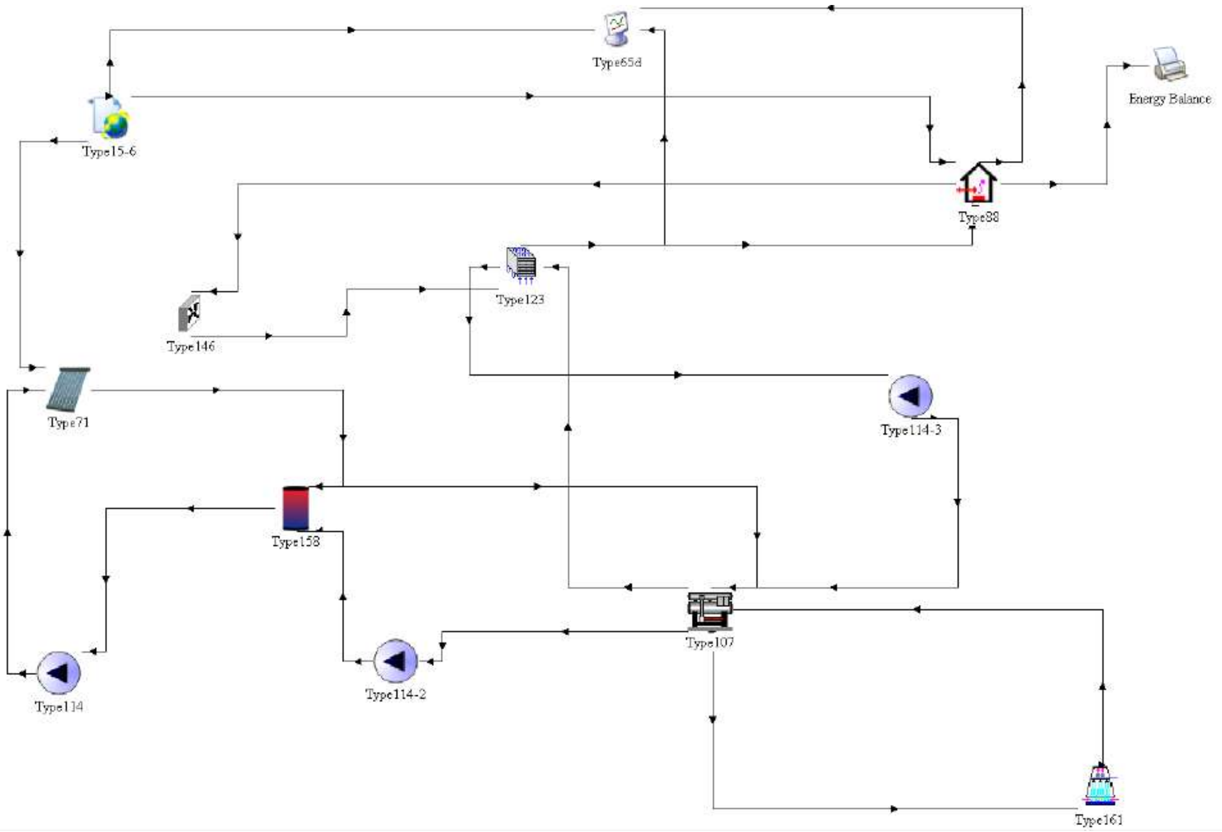


Figure.5 The absorption based solar cooling system modelled using TRNSYS

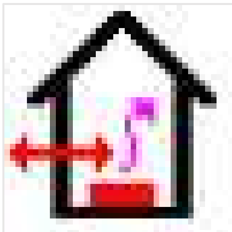
The highlighted work in Figure.5 is divided into two subsystems: solar heating and absorption cooling. A hot water storage tank connects these two subsystems, allowing heat to be transferred from the solar heating subsystem to the absorption cooling subsystem.

The cooling system consists of an evacuated tube solar collector that delivers hot water to an absorption chiller, which then provides chilled water to an air-cooling coil. A fan blows air through the cooling coil. The chiller rejects heat to the surrounding air through a cooling water circuit and a dry cooling tower. A stratified tank collects hot water from the collector and stores it to enable the chiller to run when there is insufficient solar energy (usually at night). Water is circulated throughout the system using pumps. The solar collector circuit is programmed to work only when heat is available and needed by the chiller or storage tank; the remaining components of the system runs constantly throughout the cooling season to keep the room temperature at the specified setting.

V.4 **Modell Description by Component (Types):**

The TRNSYS inbuilt components that were used to carry out the simulation. This section gives a brief about the key components used:

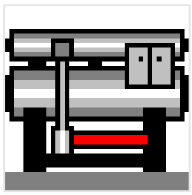
V.4.1 LUMPED CAPACITANCE BUILDING (TYPE 88)



TRNSYS Model: Type 88

This component models a simple lumped capacitance single zone structure subject to internal gains. It differs from the Type12 simple building model in that it makes no assumption about the control scheme. Furthermore, it neglects solar gains and assumes an overall U value for the entire structure. Its usefulness comes from the speed with which a building heating and/or cooling load can be added to a system simulation.

V.4.2 *HVAC* -Absorption Chiller (Hot-Water Fired, Single Effect):

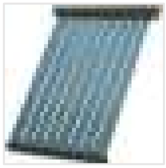


TRNSYS Model: Type 107

Type107 uses a normalized catalog data lookup approach to model a single-effect hot-water fired absorption chiller. "Hot Water-Fired" indicates that the energy supplied to the machine's generator comes from a hot water stream. Because the data files are normalized, the user may model any size chiller using a given set of data files. Example files are provided.

V.4.3 Evacuated Tube Collector

TRNSYS Model: Type 71



This TRSNSYS inbuilt type is used to model evacuated tube thermal solar collector. The main difference between this component and Type 1, used to model flat plate collectors, is the way in which it treats incidence angle modifiers (IAMs). Type 71 reads a text file containing a list of transverse and longitudinal IAMs corresponding to different values of transverse and longitudinal incidence angles

V.4.4 Weather Data Reading and Processing-Meteonorm Files (TM2):

TRNSYS Model: Type 15

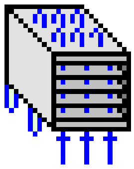
This component serves the purpose of reading data at regular time intervals from an external weather data file, interpolating the data (including solar radiation for tilted surfaces) at time steps of less than one hour, and making it available to other TRNSYS components. The model also calculates several useful terms including the mains water temperature, the effective sky temperature, and the heating and cooling season forcing functions. This version of Type15 reads data in the format generated by Meteonorm, which is identical to the Typical Meteorological Year (version 2) standard form.

V.4.5 Thermal Storage -Constant Volume -Liquid Storage- Vertical Tank No Hx:

TRNSYS Model: Type 158

This subroutine models a fluid-filled, constant volume storage tank with a vertical configuration. The fluid in the storage tank interacts with the environment (through thermal losses from the top, bottom and edges) and with up to two flow streams that pass into and out of the storage tank. The tank is divided into isothermal temperature nodes (to model stratification observed in storage tanks) where the user controls the degree of stratification through the specification of the number of "nodes". Each constant-volume node is assumed to be isothermal and interacts thermally with the nodes above and below through several mechanisms: fluid conduction between nodes and through fluid movement (either forced movement from inlet flow streams or natural destratification mixing due to temperature inversions in the tank). Auxiliary heat may be provided to the tank through the use of inputs to the model.

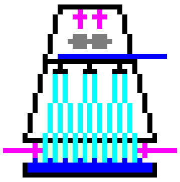
V.4.6 HVAC-Cooling Coils:



TRNSYS Model: Type 123

The simple cooling coil model provides a good estimation of the performance without the detailed geometric characteristics of the coil. The parameters of the model are only thermodynamic properties of the coil, which require no specific manufacturer's data. The simulation model is based on the ASHRAE Secondary Toolkit and modifications proposed by Chiller, et al. There are two versions of the simple cooling coil model. This version assumes that the coil is always either totally dry or wet.

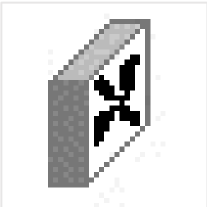
V.4.7 HVAC-Cooling Towers:



TRNSYS Model: Type 161

Type 161 estimates the performance of a cooling tower without any detailed parameters of the tower configuration. Instead, it uses the design inlet and outlet conditions to calculate an overall heat transfer coefficient (UA) for the tower and then uses that UA value to estimate performance at other inlet conditions. This version calculates the performance of a single speed cooling tower that provides cooling to the fluid stream with the fan on and fan off (natural convection). In this version of the cooling tower, the desired temperature of the fluid leaving the tower is an input. The model then determines which speed (off, natural convection, or fan operating) creates a temperature colder than the setpoint. If the capacity needed to cool the fluid down to the setpoint exceeds the capacity of the tower at the inlet conditions, the model calculates the leaving fluid temperature with the fan on.

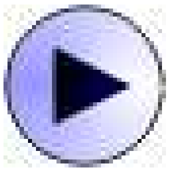
V.4.8 Hydronics-Fan- Constant Speed:



TRNSYS Model: Type 146

Type 146 models a fan that is able to spin at a single speed and thereby maintain a constant volumetric flow rate of air. As with most pumps and fans in TRNSYS, Type 146 takes mass flow rate as an input but ignores the value except in order to perform mass balance checks. Type 146 sets the downstream flow rate based on its rated flow rate parameter and the current value of its control signal input.

V.4.9 Hydronics-Pumps -Single Speed:



TRNSYS Model: Type 114

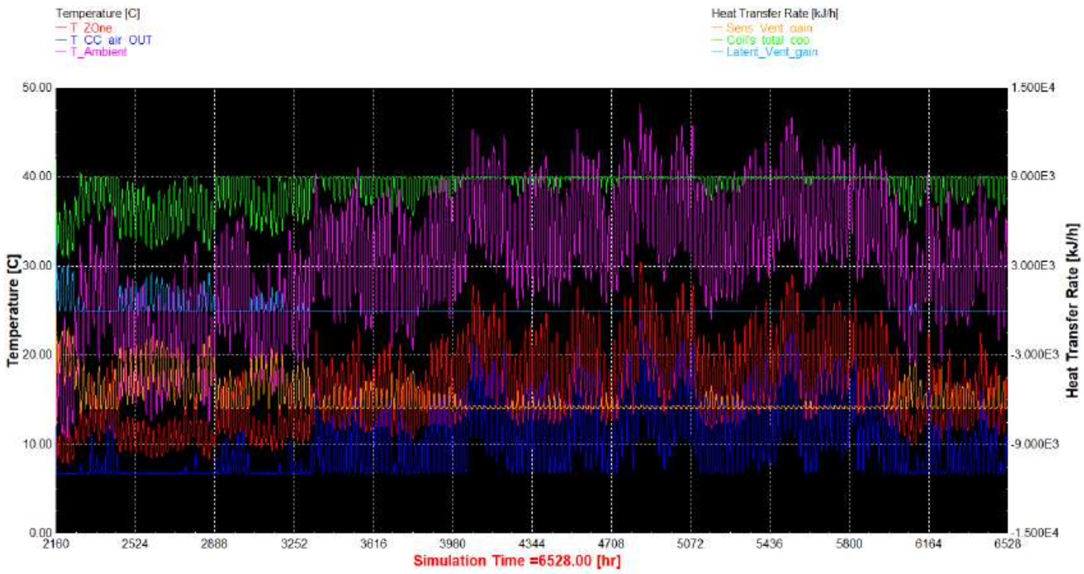
Type114 models a single (constant) speed pump that is able to maintain a constant fluid outlet mass flow rate. Pump starting and stopping characteristics are not modeled, nor are pressure drop effects. As with most pumps and fans in TRNSYS, Type114 takes mass flow rate as an input but ignores the value except in order to perform mass balance checks. Type114 sets the downstream flow rate based on its rated flow rate parameter and the current value of its control signal input.

V.4.10 Output-Online Plotter:

TRNSYS Model: Type 65 The online graphics component is used to display selected system variables while the simulation is progressing. This component is highly recommended and widely used since it provides valuable variable information and allows users to immediately see if the system is not performing as desired. The selected variables will be displayed in a separate plot window on the screen. In this instance of the Type65 online plotter, data sent to the online plotter is automatically printed, once per time step to a user defined external file. Unit descriptors (kJ/hr, kg/s, degC, etc.) are NOT printed to the output file.

V.5 Simulation results:

The TRNSYS simulation was run with 1h time step during the cooling season (April – September) and the results obtained were. Sensible energy gain from ventilation (Q_Sens_Vent) and Cooling Coil's Total Cooling (Coil_Total_cooling) through the months of: April,May,June,July,August andSeptember.



CHAPTER III:

Machine Learning Techniques and The Implementation of The Artificial Neural Network

I Machine Learning

In context of the data mining step, it is important to choose the correct approach for tackling the task appropriately. This is often done using machine learning methods. A major difference between humans and computers has been for a long time that a human beings tend to automatically improve their way of tackling a problem. Humans learn from previous mistakes and try to solve them by correcting them or looking for new approaches to address the problem. Traditional computer programs do not look at the outcome of their tasks and are therefore unable to improve their behaviour. The field of machine learning addresses this exact problem and involves the creation of computer programs that are able to learn and therefore improve their performances by gathering more data and experience.

The first scientist to create a self-learning program was A. Samuel in 1952, who created a program that became better at playing the game checkers with the number of games played. In 1967, the first pattern recognition program was able to detect patterns in data by comparing new data to known data and finding similarities between them.

Since the 1990's machine learning is used in data mining areas, adaptive software systems as well as text and language learning fields. As an example: A computer program that gathers data concerning the customers of an e-commerce shop and creates better personalized advertisements out of these pieces of information has the ability to acquire new knowledge and comes close to being artificial intelligence. Furthermore, machine learning systems are normally classified by their underlying learning strategies, which are often identified by the amount of inference the computer program is able to perform.

I.1 **Linear Regression**

linear regression, which means that our goal is to find some linear combination of the $x_1, \ldots, x_D$ input values that predict our target y.

Suppose we have an input $x \in R^D$ and a continuous target $y \in R$. Linear regression determines weights wi ∈ R that combine the values of x_i to produce y. $y = w_0 + w_1 x_1 + \ldots + w_D x_D$

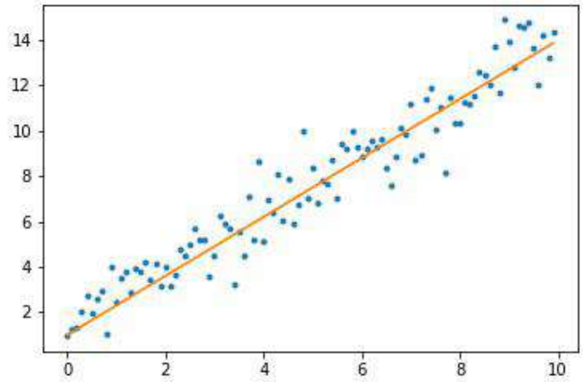


Figure 1 Data set with clear trend, best fitting line included

I.2 Decision Tree

A Decision Tree is a classification technique that focuses on an easily understandable representation form and is one of the most common learning methods. Decision Trees use data sets that consist of attribute vectors, which in turn contain a set of classification attributes describing the vector and a class attribute assigning the data entry to a certain class. A Decision Tree is built by iteratively splitting the data set on the attribute that separates the data as well as possible into the different existing classes until a certain stop criterion is reached. The representation form enables users to get a quick overview of the data, since Decision Trees can easily be visualized in a tree structured format, which is easy to understand for humans.

One of the first algorithms concerning Decision Tree training were the Iterative Dichotomiser 3 (ID3) and its successor the C4.5 algorithm, both developed by Ross Quinlan in 1986 and 1993 [7, 8]. These algorithms formed the basis for many further developments. Decision trees are directed trees, which are used as a decision support tool. They represent decision rules and illustrate successive decisions.

In Decision Trees, nodes can be separated into the root node, inner nodes, and end nodes, also called leafs. The root node represents the start of the decision support process and has no incoming edges. The inner nodes have exactly one incoming edge and have at least two outgoing edges. They contain a test based on an attribute of the data set.

For instance, such a test might ask: “Is the customer older than 35 for the attribute age?”. Leaf nodes consist of an answer to the decision problem, which is mostly represented by a class prediction. As an example, a decision problem might be the question whether a customer in an online shop will make a purchase or not, with the class predictions being yes and no. Leaf nodes have no outgoing and exactly one incoming edge. Edges represent the decision taken from the previous node.

II Introduction to Neural Networks

The human brain is considered the most complex computational component known to man. The multiple functionalities of the brain, such as thinking, saving, and problem solving, have inspired many researchers who have attempted to create a computational model that matches the functionality of the brain: they have obtained neural calculus. So the neural networks are known devices of their power and their speed in the execution of the operations they present many advantages compared to the more conventional computing method. In theory, neural networks are data processing techniques essentially understood at present; they should be part of the toolbox of all scientists who want to make the most of the data they have, including running forecasts, designing predictive models, recognizing models or signals, and so on. The number of possible neural models is however very large, with more complex models more closely representing the function of human neurons. The artificial neural networks considered here, and those that are generally used for systems and control, tend to be much simpler and easier to physically perform [9]. ANN meet several criteria of modern enterprise, including finding solutions quickly to increasingly complex problems. In addition, ANN are robust, versatile and adaptable. This technique is part of the design effort and focuses on the development of learning algorithms to provide a system of autonomy and adaptive capacity. Sometimes these intelligent systems even come to "discover" new solutions to complex and difficult to access problems for a human brain. [10] The purpose of this chapter is to explain under what circumstances neural networks are preferable to other data processing techniques and for what purposes they may be useful after general understanding.

II.1 **Properties of the biological neuron**

A biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. We will present in this part the characteristics of this basic unit of the nervous system from the biology to modeling (the artificial neuron). The human brain contains about 100 billion neurons. They break down into three main regions: cell (or nerve cell), cell body (the soma) and nucleus. The cell body analyzes and integrates the received information it ramifies to form what one names the dendrites. It is through the dendrites that the information is conveyed from outside to the soma, body of the neuron. So the dendrites ensure the reception of the nerve impulse sent by the other neurons. The information processed by the neuron then travels along the (unique) axon to be transmitted to the other neurons. Transmission between two neurons is not direct. In fact, there is an intercellular space of a few tens of angstroms (10-9 m) between the axon of the afferent neuron and the dendrites (a dendrite) of the afferent neuron. The junction between two neurons is called the synapse (Figure 1). Synapses provide the connection between neurons via chemical mechanisms of neurotransmitter exchange between dendrite branches and axon terminations of other neurons [11]. So it can be said that, a neuron can be schematized thus, it makes the sum of all the information that it receives and it emits a signal provided that the sum is sufficiently high. The need for information from outside is very necessary for brain learning [12].

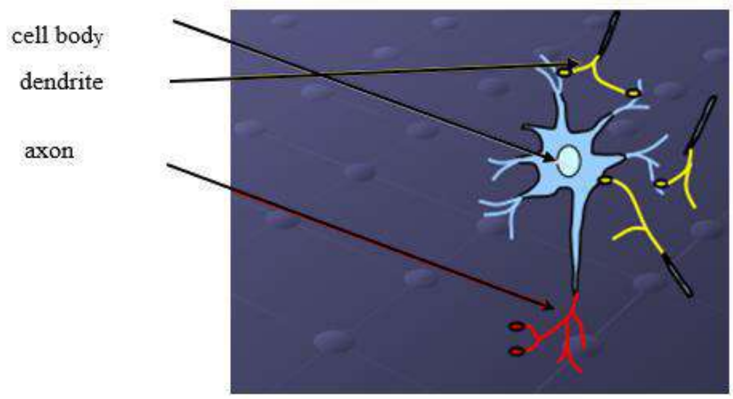


Figure 2 Biological structure of neurons

II.2 The artificial neuron

Figure 2 shows the biological neuron versus artificial neuron. Each artificial neuron is an elementary processor. It receives a variable number of inputs from upstream neurons. Each elementary processor has a single output, which then branches to feed a variable number of downstream neurons, each connection is associated with a weight.

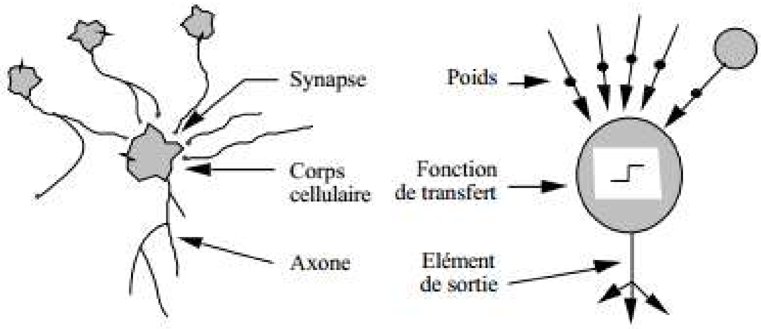


Figure 3 Biological Neuron / Artificial Neuron Mapping

What is an artificial neuron? This is the basic element of a neural network.

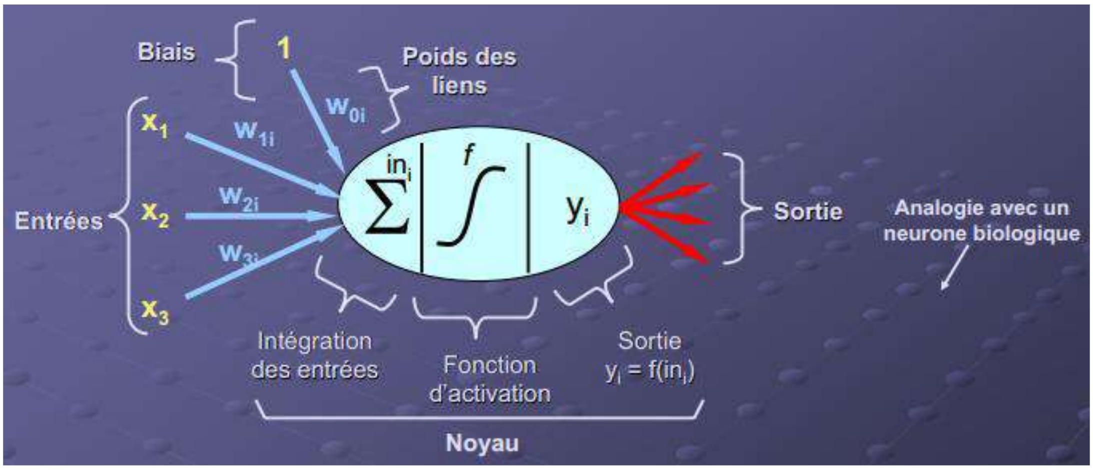


Figure 4 The generic artificial neuron

Inputs: Directly system inputs that may coming from other neurons.

Core: Integrates all inputs and bias and calculates neuron output according to an activation function that is often non-linear to give greater learning flexibility.

Output: Directly one of the outputs of the system or can be distributed to other neurons.

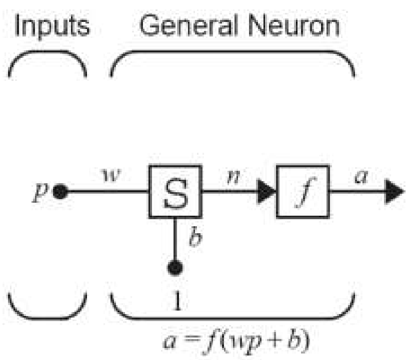
Bias: Input always 1 which allows to add flexibility to the network by allowing to vary the neuron trigger threshold by adjusting the bias weight during learning.

Weight: Multiplying factors that affect the influence of each input on the output of the neuron. The numerical value of the weight associated with a connection between two units reflects the strength of the relationship between these two units. If this value is positive the connection is called exciter, otherwise it is called inhibitory [13].

II.3 The neural network

A neural network is a network or circuit of neurons, or in a modern sense, an artificial neural network, composed of artificial neurons or nodes. Thus, a neural network is either a biological neural network, made up of real biological neurons, or an artificial neural network, for solving artificial intelligence (AI) problems. The Artificial Neural Network (ANN) is a method of artificial intelligence inspired by the biological structure - a brain. Similarly, to this structure, the artificial neural network consists of a body called processing element, inputs and outputs. The meaning of each entry is multiplied by the weight and with bias, they go to the body of the cell, the treatment element. In the first step, the multiplied inputs are summed by the summation function and in the second step they are propagated by the transfer function to an output. They are used to solve the following tasks: association, classification, grouping, pattern recognition, image processing, control, optimization and modeling, these artificial networks may be used also for predictive modeling, adaptive control and applications where they can be trained via a dataset. Self-learning resulting from experience can occur within networks, which can derive conclusions from a complex and seemingly unrelated set of information [14].

Neural networks learn by adjusting the connection weights during training. Neurons are all-or-none devices that "fire," or transmit a message to the next connected neuron, based on meeting or exceeding some threshold [15]. The basic design of the artificial neuron is very simple. It consists of three basic types of layers: an input layer, a hidden layer, and an output layer. The hidden layer can have one or more layers, usually up to three depending on the complexity of the problem solved. The weighted signal is sent to the hidden layers where it did most of the calculations. Finally, it is followed at the exit layer [16].



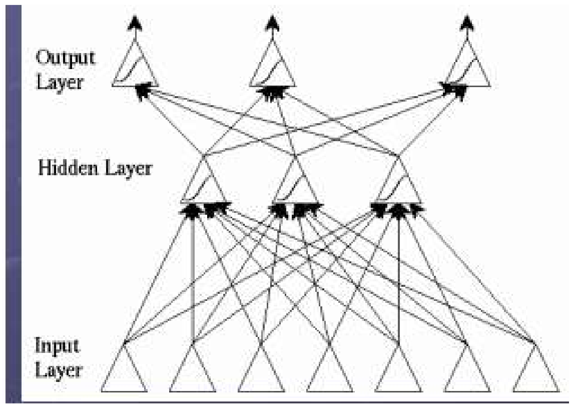


Figure 5 Structure of a neural network / Layers of artificial neural network

Artificial neural networks are a well-understood technique for data processing. These techniques fit perfectly into control strategies. Indeed, they perform identification, control or filtering functions, and extend the traditional techniques of nonlinear automation to lead to more efficient and robust solutions. They are highly connected networks of elementary processors operating in parallel. Each elementary processor calculates a single output based on the information it receives. Any hierarchical network structure is obviously a network [9]. We can also say that artificial neural networks are mathematical models that reproduce in a simple way the structure of biological neural networks, whose elements are called neurons and whose connections between neurons are called links. The principle of neural networks consists in using the information provided by health indicators of the machine or of the monitoring system, temperature, vibratory spectrum, pressure, flow ..., in order to perform recognition and identification of faulty modes or degraded states of this system. Neural networks are used in predictive maintenance to estimate and predict the trend of system state degradation using system characteristic indicator information. Artificial neurons are processing units that rely on the principles of biological neuron functions. This means that the artificial neuron receives information, elaborates on it, and then transmits further to other processing units. Connections between neurons, corresponding to biological synapses, are called weights and are especially important for learning and other adaptation processes that occur in neural networks (Figure III.5). According to biological principles, a neuron in the ANN receives one or more inputs and transmits one output that is copied and forwarded to further units. The process of training an ANN corresponds to the learning process in the human brain – the network draws conclusions of future outcomes based on previous experience. Neurons (units) in the artificial network are organized into layers. A basic ANN consists of an input, hidden, and output layer of neurons. Increasing the number of hidden layers and changing the way that neurons are interconnected can lead to greater complexity of neural networks. Input and output layers in the network serve to represent the data that is fed into the network and received as the network result, respectively, whereas the units in hidden layers apply functions and perform calculations on the presented data. It has already been accentuated that ANNs are nonlinear computational techniques. Prior to analysis, data are scaled (most software tools use 0 to 1 scaling of the data), in order for different input parameters to be comparable according to their influence on the outputs. Signals from input and hidden layers are transferred to hidden and output layers that are subsequently positioned. Neurons in the hidden layer apply certain activation function to the transmitted signal that they receive, and most commonly it is sigmoid function. In each neuron, input signals are [30] multiplied by their corresponding weights and converted to the

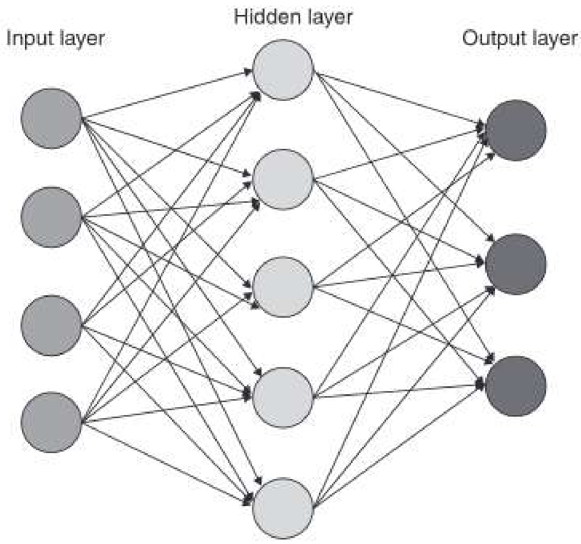


Figure 6 Simplified view of the neural network organization (all neurons are fully connected)

Output by an activation (transformation) function in the following way:

$$Yq = \Sigma Wp, q * Xp$$

II.3.1 Construction and testing the ANN

Now we have covered all the elements that ANNs contain, we can give an overview of the construction process of the ANN **(**Figure III.6**).** The first step in this process is definition of ANN architecture (topology); the number of neurons in the input, output, and hidden layers, as well as the number of hidden layers. The number of neurons in the input and output layers are determined by the studied problem and it has already been accentuated that the number of neurons in the input layer (the number of input variables) should be kept to its minimum. The most difficult task at this stage is selection of the number of hidden layers and the number of neurons in the hidden layer. The trial-and-error approach is still commonly used to resolve this issue, as well as various optimization techniques. Once the network architecture (topology) is defined, it is often necessary to select the type of transfer (activation) function, learning rate, smooth factor, etc. Some of these parameters are predefined in the software used, and some need optimization.

We should always bear in mind the difference between the ANN model (architecture, topology, and arrangement) and the ANN algorithm (method used for computation of outputs based on inputs).

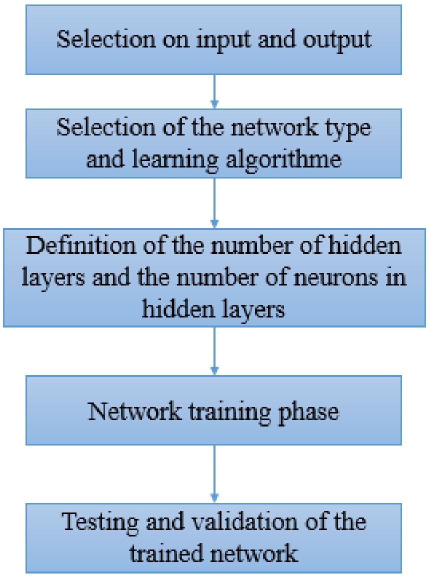


Figure 7 The most important steps in ANN construction and testing

The next step is the actual training of the network. The usual practice is to divide data into three sets: training, testing, and validation. Training and test data sets are presented to the network first, during the training process. Training data are used to define and optimize neuron weights, whereas test data are kept aside by the network and used periodically to check predictive ability of the network (during the training process). Training data should cover as much as possible of the data variability. As mentioned previously, once the test error stops decreasing or starts to rise, it is indicative of the network over fitting and the training process should be stopped. If network over fitting is likely to occur, it is advisable to reduce the number of hidden layers or neurons in those hidden layers. Validation data are completely kept aside during the training process and are used only when the training process is complete. Validation data contain samples that were not presented to the network during the training process, but it is important to note that these samples should be within the data space defined by the training data. Division of data in these three sets (training, testing, and validation) is not an easy task and there are no strict rules on this issue, for example that 65% of data should be used for training, 25% for testing, and 10% for validation [17].

Developed ANNs are often tested using the cross- validation approach. This means that the whole data set is divided into equal sized subsets. The network is then trained the number of times that is equal to the number of subsets. In the process of validation, data set values predicted by the network are compared to those experimentally obtained, and usually correlation coefficient R is calculated to check the appropriateness of the prediction.

Where experimentally obtained x values are compared to predicted (by the network) y values. ANNs are, in general, used to predict outputs for the data not input into the network during its training and testing. Therefore, it is an interpolation method. The prediction ability of the ANN is restricted to space limit of input/output data presented to the model for training. Extrapolation outside this data space should not be performed. This should be borne in mind when experiments are planned.

In order to obtain relevant and reliable results by using ANN models, it is recommended that the number of experimental runs is 10 times greater in comparison to the number of inputs; or, if this is not feasible, at least 2 to 3 times the number of inputs. It is, therefore, practical to first conduct screening experimental design, in order to select the most significant input variables that influence output properties, since this leads to a reduction in the number of the ANN inputs (and examples number of the needed for the network training at the same time). There are many possibilities to optimize an ANN.

II.3.2 Limitation of the ANN

A considerable amount of data is often needed to build a reliable ANN model. Many important steps in building and testing of the ANN are prone to errors and difficulties in optimal determination. In addition, each software tool used is different and has its own distinctive properties. It is always recommended to first thoroughly investigate the principles upon which the neural networks models are built and tested in the software used. [18].

II.3.3 Fields of application of artificial neural networks

Today, artificial neural networks have many applications in a wide variety of sectors: • Image processing: character and signature recognition, image compression, pattern recognition, encryption, classification, etc. • Signal processing: filtering, classification, source identification, speech processing ... etc. Control: process control, diagnostics, quality control, robot servoing, automatic guidance systems for automobiles and planes ... etc. • Defense: missile guidance, target tracking, face recognition, radar, sonar, lidar, data compression, noise suppression ... etc. • Optimization: planning, resource allocation, management and finances, etc. • Simulation: simulation of the flight, simulation of black box, meteorological forecast, copy of model ... etc. In particular, in the field of optimization, we can distinguish the application of ANN to perform Predictive Maintenance. With the vast amount of time series data constantly being produced by machines in factories and plants, such as sensor and control values, there is a lot of information available to predict breakdowns of the machines. There are different sensory systems from simple inductive capacitors to proximity sensors and photoelectric or laser sensors and advanced vibration sensors to industrial systems such as thermo-graphic cameras, vision systems, process control systems and measurement sensors capable of capturing large amount of machine data available for further development. Artificial neural networks show promising results as a robust tool for evaluating these data to support predictive maintenance activities. Mainly Multilayer Perceptron's (MLPs) are used for diagnosing bearing defects, induction motors, non-destructive evaluation of performance and degradation of check valves and in real-time robotic systems.

II.3.4 Architecture of Neural Networks

The architecture of neural networks consists of a network of nonlinear information processing elements that are normally arranged in layers and executed in parallel. This layered arrangement for the network is referred to as the topology of a neural network. These nonlinear information processing elements in the network are defined as neurons, and the interconnections between these neurons in the network are called synapse or weights. A learning algorithm must be used to train a neural network so that it can process information in a useful and meaningful way. Depending on the type of connections (architectures), the ANN are grouped into two categories (see Figure III.7).

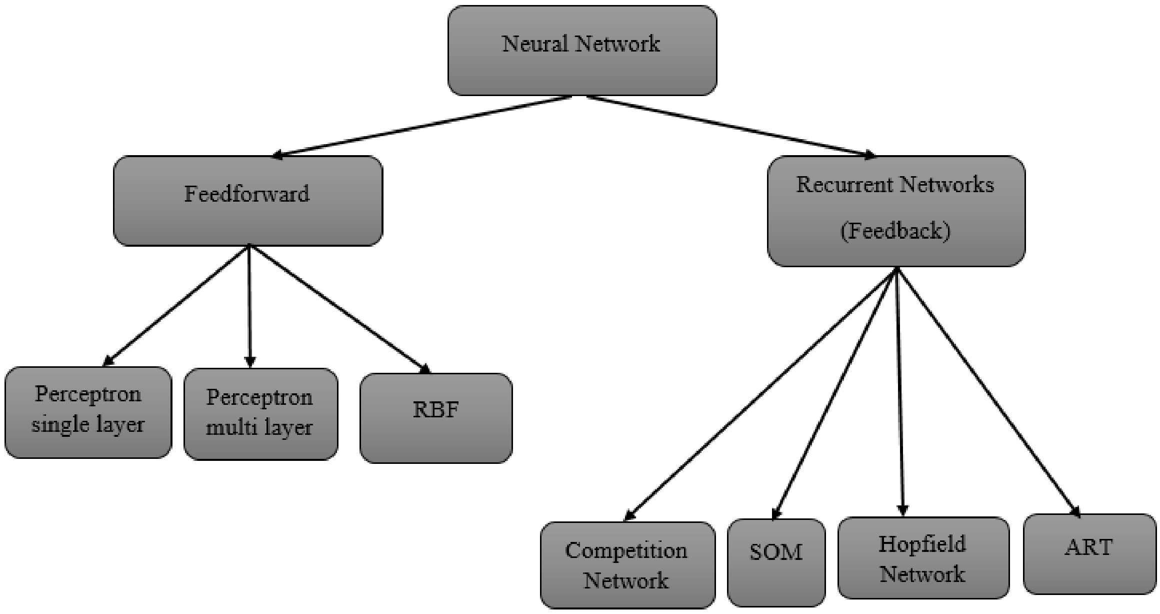


Figure 8 Different types of unconnected and recurrent networks

II.3.5 Feedforward Network

In the following example, the inputs represent values (yes/no) of four of the features used to determine if a patient who has suffered an animal bite needs to be treated prophylactically for rabies. Each connection is weighted and these weights evolve during training. This simple model is similar to the perceptron in Figure III.7, except that it includes a hidden layer and that is propagates error back to the input weights during training. The hidden layer provides additional knowledge representation internal to the system, and can provide improvements in classification performance [19]

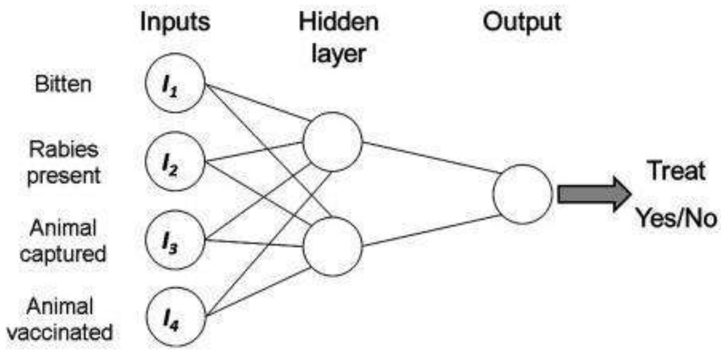


Figure 9 A feed-forward, back-propagation neural network

This network uses the feed-forward approach of the perceptron, but includes the ability to provide (propagate) feedback about the accuracy of its output to the components.

II.3.6 Recurrent Networks (Feedback)

The architecture of neural connections can be described as a combinational feed forward network. In order to insert context, as well as to provide the possibility for feedback self-correction, some networks add a form of state feedback called back propagation. Once a feedback system is in place, the possibility of machine learning is present. In the process of machine learning, system behavior and processing are altered based on the degree of approximation achieved for any specified goal. In today's systems, the human programmer sets the specified goals. Applied system feedback, however, allows the AI system to develop alternative approaches to attaining the set goals. The implementation of feedback systems can be on a real-time. An artificially produced machine-style implementation of synapses and neurons (neural network) can be set up to operate in the present state, next state, or via synaptic weightings implemented as matrices. Computer programming languages and systems have been designed to facilitate the development of machine learning for artificial neural network systems. Recurrent and reentrant neural networks implement connections from lower layers of neuron into upper layers of the network of neurons. Such a configuration can be used to provide a temporal/sequential dimension to neural network processing. From a control theory point of view, these connections can be envisioned as feedback

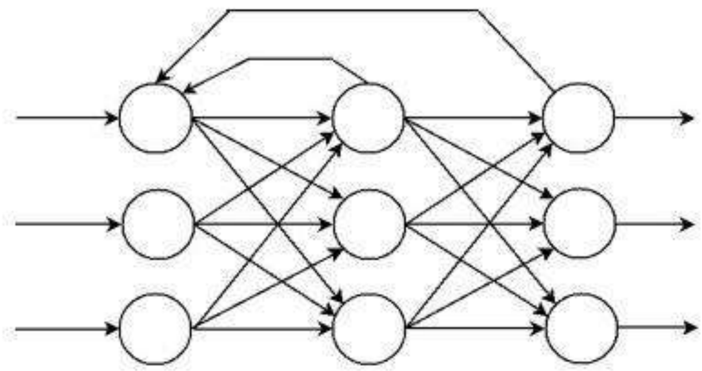


Figure 10 Partially recurrent neural network connections

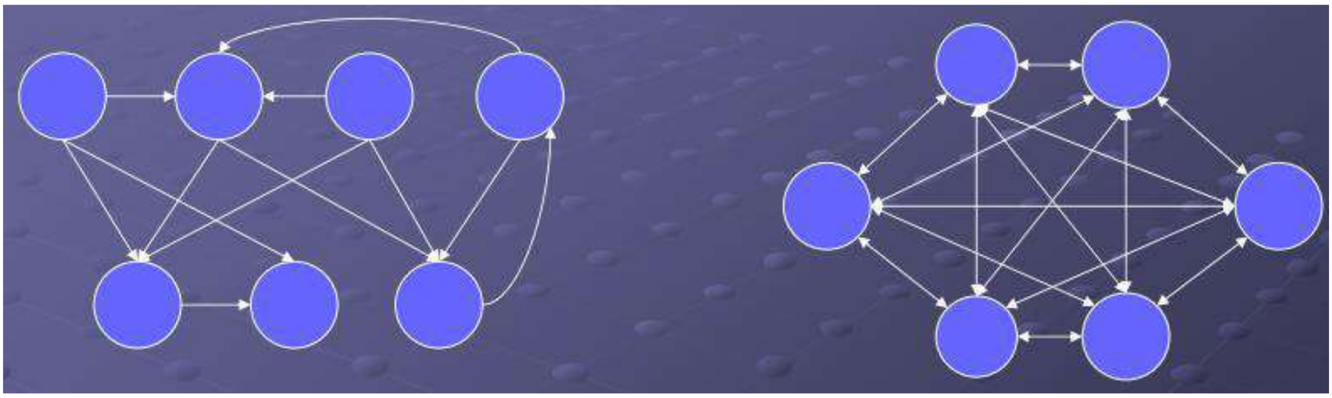


Figure 11 Interconnexion structure or a feedback network model

III . Integration Of Machine Learning Technique of ANN Into Our Case Study of a building’s Cooling System:

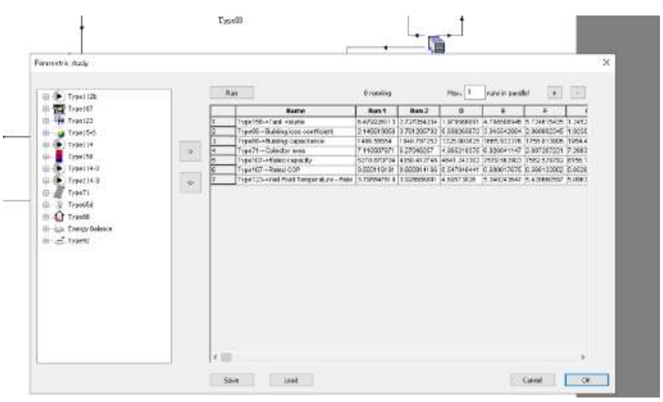
In the pursuit of energy efficiency and optimized building performance, the integration of machine learning techniques has emerged as a valuable approach. In this case study, we utilize the integration of Artificial Neural Networks (ANN) into a building's cooling system. By leveraging ANN's capabilities, we can enhance the system's efficiency, predictive capabilities, and overall performance. By a Training a machine learning model to predict the outputs of a building’s cooling energy

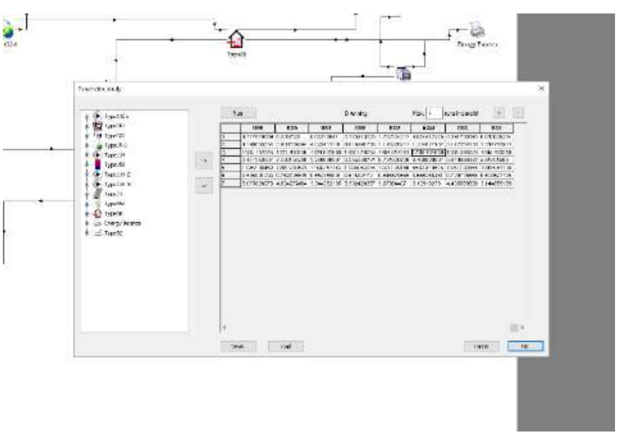
III.1 **Methodology for Training a Machine Learning Model to Predict Building Cooling Energy Outputs:**

III.1.1 Data Collection Using TRNSYS:

historical data was Collected related to the building's cooling system, as well as relevant features such as: “Tank volume” “Building loss coefficient” “Building capacitance” “Collector area” “Rated capacity” “Rated COP” “Inlet Fluid Temperature – Rated”, and “TIME”. To Ensure the data is representative in different operating conditions and the accuracy of the trained model. A parametric study has been established for the cooling system in TRNSYS with 2000 Runs been made, all with different Parameters (Inputs).

The acquired data consists of the variable parameters and their outputs (Q_Sens_Vent and Coil _Total_Cooling) with each single Run.





III.1.2 Data Processing Using Spyder Python:

The collected data was then Cleaned by handling missing values, outliers, and inconsistencies. Also normalize or scale the data to ensure uniformity and improve model performance. This operation was done using Excel then exported as Comma separated values file (.csv) Into Spyder program.

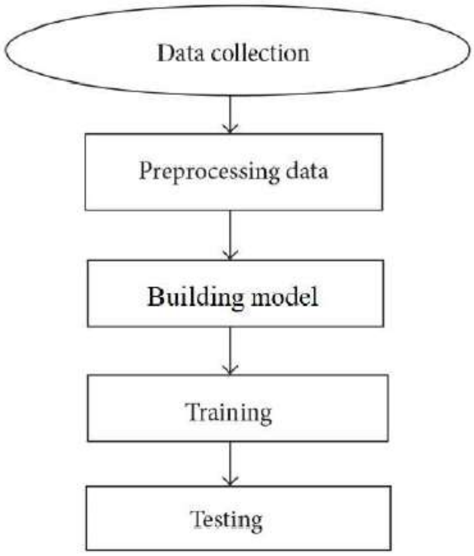


Figure 2. Basic flow for building the machine learning (ML) model. [20]

Spyder Platform:

Spyder is a highly popular integrated development environment (IDE) for Python programming. Designed specifically for scientific computing and data analysis, Spyder provides a comprehensive set of tools and features that cater to the needs of data scientists, researchers, and developers. With its user-friendly interface, powerful code editor, interactive console, and integrated help system, Spyder makes Python programming a breeze.

It offers seamless integration with essential libraries like Pandas, NumPy, and Matplotlib, enabling efficient data exploration, manipulation, and visualization. Spyder's debugging capabilities, profiling tools, and project management features further enhance productivity and code quality. With its customizable and extensible nature, Spyder provides a versatile and tailored development environment. Whether you are working on machine learning models, scientific projects, or data analysis tasks, Spyder empowers you to write, test, and debug code with ease and efficiency.

III.1.3 Importing Libraries and Loading Data:

To begin the implementation in Spyder, we import the required libraries such as Pandas, NumPy, Matplotlib, and Scikit-learn. These libraries provide functionalities for data manipulation, visualization, and machine learning algorithms. Next, we load the preprocessed data into Spyder using the Pandas library and split it into features (Input variables) and the target variable (Q_Sens_Vent and Coil _Total_Cooling).

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

III.1.4 Feature Selection and Engineering:

Feature selection involves identifying the Inputs (TIME, V_Tank, Build_coeff, Build_capac, Coll_Area, Chill_capa, Chill_COP, T_Fluid_inlet)

III.1.5 Splitting the Data into Training and Testing Sets:

To evaluate the model's performance, the data needs to be divided into training and testing sets. The training set is used to train the machine learning model, while the testing set is used to assess its predictive capabilities. Spyder provides the train_test_split function from the scikit-learn library to split the data into appropriate proportions.

III.1.6 Model Selection and Training:

In this step, we select a suitable machine learning algorithm for building cooling energy prediction. Common algorithms include linear regression, decision trees, random forests, or support vector machines. Spyder offers a range of machine learning algorithms through the scikit-learn library. We initialize the selected model, fit it to the training data, and train it on the features and target variable.

III.1.7 Model Evaluation and Optimization:

After training the model, we evaluate its performance using appropriate evaluation metrics such as mean squared error (MSE) and coefficient of determination (R-squared). Spyder provides functionalities to compute these metrics and assess the model's accuracy and precision. If the model's performance is not satisfactory, we can fine-tune the model by adjusting hyperparameters, applying regularization techniques, or exploring different algorithms. Spyder's integration with scikit-learn's grid search and cross-validation techniques allows for model optimization.

III.1.8 Prediction and Deployment:

Once the model is trained, we can use it to make predictions on new, unseen data. Spyder allows for loading new data, performing necessary preprocessing steps, and applying the trained model to predict building cooling energy outputs. Additionally, the model can be deployed in a real-time or production environment by integrating it with building management systems or control algorithms.

CHAPTER IV

Discussion & Results

IV Python Model Results:

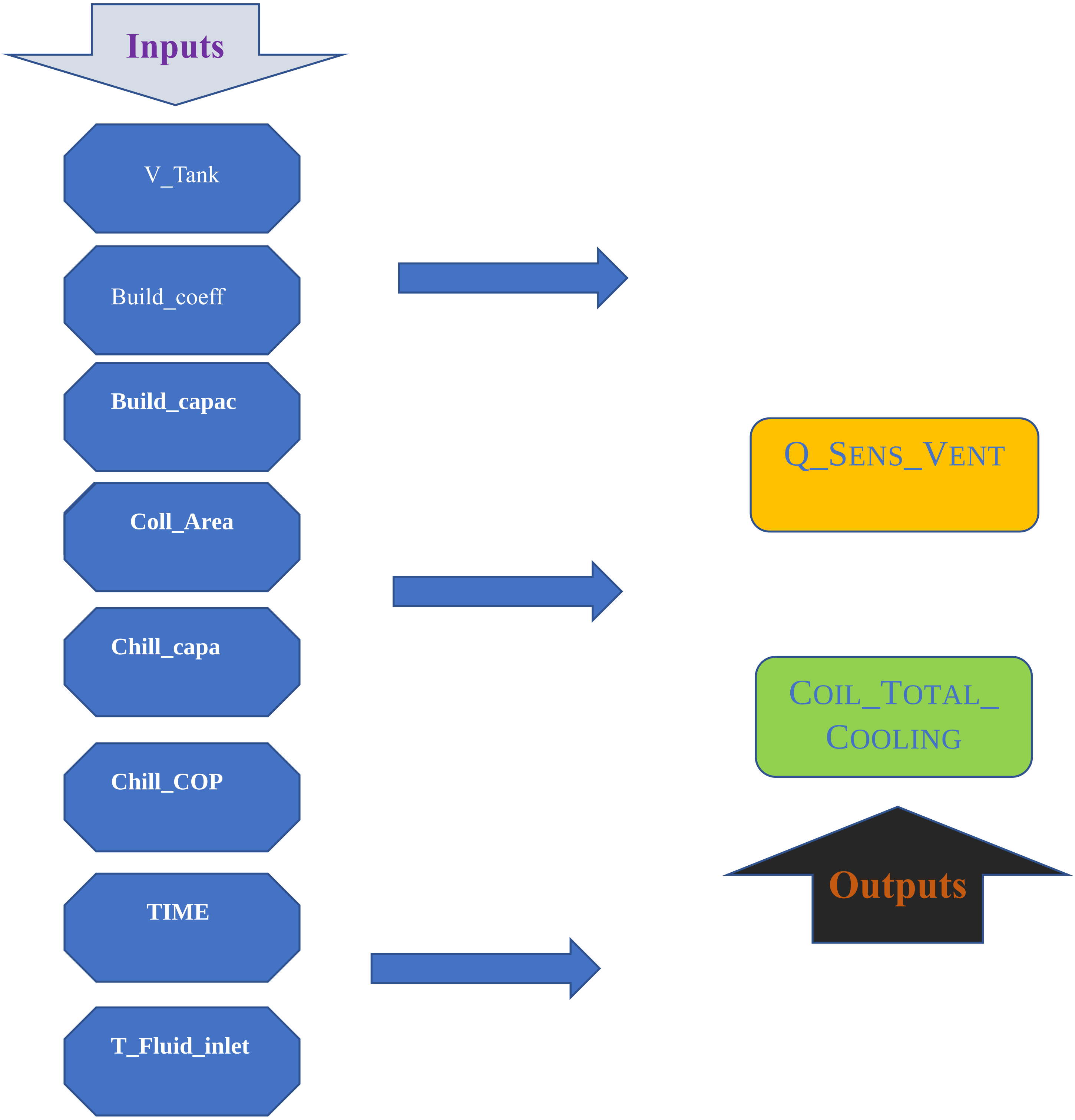


Figure.1 The Model's Variables with 8 Inputs on the left & 2 Outputs on the right.

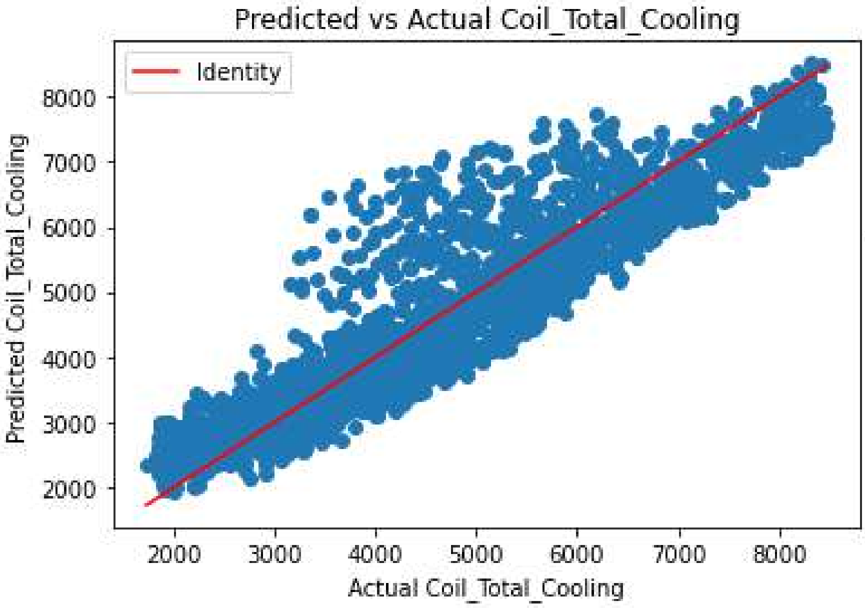
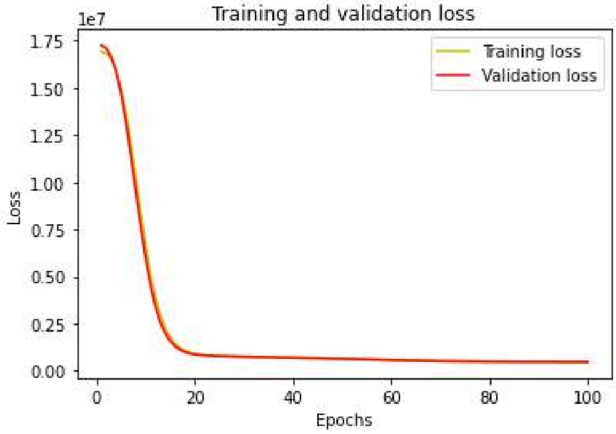
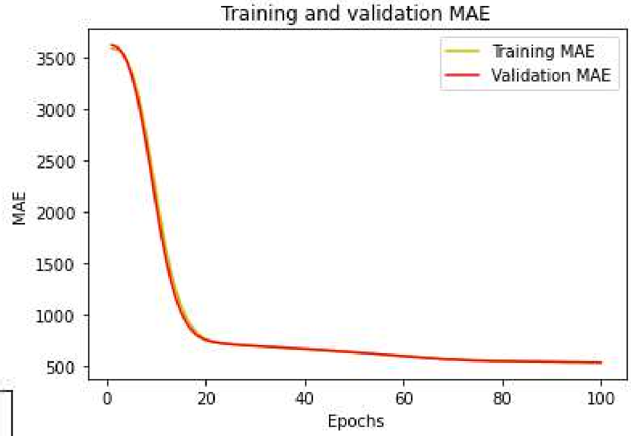


Figure.IV.1 Predicted and Actual Results (Coil's_Total_Cooling)





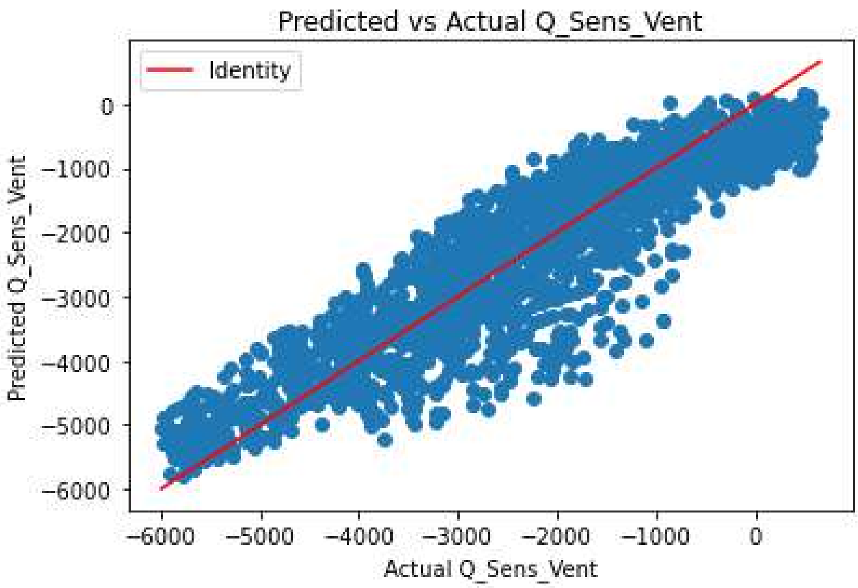


Figure.IV.2 Predicted and actual Results (Q_Sens_Vent)

Figure.IV.1 and Figure.IV.2 shows the changes in the actual Q_SENS_VENT and Coil's_Total_Cooling values in comparison with prediction values. It is important to notice that the real Q_SENS_VENT Coil's_Total_Cooling values do not match the prediction values. (error)

Algorithm	Loss (Mean squared error)	MAE (Mean absolute error)
Neural Network	**457699.75**	**526.4012451171875**
Linear Regression	**445362.1178305794**	**508.3754766174661**
Decision Tree	**6595.525277452477**	**34.03417125170279**
Random Forest	**4676.886512255525**	**29.911453642409707**

Table.IV.1 Algorithm and their exact error (Mean squared error & Mean absolute error)

From the Results in the Table.IV.1 we can clearly notice that the random Forest algorithm surpassed the other 3 algorithms in both:

Loss (Mean squared error) = 4676.886512255525

And

MAE (Mean absolute error) =29.911453642409707

R-squared for Q_Sens_Vent: $\boldsymbol{R^2}$ =0.833021526332399

R-squared for Coil_Total_Cooling: $\boldsymbol{R^2}$ 0.8350405186775041

V Conclusion:

In conclusion, this thesis has provided a comprehensive understanding of energy consumption in Algeria, with a specific focus on the substantial portion attributed to home conditioning in the southern regions. By exploring the impact of energy demands for cooling and utilizing machine learning techniques to train a model for predicting the outputs of a building's cooling energy, this research has shed light on important aspects of energy management, sustainability, and efficiency in the residential sector.

The analysis of energy consumption patterns in Algeria revealed that home conditioning, driven by the extreme heat experienced in southern Algeria, constitutes a significant portion of overall energy consumption. This finding emphasizes the urgent need for strategies to optimize energy use, reduce environmental impacts, and ensure sustainable energy supply in the face of rising cooling demands.

The simulation of a solar cooling system, using machine learning techniques, showcased the potential of renewable energy solutions in addressing the energy demands for cooling. By training a model to predict the outputs of a building's cooling energy, it was possible to optimize system design, improve energy efficiency, and make informed decisions regarding energy management.

This thesis contributes to the body of knowledge on energy consumption by highlighting the specific challenges posed by the cooling demands. The findings underscore the importance of implementing sustainable cooling solutions, leveraging renewable energy sources, and adopting energy-efficient technologies in residential buildings.

To conclude, Although the results weren't pinpoint accurate this thesis provides a comprehensive understanding of cooling energy consumption, by simulating a solar cooling system and utilizing machine learning techniques for predictive modelling, this research offers valuable insights and recommendations for addressing energy challenges, optimizing energy use, and fostering sustainability in Algeria's residential sector. It is hoped that the findings of this thesis will contribute to the development of effective strategies and policies that promote energy efficiency, mitigate environmental impacts, and ensure a sustainable energy future for Algeria.

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