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Under Semi-Arid Climate

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Dedication

إلى نفسي،
التي صبرت واجتهدت وتجاوزت لحظات التعب والضعف حتى وصلت إلى هذه المرحلة، أهديك هذا النجاح لأنك تستحقينه.

إلى والديّ العزيزين،
الذين كان دعائهما ودعمهما النور الذي رافقتي طوال هذا المشوار، وكنا دائماً مصدر قوتي وأملّي، حفظهما الله وأدامهما تاجاً فوق رأسي.

إلى عائلتي الكريمة،
شكراً لدعمكم ومحبتكم ووقوفكم بجاني في كل لحظات التعب قبل الفرح.
إلى أهل غزة الصامدين ومقاومتها الشجاعة، الذين علموا العالم معنى الكرامة والصبر والثبات رغم الألم .
إلى الطلبة الشهداء الذين رحلوا قبل أن يكملوا أحلامهم ومسيرتهم العلمية، رحمهم الله وجعل ذكراهم خالدة في القلوب.
إلى من كان سنداً ودعمًا صادقاً في هذه الرحلة، شكراً لأنك كنت جزءاً جميلاً من هذا المشوار.

إلى أساتذتي الأفاضل وأصدقائي وزملائي،
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وإلى كل من آمن بي ودعمني ولو بكلمة طيبة أو دعاء صادق، أهدي هذا العمل المتواضع، راجية أن يكون بداية لطريق مليء بالنجاح والعطاء.

بوعلام مريم





Dedication

إلى الأيادي الطاهرة التي ازالتي من طريقي اشواك الفشل إلى كل من ساندني بكل حب عند ضعفي
إلى من رسموا لي المستقبل بحطوط من الثقة والحب

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أهدي فرحة تخرجي إلى تلك الانسانة العظيمة صاحبة أحن روح وأجمل قلب التي لطالما تمننت أن
تقر عينها برويتي في يوم كهذا

إلى جنتي أمي

وإلى الشموع التي تنير لي الطريق وانتظروا هذه اللحظة كثيرا ليفخروا بي كما افخر بهم وبوجودهم

إلى إخوتي وأحبتي من قريب او بعيد

بكاير سميرة



الملخص

تتعرض المباني بشكل متزايد لظروف مناخية قاسية، خاصةً التقلبات الكبيرة في درجات الحرارة في المناطق الجافة والقاحلة، مما يفرض تحديات كبيرة للحفاظ على الراحة الحرارية الداخلية وكفاءة الطاقة. تهدف هذه المذكرة إلى دراسة استراتيجيات التصميم المناخي المناسبة لهذه المناخات، مع التركيز على تحسين الأداء الحراري للمباني المعزولة.

تقترح الدراسة نظاماً متكاملًا يجمع بين تقنيات فعالة للعزل الحراري وأنظمة التظليل بهدف تعزيز الاستقرار الحراري الداخلي وتقليل تأثير التغيرات المناخية الخارجية. وبالتوازي مع ذلك، تم تطوير مقارنة تعتمد على الذكاء الاصطناعي باستخدام الشبكات العصبية الاصطناعية للتنبؤ بدقة بدرجة الحرارة الداخلية، استناداً على البيانات المناخية الداخلية والخارجية من التجربة بوحدة البحث التطبيقي في الطاقات المتجددة بغرداية (32.36° شمالاً، 3.51° شرقاً).

أظهرت النتائج أن الدمج بين تقنيات التصميم المناخي والنظام التنبئي المعتمد على الشبكات العصبية الاصطناعية يوفر إدارة حرارية فعالة وموثوقة. كما حقق نموذج الشبكات العصبية الاصطناعية المطور دقة عالية في التنبؤ، حيث قارب معامل الارتباط حوالي 98% بين درجات الحرارة المقاسة والمتوقعة، مما يدل على توافق قوي ومتانة عالية للنموذج. وتؤكد هذه النتائج إمكانات دمج استراتيجيات البناء المناخي مع النماذج التنبؤية الذكية كحل مستدام وفعال لتحسين الراحة الحرارية والأداء الطاقوي في البيئات المناخية القاسية.

الكلمات المفتاحية: المباني الشمسية السلبية؛ الشبكات العصبية الاصطناعية؛ درجة الحرارة الداخلية، التنبؤ؛ العزل الحراري؛ تقنيات التظليل

Abstract

Buildings are increasingly exposed to severe climatic conditions, particularly large temperature fluctuations in arid regions, which create significant challenges for maintaining indoor thermal comfort and energy efficiency. This thesis investigates passive design strategies suitable for such climates, with a focus on improving the thermal performance of insulated buildings.

The study proposes an integrated system that combines effective thermal insulation and shading techniques to enhance indoor thermal stability and reduce the impact of external climatic variations. In parallel, an artificial intelligence approach based on Artificial Neural Networks (ANNs) was developed to accurately predict indoor temperature using both indoor and outdoor climatic data obtained from an experimental setup at the Applied Renewable Energy Research Unit in Ghardaïa (32.36° N, 3.51°E).

The results demonstrated that the combination of passive design and ANN-based predictive system provides reliable and efficient thermal management. The developed ANN model achieved high predictive accuracy. With a correlation coefficient of approximately 98% between measured and predicted temperatures, indicating strong agreement and model robustness. These findings confirm the potential of integrating passive building strategies with intelligent predictive models as a sustainable and effective solution for improving thermal comfort and energy performance in harsh climatic environments.

Keywords: Passive Solar Building; Artificial Neural Networks; Indoor Temperature, Prediction; Thermal Insulation; Shading Techniques

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List of abbreviations and acronyms

ANN	Artificial Neural Networks	/
BEM	Building energy modelling	/
CFD	Computational fluid dynamic	/
CSP	Concentrated solar power	/
D_v	Wind Direction	°
EAHE	Earth–Air Heat Exchanger	/
EUI	Energy use intensity	Wh/m ² ·year
FPANN	Forward Propagation Artificial Neural Networks	/
FEM	Finite element methodology	/
HVAC	heating, ventilation, air conditioning	/
I_g	Global Radiation	W/m ²
ML	Machine Learning	/
MAE	Mean Absolute Error	/
MSE	Mean Square Error	/
PMC	Multi-Layer Perceptron	/
PCM	Phase change material	/
PV	Photovoltaics	/
RH	Relative humidity	%
RMSE	Root Mean Square Error	/
RBFN	Radial Basis Function Networks	/
RLM	Multiple Linear Regression	/
R	Regression	/
R^2	Coefficient of Determination	/
T	Temperature	°C
TLL	Thermal Load Leveling	/
URAER	Renewable Energy Research Unit	/
VIP	Vacuum insulation panel	/

W	Wind Speed	m/s
$w_{(i,j)}^h$	Weight	/
WSM	Weighted Sum Model	/
y_{cal}	Predicted Value	/
y_{exp}	Experimental Value	/
σ	Sample standard deviation	°C
A	Thermal Amplitude	°C
ϕ	Thermal lag	h
$\bar{x}$	Arithmetic mean	°C

GENERAL INTRODUCTION

Buildings are among the largest consumers of energy worldwide due to the increasing demand for heating, air conditioning, ventilation, and lighting systems. Rapid urbanization, population growth, and technological development have significantly increased energy consumption in both residential and commercial sectors, leading to serious environmental issues such as greenhouse gas emissions, global warming, and the depletion of conventional energy resources. Consequently, improving building energy efficiency has become a major global challenge.

In semi-arid and arid regions, building energy performance and indoor thermal comfort often remain below desired levels because of harsh climatic conditions and large daily temperature variations. These conditions make it difficult to maintain stable indoor environments while reducing energy consumption. Therefore, there is a growing need for innovative and intelligent solutions capable of enhancing indoor climate regulation and optimizing energy use. In this context, the integration of passive solar systems into buildings has gained considerable attention as a sustainable approach for thermal management. Moreover, advanced Artificial Neural Network (ANN) techniques have emerged as effective tools for monitoring, controlling, and predicting indoor climatic conditions, thereby improving thermal comfort and overall building performance.

This study aims to propose a technique for integrating passive solar energy systems into buildings located in the Ghardaïa region of southern Algeria, which is characterized by a hot and arid climate. The experimental system incorporates polyurethane sandwich panels, double glazing filled with argon gas, and thermal curtains as sustainable solutions for improving indoor thermal conditions. In addition, this work seeks to develop a high-performance dynamic model within the Matlab environment for experimental validation. The proposed approach considers the main climatic and building-related parameters influencing indoor conditions and employs an Artificial Neural Network to predict indoor air temperature using experimental data collected from a real building at the Applied Research Unit for Renewable Energies - URAER.

This thesis is organized into four main chapters:

The first chapter highlights Algeria's significant solar energy potential and its role in improving building efficiency. It explains the basic principles of sustainable and energy-efficient buildings. The chapter also emphasizes the significance of passive and active techniques that can be used to optimize the thermal performance of buildings in hot arid climates.

The second chapter presents the fundamental concepts and theoretical background of ANNs and their applications in building thermal modeling. In addition, the state of the art related to indoor temperature prediction in buildings demonstrates the effectiveness of ANN techniques in this field.

The next chapter describes the experimental methodology adopted for the passive building prototype located in Ghardaïa to enhance thermal comfort. It presents the climate monitoring tools used and outlines the development of an AI model for predicting indoor temperature, from data processing to model validation.

The final chapter presents and discusses the results by comparing experimental data with predictions from the AI model. This comparison assesses the model's accuracy in simulating indoor building temperature and its potential for practical use in climate control systems.

Finally, the general conclusions summarize the study's key findings, along with practical suggestions to enhance the model's performance using other algorithms. These recommendations lay the groundwork for future research in building climate prediction and control.

Chapter 1

Overview of Building Physics Systems

1.1 Introduction

Transition to energy efficiency in buildings and structures has become one of the major challenges of the modern era due to climate change, rapid energy consumption, and the growing global demand for sustainable development. In this context, sustainable building systems have attracted increasing attention as effective solutions for reducing energy use, improving indoor thermal comfort, and minimizing environmental impacts. This chapter provides a theoretical overview of sustainable building concepts, with particular emphasis on solar energy applications and the different ways in which solar energy can be utilized through active and passive systems. In addition, the chapter examines the thermal properties of buildings and the influence of climatic conditions on building performance and energy demand.

Furthermore, this chapter reviews recent studies and innovative passive design approaches aimed at enhancing the thermal efficiency of buildings. Particular attention is given to advanced building materials, thermal insulation techniques, passive heating and cooling strategies, and energy-efficient HVAC systems. By analyzing the methodologies and findings of previous research, this review aims to provide a comprehensive understanding of sustainable building technologies and natural materials used in thermal management systems, while identifying the most promising design strategies and future research directions.

1.2 Solar potential

Solar energy refers to the radiation emitted by the Sun, harnessed using a range of evolving technologies such as photovoltaics (PV), concentrated solar power (CSP), and solar thermal systems. As an inexhaustible and clean energy source, it represents a promising source for the building sector in the future.

According to empirical data compiled by the World Bank's Global Solar Atlas, solar resources are heavily concentrated around the subtropical desert belts, resulting in an uneven distribution across the globe. This is illustrated in Figure 1-1, which presents a map of global

horizontal solar irradiance, where regions with higher irradiance values indicate greater solar energy potential [1].

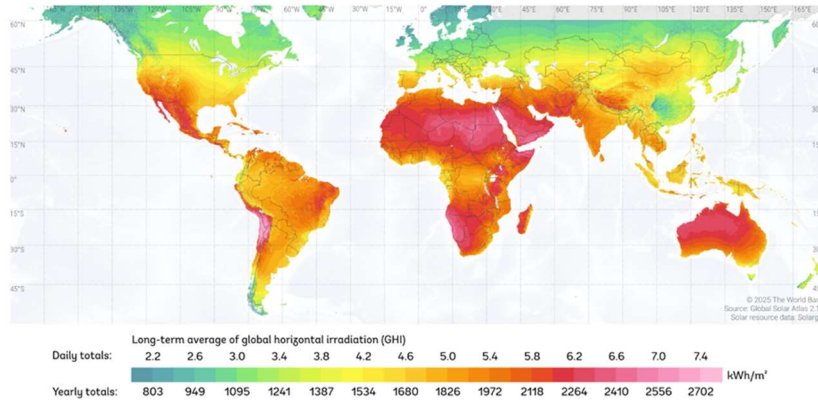


Figure 1-1: World global solar horizontal irradiation Map [1]

Algeria possesses vast solar potential, placing it among the leading countries in North Africa in terms of solar energy resources. According to the analysis conducted by Bezari et al. [2], solar radiation levels vary across the country, with the southern regions, particularly the Hoggar–Aoukar area and the Sahara Desert, recording the highest values, exceeding 2500 kWh/m² per year. These favorable conditions present a strategic opportunity for the country to reduce its dependence on fossil fuels while enhancing sustainable energy efficiency in different sectors.

Table1-1: Solar potential in Algeria [2]

Regions	Coastal region	Highlands	Sahara
Area (%)	4	10	86
Average sunshine duration (h/year)	2650	3000	3500
Daily solar energy density (kWh/m²)	4.66	5.21	7.26
Average energy received (kWh/m²/year)	1700	1900	2650

1.3 Bioclimatic Building

Bioclimatic buildings are characterized by the use of construction elements such as walls, windows, roofs, and floors to collect, store, and distribute solar thermal energy while preventing overheating. Heat transfer within these buildings mainly occurs through natural mechanisms such as convection, conduction, and radiation rather than through the use of mechanical systems like pumps and fans.

The main objective of the bioclimatic approach is to manage energy flows efficiently in order to provide optimal thermal comfort conditions in occupied spaces throughout the year and during all periods of the day.

The fundamental principle in the design of a bioclimatic building is the re-establishment of the relationship between occupants and the local climate (Figure 1.2). This approach helps reduce energy demand while ensuring thermal comfort and maintaining indoor environmental quality, including appropriate temperature levels and controlled humidity.

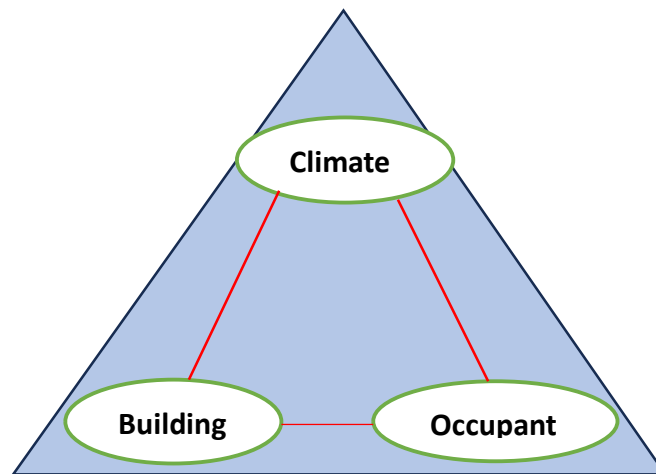


Figure 1-2: Bioclimatic architecture elements

1.3.1 Key climatic parameters

The thermal performance of a building is directly affected by the surrounding climatic parameters. These parameters are defined as the dynamic energy inputs to the building, which in turn directly influence its internal thermal stability. Among these parameters is solar radiation, which is the most important climatic parameter in desert cities, as it affects the temperature of building surfaces and increases heat gain through transparent openings [3]. Ambient air

temperature (Text) plays a crucial role in determining the rate of heat transfer by conduction and convection. The temperature difference between the inside and outside is a driving force in heat transfer across building surfaces [4]. Furthermore, wind speed (V_w) affects the external convection heat transfer coefficient. Relative humidity also influences mass transfer and ventilation processes, directly impacting thermal comfort in buildings and the energy consumption of air conditioning systems [5].

Studies analyzing the relationship between these climatic parameters and building performance (such as climate-sensitive energy consumption analysis) show that variations in temperature, solar radiation, humidity, and wind can significantly alter the amount of energy required to heat, cool, and operate a building. This makes assessing these parameters a crucial aspect of any contemporary design aimed at sustainability and energy efficiency [6].

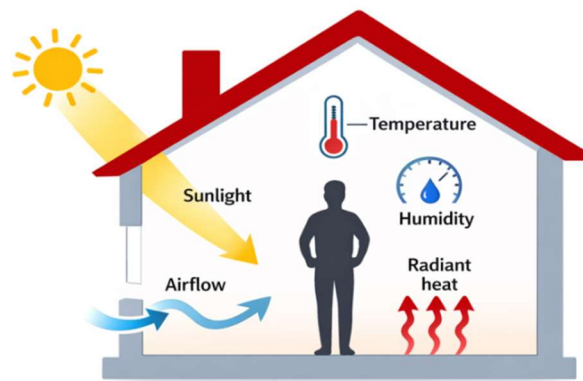


Figure 1-3: Impact of climatic parameters on the building energy balance

1.3.2 Indoor environmental factors

Indoor environmental parameter is a term used to describe the physical parameters within a building that play an important role in the health, productivity, and satisfaction of the building's occupants. The parameters form a complex indoor ecosystem, which is important to manage to achieve a high-quality of indoor life.

There are various parameters that contribute to the indoor environment; however, the most important parameters relate to the building's temperature, atmosphere, and energy. The main challenge associated with the optimal balance of the parameters is to achieve human comfort while keeping the building's footprint at a minimum.

▪ Indoor Temperature

The most important factor for human comfort inside any building is the indoor temperature. The indoor temperature is the result of the balance of the amount of heat coming into the building from outside, mainly through the sun's rays and the walls, and the activities inside the building. The main problem in hot and arid regions is to maintain the indoor temperature within a stable range for human comfort without the need for excessive cooling [7].

▪ Relative Humidity

Relative humidity (RH) has a significant influence on building physics and indoor environmental quality by affecting heat and moisture exchange between occupants and the surrounding air. Both high and low RH levels can lead to thermal discomfort. Relative humidity also influences the hygroscopic balance of building materials and the durability of the building envelope. Maintaining RH within the recommended range of 30%–60% helps protect both the health of building occupants and the structural integrity of the building, particularly in desert environments [4].

▪ Energy Consumption

Energy consumption in buildings can be defined as the total amount of power used to maintain a functional and comfortable indoor environment. This includes not only climate control but also other operational needs. The overall energy consumption is largely dependent on the way the building interacts with the external environment. This implies that a well-designed building can help to minimize the need for energy sources. Therefore, using sustainable building strategies can be the most effective way to reduce operational costs [5].

▪ Thermal Comfort

Thermal comfort is formally defined as "that condition of mind that expresses satisfaction with the thermal environment.". Despite being a psychological definition (a state of mind), this definition has generally been modeled in terms of physiology and physics [8]. From a thermodynamic perspective, achieving this state requires the human body to maintain an active homeothermic energy balance, where the metabolic heat generation within the body precisely equals the net heat dissipation to the surrounding microclimate.

The goal of those who study comfort is to define the thermal environment that a heating, ventilation, and air conditioning (HVAC) system must provide in order to ensure a comfortable

environment. Much of the research on which these standards are based has been conducted in thermally controlled laboratories. In order to illustrate the intricacy of the indoor environment, Figure 1-4 provides a summary of the four major parameters of the indoor environment, namely thermal, visual, acoustic, and air quality. These parameters must be well balanced in order to achieve satisfaction and health of the occupants, as well as the optimization of the energy performance of the building.

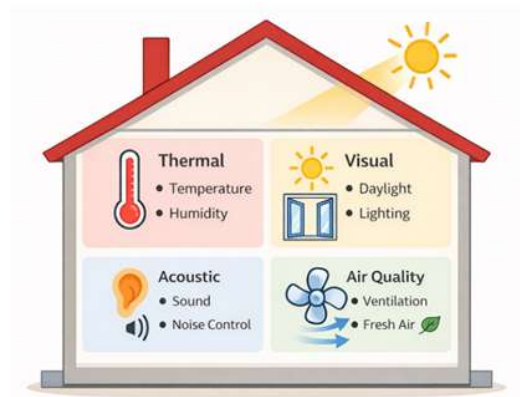


Figure 1-4: Overview of indoor environmental parameters

1.4 Building Physics

From a physical point of view, the building is a mass and a volume. The mass (opaque and transparent walls) constitutes the link between the internal microclimate and the fluctuations of climatic stresses. The form, orientation, and organization of spaces characterize the modalities of interactions and energy transfers between the interior and the exterior [9].

1.4.1 Heat transfer mechanisms

The thermal performance of buildings encompasses how thermal energy is absorbed, stored, transferred, and released within building structures, such as walls, roofs, and floors, through thermal conduction, convection, and radiation (Figure 1-5). The thermal properties of building materials and the design of the building envelope system have a significant impact on this factor. Understanding these principles is fundamental to enhancing energy efficiency and thermal comfort within buildings, and can be assessed through mathematical models and measurements [10].

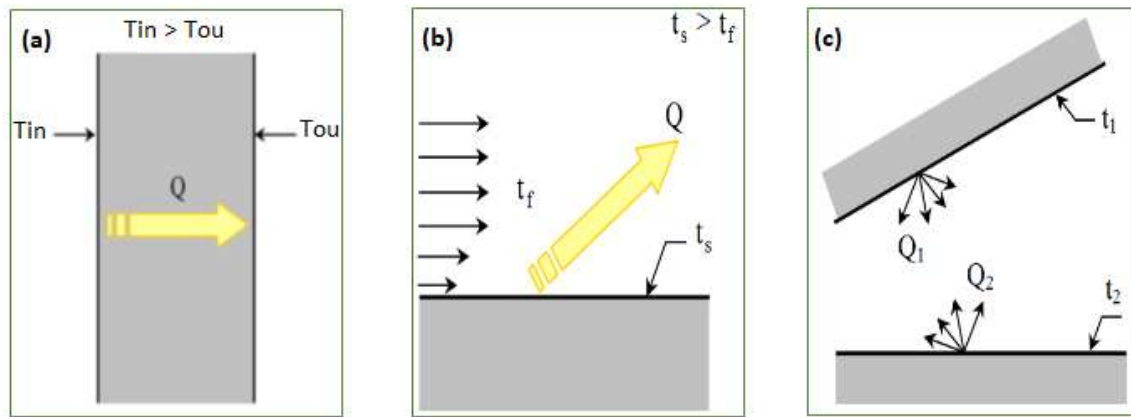


Figure 1-5: Thermal transfer mode in a building: (a) conduction, (b) convection , (c) radiation

1.4.2 Mass transfer and air exchange

The flow of heat into or out of a building, the thermal behavior is also influenced by the flow of mass into or out of a building. This involves the transfer of air and water vapor through the envelope. This includes natural or mechanical ventilation and infiltration by air, which carries latent and sensible heat and has a major impact on indoor air comfort levels [5]. The interplay between these flows involving both heat and mass transfer, along with the actions of users on the building envelope by opening vents, creates a complex thermal response that requires detailed modeling for forecasting building thermal performance [11].

1.5 Building systems classification

Buildings can be either low-tech or high-tech depending on the level of technological integration and indoor climate control. A low-tech building uses passive techniques and natural ventilation, whereas a high-tech building is characterized by the application of advanced automated lighting, HVAC, and other techniques to increase the efficiency of the building.

1.5.1 Heating systems

Heating systems in buildings are fundamental to maintaining thermal comfort and indoor environmental quality. An effective heating system must balance adequate heat output with controlled ventilation to prevent pollutant accumulation and moisture issues. The optimal choice of system whether electric resistance, combustion-based (natural gas, oil, biomass), or renewable-driven (solar thermal, heat pumps) is contingent upon local climatic conditions, energy infrastructure, economic constraints, and increasingly, decarbonization targets. [12].

1.5.2 Cooling systems

Essential to the structure, especially in warmer regions, is the cooling system. Three primary methods exist for cooling buildings [8]:

Natural ventilation: The architectural design of the building is such that natural air enters the building through the designed ventilation openings. This is an effective method of saving energy during mild climatic conditions.

Forced ventilation and mechanical air conditioning: This method is used when the temperature is extremely high. The air is circulated using pumps and fans, thus cooling the air.

Shading: is the process of using blinds or other devices that prevent solar radiation from entering the building through the windows, thus maintaining the indoor climate.

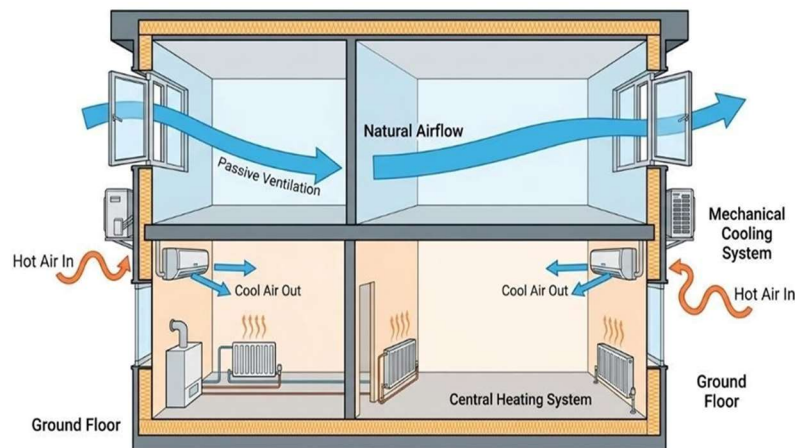


Figure 1-6: Active and passive building climate control systems

1.5.3 Thermal insulation

The building envelope represents the interface between the indoor environment and the external climate. Its primary function is to regulate heat transfer and protect the building from climatic variations, thereby contributing to indoor thermal comfort and energy efficiency.

The envelope is not limited to opaque structural components such as walls, roofs, and floors, but also includes thermal insulation layers and openings such as doors and windows. These elements strongly influence heat exchange, natural ventilation, daylight penetration, and overall indoor environmental quality within the building.

As illustrated in Figure1-7, thermal insulation materials can be classified according to their nature and composition into several categories [8]:

- **Fibrous and Cellular Insulation:** Examples of such materials include rock wool and polystyrene. They function based on entrapment of air in their pores; hence, they utilize still air as a natural insulator. They are known to reduce heat transfer through conduction.
- **Reflective Insulation:** They mainly act by reflecting solar rays before they enter the enclosure. They are highly effective in deserts where there is high radiation.
- **Bio-based Materials:** This comprises natural materials like palm fibers and cork. These building materials have very good properties when it comes to controlling moisture and temperature, and they can be considered as the best option for environmentally friendly buildings in southern Algeria (as in Ghardaïa), since they can be found easily there.
- **Advanced Technology:** One example is aerogel. They provide the highest degree of insulation with a very thin layer, but they are more costly than the conventional insulation material.

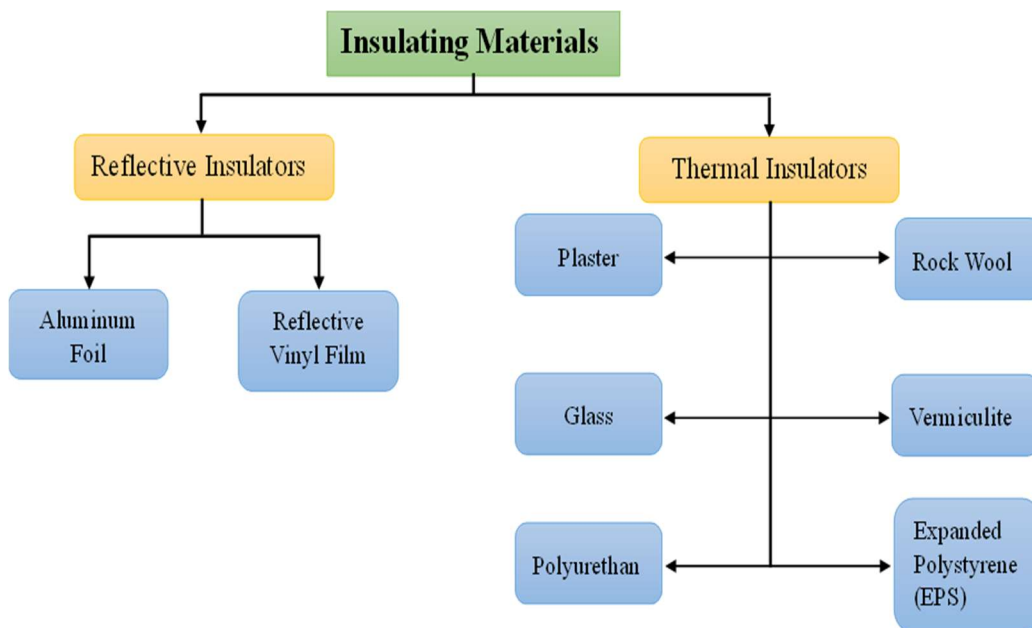


Figure 1-7: Simplified classification of insulating materials

1.6 Literature Review

Sustainable building management plays a crucial role in reducing energy consumption, improving indoor thermal comfort, and minimizing environmental impacts. To achieve these objectives, recent studies have focused on the development of innovative building materials and efficient passive design strategies. Advanced building envelope materials, thermal insulation techniques, passive solar concepts, and optimized heating and cooling systems contribute significantly to enhancing the thermal performance of buildings while reducing reliance on conventional energy systems. In this context, the following review highlights recent developments in sustainable building technologies, with particular emphasis on building envelope materials, heating and cooling systems, thermal comfort, thermal insulation, and passive solar energy concepts.

Figure 1-8 illustrates the evolution in the number of publications related to sustainable buildings and energy-efficient systems between 2010 and 2026. The results show a continuous increase in scientific publications over the years, reflecting the growing global interest in sustainable construction, renewable energy integration, and thermal performance optimization in buildings. From approximately 7,000 publications in 2010, the number steadily increased to nearly 30,000 publications by 2023. A particularly significant rise can be observed between 2024 and 2025, where the number of publications reached around 50,000, indicating intensified research activity driven by climate change concerns and the demand for energy-efficient technologies. Although a decrease appears in 2026, this may be attributed to incomplete annual indexing.

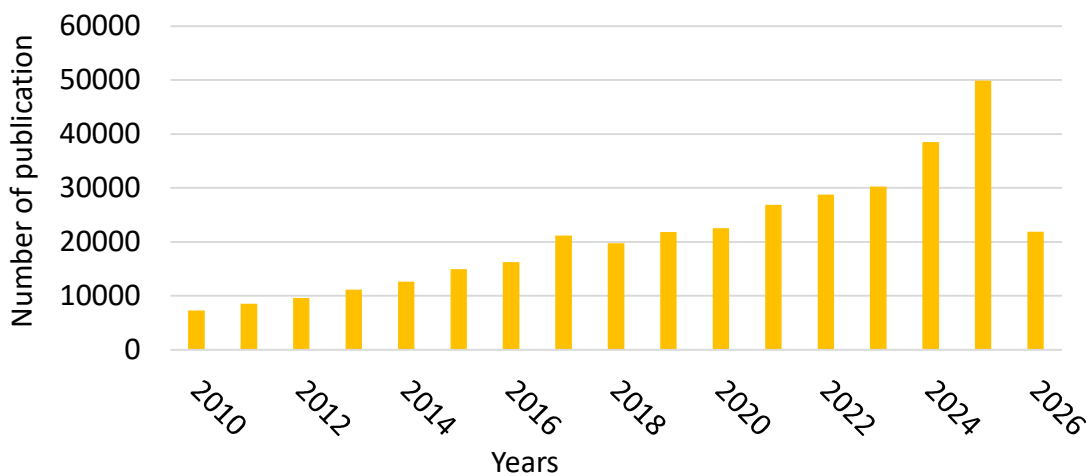


Figure 1-8: Development of research on the building systems efficiency

(Source: ScienceDirect)

Taleb et al. [13] conducted a study on the effectiveness of passive cooling strategies in residential buildings located in hot-arid climates, specifically in Dubai, United Arab Emirates. The research evaluated a range of passive design techniques, including solar shading, natural ventilation, thermal mass optimization, double glazing, and green roofs, in order to enhance indoor thermal comfort while reducing energy consumption. The results demonstrated that combining multiple passive strategies can significantly reduce heat gains and improve thermal stability within buildings by up to 23.6% .

Wąs et al. [14] investigated the thermal comfort performance of a lightweight passive house under different seasonal conditions. The study monitored indoor environmental parameters across various periods of the year in order to evaluate the building's thermal behavior. The results showed that lightweight construction systems require careful control of thermal mass and solar gains to avoid overheating during summer and to ensure adequate heating performance in winter. The study also incorporated occupant feedback, which confirmed the effectiveness of passive design strategies in maintaining acceptable indoor comfort levels .

Athmani et al. [15] conducted a study on the effectiveness of passive cooling roof strategies in improving the thermal performance of residential buildings. The research focused on the climatic conditions of Biskra, Algeria, as a representative hot-arid environment. The study evaluated several passive roof techniques, including cool roofs, green roofs, and solar shading systems, using EnergyPlus simulation software to model and analyze building envelope performance. The results showed that these passive strategies can significantly reduce indoor air temperatures and improve overall thermal comfort.

The findings also highlighted the strong thermal damping capacity of passive building envelope systems, demonstrating their effectiveness in mitigating heat gains and enhancing indoor environmental stability in hot climates.

In a comparative study conducted by **Jahangir et al.** [16], the use of phase change materials (PCMs) for latent heat storage in buildings was investigated as an effective strategy for reducing energy consumption and improving indoor thermal comfort. The study emphasized that the selection of an appropriate PCM depends strongly on its melting and freezing temperatures in relation to local climatic conditions. Different PCM types were analyzed according to their thermal properties, including latent heat capacity, thermal conductivity, and

charging/discharging behavior. The results demonstrated that bio-based PCMs represent a reduction of cooling and heating loads while maintaining competitive thermal storage performance. Also showed that the placement and thickness of PCM layers influence the thermal behavior of the global building .

Taha et al. [17] investigated the optimization of the Window-to-Wall Ratio (WWR) as an effective strategy for reducing building energy consumption and improving energy-efficient building design. The study focused on low-rise residential buildings located in a hot-summer Mediterranean climate and examined the influence of different WWR configurations on building energy performance. The authors examined the effect of window sizes in various orientations by employing Autodesk Revit and Insight Cloud simulation tools.

The results demonstrated that optimizing the WWR can significantly reduce energy use intensity (EUI), particularly for south-facing façades, where solar gain can be effectively utilized during winter conditions. The study also highlighted that the transparency of the building envelope strongly affects passive solar performance and indoor energy efficiency. Recommended WWR values varied according to orientation, confirming that façade design should be adapted to climatic conditions and solar exposure to achieve optimal thermal and energy performance .

Ali et al. [18] investigated the potential of nanotechnology to transform the field of building insulation. The study highlights that nanomaterials such as silica aerogels and vacuum insulation panels (VIPs) exhibit extremely high thermal resistance (R-values), significantly outperforming conventional insulation materials like glass wool and expanded polystyrene. These advanced materials enable the reduction of wall thickness while maintaining high thermal performance, contributing to more efficient and compact building envelope designs. The authors further emphasize that integrating nanotechnology into building envelopes represents a promising strategy for reducing energy demand in HVAC systems and mitigating the environmental impact of buildings, particularly in the context of global warming.

Viviana Mora-Ruiz et al., [19] conducted a systematic review and meta-analysis investigating the environmental, mechanical, and thermal performance of earthen construction materials, including adobe, compressed earth blocks (CEBs), and rammed earth walls (REWs). The study highlighted the significant potential of these materials to reduce the environmental impact of buildings compared with conventional construction materials. Earthen materials were recognized for their high thermal mass, which contributes to passive cooling and improved indoor thermal stability. Furthermore, the study underlined the importance of numerical methods, such as finite element modeling, for predicting the structural and thermal behavior of earthen constructions. From a life cycle assessment perspective, the authors concluded that stabilized earthen materials represent a promising and sustainable solution for passive building envelopes, although further standardization and environmental assessment are still required.

Extending the application of PCMs in buildings, another study investigated the thermal performance of building envelopes integrated with PCMs under tropical climatic conditions. **Elenga et al.**, [20] applied a multi-objective genetic algorithm coupled with EnergyPlus simulations to optimize the PCM melting temperatures and improve the overall energy performance of the building. The study highlighted that the effectiveness of PCMs is strongly dependent on climatic conditions and the thermal characteristics of the building envelope. By optimizing the PCM integration within the envelope, the researchers achieved significant reductions in both building energy consumption and greenhouse gas emissions.

Lashgari et al. [21] investigated the application of a hybrid passive heating system combining a Trombe wall with an Earth–Air Heat Exchanger (EAHE) for residential buildings located in cold and dry winter climates (Figure 1-9). The study demonstrated the potential of integrating solar thermal energy with geothermal energy to provide indoor heating without relying on active mechanical heating systems.

The results confirmed that the hybrid system significantly improved indoor thermal conditions and maintained thermal comfort despite large fluctuations in outdoor temperature. The research highlighted the effectiveness of combining passive solar heating with ground-based thermal storage as a sustainable and energy-efficient solution for residential buildings in harsh climatic conditions .

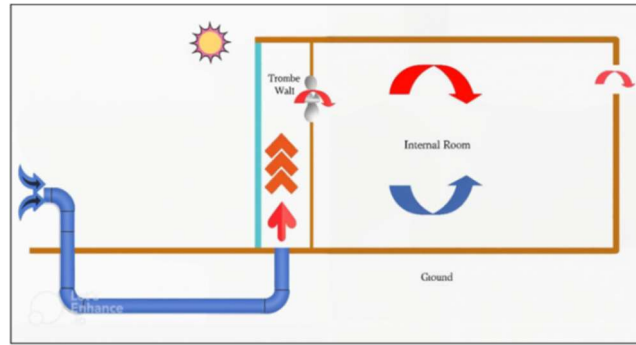


Figure 1-9: Air circulation in the combined EAHE open loop and Trombe wall system [21]

Li et al. [22] investigated an improved coupled system combining a Solar Chimney with an Earth–Air Heat Exchanger (SCEAHE) for low-carbon building climate control (Figure 1-10). The study addressed the limited heating capacity of conventional systems during winter, mainly due to the restricted thermal exchange capacity of the soil. To overcome this limitation, the authors proposed an enhanced configuration in which solar energy is simultaneously used to generate thermal pressure and to provide direct heating.

The results showed that the improved system significantly enhanced indoor thermal performance, increasing indoor temperatures by $6.3\text{ }^{\circ}\text{C}$ during the day and $1.6\text{ }^{\circ}\text{C}$ at night over a typical heating period. In addition, the system optimized airflow behavior, reducing daytime ventilation rates to limit heat losses while improving nighttime heat recovery from the soil. When combined with auxiliary heating, the enhanced SCEAHE system achieved a reduction of approximately 26.5% in supplemental heating demand while maintaining effective ventilation performance.

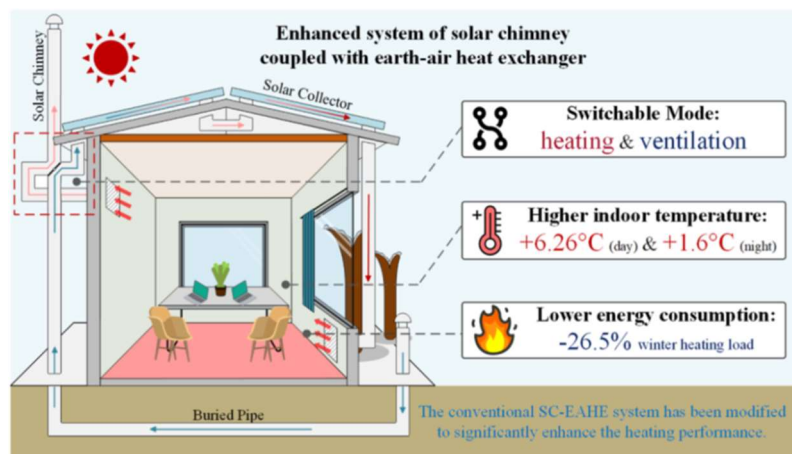


Figure 1-10: Coupled Solar Chimneys and Geothermal Heating [22]

Char et al. [23] proposed the development of sustainable thermal insulation materials derived from agricultural waste fibers such as palm, reed, olive, esparto grass, and fig, using gum Arabic as a natural binder (Figure 1-11). The study aimed to evaluate the potential of these locally available bio-based composites for application in building envelopes, particularly in semi-arid climatic conditions. The materials were fully characterized in terms of their structural and thermophysical properties, revealing notable variations in density that directly influence thermal behavior. Among the tested samples, palm leaf-based composites exhibited the best insulating performance, with a thermal conductivity as low as $0.071 \text{ W/m} \cdot \text{K}$, while esparto-based materials showed the highest volumetric heat capacity. Overall, the developed composites demonstrated thermal conductivity values comparable to conventional insulation materials, ranging from 0.071 to $0.111 \text{ W/m} \cdot \text{K}$. The findings confirm that agricultural waste-based composites can serve as effective, low-impact insulation materials, offering both environmental benefits through waste valorization.

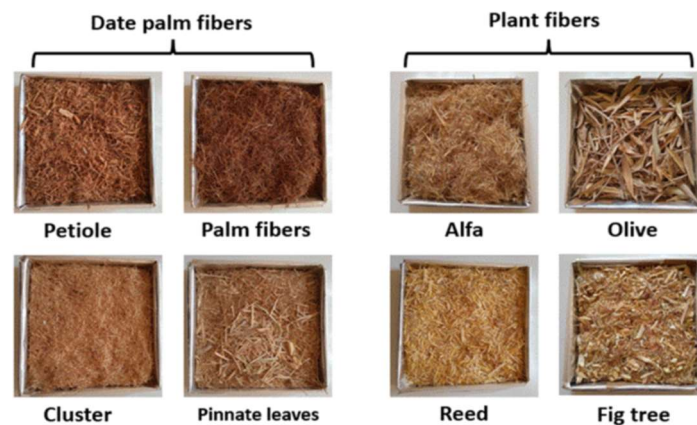


Figure 1-11: Date palm fibers and plant fibers [23]

Mohammad Abousaeidi et al. [24] examined thermal comfort challenges in passive retrofit strategies for high-rise social housing in Sydney, Australia. The study used building energy modelling (BEM) to assess retrofit performance under current and future climate scenarios (2050, RCP4.5), considering variations in orientation, floor level, and seasonal conditions. A Weighted Sum Model (WSM) was applied to evaluate thermal comfort alongside cost, environmental impact, and construction feasibility. The results showed that passive retrofits can significantly improve indoor comfort and building resilience, but optimal performance requires a balanced combination of insulation and shading/ventilation strategies. Among the tested options, combined measures such as overhang shading with external mineral wool insulation

provided the best thermal comfort performance, while other configurations performed better in terms of cost and environmental efficiency, highlighting the need for integrated multi-criteria design approaches.

Ramful, Raviduth [25] reviewed the performance of natural fiber-reinforced composite (NFRC) materials for building applications. The study highlights natural fibers such as hemp, flax, and bamboo as sustainable alternatives due to their low environmental impact and reduced carbon footprint. The review discusses the key parameters governing the performance of these materials, emphasizing that density and moisture content are critical factors influencing their thermal and mechanical behavior. Proper control of these parameters is essential to optimize insulation efficiency and long-term durability. The study further suggests that NFRC materials represent a promising solution and the review supports the integration of natural fiber composites as a sustainable option for future building envelope applications [25].

1.7 Conclusion

This chapter demonstrates that achieving energy efficiency in buildings within the Algerian climate is not merely a technical choice, but rather an integrated system that begins with understanding solar radiation and culminates in intelligent control of the building's thermal envelope. We have explored how passive and active systems can be integrated to provide a comfortable indoor environment, but the greatest challenge remains the ability to accurately predict this variable performance. This is where the importance of artificial neural networks (ANNs), whose mathematical and technical foundations we have presented in the second chapter.

Chapter 2

ANN Approach & Review of Application in Building

2.1 Introduction

Artificial Neural Networks (ANNs) have emerged as powerful computational tools capable of modeling complex and nonlinear systems in various engineering applications. Inspired by the functioning of the human brain, ANNs are designed to process information through interconnected artificial neurons that learn from data and improve prediction accuracy. This chapter presents the theoretical foundations and historical evolution of ANN models, highlighting their development from biological inspiration to modern computational approaches. It also discusses the mathematical representation of artificial neurons, network architectures, and the structure of multi-layer perceptrons commonly used in prediction tasks. In addition, a review of recent studies related to ANN applications in building thermal modeling and indoor temperature prediction is presented. The chapter aims to provide the essential theoretical background necessary for understanding the ANN methodology adopted in this work.

2.2 Evolution and historical development of ANN

Among the most significant artificial intelligence techniques for processing complex data and solving nonlinear problems are Artificial Neural Networks (ANNs). Inspired by the structure of the human brain, ANNs are based on interconnected computational units known as artificial neurons. Unlike conventional rule-based programming approaches, neural networks are capable of learning directly from data. Through training on large datasets, they identify complex relationships and hidden patterns, enabling accurate prediction, classification, and modeling of scientific phenomena. Consequently, ANN-based approaches represent a major advancement toward data-driven modeling, offering high flexibility and strong adaptability to complex and dynamic systems [26]. Historical trajectory of ANNs: from biological inspiration to modern optimization is summarized in Figure 2.

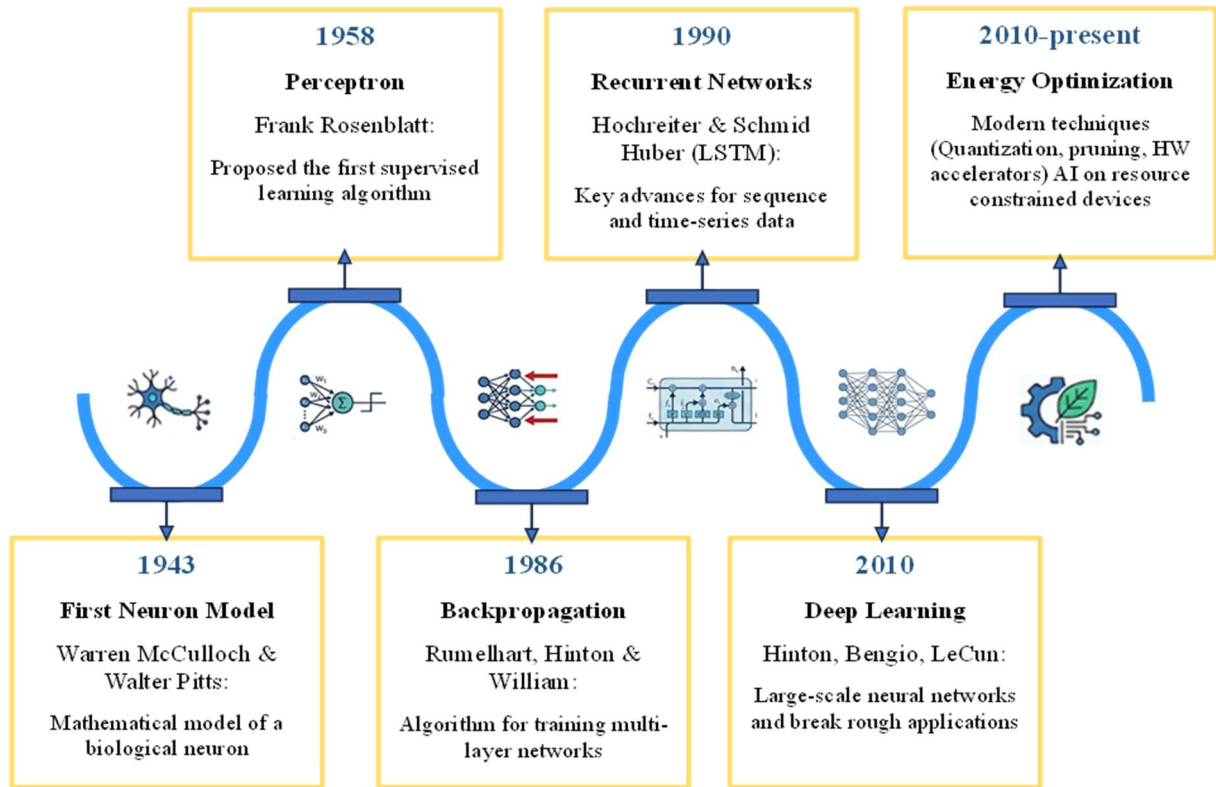


Figure 2-1: The evolution of artificial neural networks

2.3 Artificial Neural Networks

2.3.1 Biological inspiration and analogy

ANNs are conceptually inspired by biological nervous systems. Morozov et al. [27] note that the human brain contains billions of neurons operating in parallel, each receiving, processing, and transmitting signals to other neurons within intricate networks

- The dendrite serves as the input pathway to receive signals from other neurons.
- The cell body (soma) adds up the signals received.
- The axon conveys the output signal to other neurons upon attaining a specific threshold.

As per Hagan et al. [28], the model of ANN is such that it replicates these functions by means of mathematical networks where the neurons are connected using links which have weights attached to indicate the strength of the connections as in the case of biological neurons.

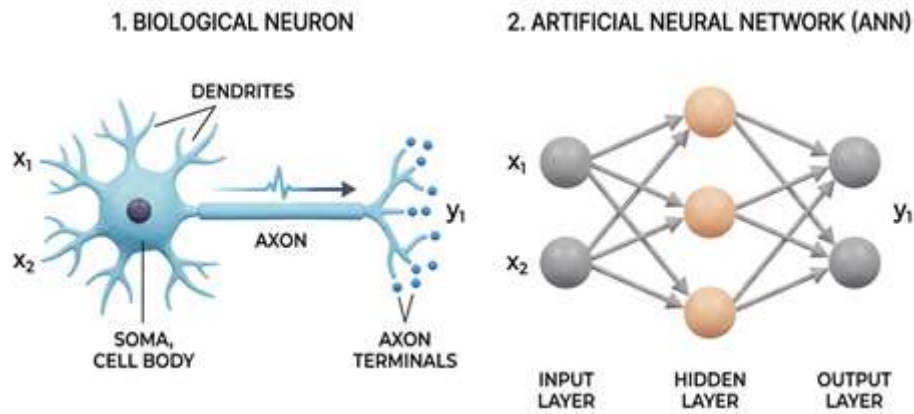


Figure 2-2: Biological inspiration of artificial neural networks

2.3.2 Mathematical representation of artificial neurons

Artificial neurons are the fundamental processing units that constitute an ANN. As per the mathematical representation stated by Hagan in neural network design [28], the transformation process comprises multiplying the input by a weight and adding a bias to it.

The net input (n) to the activation function can be expressed mathematically as follows:

$$n = w \cdot p + b \quad (1-1)$$

The final output (a) from the neuron can be found out by applying the net input to a particular transfer function (f) as follows:

$$a = f(w \cdot p + b) \quad (1-2)$$

This makes it possible for the network to represent non-linear functions and hence predict physical variables.

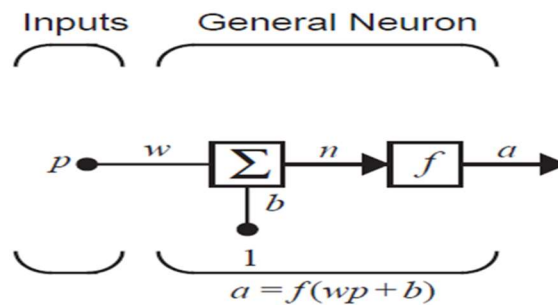


Figure 2-3: Single-input neuron [28]

2.4 Network Architecture

2.4.1 Basic Components

Based on the technical explanation provided in the literature by Kılıçarslan et al. [29] and the basic theory of neurons explained by Hagan [28], the following basic elements are included in the model of the neuron:

Inputs (p) : The input parameters form the input layer of the ANN, where data is received from external sources. Each node is connected to nodes in the subsequent hidden layer through weighted connections that determine the relative importance of the transmitted data for the target task.

Weights (w) : These are the variables used by the model to weigh how relevant the information of each input is for making predictions. Throughout the learning process, the network will adjust these weights in order to minimize errors in its predictions.

Bias (b) : This parameter, commonly referred to as the bias term, is an adjustable variable that shifts the activation function horizontally. Its role is to enhance the flexibility of the neuron by enabling activation even when the weighted input signals are weak or insufficient.

2.4.2 Layer Organization

The ANN can be arranged into different layers, each playing a role in transforming the data in the network (See Figure 2-4). As stated by Hagan et al. [28], an artificial neural network normally includes:

- **Input layer:** This is the initial layer receiving inputs from outside (e.g. data on weather, time and solar radiation). This layer is only responsible for passing the data received to the next layer.
- **Hidden layer(s):** These refer to one or several layers between the input and output layers. This layer performs the main processing operations using weighted sums and activation functions. Therefore, the neural network captures any non-linear patterns contained in the thermal data.
- **Output layer:** The last layer that provides the output from the ANN (e.g. predicted indoor temperature).

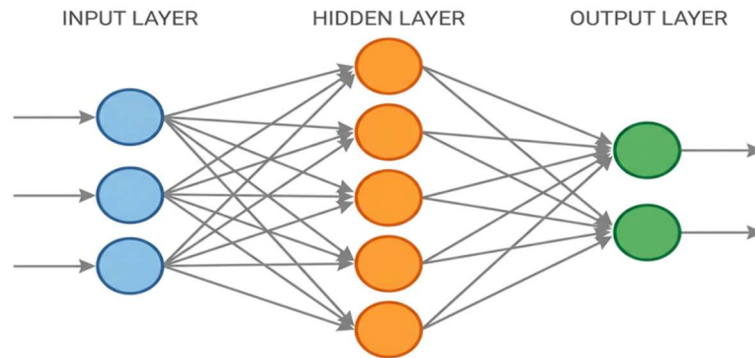


Figure 2-4: Structure of a multilayer neural network

2.4.3 Structure of multi-layer perceptron

The Multi-Layer Perceptron (MLP) is the most commonly used feedforward network model. As noted in the systematic study conducted by Ekanayaka et al. [30], MLP is frequently employed in energy informatics since it can mimic any continuous function. In MLP, the data moves linearly from the input nodes to the output nodes without looping back or going forward. The advantage of the MLP network is that each neuron is interlinked such that all nodes of a layer are linked to all the nodes in the next layer.

2.5 Transfer functions

A transfer function is an essential component in the design of artificial neurons, as it decides the output based on the input that has been weighted.

a. Non-linearity in neural networks

It is important to understand that one of the key benefits of activation functions is that they allow for the introduction of non-linearity to the network. Without the presence of non-linearities, the neural network can be treated simply as a linear regression system, regardless of the number of its layers. This allows the NN to learn intricate and complex patterns, such as abrupt changes in internal building temperature, depending on weather conditions [28, 31].

b. Linear transfer function (purelin)

The linear transfer function (purelin) is commonly used in the output layer of ANN models designed for regression problems. Unlike nonlinear activation functions, it produces a continuous and unbounded output, allowing the network to predict values outside the $[0,1]$ interval. This characteristic makes it particularly suitable for estimating physical and engineering variables such as temperature, energy consumption, and humidity levels [28, 32].

c. Hyperbolic tangent sigmoid function (tansig)

Tansig is among the widely used functions in hidden layers. It produces values that fall within the range of -1 and 1 and can be differentiated, making its training easier [28, 33]. Function shares a well-known problem with deep neural network training, the vanishing gradient problem, with the sigmoid function. As the output approaches the domain boundaries $[-1,1]$, the derivative value approaches zero, slowing down the learning process in deeper layers. Therefore, this function is similar to the bipolar axis function used in some neural network models, whose domain is also limited to values between -1 and $+1$, [29].

d. Log sigmoid (logsig)

The log-sigmoid (logsig) activation function maps input values, which may range from negative to positive infinity, into a bounded interval of $[0,1]$. This nonlinear transformation is widely used in neural networks, particularly in contexts where outputs must be constrained to positive probabilities or normalized values. However, the function may suffer from the vanishing gradient problem when inputs lie in the saturation regions near 0 or 1 , which can slow down the learning process [28, 34].

Table 2-1 summarizes the most commonly used transfer (activation) functions in artificial neural networks, namely the linear (purelin), logistic sigmoid (logsig), hyperbolic tangent sigmoid (tansig), and exponential functions. It presents both their standard notations and mathematical expressions, highlighting their role in transforming the weighted sum of inputs into an output signal.

Table 2-1: Principal activation functions used in ANNs

Transfer Function				
Notation	Linear	Logistic Sigmoid	Hyperbolic Tangent Sigmoid	Exponential Function
	Purelin	Logsig	Tansig	Exponential
Equation	$f(x) = x$	$f(x) = \frac{1}{1 + e^{-x}}$	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	$f(x) = e^{-x}$

2.6 State of the art in building modeling

Building simulation is a cornerstone of physical modeling for building energy performance. The goal is to improve energy efficiency and reduce consumption. Consequently, many studies have adopted a classification of simulation methods used in building studies.

These methods are mainly divided into two categories: classical methods and artificial intelligence (AI)-based approaches. Classical methods rely on physical models to describe heat and mass transfer phenomena in buildings, while AI techniques use data-driven approaches such as ANN, Fuzzy Logic Systems (FLS), and Genetic Algorithms (GA) to predict and optimize building performance (Figure 2-5). This classification highlights the evolution from conventional physical modeling toward intelligent and hybrid simulation techniques in building applications.

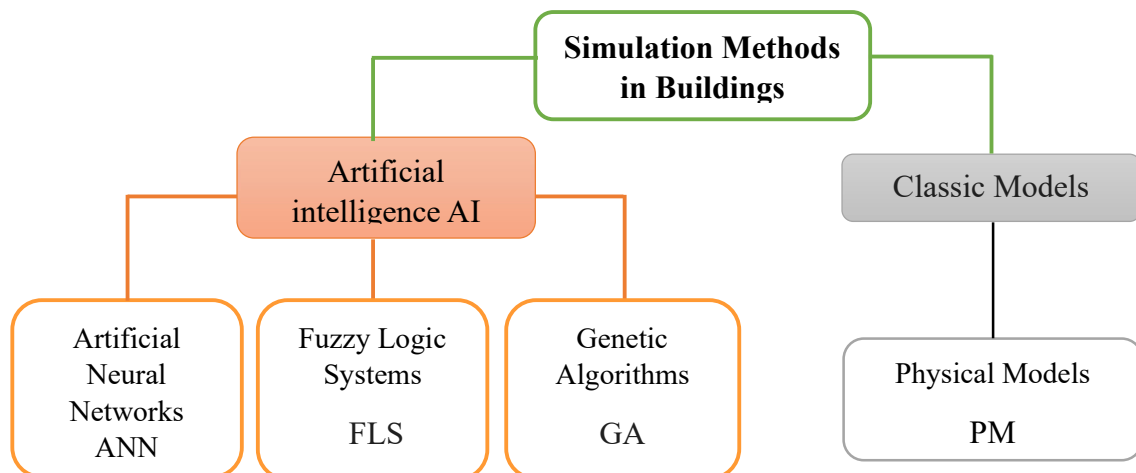


Figure 2-5: Flowchart of simulation methods in buildings

prior knowledge of the system and are highly suitable for modeling real-time dynamic systems [36, 37].

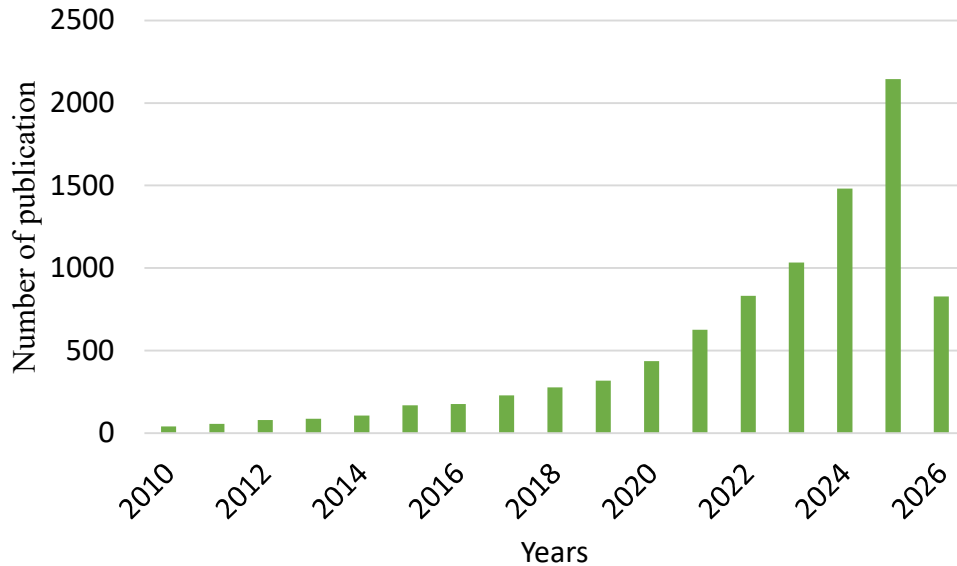


Figure 2-7: Development of research on the use of ANN in buildings

Source:(ScienceDirect)

This review examines the application of ANNs to building-parameter indoor temperature climate prediction, focusing on various network architectures, training algorithms, and input variables.

M. Soleimani-Mohseni et al., [38], investigated the estimation of operative temperature in buildings using both linear and non-linear modeling approaches. Experimental identification studies were conducted in two different buildings to develop predictive models based on easily measurable variables, including indoor and outdoor air temperatures, electrical power consumption, wall temperatures, ventilation flow rates, and time of day. The study demonstrated that operative temperature can be accurately estimated using these parameters. Furthermore, the results revealed that non-linear ANN models generally provide better prediction performance than linear Auto-Regressive with Exogenous Input (ARX) models. Among the tested approaches, feed-forward ANN models with a single hidden layer trained using the Levenberg-Marquardt algorithm achieved the highest prediction accuracy.

Zamora Martinez et al., [39] Proposed an indoor temperature prediction approach for a smart residential building using Multimodal Time Correlation Analysis combined with ANNs.

The developed model was evaluated under real operating conditions and demonstrated reliable short-term temperature forecasting performance. The study showed that incorporating historical energy consumption data together with meteorological parameters significantly enhanced prediction accuracy. In addition, the results indicated that the energy required to maintain indoor thermal conditions represented only 30%–38.9% of the energy needed for active cooling operations. The authors concluded that integrating predictive temperature control with home automation systems can improve building energy management by enabling proactive adaptation to future indoor thermal conditions .

Z. Afroz et al., [40] applied ANNs to predict indoor temperature in an institutional building located in Australia. The study focused on optimizing the ANN architecture through appropriate selection of input variables, hidden layers, and hidden neurons while minimizing the risk of overfitting. The developed prediction model demonstrated satisfactory accuracy in estimating indoor thermal conditions. The findings revealed that careful configuration of the ANN structure significantly improved prediction performance and contributed to achieving a balance between indoor thermal comfort and reduced air-conditioning energy consumption .

N. Attoue et al. [41] developed an ANN model to predict indoor temperature in an old building at Polytech Lille. The proposed approach simplified the ANN structure by considering only two primary input parameters: outdoor air temperature and façade temperature. The results demonstrated that the simplified ANN model was capable of providing accurate temperature predictions despite the reduced number of input variables. The study further indicated that façade temperature effectively represented the influence of the building's thermal mass, serving as an indirect indicator of heat storage and transfer effects within the prediction process .

E. Soherwardy et al., [42] investigated the integration of building material selection with thermal prediction using ANNs. This study evaluated the thermal performance of construction materials, including bricks and concrete, through ANN-based predictive analysis. The findings revealed that the selection of materials with low embodied energy, combined with intelligent thermal prediction models, can significantly reduce the environmental impact of buildings. In addition, the developed ANN model was capable of quantifying the individual thermal contribution of each material to overall building thermal performance .

Thermal design strategies for hot climatic regions were examined by **S.N. Kharrufa and F. Noori** [43] through a combination of experimental analysis and ANN modeling. The study compared the thermal performance of traditional and modern architectural designs commonly used in Middle Eastern environments. The findings showed that some traditional passive techniques, such as courtyards, may not always provide effective thermal performance under certain conditions. Furthermore, the study demonstrated that ANN-based comparative analyses produced more reliable results when building designs emphasized thermal insulation and thermal mass rather than purely aesthetic considerations .

A Talib et al., [44] developed an ANN model for multistep-ahead prediction of indoor air temperature in building HVAC systems using experimental data from the Oak Ridge National Laboratory Flexible Research Platform. The study compared a grey-box RC thermal model with a feed-forward ANN approach within a Model Predictive Control framework. The ANN was trained using historical indoor temperature and environmental variables to capture nonlinear thermal dynamics. Performance was evaluated using Root Mean Square Error (RMSE), showing values of 1.02 °C for the ANN compared to 0.89 °C for the grey-box model. Although slightly less accurate than the physics-based approach, the ANN demonstrated strong capability for real-time prediction with low computational cost, making it suitable for control-oriented applications in smart buildings .

B.K. Park and C.J. Kim [45] investigated short-term indoor air temperature prediction using a Multilayer Perceptron (MLP) neural network in a controlled experimental room environment. The model was trained using high-frequency sensor data (1-second intervals), including indoor temperature and environmental conditions. The study evaluated the influence of sampling intervals on prediction accuracy and found that ANN models perform best for short-term forecasting horizons. The results indicated that the model achieved high predictive reliability, but performance degraded significantly for long prediction intervals beyond 900 seconds, where the coefficient of determination (R^2) dropped below 0.5. This study highlights the sensitivity of ANN models to temporal resolution in building thermal systems .

P. Norouzi et al., [46] reviewed the applicability of deep learning and ANN-based approaches for predicting indoor temperature as part of digital twin HVAC systems. The study highlighted the transition from classical ANN models toward deep learning architectures such as LSTM and attention-based neural networks. These advanced models allow improved prediction of transient indoor temperature behavior under dynamic conditions, including ventilation changes and occupancy variability. The review emphasized that ANN remains a core component of building energy modeling but is increasingly integrated into hybrid and digital twin frameworks for enhanced prediction accuracy and real-time control .

In a related 2024 study, **Alshammari** [47] applied an ANN model optimized using GridSearchCV for indoor temperature prediction in smart home environments. The model incorporated environmental variables such as outdoor temperature and occupancy-related signals to improve prediction robustness. The study demonstrated that hyper-parameter optimization significantly enhances ANN performance, reducing prediction error and improving generalization under varying climatic conditions. The findings confirm that optimized ANN architectures are more stable and accurate compared to conventional manually tuned networks, especially in real-world smart home applications .

More recently, **J. Penuela et al.**, [48] Proposed a Bayesian deep learning framework combining ANN structures with Kalman filtering for indoor thermal dynamics prediction under noisy sensor conditions. The model achieved high prediction accuracy ($RMSE \approx 0.245$ °C, $R^2 \approx 0.926$) for up to 150-minute forecasting horizons. Unlike traditional ANN models, this hybrid approach incorporates uncertainty estimation and improves robustness against measurement noise and incomplete datasets. The study demonstrates a significant evolution of ANN-based indoor temperature prediction toward probabilistic and hybrid AI systems in modern building control applications.

Previous studies have confirmed the potential of ANN models for indoor temperature prediction. However, limited research has addressed passive buildings in semi-arid climates. Therefore, a research gap remains in evaluating ANN-based models under these climatic conditions. This study aims to address this gap using experimental data from a passive test cell in Ghardaïa, Algeria.

Table 2-2: ANN-Based indoor temperature prediction in buildings

Reference	Inputs	Output	Architecture	Commentary
Soleimani-Mohseni. M et al., (2006) [38]	- Outdoor temperature - Heating power - Wall temperature - Ventilation flow rate - Solar radiation	Indoor temperature	MLP (Feed-forward)	ANN models showed higher flexibility than linear ARX models, especially in capturing nonlinear ventilation temperature relationships.
Zamora Martinez. F et al., (2013) [39]	- Outdoor temperature - humidity - Solar irradiance - CO2 concentration - Time (hour)	Indoor temperature	MIMO MLP (Ensemble)	Combined multiple ANNs to reduce overfitting and improve generalization in a smart house system.
Afroz . Z et al., (2017) [40]	- Temp set-point - Outdoor temp - Wind speed/direction - Solar radiation - Humidity & Pressure	Indoor temperature	NARX (8-10-1)	Levenberg–Marquardt identified as the best training algorithm for short-term prediction in institutional buildings.
Soherwardy. E et al., (2020) [42]	- Thermal conductivity; - Embodied energy; - Material cost; - External environment temperature	Indoor temperature	MLP (20 hidden layers)	Integrated material selection with thermal prediction; AAC blocks showed best thermal performance.
Talib. A et al., (2023) [44]	- Ambient temperature - Solar radiation; - Internal heat gains - Adjacent zone temperature	Indoor temperature	Hybrid (Grey-box + ANN)	ANN corrected residuals of RC model, outperforming traditional black-box ANN models.
Alshammari.T (2024) [47]	- Outdoor temperature, - Occupancy-related signals, - Historical indoor temperature	Indoor temperature (smart home prediction)	Optimized ANN using GridSearchCV (tuned MLP model)	Optimization to ANN models significantly improving prediction accuracy and stability.
Penuela. J et al., (2025) [48]	- Indoor temperature, - Noisy measurements, - Historical time-series data	temperature (medium-term forecasting with uncertainty)	Bayesian deep learning ANN + Kalman filtering hybrid model	Achieved high accuracy ($R^2 = 0.926$) and strong robustness under noisy sensor conditions,

2.7 Conclusion

This chapter presented the fundamental concepts and theoretical background of Artificial Neural Networks and their applications in building thermal models. Different transfer functions and their importance in nonlinear prediction processes were also introduced. In addition, the state of the art related to indoor temperature prediction in buildings demonstrated the effectiveness of ANN techniques in this field. These theoretical foundations provide the necessary basis for the following chapter, which will focus on the practical implementation of ANN models for building temperature prediction systems.

Chapter 3

Experimental Study and Predictive Modeling

3.1 Introduction

Experimental studies are essential for directly evaluating the influence of engineering design characteristics on the real operating conditions of buildings. To address this need, an innovative experimental model was specifically designed to investigate thermal comfort parameters in arid regions, where experimental assessments remain limited, while simultaneously examining the influence of local climatic conditions on the overall thermal performance of the system.

This chapter presents the materials and methods adopted to investigate the thermal performance of a south-oriented passive building prototype installed at the Applied Renewable Energy Research Unit (URAER). The study combines experimental measurements and numerical analysis to evaluate the effectiveness of key building envelope components, namely polyurethane sandwich panels and double glazing filled with argon gas. First, the chapter describes the climatic characteristics of the experimental site, particularly solar radiation and air velocity conditions. Next, it details the experimental setup and the high-accuracy measurement instruments used during the investigation. Finally, the chapter presents the methodology employed for the development of an Artificial Neural Network approach aimed at predicting indoor temperature based on environmental parameters.

3.2 Site description

This work was carried out in collaboration with the Applied Renewable Energy Research Unit (URAER), located approximately 20 kilometers east of Ghardaïa (see Figure 3.1). The latter is characterized by its geographical location (32°38'N, 3°81'E) at an altitude of approximately 469 meters above sea level, and falls within the semi-arid climate category of southern Algeria.

Choosing Ghardaïa as the experimental ground is due both to its favorable geographical position and to the huge solar power potential of the place. Specifically, in this place, you can expect to have 3,000 hours of sunshine per year and more than 6 kWh of sunlight per m² per

day. These are very good conditions for a proper "laboratory test ground" for the testing of renewable energy sources and in particular for solar energy uses in buildings.

However, such conditions come along with some difficulties, especially in the matter of weather changes. Specifically, in winter, Ghardaïa experiences cold winds blowing from the high plateaus, while the end of winter sees sand storms coming from the southwest. It is these fluctuations in temperature that make us apply artificial neural networks, because of their greater prediction capacity.

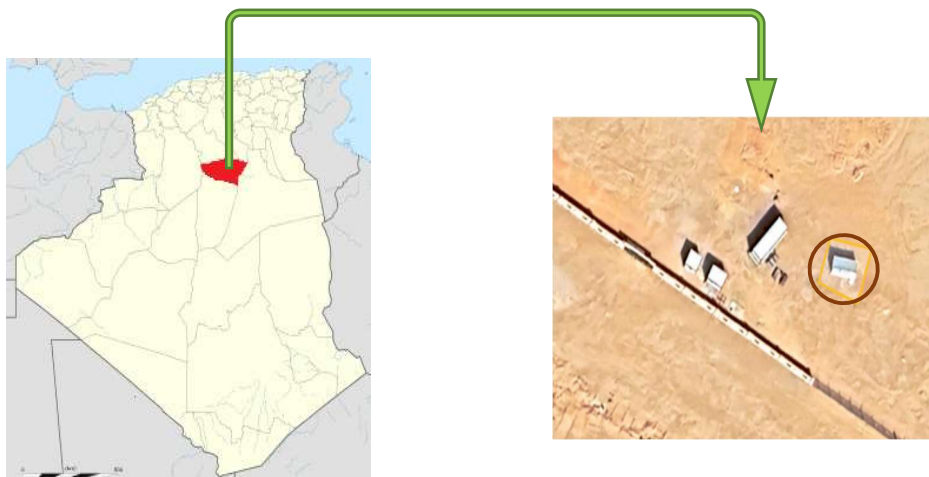


Figure 3-1 : General view of the studied building in URAER, Location carte (left) and geographical position (right)

The following part of this study provides the meteorological data (external conditions), including the average daily global solar radiation, ambient temperature, and relative humidity during the year 2025, corresponding to the period preceding the experimental campaign.

Figure 3.2 displays the average of daily global solar radiation data during the entire time period under study. Higher solar radiation is noted during summer seasons, mainly between May and August. On the other hand, low solar radiation values are noted during winter seasons, in agreement with the prevailing climatic conditions in Ghardaïa.

In Figure 3.3, the average of daily ambient temperature variations has been provided. Maximum temperatures exceed 37°C during summer seasons while during winter seasons they become very low, with the minimum values close to 5°C . Such a temperature variation is quite typical for the Saharan region.

The evolution of the relative humidity is illustrated in Figure 3.4. There is an inverse relation to the temperature; the lowest values of relative humidity are maintained (10% to 20%) during the summertime, while the maximum value is recorded at approximately 93% during the wintertime.

Figure 3.5 represents the annual variations of the wind speed. Wind speed variation can be described as stochastic, with many changes occurring throughout all four seasons of the year. Higher wind speed and even some gusts occur predominantly in the late wintertime and during springtime, influencing the convective heat transfer of the investigated system.

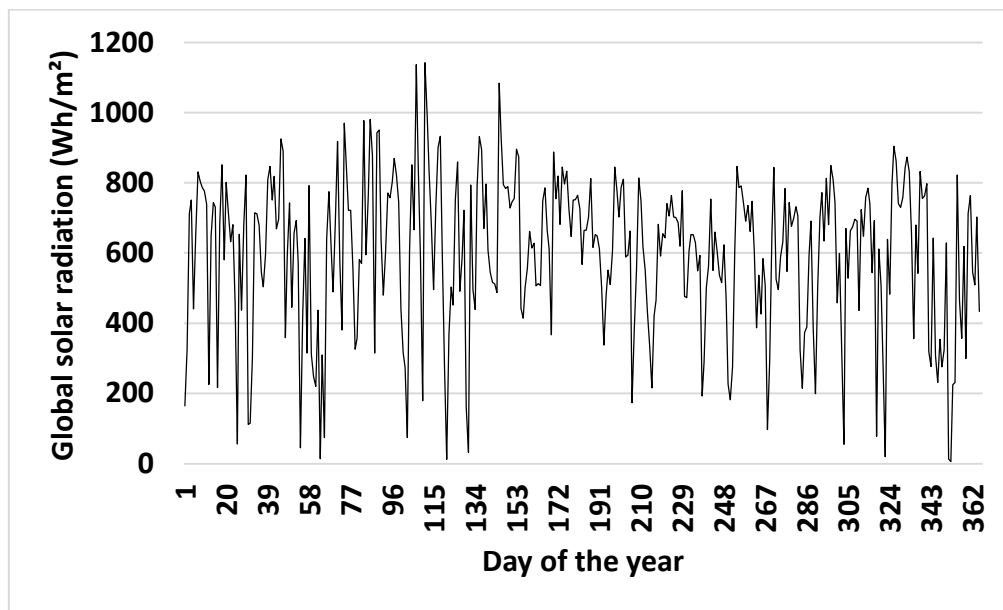


Figure 3-2: Variation of global solar irradiation

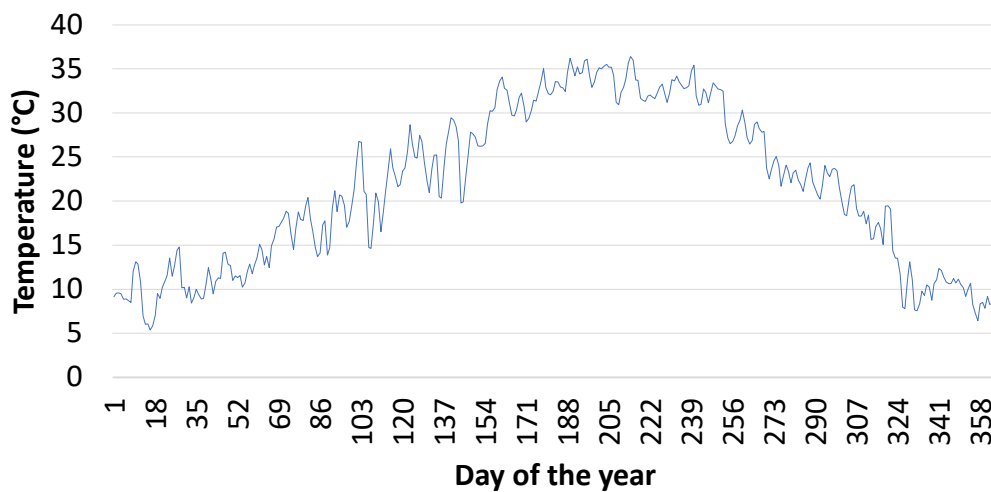


Figure 3-3: Variation of ambient temperature

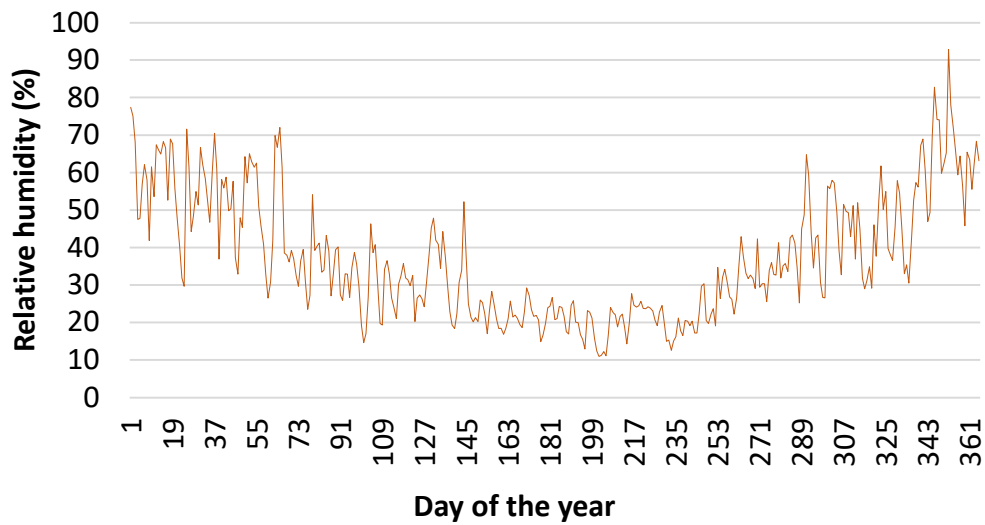


Figure 3-4: Variation of relative humidity

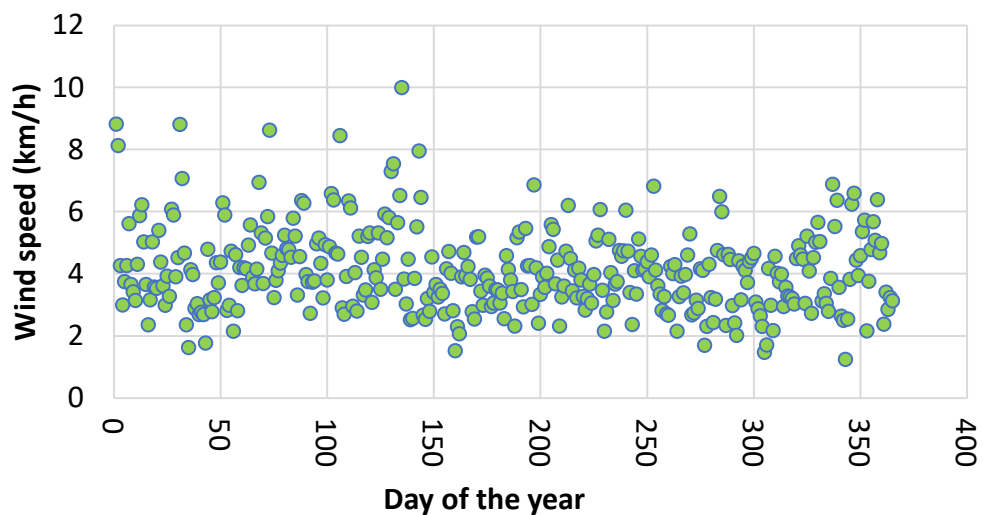


Figure 3-5: Variation of wind speed

3.3 Experimental setup

3.3.1 Building system

The study building is an experimental office room for research and technical tasks in the Ghardaia Scientific Research Station, which exists in a semi-arid zone that experiences adverse climatic conditions and great variations in temperature.

3.3.2.2 Building description

This experimental office room, illustrated in Figure 3.6, has a rectangular geometry with external dimensions of 4.00 m in length and 2.30 m in width, and an internal height of 2.20 m. The layout corresponds to a compact office-scale prototype designed for controlled thermal performance analysis.

The building is fully insulated from external environmental disturbances, which allows it to be considered a representative passive configuration for thermal studies without the influence of active cooling systems. This configuration enables the investigation of the building's intrinsic thermal behavior under real climatic conditions.

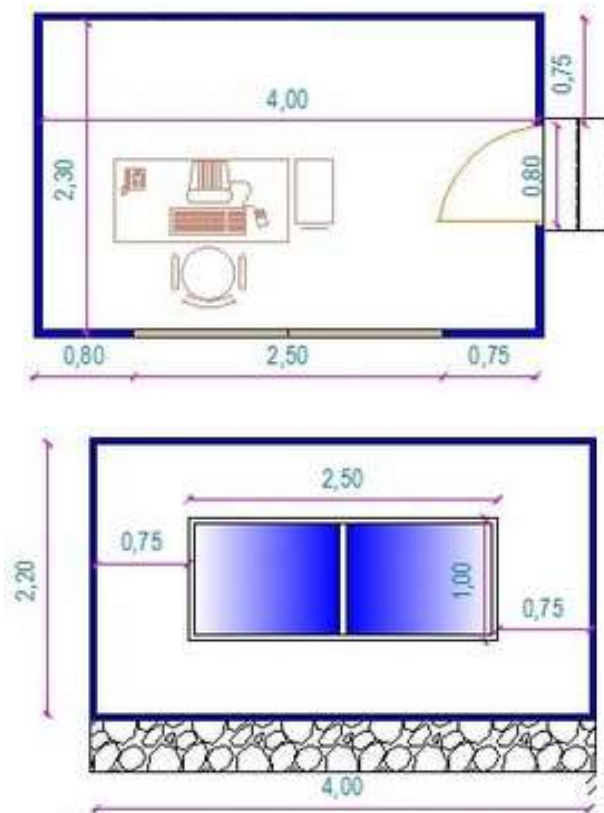


Figure 3-6: Dimensions and structural configuration of the experimental building

From the structure point of view, the building design utilizes high-level insulation to counter the effects of heat within the locality. This is done through the use of polyurethane panels that form the whole building shell; this is used as a barrier against any heat exchange. Further, the double-glazing windows are filled with argon gas to reduce the conductivity of heat transfer (see Figure 3.7). Despite the high levels of insulation in place, natural air vents have been strategically included for ventilation and cooling purposes.

As for the internal design, the office has a very clever design for its entrance, which comprises two doors, where the first one is the main external door, and then there is another door that is placed on the left side. The shape of this design serves as an airlock that prevents any flow of hot air from coming into the working area as well as protects the openings through which the air naturally comes from being affected by the strong desert winds (see Figure 3.8).



Figure 3-7: Outdoor view of the experimental building

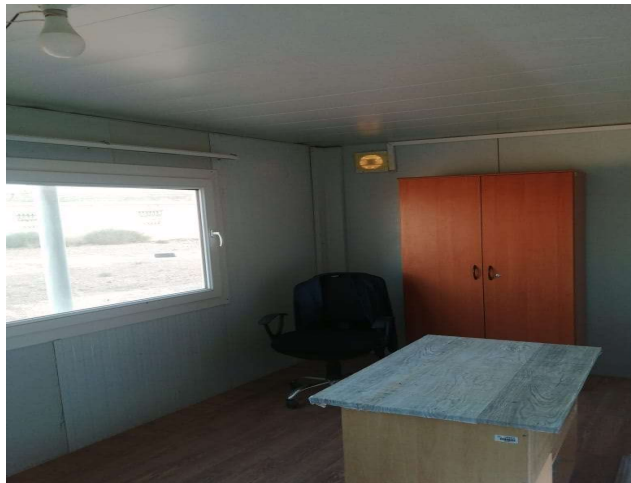


Figure 3-8: Indoor view of the experimental building

3.3.2.2 Building Envelope

The thermal behavior of the office is highly dependent on the makeup of its exterior shell. The polyurethane panels act in two ways; they help keep the interior cool while also shielding it. For one thing, this particular material has excellent heat resistance, thus blocking any thermal

exchange from the hot exterior surrounding the area in Ghardaïa. In another way, the type of walls used in the construction results in unique thermal mass properties for the building. As the polyurethane is much lighter than the conventional materials such as concrete, it exhibits low thermal inertia (Figure 3.9).



Figure 3-9: Sandwich panel material used in the experimental building

The density of the panels' structure plays an essential role in the decrease of thermal energy transfer at the most intense exposure to the sun [49]. This property affects the "time signature" of internal temperature variations due to the fact that the envelope itself is a buffer filter against environmental temperature fluctuations. With the help of modern insulation, it becomes possible to compensate for the lack of thermal mass and achieve an optimal combination.

3.3.2.2 Openings and external cover

Windows and openings have an important role in regulating heat exchange within the office, particularly under the intense solar radiation conditions characteristic of the semi-arid environment.

The opening aspect is concerned; the facade consists of a double-glazed glass unit having a size of 1m by 2.50m with argon gas filling to minimize its thermal conductivity to a great extent (See Figure 3.10). Along with such effective insulation, strategic openings for natural ventilation have been provided to renew air and cool down the space (See Figure 3.11).

The combination of all these components has helped to achieve substantial energy performance for this particular building. The use of the insulating panels along with the glassing system and the natural ventilation has ensured optimum adaptation of the structure according to the extreme environmental conditions.



Figure 3-10: Transparent interface: argon-injected double-glazing system



Figure 3-11: Ventilation system: high and low positions

3.3.2 Measurement instrumentation

This section deals with monitoring all weather-related factors that serve as essential inputs for the digital model. The measuring devices have been installed at strategic points around the building to ensure the accuracy of the data obtained.

3.3.2.1 External measurement system

Air temperature and ambient humidity: Ambient temperature was measured using atmospheric sensors with a measurement range of -29.9°C to $+79.9^{\circ}\text{C}$ and an accuracy of $\pm 0.8^{\circ}\text{C}$. Relative humidity was monitored simultaneously within a range of 1% to 99% with an accuracy of $\pm 5\%$ (See Figure 3.12). These readings play a crucial role in determining the enthalpy of the outside air and its impact on heat exchange through the office's insulation.

Wind speed and direction: Wind speed is monitored via the weather station shown in Figure 3-12, which allows for the measurement of speeds up to 200 km/h with a resolution of 0.1 km/h. These readings are important for calculating the convection heat transfer coefficient on the exterior sandwich panels.

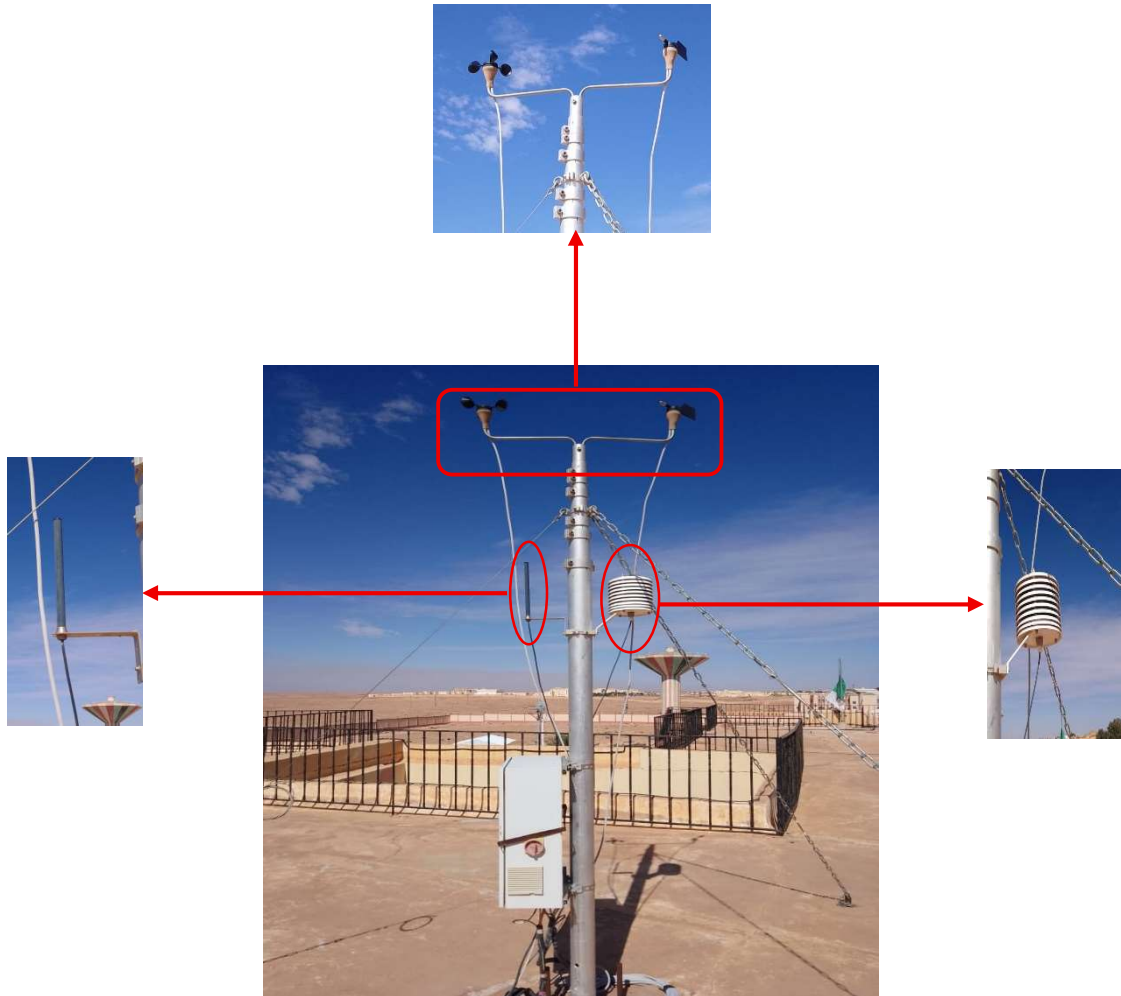


Figure 3-12: Sensors measuring air temperature, external relative humidity, speed and direction of wind within the weather station

Solar radiation monitoring system: Solar radiation is measured through an innovative solar tracker device called SOLYS 2, which has an accuracy rate above 98% for tracking solar radiation on a daily basis. The tracking system makes use of specific radiometers that help classify the different parts of radiation, such as direct, diffuse, and total. Additionally, the tracking system accommodates a global radiation pyrometer called CMP11, which is capable of measuring a global radiation level of up to 4000 W/m² and with an error rate below 2%. (Figure 3-13).



Figure 3-13: SOLYS 2 solar radiation tracking and measurement system at URAER

3.3.2.2 Internal measurement system

Inside the building, K-type thermocouples with a measurement accuracy of up to ± 0.3 °C were installed to monitor the indoor air temperature.

The indoor temperature was measured at several locations within the building system, as presented in Figure 3.14, including the center of the room and at different heights above the floor level (0.5 m, 1.25 m, and 2 m), in order to evaluate the vertical temperature distribution and thermal stratification inside the experimental space.

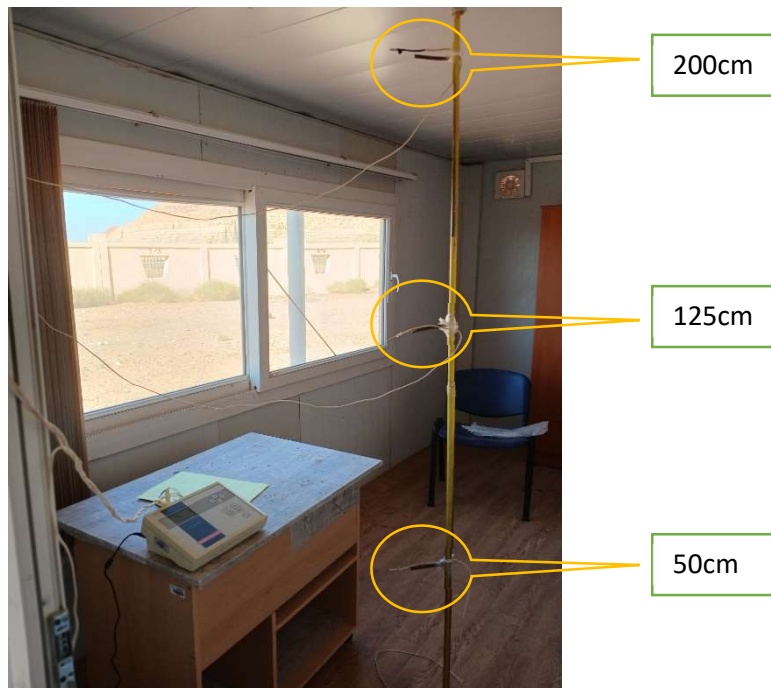


Figure 3-14: Distribution of sensors at different heights

3.3.3 Data Collection and Storage

All data collection and storage are carried out using the Consort T8710 digital data logger, as illustrated in Figure 3.15. All indoor sensors are connected to this unit, which provides high measurement accuracy (up to 0.05%) and supports multiple thermocouple types (J, K, T, and E). This ensures reliable and continuous recording of temperature variations, capturing both indoor air conditions and fluctuations associated with natural ventilation through openings.

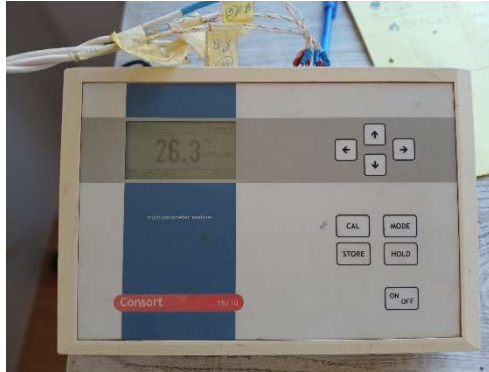


Figure 3-15: Consort T8710 digital data logger

The following Table 3.1 illustrates some of the physical and thermal properties of four basic materials: air, argon gas, glass, and polyurethane, each of which plays an important role in the mechanisms of heat transfer through the building envelope.

Table 3-1: Thermophysical properties of different materials [50, 51]

Elements	Density [kg/m ³]	Thermal conductivity [W/m. C°]	Specific heat [J/kg. C°]
Air	1.20	0.026	1005
Argon gas	1.66	0.016	520
Polyurethane	30–40	0.022–0.028	1400–1500
Glass	2500	1.0–1.1	840

3.4 Artificial neural network modeling

The simulation of microclimatic conditions in experimental buildings using ANNs has emerged as an effective application of artificial intelligence in the building sector. This approach enables the accurate prediction of indoor environmental parameters, such as temperature, based on data collected from in-situ sensors installed within the building. By capturing the complex and nonlinear relationships between environmental variables, ANN models provide reliable tools for analyzing thermal behavior and improving building energy performance. Furthermore, these predictive models contribute to the development of intelligent and energy-efficient building systems capable of ensuring better indoor comfort under varying climatic conditions.

The following diagram Figure 3.16 illustrates the flowchart for the methodology of building and training an artificial intelligence model based on neural networks. The process starts with data preparation, including input selection and preprocessing, followed by ANN design and training using the Levenberg backpropagation algorithm to minimize errors efficiently. If the results are unsatisfactory, the model is adjusted iteratively until the lowest error is achieved, after which the final outputs are obtained.

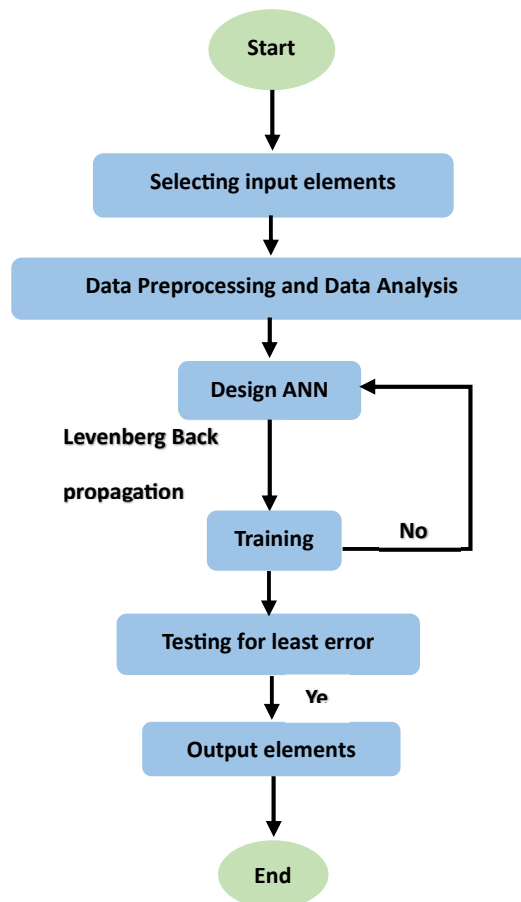


Figure 3-16: Flowchart of prediction system

3.4.1 Data acquisition process

The monitoring campaign was conducted over seven consecutive days, specifically on March 18 and 25. Measurements were taken at regular intervals of one hour, resulting in a total of 174 valid data points. The dataset consists of a time series including independent climatic variables such as outdoor temperature, humidity, wind speed, and solar radiation rates, which were imported and converted into a numeric matrix to ensure compatibility with the learning algorithms.

The structured data acquisition process enabled the establishment of a comprehensive and high-quality dataset (Figure 3.17), providing a robust foundation for the development and training of predictive models based on artificial intelligence techniques.

Table 3-2: Screenshot of the data base

	A	B	C	D	E	F
1	Temps	Outdoor Temperature	Hmidity	Wind Speed	Rayonnement	Indoor Temperature
2	12.00	23,69	12,19	3,53	930,27	21,6
3	13.00	24,81	11,83	3,41	914,64	22,5
4	14.00	25,47	11,5	3,2	853,15	23,3
5	15.00	25,74	11,26	2,96	305,44	24,5
6	16.00	25,52	11,35	2,74	537,81	19,4
7	17.00	24,74	11,84	2,6	523,11	20,4
8	18.00	22,05	18,08	1,86	313,66	21,2
9	19.00	18,69	21,12	2,38	0	21,8
10	20.00	17,32	22,26	2,63	0	20,9
11	21.00	16,43	23,23	2,76	0	20
12	22.00	15,46	24,37	2,82	0	18,9
13	23.00	14,76	25,21	2,75	0	18,5
14	1.00	14,3	25,76	2,58	0	17,9
15	2.00	13,92	26,1	2,39	0	16,8
16	3.00	13,39	26,51	2,34	0	15,7
17	4.00	12,56	27,35	2,51	0	15,3
18	5.00	11,74	28,32	2,75	0	15,2
19	6.00	11,09	29,22	2,93	0	15,4
20	7.00	11,06	29,86	2,98	3,22	15,2
21	8.00	14,87	23,82	3,34	157,02	15
22	9.00	17,91	19,85	3,22	320,16	14,7
23	10.00	22,78	13,76	3,72	389,59	16
24	11.00	25,57	11,78	4,06	476,19	18,1
25	12.00	27,44	11,21	4,17	484,11	19

The Table 3.3 summarizes the statistical characteristics of the study variables, showing a sharp variation in solar irradiance, which peaks at 1048.91. While the outside temperature fluctuates between 9.38°C and 33.89°C, the inside temperature is more stable, averaging 20.84°C. The data also reflect a very dry climate with an average relative humidity of no more than 4.37% and significant wind activity with an average speed of 27.23. This data is used as input within the process to design and train an artificial intelligence model aimed at achieving the most accurate predictions (Figure 3.18).

Table 3-3: Summary statistics of data

Category of value	Parameters	Moy	Min	Max	St-Dev
Input parameters	Solar radiation	306.17	0	948,91	360,20
	Outdoor Temperature	20,78	9,38	33,89	6,61
	Wind Speed	4.37	0.63	13.62	14,69
	Relative Humidity	27.22	10.88	71.6	2,18
Output parameters	Indoor Temperature	20,84	14,70	27,60	2,85

	A	B	C	D	E	F
1	1	23.6900	12.1900	3.5300	93.9146400	Converted To [Type: Number, Value: 914.64]
2	2	24.8100	11.8300	3.4100	914.6400	22.5000
3	3	25.4700	11.5000	3.2000	853.1500	23.3000
4	4	25.7400	11.2600	2.9600	305.4400	24.5000
5	5	25.5200	11.3500	2.7400	537.8100	19.4000
6	6	24.7400	11.8400	2.6000	523.1100	20.4000
7	7	22.0500	18.0800	1.8600	313.6600	21.2000
8	8	18.6900	21.1200	2.3800	0	21.8000
9	9	17.3200	22.2600	2.6300	0	20.9000
10	10	16.4300	23.2300	2.7600	0	20
11	11	15.4600	24.3700	2.8200	0	18.9000
12	12	14.7600	25.2100	2.7500	0	18.3000
13	13	14.3000	25.7600	2.5800	0	17.9000
14	14	13.9200	26.1000	2.3900	0	16.8000
15	15	13.3900	26.5100	2.3400	0	15.7000
16	16	12.5600	27.3500	2.5100	0	15.3000
17	17	11.7400	28.3200	2.7500	0	15.2000
18	18	11.0900	29.2200	2.9300	0	15.4000
19	19	11.0600	29.8600	2.9800	3.2200	15.2000
20	20	14.8700	23.8200	3.3400	157.0200	15
21	21	17.9100	19.8500	3.2200	320.1600	14.7000
22	22	22.7800	13.7600	3.7200	389.5900	16
23	23	25.5700	11.7800	4.0600	476.1900	18.1000
24	24	27.4400	11.2100	4.1700	484.1100	19
25	25	28.8100	10.9600	4.2300	655.1100	19.8000
26	26	29.7000	10.8800	4.3700	754.2200	20.3000
27	27	30.1400	10.9100	4.6600	720.2400	20.4000
28	28	30.1500	11.0800	5.0300	680.8800	21.1000
29	29	29.6500	11.5000	5.4000	593.2500	21.4000

Figure 3-17: Database used as input for the artificial intelligence modeling process

3.4.2 Database division

The findings of the neural fitting model in Figure 3.19, reveal that the accuracy of neural network learning improves gradually as the proportion of training data increases. At the 60% level of the training data set, we observed high error values and low correlation coefficient values, indicating that the network has poor generalization ability. When the percentage of

training data increased to 70%, there was a marked improvement in training; however, the test results were still inconsistent, which means that the signs of over-learning had started. At 80% training data percentage, there was a marked reduction in the MSE values together with an increase in R values close to one.

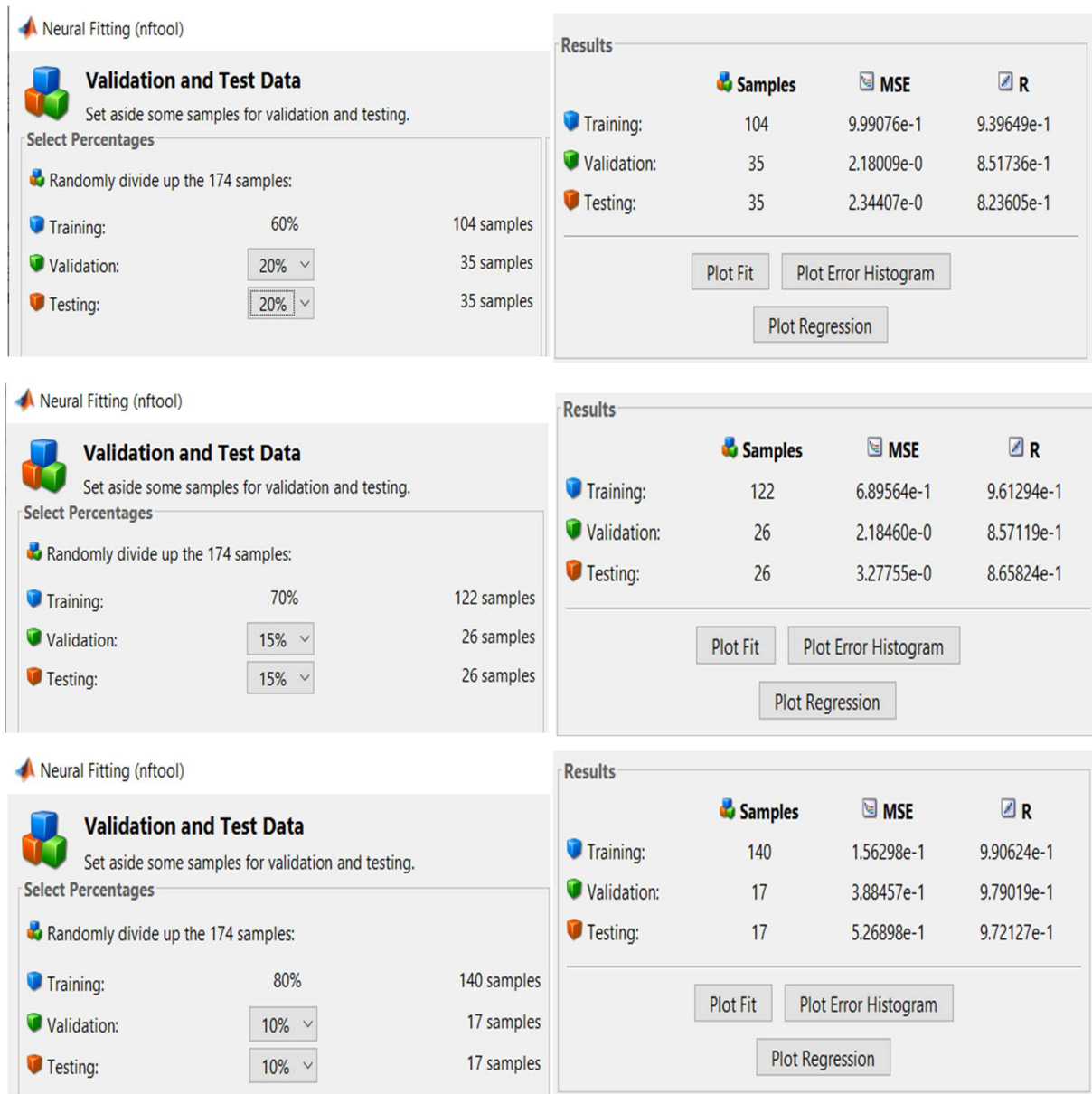


Figure 3-18: Database splitting based on the Levenberg-Marquardt algorithm

Based on the results shown in Table 3.3 for the distribution of training, validation, and testing data, the (80%, 10%, 10%) data split achieved the best model performance. The correlation coefficient approached one, reflecting high predictive accuracy and strong agreement between experimental and predicted values.

Table 3-4: Comparative analysis of data distribution

Percentage	60%, 20%, 20%	70%, 15%, 15%	80%, 10%, 10%
Training	0.939649	0.961294	0.990624
Validation	0.851736	0.857119	0.979019
Testing	0.823605	0.865824	0.972112

3.4.3 Neural network architecture

After data preprocessing and integration into the model, a multilayer neural network (MLN) architecture was selected, consisting of five input parameters and one target output corresponding to the indoor temperature of the building. The determination of the optimal ANN architecture (Figure 3-20), particularly the number of neurons in the hidden layer, represents a critical step due to the absence of a universally accepted selection rule in the literature [52, 53]. Consequently, an empirical optimization approach was adopted by varying the number of hidden neurons and assessing the model performance using the regression coefficient according to authors [54, 55]. Following several iterative tests, the configuration containing 25 neurons in the hidden layer provided the highest regression coefficient, demonstrating the best predictive accuracy and overall model performance.

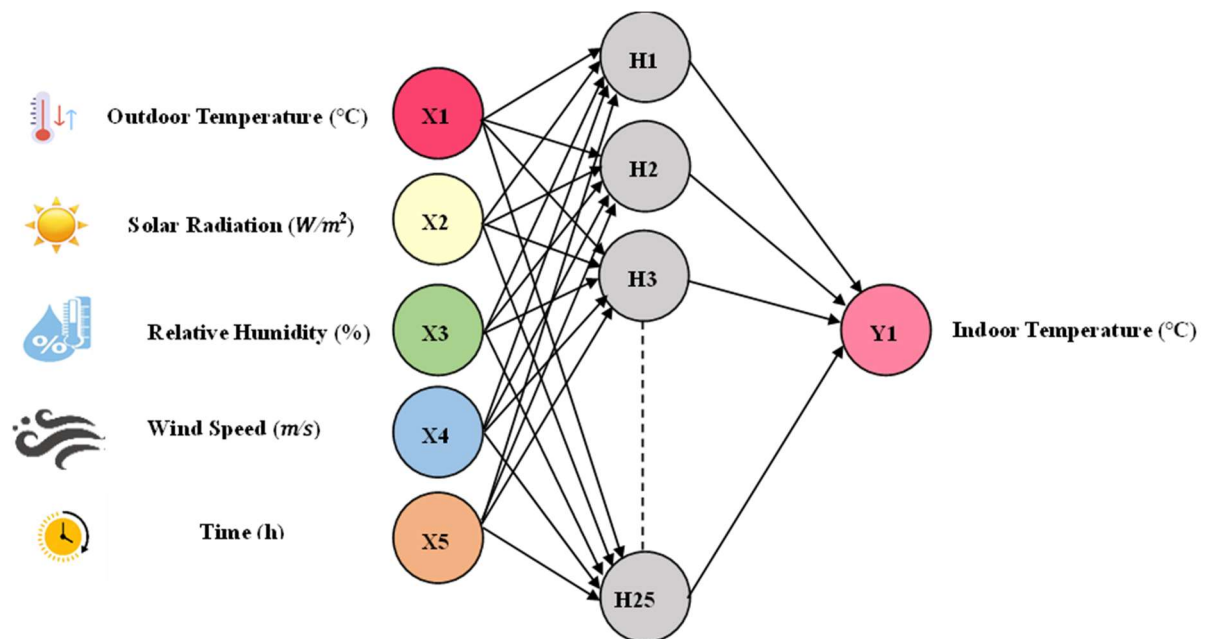


Figure 3-19: Schematic of the building ANN optimal architecture

Table 3.4 presents the numerical simulation results used to identify the optimal number of neurons in the hidden layer for predicting the building's internal temperature. Different ANN models with 1 to 30 neurons were tested, showing variations in prediction accuracy.

Table 3-5: Comparative analysis of the number of neurons

Hidden	Training	Validation	Test	All
1	0.5436	0.3388	0.5312	0.5195
2	0.7936	0.40505	0.87011	0.78404
3	0.59309	0.89765	0.65595	0.62844
4	0.85624	0.83801	0.7126	0.83702
5	0.84557	0.85747	0.66274	0.83186
6	0.90092	0.92276	0.95903	0.90653
7	0.88258	0.88861	0.93742	0.88765
8	0.9343	0.91762	0.71587	0.91758
9	0.97584	0.88643	0.92876	0.96417
10	0.94033	0.93572	0.84901	0.92575
11	0.95063	0.79539	0.85745	0.91756
12	0.96796	0.93814	0.9216	0.95946
13	0.96232	0.8981	0.88082	0.95002
14	0.94512	0.82565	0.86635	0.92151
15	0.94955	0.95099	0.92155	0.94652
16	0.92877	0.92614	0.66746	0.91792
17	0.97194	0.88701	0.93468	0.95759
18	0.96118	0.83138	0.90794	0.9398
19	0.99068	0.93389	0.54098	0.9332
20	0.98898	0.90358	0.87675	0.97227
21	0.97427	0.9231	0.93967	0.96312
22	0.9032	0.8594	0.9104	0.89767
23	0.97395	0.86421	0.78792	0.94396
24	0.98212	0.93554	0.96541	0.9793
25	0.99062	0.97902	0.97213	0.98671
26	0.98247	0.90971	0.73826	0.96071
27	0.98998	0.89913	0.94873	0.9779
28	0.94597	0.95272	0.91058	0.94125
29	0.9978	0.84259	0.78526	0.97088
30	0.96421	0.8896	0.80058	0.93749

3.4.4 Training for artificial neural network

The proposed neural network was designed using a feed-forward backpropagation model. For network training, the Levenberg-Marquardt algorithm was employed due to its ability to converge quickly, with the mean squared error used as the primary performance metric. As observed from our results, training concluded on the 13th iteration, achieving a performance of 0.182, with the validation maxed out at 6.

A Logsig transition function is employed to ensure efficient handling of nonlinear relationships in Figure 3.21. This is further supported by the Learngdm adaptive learning function, which utilizes gradient momentum to enhance weight stability.

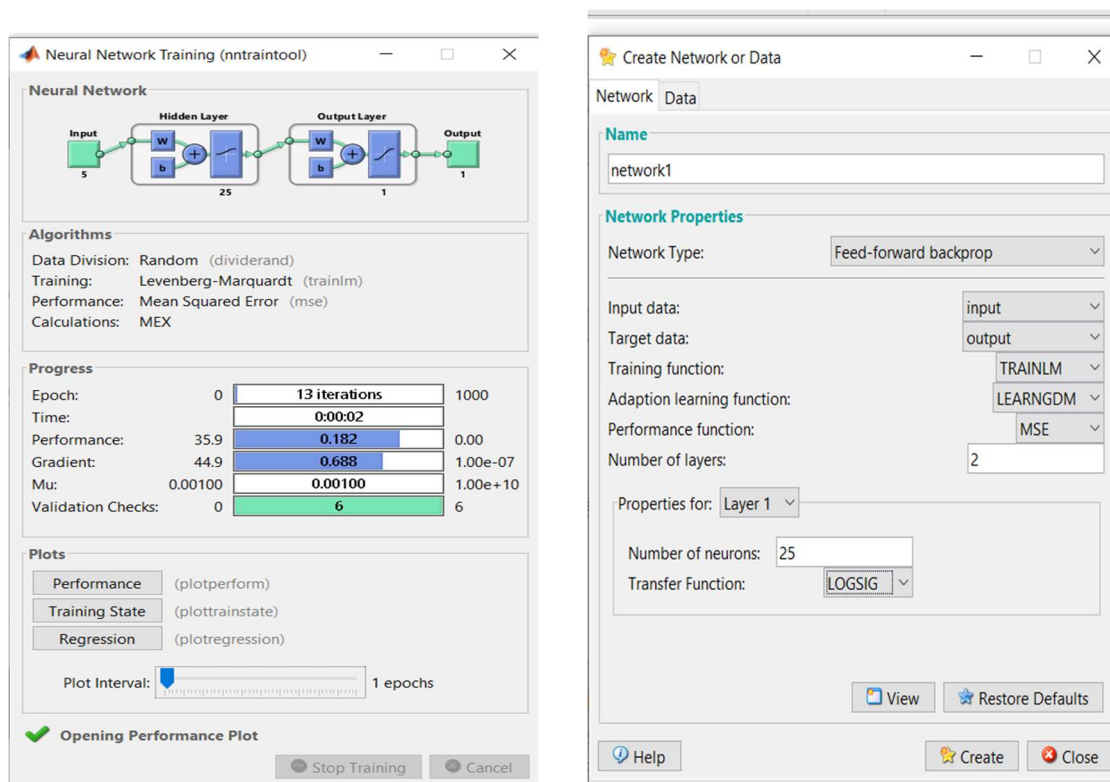


Figure 3-20: ANN model structure in Matlab

The data manager interface summarizes the final stage of data organization in Figure 3-22, displaying the prepared neural network (network1) alongside its predictive outputs (network1) and associated error data (network1). This structure reflects the integrated relationship between input data and experimental objectives (output), allowing for the evaluation of model accuracy and the export of final results for statistical analysis.

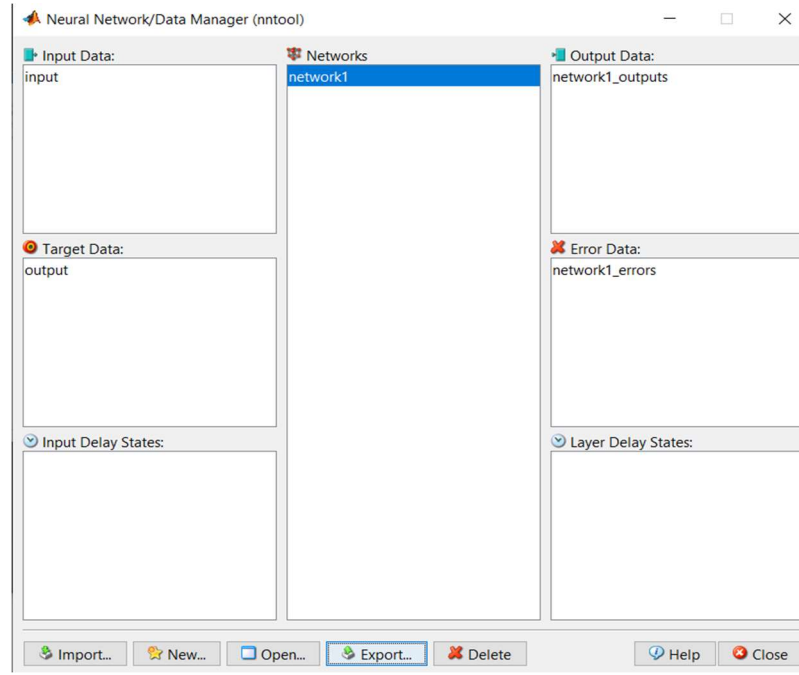


Figure 3-21: Data management and structure for the neural model

3.5 Evaluation Measures

To assess the accuracy and reliability of the developed model, as well as the thermal behavior of the studied system, several evaluation measures were employed. These measures include statistical metrics [56] used to quantify the agreement between experimental and predicted results, in addition to thermal performance indicators [57, 58] used to analyze the thermal response of the building. The selected parameters provide a comprehensive evaluation of prediction quality, thermal stability, and energy performance under the investigated operating conditions.

3.5.1 Statistical metrics

- **Coefficient of Determination (R^2):** It is measured to the degree of agreement between predicted and experimental values. Physically, it indicates how well the model explains the variability of the measured data.

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_{exp} - Y_{pred})^2}{\sum_{i=1}^n (Y_{exp} - \bar{y})^2} \quad (3-1)$$

- **Root Mean Square Error (RMSE):** represents the square root of the average squared differences between predicted and experimental values. Physically, it indicates the overall magnitude of prediction errors, giving greater importance to large deviations.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_{exp} - Y_{pred})^2} \quad (3-2)$$

- **Mean Absolute Error (MAE):** represents the average absolute difference between predicted and experimental values. Physically, it reflects the average prediction error magnitude without considering its direction.

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_{exp} - Y_{pred}| \quad (3-3)$$

- **Sample standard deviation (σ):** represents the measure of dispersion in statistics that measures the deviations of instantaneous temperatures from the arithmetic mean. In thermodynamics, it serves as an indicator of thermal stability. The smaller the values, the higher the uniformity and stability of the thermal system.

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (3-4)$$

- **Arithmetic mean ($\bar{x}$):** This is a statistic that evaluates the center of the distribution of temperatures over a certain time interval (n number of samples). It gives the point where the temperatures reach thermal equilibrium.

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (3-5)$$

3.5.2 performance indicators

- **Thermal Amplitude (A):** It is an arithmetic difference between the maximum and minimum values of temperature per full period of time. It defines the degree of thermal changes which can occur on the building's outer shell or inside.

$$A = T_{max} - T_{min} \quad (3-6)$$

- **Thermal lag (Φ):** It is an indicator showing the time period between the occurrence of the maximum temperature value at the exterior surface of the structure and the maximum point of the corresponding temperature wave at the interior surface of the wall. This indicator is influenced by the thermophysical properties of the material including heat diffusion and thickness.

$$\Phi = t(T_{int_{max}}) - t(T_{out_{max}}) \quad (3-7)$$

- **Thermal Load Leveling (TLL):** It is the dimensionless characteristic measuring the performance of thermal attenuation of a structure. The thermal load leveling allows comparing the degree of temperature changes inside versus outside of a building. It indicates how well a construction can absorb the impact of thermal waves.

$$TLL = \frac{T_{int_{max}} - T_{int_{min}}}{T_{out_{max}} - T_{out_{min}}} \quad (3-8)$$

3.6 Conclusion

In this chapter, we provided a description of both the experimental and computational methods applied in investigating the thermal performance of a passive solar south oriented building in Ghardaïa. In applying efficient insulation systems together with an advanced measurement system, a complete database of climate and thermal conditions has been created. This experimental study enabled the creation of a database from which an artificial neural network model capable of predicting internal temperature was developed based on the Levenberg-Marquardt algorithm. Optimization of ANN model parameters is done successfully which will form the basis of simulations and results in the next chapter.

Chapter 4

Results and Discussion

4.1 Introduction

Energy efficiency in the building and construction sector plays a crucial role in sustainable development, particularly in regions characterized by harsh thermal conditions. This research focuses on investigating the thermal behavior of south-oriented buildings, with particular emphasis on the effectiveness of passive techniques. In addition, the study explores the prediction of indoor temperature using intelligent methods based on artificial intelligence.

The research is structured around two complementary contributions: an experimental investigation of a building located in a semi-arid climate and a numerical modeling approach using artificial intelligence techniques.

On the one hand, the experimental study is based on practical measurements of external climatic parameters, including solar radiation, ambient temperature, relative humidity, and wind speed, together with the technical characteristics of the building under investigation. The experimental analysis focuses on evaluating heat losses caused by natural convection through the monitoring of solar radiation and indoor temperature variations at different heights. Furthermore, the study examines the influence of blinds used as opaque shading elements on the indoor thermal environment.

On the other hand, the numerical approach involves the application of artificial intelligence techniques, particularly artificial neural networks, for predicting indoor temperature within the building.

4.2 Analysis of experimental results

The experimental campaign was initially conducted over a period of two month during March – April in the Ghardaïa region. However, after analyzing the collected database, several constraints were identified, including missing measurements, inconsistent or erroneous data, and limited availability of certain measuring instruments during some periods of acquisition.

To ensure the reliability, coherence, and scientific validity of the analysis, the experimental database was carefully processed and filtered. Consequently, a representative period of three consecutive days with complete and consistent measurements was selected for the detailed investigation of the solar masking and solar protection phenomena. This selected period provided stable climatic conditions and sufficiently reliable data for an accurate comparative thermal analysis.

4.2.1 Solar radiation parameter

Figure 4-1 illustrates the variation of global solar radiation measured on both horizontal and vertical planes during the experimental period in the Ghardaïa region. The results reveal a clear diurnal profile characterized by a gradual increase in solar radiation after sunrise, reaching maximum values around midday, followed by a progressive decrease toward sunset.

The horizontal surface consistently received higher solar radiation intensity compared to the vertical surface throughout the measurement period. Peak values on the horizontal plane approached approximately 850–900 W/m², whereas the vertical plane recorded lower maximum values ranging between 500 and 650 W/m². This difference is mainly attributed to the angle of solar incidence, since the horizontal plane is more directly exposed to solar rays during midday hours.

The figure also shows day-to-day fluctuations in solar radiation intensity, particularly during the second experimental day where irregular variations and short-term decreases were observed. These fluctuations may be associated with transient atmospheric conditions such as partial cloud cover, dust particles, or variations in air transparency, which are common in arid desert climates like Ghardaïa.

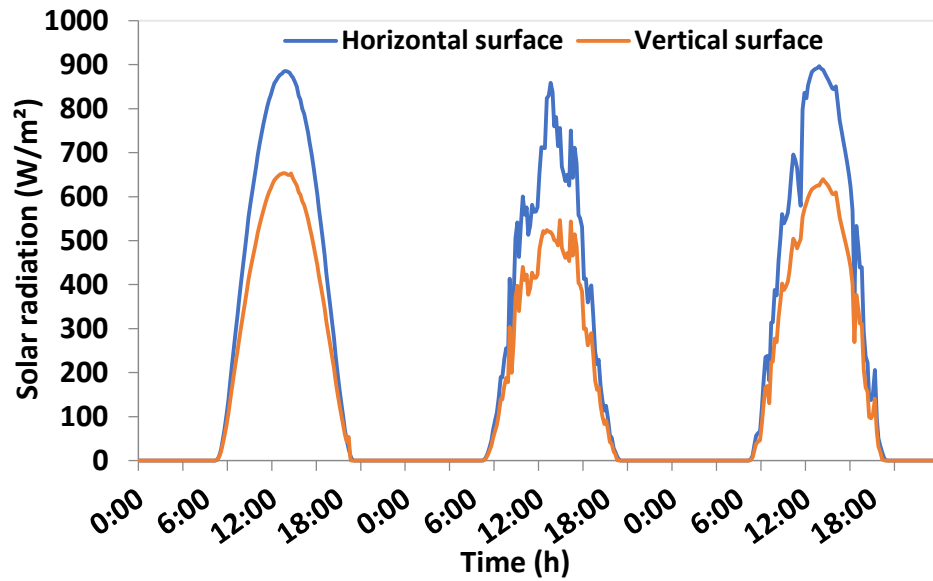


Figure 4-1: Variation of global solar radiation on a horizontal plane vertical plane

The results confirm the high solar potential of the Ghardaïa region and demonstrate the significant influence of surface orientation on solar energy reception. The higher radiation levels on the horizontal surface indicate a greater potential for heat gain and thermal energy storage, while the vertical surface receives comparatively lower solar input, which may contribute to reducing excessive thermal loads on building walls.

4.2.2 Temperature parameter

The experimental results illustrating the temporal variation of indoor temperature at two different heights (200 cm and 50 cm) reveal a clear cyclic behavior associated with day–night thermal variations. As shown in Figure 4-2, the temperatures recorded at 200 cm were consistently higher than those measured at 50 cm, particularly during daytime heating periods. This phenomenon can be explained by thermal stratification caused by the upward movement of warm air inside the building. Moreover, the indoor temperature increased progressively during the daytime, reaching peak values between 26 °C and 28 °C under the influence of solar radiation. During nighttime, the temperature gradually decreased to values ranging from 15 °C to 17 °C due to the absence of solar gains.

In contrast, the temperature curves at the two heights tended to converge during the night, indicating a more homogeneous indoor temperature distribution. Overall, the obtained results highlight the strong interaction between indoor thermal conditions and the external environment, with significant vertical temperature differences observed mainly during daytime periods.

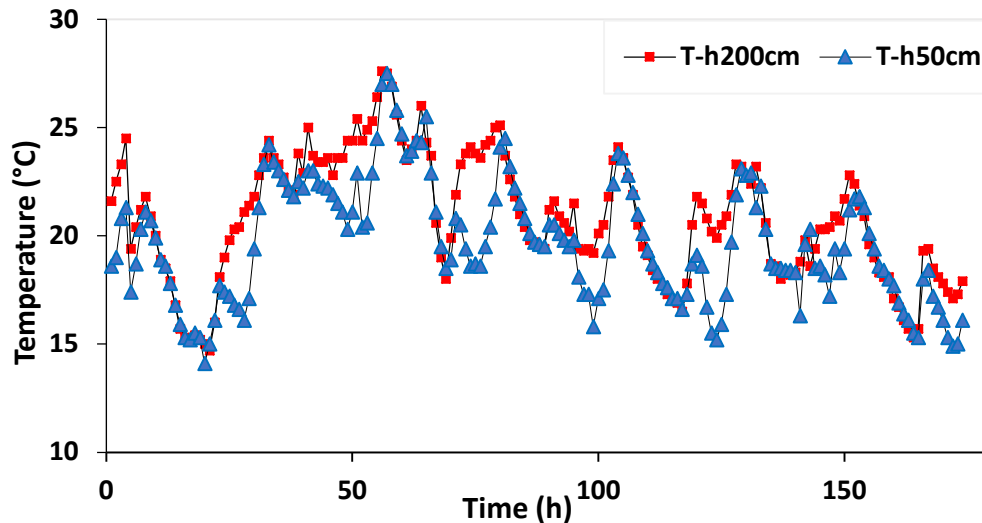


Figure 4-2: Evolution of indoor air temperature at different heights

In the first case, corresponding to the configuration without solar gains (with curtains), Figure 4-3 demonstrates the high effectiveness of the curtains as insulating and shading elements in regulating the indoor thermal environment. The indoor temperature remained relatively stable despite the significant fluctuations observed in the outdoor temperature throughout the day. While the outdoor temperature reached a maximum value exceeding 31 °C around midday (approximately 2:00 PM), the indoor temperature remained nearly 11 °C lower due to the reduction of direct solar radiation entering the building through the curtains. This result confirms the important role of shading devices in minimizing solar heat gains and improving indoor thermal comfort.

The obtained results also reveal the phenomenon of thermal inertia, as the indoor environment reached its maximum temperature around 6:00 PM, approximately four hours after the peak outdoor temperature. This delayed thermal response can be explained by the heat storage capacity of the building materials, which absorb thermal energy during the daytime and release it gradually over time.

During nighttime, when the outdoor temperature decreased considerably, the curtains contributed to reducing heat losses from the indoor space by limiting heat transfer through the glazed surfaces. Consequently, the indoor environment maintained a relatively warm and stable thermal condition compared to the outdoor atmosphere.

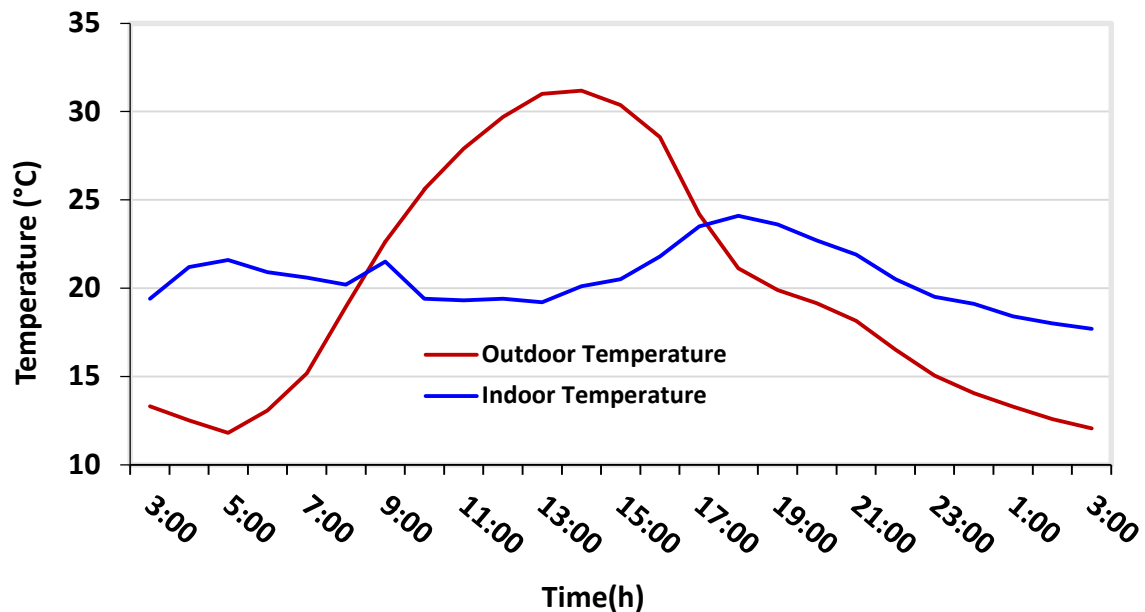


Figure 4-3: Impact of curtains on indoor thermal stability: Case with curtains

In the second case, corresponding to the configuration with solar gains (without curtains) in Figure 4-4, the windows allowed a greater penetration of solar radiation into the building, thereby increasing heat absorption within the indoor environment. This configuration illustrates the influence of direct solar gains on the thermal behavior of the building.

During nighttime and early morning periods, the outdoor temperature remained relatively low, ranging between approximately 10 °C and 12 °C, while the indoor temperature stayed higher at around 18 °C. This difference can be explained by the thermal inertia of the building materials, which store heat during the daytime and gradually release it during the night. As the outdoor temperature increased in the morning, reaching peak values of approximately 23–24 °C around midday, the indoor temperature also increased progressively, although at a slower rate. This delayed response is mainly due to the combined effects of thermal lag and the insulating properties of the building envelope, which reduce the rate of heat transfer between the outdoor and indoor environments.

During the afternoon period, the outdoor temperature became higher than the indoor temperature, promoting heat transfer into the building through direct solar radiation entering the unshaded windows. Consequently, additional thermal energy was accumulated inside the building, leading to a noticeable rise in indoor temperature. After 17:00, the outdoor temperature decreased rapidly; however, the indoor temperature declined more gradually and remained relatively high compared to the outdoor conditions. This behavior further confirms the effect of thermal inertia, where the building continues to release the heat previously stored within its walls, floor, and internal components.

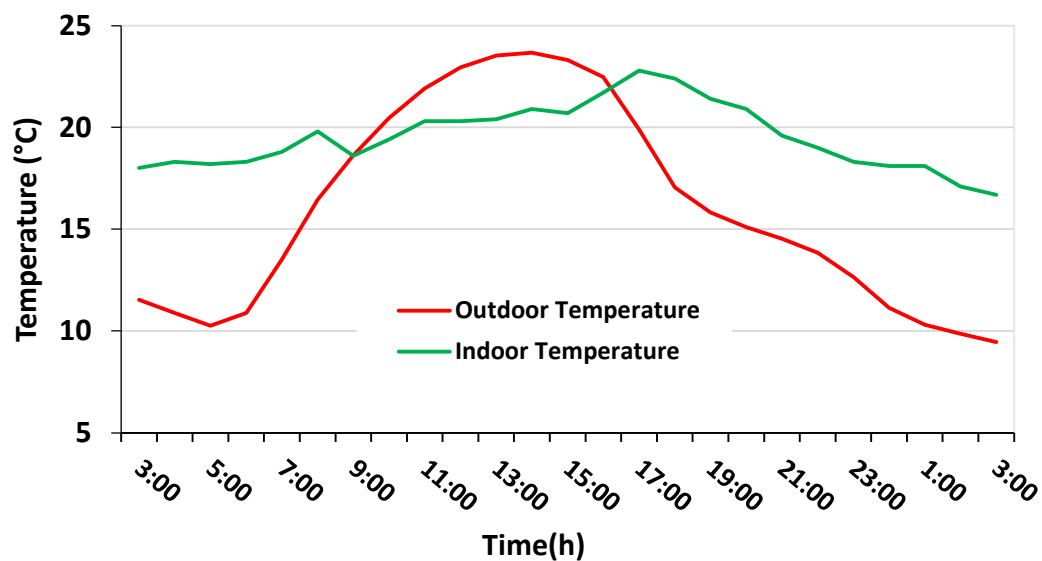


Figure 4-4: Impact of curtains on indoor thermal stability: Case without curtains

The absence of curtains increased solar heat gains and enhanced heat storage inside the building, resulting in higher indoor temperatures during the daytime and improved heat retention during nighttime. These results demonstrate the important role of solar gains and thermal mass in regulating indoor thermal conditions and reducing rapid temperature fluctuations.

4.2.3 Thermal performance

The evaluation of thermal performance constitutes a fundamental stage in the assessment of building energy behavior and indoor environmental quality, particularly under semi-arid climatic conditions.

In this section, several thermal indicators are analyzed to quantify the influence of solar protection curtains on the dynamic thermal response of the experimental building. The objective

of this analysis is identifying the underlying physical mechanisms governing heat transfer, thermal storage, and indoor thermal stabilization.

The interpretation of these results is based on key thermal parameters, namely: the indoor/outdoor temperature difference, indoor thermal amplitude, thermal lag (phase shift), thermal attenuation factor, and Thermal Load Level (TLL). Each parameter provides complementary information regarding the effectiveness of the building envelope and the contribution of the curtain system to passive cooling performance. Through the experimental study, the results obtained for the aforementioned thermal parameters are presented as follows:

a. Thermal difference

Figure 4-5 illustrates the evolution of the building indoor/outdoor temperature difference ($\Delta T = T_{\text{inside}} - T_{\text{outside}}$) over a 24-hour cycle for two configurations: with solar protection (curtains) and without solar protection. The error bars ($\pm\sigma$) represent the standard deviation of the measurements for each hourly interval, thereby indicating the variability and reliability of the recorded average values.

The temporal evolution of the indoor/outdoor temperature difference reveals three distinct thermal phases that characterize the dynamic thermal response of the building.

During the night and early morning period (0:00–8:00), a high positive ΔT (8–9°C) indicates that the building behaves as a thermal buffer by releasing the heat stored during the previous day.

During the solar exposure period (9:00–16:00), ΔT decreases rapidly and becomes negative between 11:00 and 16:00, showing a thermal inversion where the indoor environment remains cooler than outdoors; the curtains reduce the inversion intensity and improve thermal regulation.

In the evening and night period (17:00–23:00), ΔT increases again as outdoor temperatures decrease, leading to thermal recovery and the restoration of indoor thermal stability due to the delayed heat release from the building envelope.

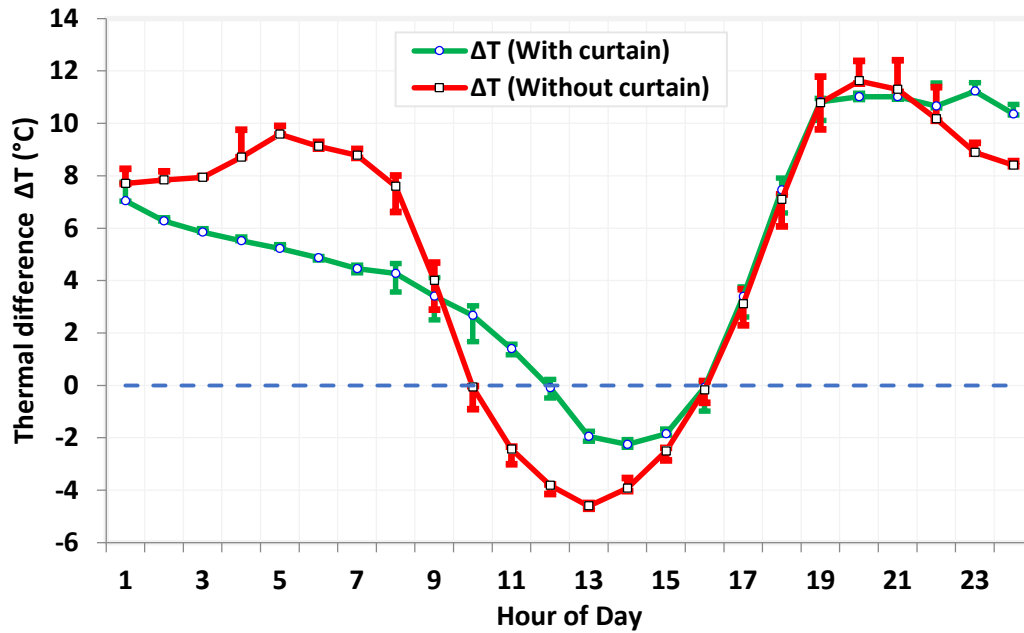


Figure 4-5: Temporal evolution of the hourly temperature difference

b. Indoor Thermal Amplitude

Indoor thermal amplitude remained nearly constant in both configurations (4.9°C with curtains and 4.8°C without), indicating the strong thermal stability provided by the insulated envelope and double glazing. However, the curtains effectively lowered the average indoor temperature, thereby improving thermal comfort and reducing overheating under semi-arid climatic conditions.

c. Thermal Lag (Phase Shift)

The use of curtains increased the thermal lag by approximately one hour, extending the phase shift to about 3–4 hours due to reduced solar heat transfer and enhanced thermal inertia effects. This delayed indoor heat propagation helps reduce daytime overheating and improves thermal comfort under semi-arid climatic conditions.

d. Thermal Attenuation

The using of curtains reduced the thermal attenuation factor from 0.357 to 0.252, indicating a stronger ability of the building envelope to filter outdoor thermal fluctuations. This improvement is mainly attributed to the reduction of solar heat gains through the glazing system, leading to enhanced passive thermal regulation and indoor thermal stability.

The Table 4-1 indicates results that support and confirm the aforementioned interpretation of the building's dynamic thermal behavior under different operating conditions.

Table 4-1: Comparative analysis: effect curtains

Parameter	With curtains	Without curtains	Impact
Pic ΔT	11.0 °C (23h)	11.8 °C (23h)	−0.8 °C
Min ΔT	−2.0 °C (14h)	−4.5 °C (15h)	+2.5 °C
Amplitude	13.0 °C	16.3 °C	−3.3 °C
Durée inversion	4 hours	5 hours	−1h
σ moyen	0.58 °C	0.66 °C	−0.08 °C

4.2.4 Thermal Load Level

Figure 4-6 presents a comparison of the Thermal Load Level (TLL) values for the studied building under two configurations: with curtain and without curtain, during different periods of the day. The analysis highlights the significant influence of the solar protection curtain on the thermal behavior of the building.

Globally, the configuration with curtain exhibits the highest TLL value 0.187 compared to the configuration without curtain 0.162. This result indicates that the use of the curtain improves the overall thermal performance of the building by enhancing thermal regulation and reducing excessive heat transfer fluctuations.

During the night period (00–8 h), the TLL value with curtain 0.111 remains higher than that without curtain 0.08. This behavior suggests that the curtain contributes to better thermal retention inside the building during nighttime, limiting heat losses through the building envelope and maintaining a more stable indoor thermal environment.

Similarly, during the daytime period (8–16 h), the TLL value with curtain 0.112 is noticeably greater than the value without curtain 0.073. This demonstrates the effectiveness of the curtain in reducing direct solar heat gains and attenuating outdoor thermal disturbances during periods of high solar radiation. The curtain acts as a passive thermal control element that moderates indoor temperature variations.

In contrast, during the evening period (16–24 h), the configuration without curtain presents a significantly higher TLL value 0.152 compared to the configuration with curtain 0.061. This increase may be attributed to the rapid release and accumulation of stored heat in the absence of solar protection, resulting in greater thermal instability and delayed cooling effects inside the building.

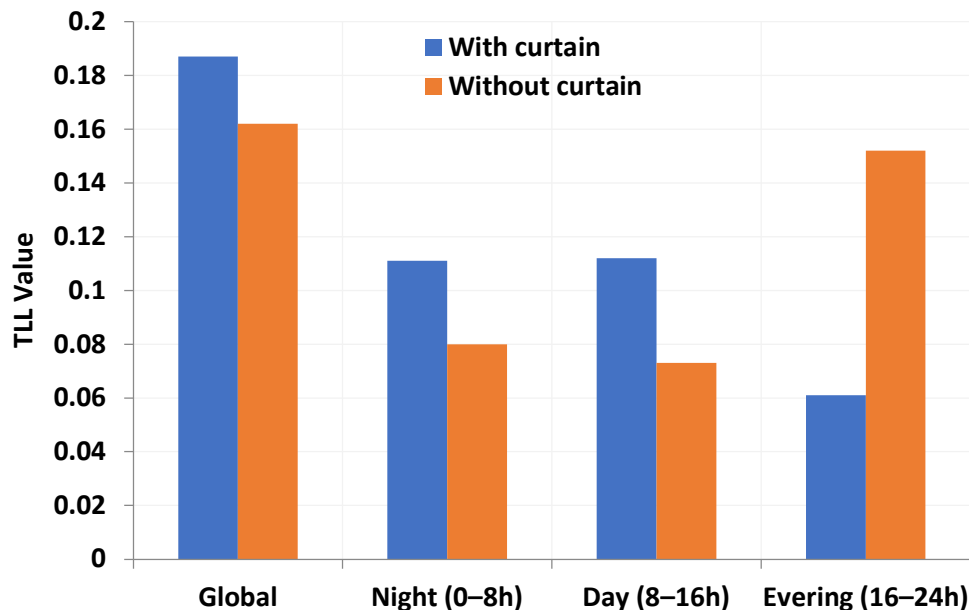


Figure 4-6: Comparison of TLL values for the studied building

Overall, the integration of curtains improves the thermal regulation of the building throughout most of the day, particularly during daytime and nighttime periods. The curtain system contributes to enhanced thermal stability, reduced heat exchange intensity, and improved indoor thermal comfort under desert climatic conditions according to Key results of physical mechanisms in Figure 4-7.

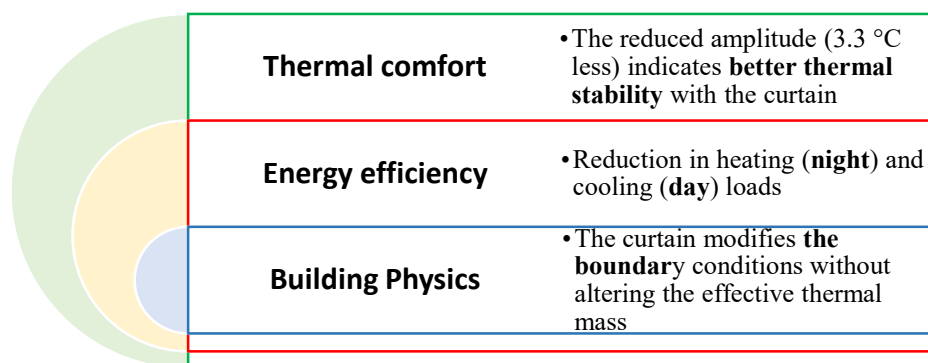


Figure 4-7: Key result of physical mechanisms

4.3 Analysis of the modeling results

In this study, ANN model was developed to predict the indoor temperature of the building using the previously described climatic parameters as input variables. To determine the optimal neural network architecture, several training and testing procedures were conducted for the time periods defined in Chapter 3 (Section 3.4).

Different ANN configurations were evaluated by varying the number of neurons in the hidden layer and comparing their performance using several statistical indicators, including the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), and Maximum Error. The simulation results demonstrated that the optimal neural network architecture was the (5–25–1) structure, which provided the highest prediction accuracy and the best overall performance among the tested models.

Based on this optimized ANN architecture, the following figures present the modeling results and illustrate the comparison between the predicted indoor temperature values and the corresponding experimental measurements for the investigated cases.

4.3.1 ANN training state and error assessment

Figure 4-8 show the training process of the developed artificial neural network model was terminated after 13 training cycles (epochs). The stopping criterion was based on the early stopping technique, which occurred when the average validation Mean Squared Error (MSE) increased continuously for six consecutive validation iterations. This approach was adopted to prevent overfitting and to ensure better generalization capability of the model.

Among all training cycles, Epoch 07 was identified as the optimal training point since it corresponded to the minimum validation error, with an MSE value of approximately 0.86449. The evaluation of the validation error was carried out using normalized input and output data in order to improve the numerical stability and convergence performance of the neural network during training. The obtained low MSE value indicates that the ANN model achieved a high level of prediction accuracy and demonstrated a strong capability to reproduce the thermal behavior and heat transfer dynamics occurring inside the building. Physically, this result confirms that the selected climatic input parameters successfully captured the main factors influencing indoor temperature evolution, including solar radiation, outdoor temperature variations, and the thermal inertia of the building envelope.

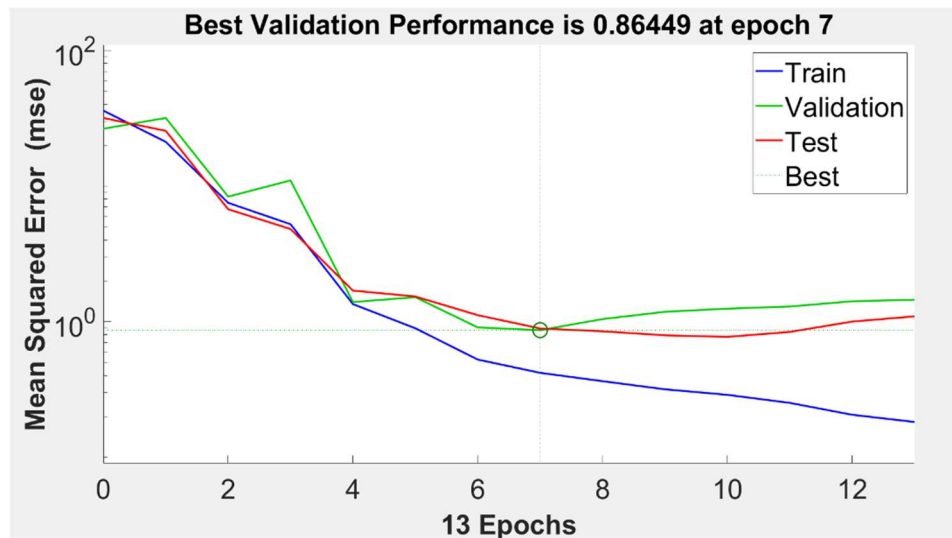


Figure 4-8: MSE performance vs number of epochs

Figure 4-9 illustrates the distribution of prediction errors between the target (experimental) values and the outputs generated by the developed digital building model. The horizontal axis represents the error values calculated according to the relation $\text{Error} = \text{Targets} - \text{Outputs}$, whereas the vertical axis indicates the frequency of occurrence of these errors. The histogram shows that the majority of the data points are highly concentrated around the zero-error line, with a central error value close to 0.01868, demonstrating a very small deviation between the predicted and experimental temperatures. In addition, the distributions corresponding to the training (blue), validation (green), and testing (red) phases exhibit a nearly symmetrical and normal distribution pattern, indicating that the errors are uniformly distributed throughout the different stages of the modeling process without significant bias or abnormal deviations.

From a physical modeling perspective, the strong concentration of errors around zero confirms the high predictive capability of the artificial neural network in reproducing the thermal behavior of the building. This result indicates that the ANN model successfully captured the complex nonlinear thermal interactions between climatic conditions and indoor temperature evolution, including the effects of solar radiation, heat storage, thermal inertia, and heat transfer through the building envelope. Moreover, the absence of large error dispersion demonstrates the stability, reliability, and generalization performance of the developed model for indoor thermal prediction applications.

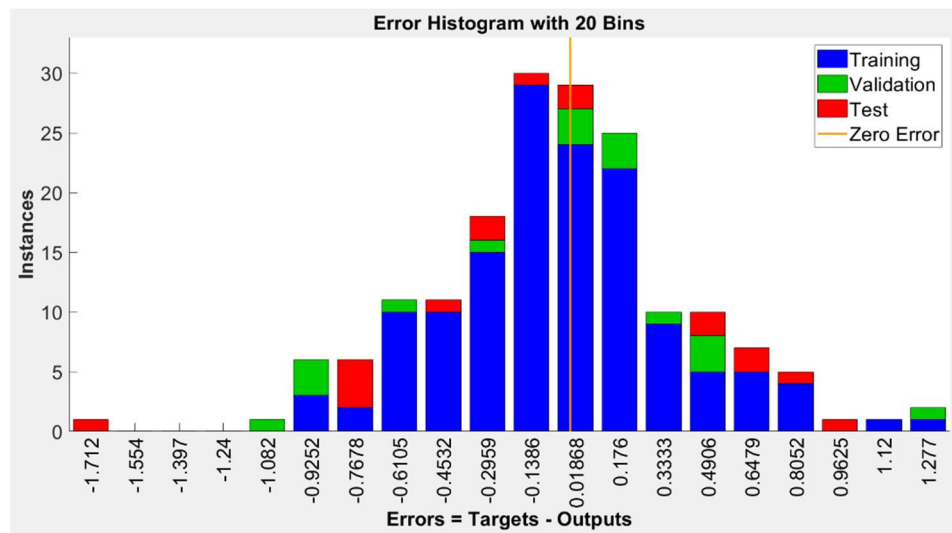


Figure 4-9: Error histogram with 20 bins for the neural network model

Figure 4-10 illustrates the evolution of the neural network training process and the associated optimization parameters used within the gradient-based learning algorithm. The training procedure was terminated at Epoch 23 after the number of consecutive validation failures reached the predefined maximum limit of six, according to the early stopping criterion employed to prevent overfitting. The gradient curve exhibits a continuous decreasing trend, reaching a final value of approximately 0.17745, which indicates that the network progressively converged toward an optimal or near-optimal solution during the learning process. In addition, the damping coefficient (μ) remained stable at 0.001 throughout the training phase, reflecting the efficiency of the Levenberg–Marquardt optimization algorithm in controlling the learning rate and ensuring stable convergence behavior.

The validation performance curve further reveals that the model's generalization capability began to deteriorate after Epoch 17, suggesting the onset of overfitting beyond this stage. Consequently, the early stopping mechanism successfully limited unnecessary training iterations and preserved the predictive capability of the model.

The results confirm the robustness of the ANN model in learning the nonlinear thermal dynamics of the building system. The progressive reduction of the gradient and the stability of the optimization parameters indicate that the network effectively captured the complex interactions between climatic variables and indoor thermal responses, including heat storage, thermal inertia, and solar heat transfer effects. Furthermore, the controlled convergence behavior

demonstrates the reliability of the developed ANN model for accurately predicting indoor temperature variations under varying environmental conditions.

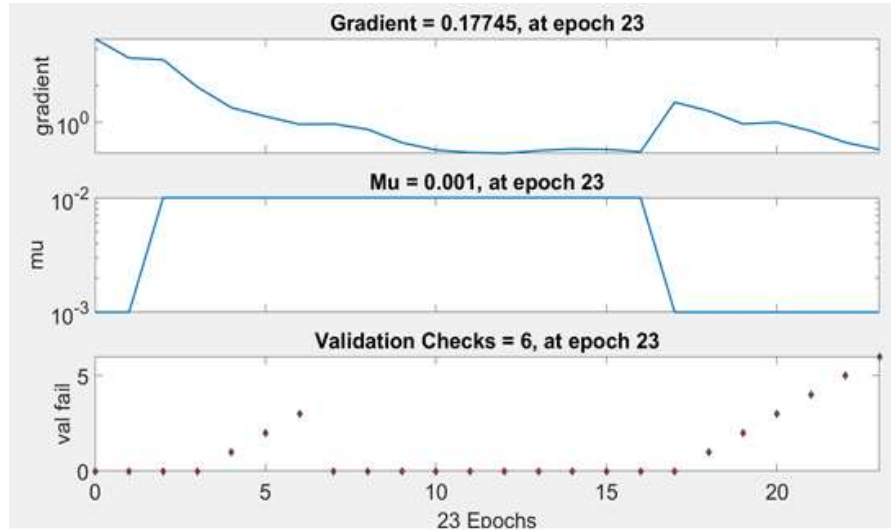


Figure 4-10: Evolution of the neural network training state

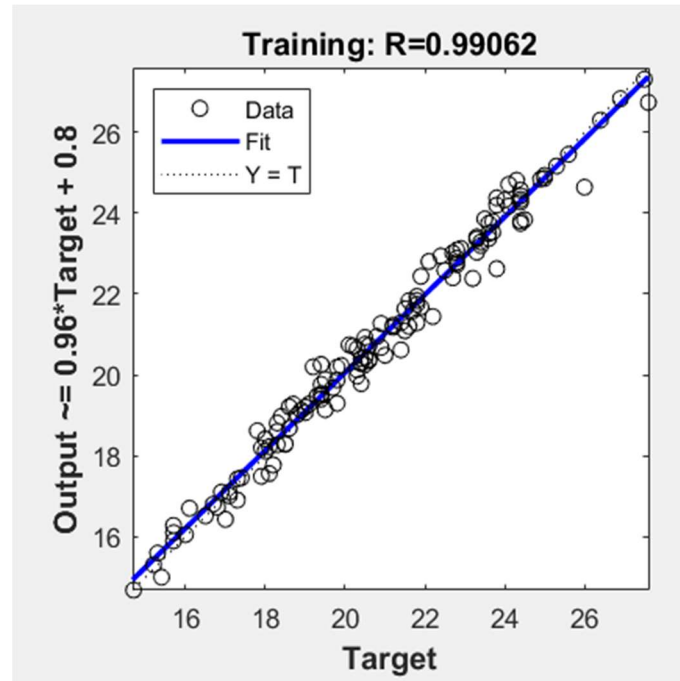
4.3.2 Neural network performance

Figure 4-11 presents the Regressions obtained from the comparison between the experimentally measured indoor temperatures and the values predicted by the ANN model during the four main evaluation phases: (a) training, (b) validation, (c) testing, and (d) overall performance assessment.

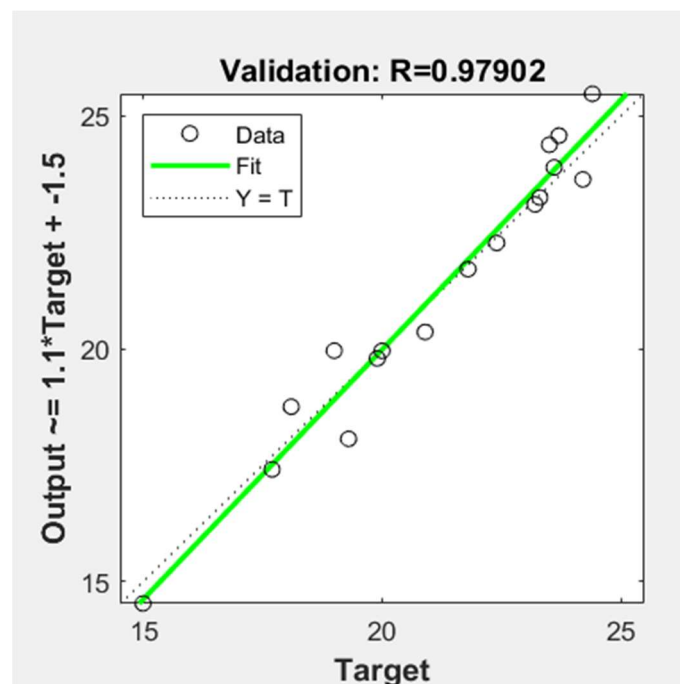
The R^2 coefficient is an important statistical indicator used to evaluate the predictive accuracy of the model, where values approaching 1 indicate a strong correlation between predicted and experimental data and, consequently, a high modeling performance. During the training phase, the ANN model achieved an excellent coefficient of determination of approximately 0.98, indicating that the network successfully learned the thermal behavior and dynamic heat transfer characteristics of the building from the training dataset.

In the validation phase, the model maintained a high R^2 value exceeding 0.95, demonstrating its strong capability to predict indoor temperature using unseen validation data without significant loss of accuracy. Similarly, the testing phase produced an R^2 value greater than 0.94, confirming the robustness and generalization ability of the model when applied to completely

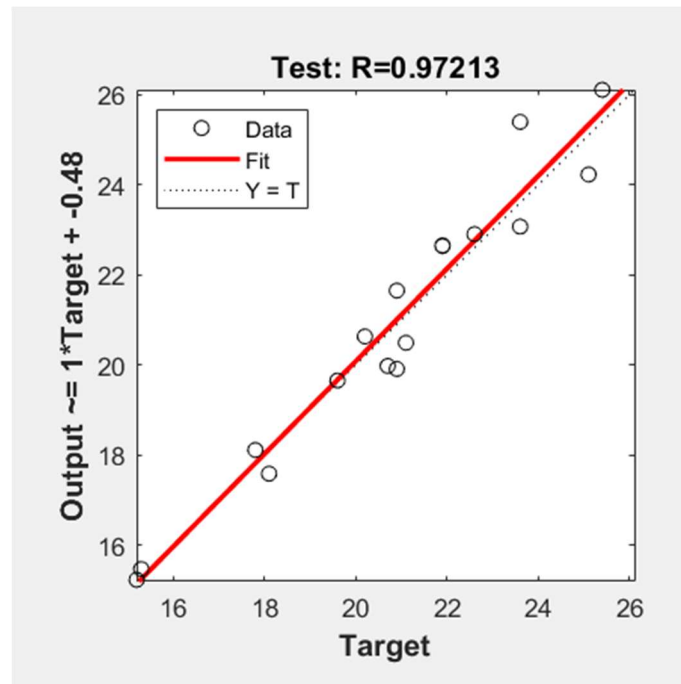
independent datasets. The overall evaluation also revealed a high global correlation coefficient exceeding 0.96, highlighting the consistency and reliability of the developed ANN model across all stages of prediction.



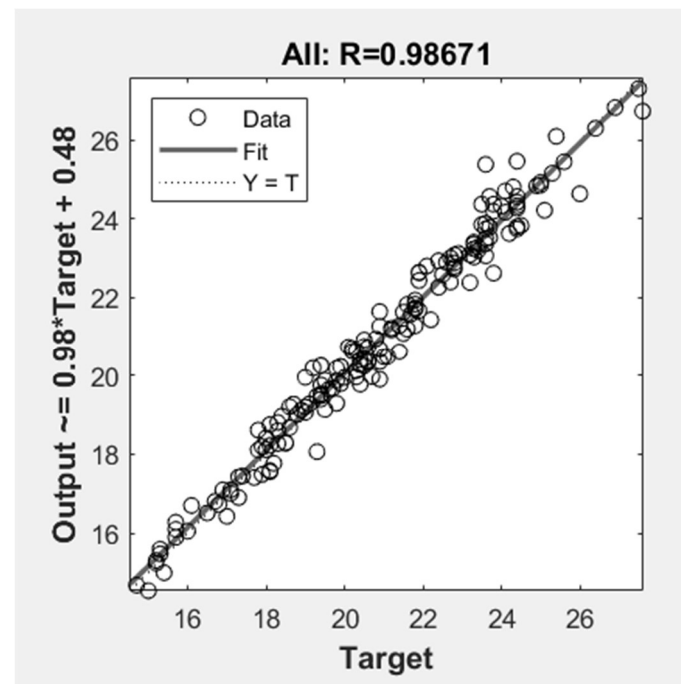
(a)



(b)



(c)



(d)

Figure 4-11: Results of the correlation coefficient (R) for the four modeling phases:

(a) Training, (b) Validation, (c) Test, and (d) All

The modeling results confirm that the artificial neural network effectively captured the nonlinear thermal interactions governing indoor temperature evolution, including the influence of solar radiation, outdoor climatic conditions, thermal inertia, and heat transfer through the building envelope. The high correlation between predicted and measured values demonstrates the capability of the ANN model to accurately reproduce the building's thermal response and to serve as a reliable predictive tool for indoor thermal behavior analysis and energy performance studies.

4.3.3 Validation metric of results

The comparison presented in Figure 4-12 demonstrates the remarkable capability of the developed ANN model with 25 hidden neurons to accurately reproduce the thermal behavior of the building under varying climatic conditions. The predicted temperature profile closely follows the experimental measurements throughout the entire observation period, successfully capturing the daily thermal fluctuations, daytime temperature peaks and nighttime cooling phases without noticeable temporal delay or significant deviations in amplitude. This strong agreement between experimental and simulated data confirms the high predictive accuracy, robustness, and stability of the proposed model.

The obtained results indicate that the ANN model effectively represented the complex thermal dynamics governing the indoor environment, including the effects of solar radiation, outdoor temperature variations, thermal inertia, heat storage within the building envelope, and heat transfer mechanisms through walls and glazing systems. Furthermore, the model's ability to reproduce both rapid and gradual thermal responses demonstrates its effectiveness in learning the nonlinear relationships between climatic parameters and indoor thermal conditions. These findings confirm that the proposed ANN model constitutes a reliable and efficient tool for predicting indoor temperature evolution and for supporting building thermal performance assessment, thermal comfort analysis, and energy management applications.

Based on the information provided and the results obtained in this study, several important conclusions can be drawn. Referring to Figures 4-12, together with the RMSE (1.017) and MAE (0.763) values presented in Table 4-2, it can be observed that the predicted indoor temperatures are in strong agreement with the experimentally measured values over the 8-day monitoring period.

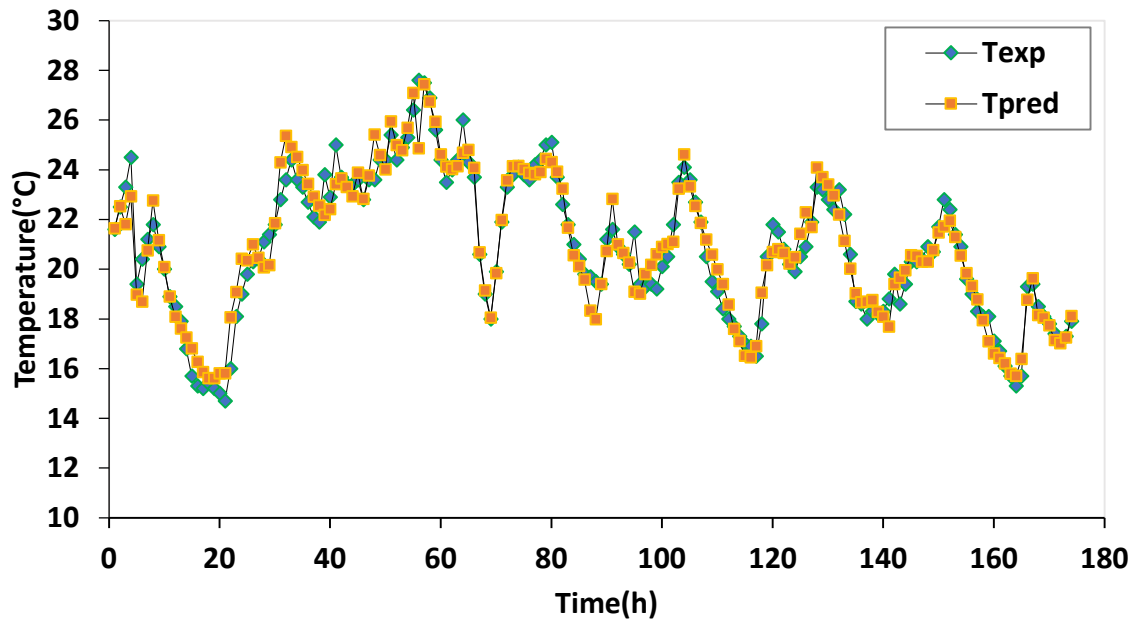


Figure 4-12: Indoor temperature: Experimental versus predicted results

Table 4-2 : Performance indicators

Hidden neurons	Structure ANN	RMSE (°C)	MAE (°C)	R ²
		Indoor temperature		
25	5-25-1	1.017	0.763	0.973

4.4 Conclusion

The results obtained from the experimental campaigns demonstrate the effectiveness of partially insulated walls in improving thermal stability under semi-arid climatic conditions, such as those prevailing in Ghardaïa. The integration of the blind-glass window system significantly reduced day–night temperature fluctuations, thereby contributing to the creation of a more stable and favorable indoor microclimate within the building. In addition, the developed an ANN model achieved high predictive accuracy for indoor temperature estimation. These results confirm the capability of the ANN approach as an efficient and reliable tool for supporting intelligent thermal comfort management and advanced control strategies in office buildings.

GENERAL CONCLUSION

As part of our master's project, we presented a contribution to the study and forecasting of indoor temperature in passive solar buildings under semi-arid climatic conditions is presented. This work focuses on evaluating the thermal behavior of a south-oriented passive building located in Ghardaïa and developing an intelligent predictive model capable of estimating indoor temperature with high accuracy.

An experimental study was conducted to investigate the thermal performance of the passive solar building under arid climate. A setup incorporating cooling techniques and passive strategies was utilized to establish a suitable indoor climate for mitigating temperature fluctuations. Field experiments were carried out to monitor key climatic parameters, including indoor and outdoor air temperatures and solar radiation, in order to create a database that subsequently enabled the development of an ANN-based predictive model using the Levenberg–Marquardt algorithm.

The experimental study involved the use of natural solar shading devices, in the form of curtains, to provide solar protection for the glazed walls of the prefabricated shelter. The obtained results describe the evolution of indoor temperatures as well as the stratification phenomena observed at different heights inside the building.

The results demonstrated the effectiveness of the system in improving the indoor environment of the building. It should be noted that the use of curtains increased the thermal lag by approximately one hour, extending the phase shift to about 3–4 hours due to reduced solar heat transfer and enhanced thermal inertia effects.

In the second phase of the research, an artificial neural network (ANN)-based predictive model was developed to estimate indoor building temperature. The model demonstrated high predictive accuracy and a strong correlation with the observed data, with a correlation coefficient of 0.973, confirming its reliability as a tool for supporting smart environmental control strategies and improving thermal comfort.

Overall, this work demonstrates the potential of combining passive solar design strategies with advanced artificial intelligence techniques to enhance thermal comfort and reduce energy demand in buildings located in arid regions.

GENERAL CONCLUSION

To extend the scope of this research, several future research directions are proposed:

- **Seasonal Extension of Monitoring:** Extending the experimental monitoring period to cover full seasonal cycles, particularly the summer and winter seasons, in order to investigate both cooling and heating loads.
- **Multi-Parameter Comfort Evaluation:** Integrating additional indoor environmental parameters such as relative humidity, CO₂ concentration, and indoor air quality (IAQ) indicators to achieve a comprehensive assessment of indoor environmental quality (IEQ).
- **Renewable Energy Systems Integration:** Investigating the integration of renewable energy sources, such as solar photovoltaics and solar thermal systems, to enhance building sustainability and energy efficiency.
- **Comparative Machine Learning Benchmarking:** Comparing the performance of the developed ANN model with other advanced machine learning and deep learning architectures (e.g., LSTM and Random Forest) to improve forecasting robustness.
- **Parametric Optimization:** Conducting comprehensive parametric studies involving different passive techniques, such as alternative insulation materials, advanced glazing systems, and optimal building orientations.

Reference

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SCIENTIFIC VALORISATION

International conference

- Boualem, M. (2026). Artificial Neural Network Applications for Predicting Indoor Environmental Parameters in Buildings: A Comprehensive Analysis. Istinye International Interdisciplinary Academic Studies Congress. Istanbul.
- Bekkair, S. (2026). Assessment in Building Aeration Technologies A Comprehensive Analysis. Istinye International Interdisciplinary Academic Studies Congress. Istanbul.

National Conference:

- Boualem, M. (2026). Application of Artificial Neural Networks for Building Thermal Modeling: A Case Study in Ghardaïa. 2nd National Seminar on Energy and Renewable Energies. University of Batna 1.
- Bekkair, S. (2026). Natural Ventilation in a Building under Semi-Arid Climate: Experimental Analysis – Ghardaïa Region. 2nd National Seminar on Energy and Renewable Energies. University of Batna 1.

NB: Conference participation certificates are listed below.



CERTIFICATE OF PARTICIPATION

THIS IS TO CERTIFY THAT

M. Boualem

attended the *Istinye International Interdisciplinary Academic Studies Congress*
held on March 08-10, 2026 / Istanbul, Türkiye
with an oral presentation entitled

ARTIFICIAL NEURAL NETWORK APPLICATIONS FOR PREDICTING INDOOR ENVIRONMENTAL
PARAMETERS IN BUILDINGS: A COMPREHENSIVE ANALYSIS

Assoc. Prof. Dr. E. İlhan Şahin
Member of the Organizing Committee





CERTIFICATE OF PARTICIPATION

THIS IS TO CERTIFY THAT

S. Bekkair

attended the *Istinye International Interdisciplinary Academic Studies Congress*
held on March 08-10, 2026 / Istanbul, Türkiye
with an oral presentation entitled

ASSESSMENT IN BUILDING AERATION TECHNOLOGIES: A COMPREHENSIVE ANALYSIS

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Université de Batna 1
Faculté des Sciences de la matière
Laboratoire de Physique Energétique Appliquée (LPEA)



ATTESTATION DE PARTICIPATION



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BOUALEM Meriem

a présenté une communication Poster intitulée :

Application of Artificial Neural Networks for Building Thermal Modeling: A Case Study in Ghardaïa

Co- Auteur (s): S. Bezari , S. Bekkair

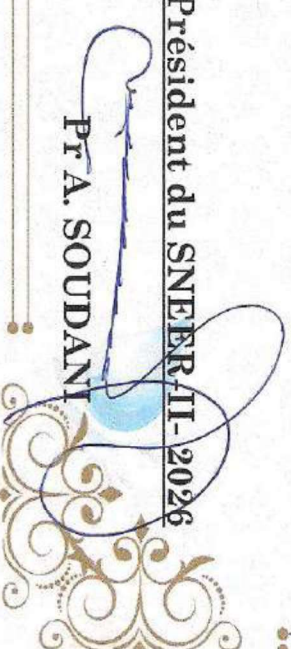


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ATTESTATION DE PARTICIPATION

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(SNEER-II- 2026) atteste que :

BEKKAIR Samira

a présenté une communication Poster intitulée :

Natural Ventilation in a Building under Semi-Arid Climate: Experimental Analysis - Ghardaïa Region

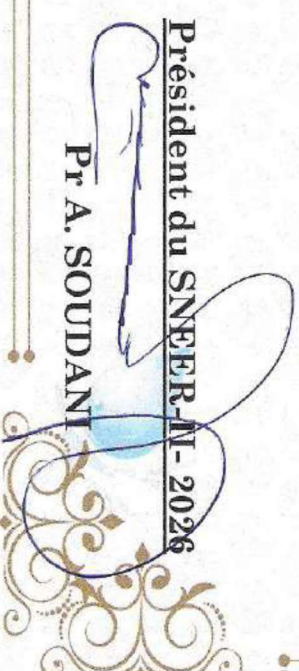
Co- Auteur (s): S. Bezari , M. Boualem



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Pr A. SOUDANI





Approval for Final Printing of a Master's Dissertation

	Name and Surname	Signature
Examiner 1	Ahmed BAHRI	
Examiner 2	Tawfiq CHEKIFI	
Supervisor	Salah BEZARI	

I, the undersigned, Mr: **Salah CHERIF**

President of the jury for the student(s):

- BOUALEM Meriem
- BEKKAIR Samira

Field: Material Sciences; **Specialization:** Energy Physics and Renewable Energies

Thesis Title: Forecasting Indoor Temperature in a Passive Solar Building Under Semi-Arid Climate

Hereby authorize the above-mentioned student(s) to print and submit their final manuscript to the department.

Ghardaia : 2026 / جوان / 14

President of the jury

Head of the department

