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Contribution to the study of the microclimate in greenhouse equipped with thermal storage north wall

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DEDICATION

I extend my deepest gratitude and appreciation to my father, who has always supported me in every aspect of my life. I ask God to prolong his life and reward him abundantly

I also extend my sincere thanks to my mother, who has never forgotten me in her prayers. May God protect and care for her

To my dear husband, Salah, who has always encouraged me

To my daughters, Maria, Sirine, and Hanane, and to my dear brothers and sisters, who have been a great help to me. May God protect them and fulfill their wishes.

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DEDICATION

I dedicate this success to everyone who walked with me on this journey may you always remain a pillar of support for me.

With all my love, I dedicate the fruit of my efforts to my dear parents, the source of my strength and the guiding light of my path.

To my brothers and sisters, and to everyone who supported and encouraged me with kind words or sincere prayers this is for you.

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الملخص

تتواجه الزراعة المحمية تحديات مناخية حادة، أبرزها التفاوت الكبير في درجات الحرارة بين الليل والنهار، مما يتطلب حلو الً تقنية متقدمة لضمان مناخ ملائم داخل الدفيئة وتعزيز الإنتاجية. تهدف هذه الدراسة إلى تطوير نموذج متكامل يجمع بين التصميم الهندسي الفعّال وتقنيات التخزين الحراري، مع استخدام الذكاء الصَّطناعي للتنبؤ بدرجة الحرارة الداخلية.

تم إنشاء دفيئة شمسية مدمجة بجدار شمالي لتخزين الطاقة الشمسية، وذلك ضمن وحدة البحث التطبيقي في الطاقات
المتجددة بغرداية (32.36° شما الً، 3.51° غربا). يعتمد النظام الحراري على جدار بمساحة 1.62 مت ارا مربعا، مشيّد من صخور محلية مختارة لخصائصها الحرارية الممتازة. يعمل هذا الجدار على تخزين الحرارة الزائدة خلال النهار وإطلاقها لي الا لتحسين الظروف المناخية داخل الدفيئة .أظهرت القياسات التجريبية أن درجة حرارة الهواء داخل الدفيئة المجهزة بالجدار الشمسي كانت أعلى بحوالي 2.7 درجة مئوية مقارنة بالهواء الخارجي خلال الليل، مما يدل على فعالية النظام في تقليل الفارق الحراري الليلي .طُ ّ ِور نموذج عددي قائم على نهج الشبكات العصبية الصَّطناعية للتنبؤ بدقة بدرجة الحرارة الداخلية، استنادا إلى بيانات المناخ الداخلية والخارجية من التجربة. وقد أظهرت نتائج النموذج أدا ء عاليا، حيث تجاوز معامل الرَّتباط 98%، مما يؤكد فعاليته وموثوقيته كحل مستدام لتحديات الزراعة المحمية في البيئات المناخية القاسية.

الكلمات المفتاحية: الدفيئة، التخزين الحراري، الشبكات العصبية الصَّطناعية، التنبؤ، درجة الحرارة.

RESUME

L’agriculture protégée fait face à des défis climatiques majeurs, notamment une variation importante des températures entre le jour et la nuit, ce qui nécessite des solutions technologiques avancées pour garantir un climat intérieur adéquat et améliorer la productivité. Cette étude vise à développer un système intégré combinant un design efficace, des techniques de stockage thermique et l’utilisation de l’intelligence artificielle pour prédire la température intérieure. Une serre solaire a été réalisée au sein de l’Unité de Recherche Appliquée en Énergies Renouvelables de Ghardaïa (32.36° Nord, 3.51° Ouest), intégrant un mur nord destiné au stockage de l’énergie solaire. Ce mur à une superficie de 1,62 m², il est constitué de roches locales soigneusement sélectionnées pour leurs excellentes propriétés thermiques. Il emmagasine la chaleur excédentaire durant la journée et la restitue pendant la nuit, permettant ainsi d’atténuer les écarts thermiques nocturnes. Les mesures expérimentales ont montré que la température de l’air à l’intérieur de la serre équipée du mur nord était supérieure d’environ 2,7 °C à celle de l’air extérieur durant la nuit, témoignant de l’efficacité du système. Une modélisation numérique base sur l'approche de réseaux neurones artificiels a été mis au point afin de prédire avec précision la température intérieure, en se basant sur des données climatiques internes et externes issues de l’expérimentation. Les résultats du modèle ont montré une performance élevée, avec un coefficient de corrélation dépassant 98 %, ce qui confirme son efficacité et sa fiabilité en tant que solution durable pour les défis de l’agriculture protégée dans des environnements climatiques extrêmes.

Mots clés : Serre, Stockage Thermique, Réseaux de Neurones Artificiels, Prédiction, Température.

ABSTRACT

Protected agriculture faces major climatic challenges, particularly the significant temperature difference between day and night. This requires advanced technological solutions to ensure a suitable indoor climate and enhance productivity. This study aims to develop an integrated system combining efficient design, thermal storage techniques, and artificial intelligence to predict the internal temperature. A solar greenhouse was constructed at the Applied Research Unit for Renewable Energy in Ghardaïa (32.36° North, 3.51° West), incorporating a north wall designed to store solar energy. This wall, with an area of 1.62 m², was built using locally sourced stones selected for their excellent thermal properties. It stores excess heat during the day and releases it at night, thereby reducing nighttime temperature fluctuations. Experimental measurements showed that the air temperature inside the greenhouse equipped with the thermal wall was about 2.7 °C higher than the outside air temperature at night, demonstrating the system's effectiveness.

This system was coupled with an artificial intelligence model based on artificial neural networks to accurately predict the internal temperature, using indoor and outdoor climatic data collected from the experimental setup. The model showed high performance and good agreement between predicted and measured values, with a correlation coefficient exceeding 98%, confirming its efficiency and reliability as a sustainable and effective solution to the challenges of protected agriculture in harsh environments.

Keywords: Greenhouse; Thermal Storage, Artificial Neural Networks, Prediction, Temperature.

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Nomenclature and Abbreviation

D_v	Wind Direction	°
H	Humidity	%
I_g	Global Radiation	W/m²
R	Regression	/
R^2	Coefficient of Determination	/
T	Temperature	℃
V_n	Error Function	/
V_v	Error Interval	m/s
W	Wind Speed	/
$w^h_{(i,j)}$	Weight	/
y_{cal}	Predicted Value	/
y_{exp}	Experimental Value	/
PMC	Multi-Layer Perceptron	/
RLM	Multiple Linear Regression	/
MSE	Mean Square Error	/
RMSE	Root Mean Square Error	/
MAE	Mean Absolute Error	/
ANN	Artificial Neural Networks	/
RBFN	Radial Basis Function Networks	/
FPANN	Forward Propagation Artificial Neural Networks	/

GENERAL INTRODUCTION

GENERAL INTRODUCTION

The world is seeing an increase in population growth, and this is being accompanied by a significant consumption of food products and daily necessities in various areas. On the other hand, the threats that have become threats to the world, such as environmental pollution and the need for food, research has turned to the optimal solution to achieve balance: the use of renewable energy, or what we call "unlimited and clean energy," and the exploitation of artificial intelligence to serve humanity [1]. One of the most important sustainable energies that humans are trying to exploit is solar energy, which has been used in several fields, including agriculture, particularly in developing greenhouses to overcome climate fluctuations and improve agricultural production, food quality, and availability in various regions of the world [2].

In general, the effectiveness of greenhouse and crop protection systems remains far from the desired results due to the harsh climate and daytime temperature fluctuations in semi-arid and arid regions. These pose serious challenges to plant growth, resulting in crop damage and consequently reduced yields. Given these challenges, it has become imperative to adopt innovative methods and approaches that create local climates favorable to plants. In this context, the integration of solar thermal storage systems with greenhouses has become imperative. This is coupled with the establishment and implementation of advanced technologies by Artificial Neural Network (ANN) to manage and predict internal climatic conditions to improve yields, both quantitatively and qualitatively [3].

In the context of the global shift towards sustainable and renewable energy sources, Algeria enjoys a strategic geographic location within the global solar belt, giving it exceptional potential for solar energy.

This study aims to propose a new greenhouse design featuring a north-facing thermal storage wall as an innovative solution to improve agricultural conditions in arid and semi-arid climates. The model was implemented in the Ghardaia region of southern Algeria, known for its hot and arid environment. Additionally, the objective of this work is to develop a high-performance dynamic model of the Matlab software environment for experimental validation. The proposed modeling approach considers all parameters affecting the microclimate and greenhouse characteristics, using an artificial neural network to predict indoor air temperature based on experimental data from a real greenhouse installed in URAER.

This thesis is structured in four chapters:

The first chapter highlights Algeria's significant solar energy potential and its role in boosting agriculture. It reviews the national and global distribution of greenhouse areas, types of greenhouse structures, and key heat transfer mechanisms. The chapter also examines microclimate control factors and thermal storage technologies that enhance energy efficiency in greenhouses.

The second chapter reviews recent studies on sensible and latent thermal storage systems, along with AI applications for predicting greenhouse climate. It analyzes system performance in improving indoor conditions and supports the development of smart control models for optimal plant growth and energy efficiency.

The third chapter details the construction of a greenhouse model in Ghardaia with a thermal storage wall to enhance night-time heat retention. 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, comparing experimental data with predictions from the AI model. This comparison assesses the model's accuracy in simulating greenhouse temperature and its potential for practical use in climate control systems.

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

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CHAPTER I.

General Overview of Greenhouses Systems

I.1. Introduction

A greenhouse is a controlled agricultural structure designed to optimize plant growth by regulating key environmental factors, such as temperature, humidity, and light. These controlled conditions promote crop growth while protecting plants from harsh climatic conditions. Greenhouses are widely used in modern agriculture as highly efficient systems designed to grow plants year-round, regardless of climatic conditions.

A greenhouse is an engineered agricultural structure specifically designed to create controlled environmental conditions that optimize plant growth. By regulating key microclimatic parameters such as temperature, humidity, light intensity, and, in some cases, carbon dioxide concentration, greenhouses enable consistent and efficient crop production. These controlled conditions not only enhance photosynthetic activity and plant development but also provide protection against adverse external factors such as extreme temperatures, wind, and pests. In modern agriculture, greenhouses play a crucial role in ensuring food security and increasing productivity, especially in regions with unfavorable or highly variable climates. Their ability to support year-round cultivation makes them indispensable for the production of high-value crops, including vegetables, fruits, and ornamental plants. With growing interest in sustainable farming practices and resource optimization, greenhouse technology continues to evolve incorporating advanced materials, energy-efficient systems, and smart control strategies such as artificial intelligence to further enhance performance.

This chapter introduces the fundamental concepts of greenhouse systems, highlighting their global relevance, structural components, and environmental control mechanisms, with a particular focus on their thermal behavior and the integration of renewable energy sources such as solar power.

I.2. Solar potential

I.2.1. Solar potential in the world

The distribution of annual solar radiation across the Earth's surface varies, reflecting the availability of solar energy in different regions of the world. Areas near the equator, particularly the deserts of North Africa, the Middle East, and parts of Australia and South America, have the highest levels of solar radiation, making them ideal for harnessing solar energy. In contrast, radiation levels are lower in northern and southern regions far from the equator due to fewer hours of sunshine and high cloud cover, limiting the feasibility of solar energy exploitation there [1]. This data is essential for identifying suitable locations for developing large-scale solar energy projects and supporting the global transition to clean and sustainable energy sources (Figure I.1).

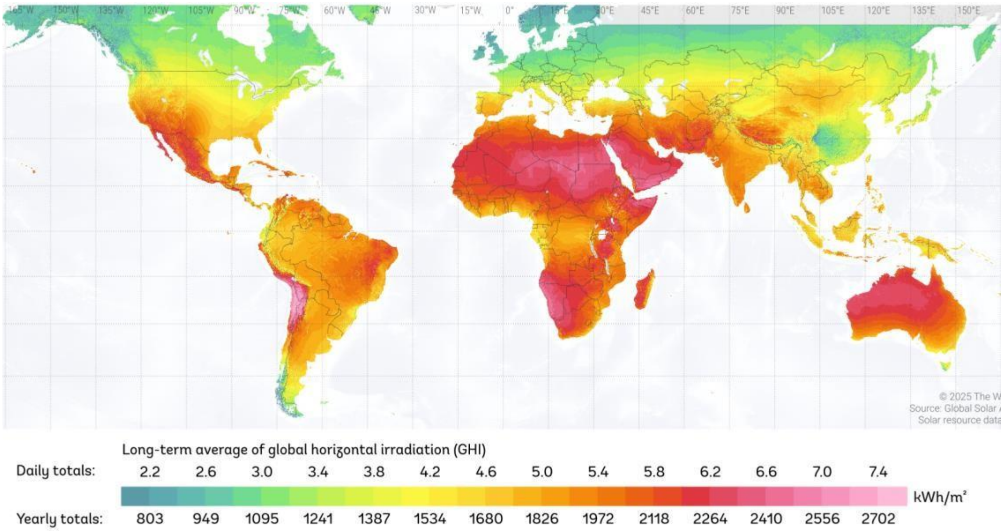

Figure I.1. Global horizontal irradiation [2]

I.2.2. Solar potential in Algeria

Solar radiation is a major source of renewable energy. It can be converted into heat or electricity and is used in various applications, including solar heating, solar buildings, and air conditioning. Algeria is currently focusing on harnessing solar energy as a free and environmentally friendly source and benefits from a high level of solar radiation [3] (Fig I.2).

Table.I.1. Solar potential in Algeria [4]

Regions	Coastal region	Highlands	Sahara
Area (%)	4	10	86
Average sunshine duration (h/year)	2650	3000	3500
Daily solar energy density (kWh/m^2)	4.66	5.21	7.26
Average energy received ($kWh/m^2/year$)	1700	1900	2650

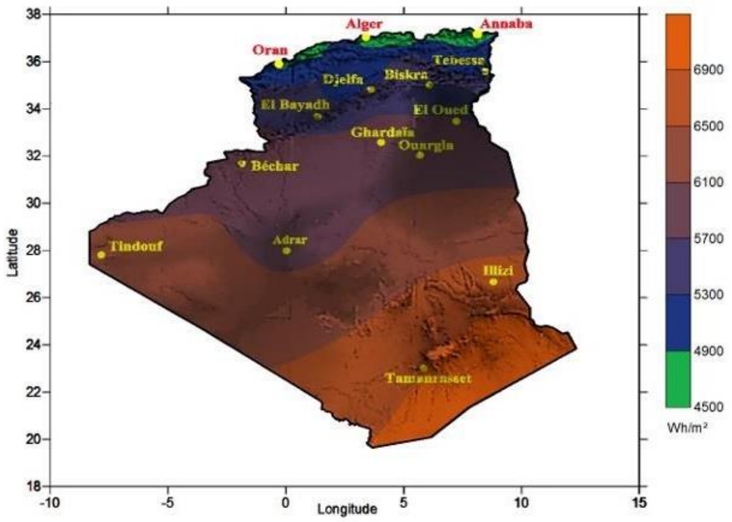

Figure I.2. The average annual global irradiation incident on a horizontal plane [3]

I.3. Greenhouse cultivation

I.3.1. Global areas of greenhouse cultivation

Protected agriculture has experienced significant global advancement, driven by ongoing technological innovations. According to a recent report by the Food and Agriculture Organization (FAO) of the United Nations, the total area under greenhouse cultivation worldwide was estimated at approximately 4.9 million hectares in 2019. Figure I.3 represent a substantial increase compared to earlier estimates 100,000 ha in 1980 and 450,000 ha in 1998.The majority of greenhouse crops are cultivated in Asia, which accounts for 59% of the global total, followed by Europe at 21% and North America at 16%. [5].

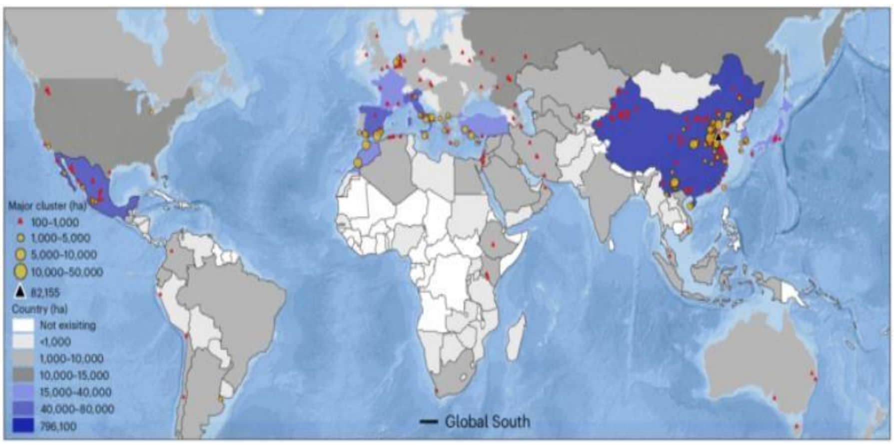

Figure I.3. Global inventory of greenhouse cultivation [6]

I.3.2. Algerian areas for greenhouse cultivation

Greenhouse agriculture has seen substantial growth across the Mediterranean region, with an estimated 220,000 (ha) dedicated to this practice. The vast majority about 90% utilizes plastic coverings due to their cost-effectiveness, ease of installation, and flexibility, particularly in countries like Algeria [7]. The province’s agricultural development has accelerated notably since 2010, marked by a steady expansion in both greenhouse area and productivity [5]. Figure I.4 represents a view of agricultural greenhouses in different regions of Biskra and Tipaza.

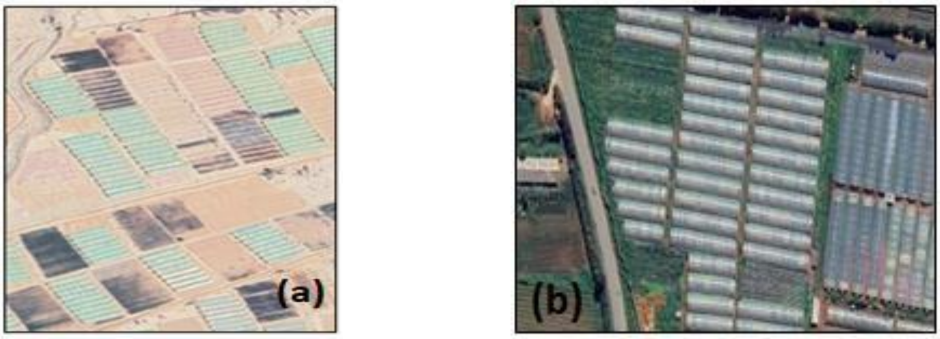

Figure I.4. View of agricultural greenhouses in the regions Biskra and Tipaza respectively

I.4. Greenhouse system

I.4.1. Thermal behavior

a. Heat Transfer

Heat exchange within greenhouses typically occurs through three primary modes of heat transfer: conduction, convection, and radiation. These thermal processes usually take place simultaneously and interactively [8].

b. Mass transfer

Mass transfer in greenhouses is closely linked to plant processes such as evapotranspiration, where moisture released by plants affects the internal temperature and humidity. Additionally, thermal mass such as the soil or water tanks inside the greenhouse plays a role in regulating temperature by storing heat during the day and releasing it at night [9].

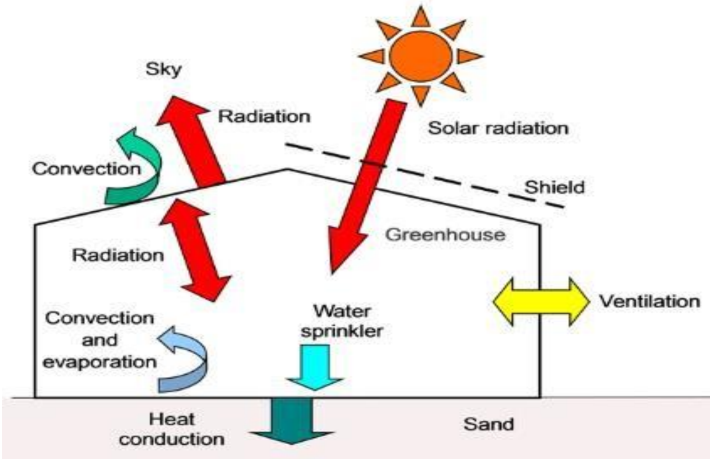

Figure I.5. Thermal transfer processes in a greenhouse [8]

I.4.2. Type of greenhouse

Greenhouses come in various types and can be classified based on shape, structure, and environmental control systems [10]. Common types include lean-to, even-span, ridge-and-furrow, quonset, and gothic arch structures (see Figure I.6).

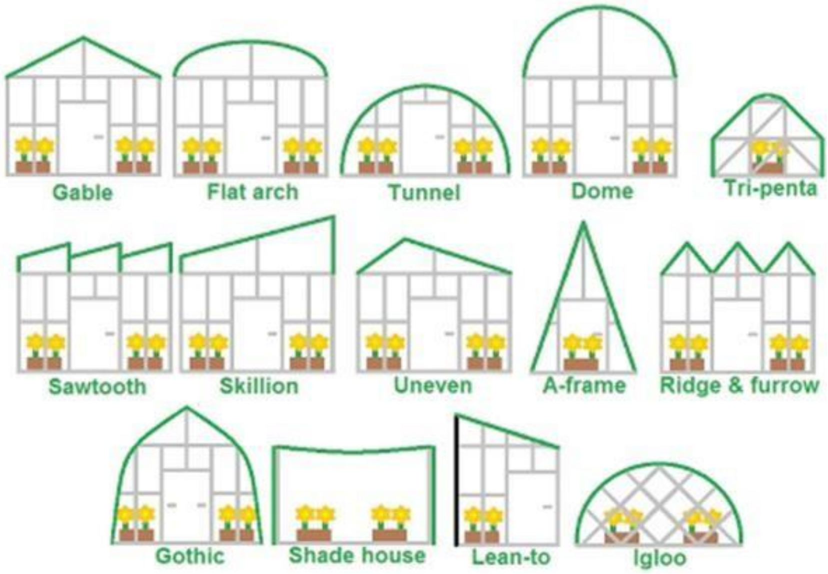

Figure I.6. Greenhouse type [11]

I.4.3. Cover material

The choice of cover material plays a crucial role in greenhouse efficiency; common materials include glass, polyethylene film, polycarbonate sheets, and acrylic panels. Glass offers excellent light transmission and durability, while plastics like polyethylene are lightweight and cost-effective, making them suitable for a variety of climates and growing needs [10].

Table I.2. Comparison of different cover materials [10]

Material	Advantages	Disadvantages
Glass	- High Light Transmission: Offers excellent transparency and allows the full spectrum of sunlight, crucial for photosynthesis. - Durability: Resistant to UV degradation and maintains clarity over time. - Aesthetic Appeal: Provides a clear and polished appearance, enhancing visual appeal	- High Cost: Expensive in both material and installation. - Fragility: Prone to breakage under hail, high winds, or impact. - Heavy Weight: Requires a strong supporting structure. - Poor Insulation (single-pane): Leads to heat loss and higher energy costs. - Overheating Risk: Can trap excessive heat without proper ventilation. - Maintenance: Requires regular cleaning; more labor-intensive.
Polycarbonate	- Transparency: High visible light transmission, suitable for plant growth. - Impact Resistance: Extremely durable and shatter-resistant. - Lightweight: Easier handling and installation. - Thermal Insulation: Superior insulating properties, especially in multi-wall panels. - UV Protection: Can be coated to block harmful UV rays and extend lifespan	- Higher Initial Cost: More expensive than plastic films. - Yellowing: May degrade and discolor over time without proper UV coating. - Scratching: Surface is prone to scratches, affecting light diffusion. - Condensation: Multi-wall panels may trap moisture, promoting fungal growth
Plastic (Polyethylene Film)	- Good Light Transmission: Adequate for plant needs, especially when new. - Temperature Regulation: Traps heat effectively, maintaining a stable environment. - Protective Barrier: Shields against pests, wind, and other external threats. - Cost-Effective: Lower cost and easy to replace.	- Poor Insulation (single layer): Rapid heat loss in cold weather; not suitable for heat-sensitive crops. - UV Sensitivity: Requires UV-stabilized variants to avoid rapid degradation. - Low Durability: Prone to tearing and damage under harsh weather. - Maintenance Difficulty: Can be difficult to clean and maintain

I.4.4. Key climatic parameters

The microclimate inside greenhouses represents the dynamic interaction of energy transfer, including radiation and heat, and mass transfer, such as water vapor flux and carbon dioxide concentration, within the plant canopy. This interaction involves exchanges between air, plant elements, and surrounding surfaces [12], making precise control of environmental factors essential for achieving optimal growth conditions. By regulating key factors such as solar radiation, air temperature (T), relative humidity (RH), and carbon dioxide (CO_2) concentration, growers can optimize environmental conditions, enhance plant adaptation, improve energy efficiency, and optimize water consumption [13].

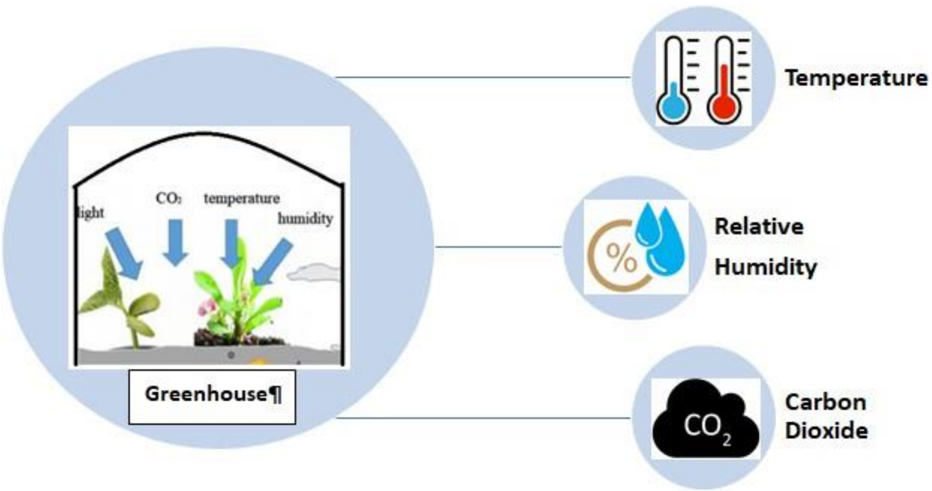

Figure I.7. Greenhouse microclimate parameters

I.4.5. Greenhouses systems classification

Greenhouses are typically classified as low-tech, medium-tech, or high-tech depending on their level of automation and climate control features. Low-tech greenhouses often rely on natural ventilation, while high-tech greenhouses incorporate advanced systems like automated irrigation, heating, cooling, and artificial lighting [14].

I.4.5.1. Cooling Systems

Maintaining optimal temperatures in greenhouses is essential for healthy plant growth and high productivity. Excessive heat or cold can negatively affect plant development. The three primary methods used for cooling greenhouses include:

- Natural Ventilation:

Passive ventilation is the most common cooling method in greenhouses. It relies on strategically placed openings that allow fresh air to enter and circulate naturally. Among the different designs, roof vents are five times more effective than side vents in promoting air exchange.

- Forced Ventilation:

Active ventilation involves the use of mechanical equipment, such as exhaust fans, to drive air movement within the greenhouse. It is important to conduct airflow studies across the length of the greenhouse to prevent localized overheating. Circulation fans are often used even in greenhouses with natural openings to ensure even air distribution throughout the structure.

- Shading:

During periods of intense sunlight and high temperatures, shade curtains can be deployed to reduce solar radiation by 30% to 50%, helping to maintain optimal internal conditions.

I.4.5.2. Heating Systems

An efficient and uniform heating system is one of the most critical factors in achieving successful agricultural production in greenhouses. Any heating system that maintains consistent temperature control without emitting harmful substances to the plants is considered acceptable. The choice of energy source depends on factors such as availability and cost in a given region.

I.4.5.3. Dehumidification

Warm air inside the greenhouse has a higher capacity to hold water vapor, which is beneficial for plants that thrive in humid conditions. However, excessive humidity can disrupt nutrient uptake particularly calcium leading to physiological disorders. On the other hand, insufficient humidity may also hinder plant development. Ventilation, both natural and forced, is a key strategy for regulating humidity levels, especially when they become too high.

Figure I.8 illustrates a comprehensive classification of greenhouse (GH) systems based on their functional purposes, including crop production, crop drying, and energy management. For crop production, greenhouses utilize heating and cooling systems. Heating strategies can involve natural or forced ventilation, while cooling methods include both natural and forced ventilation, along with evaporative cooling techniques such as pad-fan systems and fogging.

In the context of crop drying, the use of active solar greenhouse driers is emphasized, which may also incorporate evaporative cooling. For thermal management, systems may utilize space heating and solar energy collectors, with ventilation categorized as either natural or forced. To support efficient energy use and climate control, various thermal energy storage and insulation solutions are integrated, including buried pipes, movable insulation, north walls, ground air collectors, and water tanks. This classification highlights the diversity and complexity of greenhouse climate control systems and underscores the importance of tailored design based on specific agricultural and climatic needs.

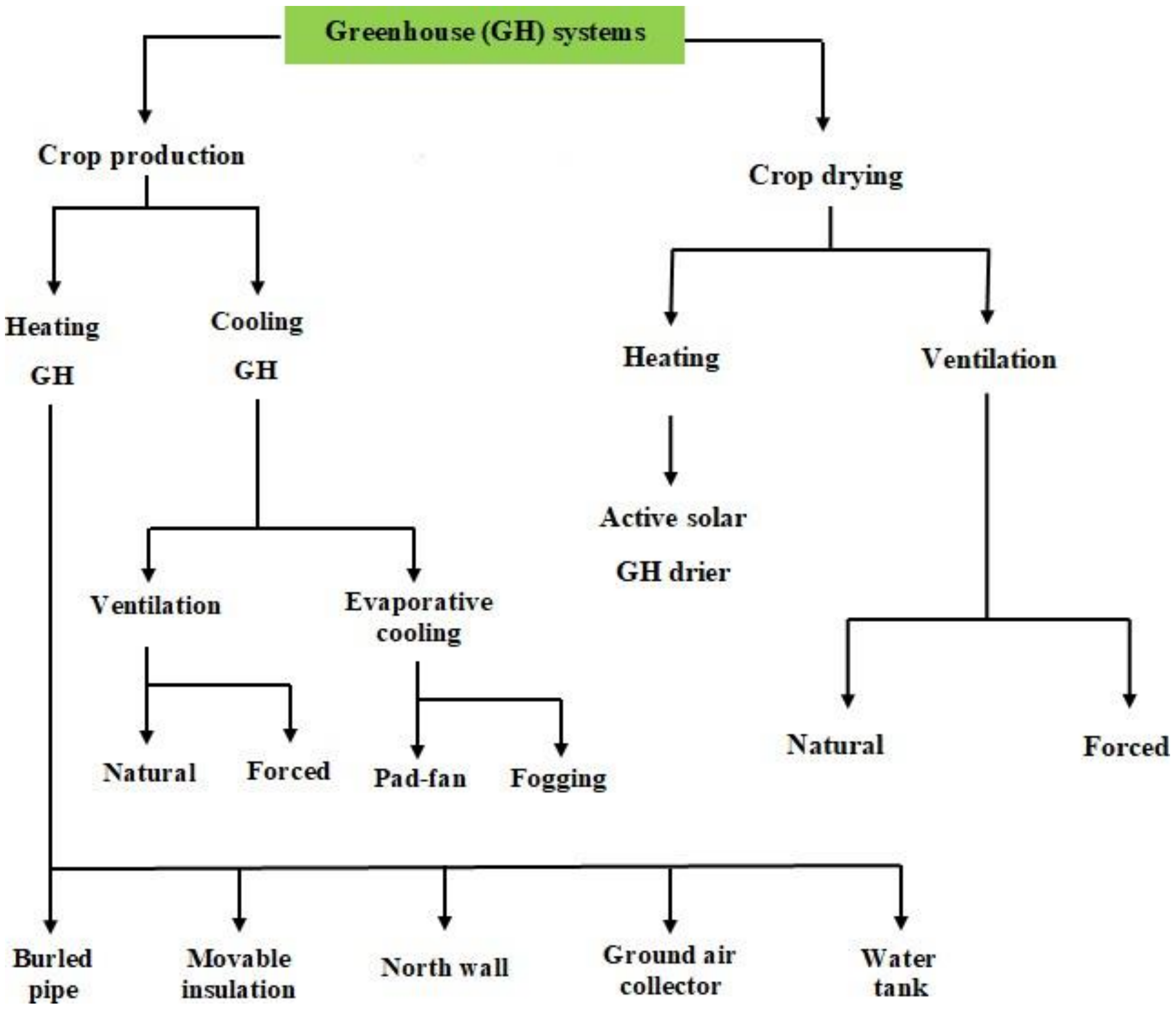

Figure I.8. Greenhouse systems classification

I.5. Conclusion

This chapter provided a detailed overview of the fundamental aspects relevant to greenhouse cultivation with a particular focus on solar potential, greenhouse systems, and their thermal behavior. The global and Algerian contexts of solar energy availability were examined, confirming the high solar potential in regions like Algeria, which offers promising conditions for solar-driven greenhouse agriculture.

A comprehensive review of greenhouse cultivation areas worldwide and within Algeria highlighted the growing importance of protected agriculture as a solution to climatic variability and the demand for year-round crop production. In this context, understanding the types of greenhouses, the selection of appropriate cover materials, and the classification of greenhouse systems is critical for optimizing crop yield and resource use.

The chapter also addressed the thermal dynamics of greenhouse environments, including heat and mass transfer processes and their interaction with key climatic parameters such as temperature, humidity, and solar radiation. These parameters are central to maintaining optimal conditions for plant growth and energy efficiency.

By integrating knowledge of regional solar potential with technical aspects of greenhouse systems, this chapter lays the groundwork for advancing sustainable and climate-resilient agricultural practices, particularly in sun-rich countries like Algeria. These insights will serve as a foundation for the following chapters, which explore advanced control strategies and the application of artificial intelligence in greenhouse climate management.

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CHAPTER II.

A Comprehensive Review: Heating Systems and ANN-application for greenhouse

II.1. Introduction

Effective management of the indoor climate in greenhouses is essential for minimizing energy consumption, enhancing agricultural productivity, and promoting sustainability. To achieve these objectives, two key technologies have emerged as critical: thermal energy storage systems and advanced climate prediction models. Thermal energy storage systems regulate internal temperatures within greenhouses, thereby reducing dependency on conventional energy sources. On the other hand, Artificial Neural Networks (ANNs) serve as powerful tools for modeling and predicting the complex, nonlinear interactions between various environmental parameters within the greenhouse, such as temperature, humidity, solar radiation, and CO_2 concentration. Integrating these two technologies holds significant potential for creating a more intelligent and energy-efficient agricultural environment, which can adapt to changing climate conditions and support long-term sustainability goals.

In this literature review, we will delve into existing research and studies focused on various storage methods used in greenhouse systems. We will explore the properties, advantages, and limitations of these phenomena, highlighting their potential to improve greenhouse heating efficiency. By examining the results and methodologies of previous studies, we aim to gain a comprehensive understanding of the various natural materials used in thermal storage for heating and/or cooling. This knowledge will help identify the most promising greenhouse design and materials and inform future research directions. Furthermore, this literature review will provide a solid foundation for our own research, allowing us to propose numerical approaches using artificial intelligence methods and innovative strategies to optimize thermal storage performance in greenhouses using natural materials. Overall, this literature review will be a valuable resource for researchers, practitioners and stakeholders in the field of greenhouse technology, providing a comprehensive overview of the current state of knowledge regarding natural thermal storage materials for improving the internal climate of greenhouses.

II.2. Thermal energy storage systems

Greenhouse growers strive to maximize yields while minimizing operational costs, with heating representing the most significant expense, primarily reliant on fossil fuels. However, the environmental impact of fossil fuel consumption and concerns over energy security underscore the urgent need for renewable energy sources and enhanced efficiency. Since the 1970s, Thermal Energy Storage (TES) systems have emerged as a highly effective solution for improving energy efficiency compared to conventional methods, while also providing alternative heating and cooling strategies [1]. The primary function of TES systems is to reduce heat loss by storing excess thermal energy for later use [2]. TES technologies are broadly classified into three main categories: Sensible thermal energy storage (STES), Latent thermal energy storage (LTES), and Thermo-chemical energy storage (TCES) [3].

Efficient thermal storage plays a crucial role in improving greenhouse microclimates, reducing energy consumption, and enhancing sustainability. Figure II.1explores Development of research on the use of thermal storage in greenhouses.

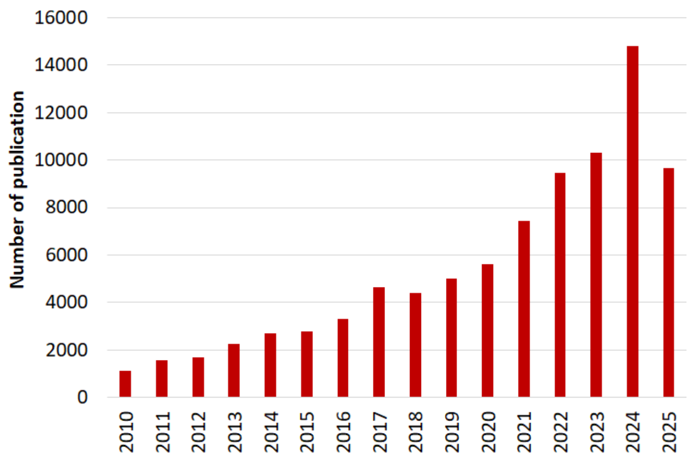

Figure II.1. Development of research on the use of thermal storage in greenhouses
(Source : The authors, 2025)

II.2.1 Water tank storage system

Utilizing water tanks as Thermal Energy Storage (TES) systems in greenhouses presents a practical and energy-efficient solution, particularly in cold regions with harsh winter conditions. Water functions effectively as a thermal mass, capable of absorbing and storing substantial amounts of heat during the day and releasing it at night or during periods of low ambient temperatures. This thermal buffering helps maintain a stable and optimal microclimate within the greenhouse, reducing temperature fluctuations and enhancing plant growth conditions by protecting crops from extreme cold stress [4].

Water's widespread use in active thermal energy systems is largely attributed to its dual role as both a heat transfer fluid (HTF) and a storage medium. This versatility is supported by several advantageous thermo-physical properties, including a high specific heat capacity (4.184 kJ.kg^{-1}.K^{-1}), non-toxicity, low cost, and abundant availability. Additionally, water can exist in multiple physical states solid, liquid, and vapor making it adaptable to a wide range of thermal applications. While ice is predominantly used in cold storage systems, the liquid phase is most suitable for low-temperature thermal energy storage, especially below 100 °C.

In its liquid form, water enables the formation of thermocline storage systems due to the natural stratification caused by temperature-induced density differences. This stratification, driven by buoyancy forces, facilitates the efficient separation of thermal layers hot water remaining at the top and cold water settling at the bottom thus enhancing the thermal performance and energy efficiency of the storage system. One of the most prominent applications of water-based TES in greenhouses is through Tank Thermal Energy Storage (TTES) systems [5]. These are typically constructed from durable materials such as reinforced concrete, steel, or fiber-reinforced plastics, with internal linings to ensure water-tightness and thermal insulation. TTES tanks are often buried partially or fully underground to minimize heat loss due to ambient temperature fluctuations, thereby reducing the need for additional insulation.

S. Bezari et al., (2007) is based on the study of the thermal balance of a solar greenhouse, equipped with a thermal storage device in the water (Figure II.2). The function of the greenhouse - storage device system is established as a simplified mathematical model in transient mode. The mathematical model is solved by the numerical method of Runge Kutta to order 4. The results were compared with the measurements obtained in an experimental greenhouse carried out at the station of the National Institute of Agronomic Research [5].

Figure II.2. Water thermal storage system in greenhouses [5]

P. Lorenzo et al., (2024) studied a hybrid system combining passive cooling (evaporative screens) and heating (water-filled sleeves) with a shading/thermal screen in a sweet pepper greenhouse at IFAPA La Mojonera (Figure II.3). Compared to a standard greenhouse, the system improved climate control by reducing the vapor pressure deficit in warm periods and increasing nighttime air and substrate temperatures in cold periods. It also boosted early plant growth and increased marketable yield by 25%, while reducing irrigation water use by 8% and improving water use efficiency by 20%. [6].

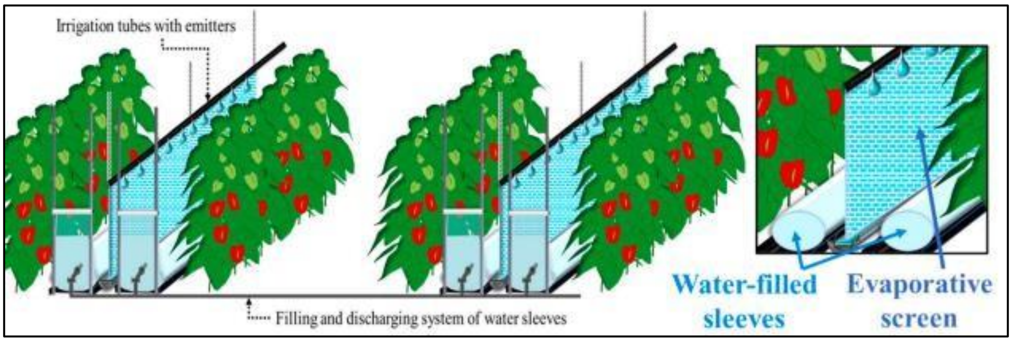

Figure II.3. Schematic of the concept of the water-tube greenhouse [6]

G.K. Ntinas et al., (2015) evaluated a hybrid solar energy-saving system (HSESS) in a heated greenhouse for hydroponic tomato cultivation. The system, using water-filled solar sleeves and air tubes, improved air temperature and root growth conditions. It increased total yield by 7.1% and marketable yield by 10.8%, despite a 2.9% decrease in total fruit count. Marketable fruits rose by 6.8%, and antioxidant capacity improved by 18.4%, enhancing fruit quality [7].

II.2.2 Rock bed storage system

Rock bed storage, composed of materials such as pebbles, gravel, and bricks, is a cost-effective and widely used medium for sensible heat storage. When integrated with an air-based heat transport system, underground rock bed storage provides a large and economical heat transfer surface. These storage units are commonly installed at depths of 40 to 50 cm, either beneath or outside greenhouses, often enclosed within insulated concrete structures to enhance thermal retention. During the day, excess heat from the greenhouse is transferred to the rock bed using a ventilator. At night, the process is reversed, where cool air circulates through the storage unit, absorbing heat from the rocks before returning to the greenhouse to regulate temperature [8].

S. Bezari et al., (2020) designed and tested a thermal storage system based on a rock bed with an H-shaped channel integrated into a greenhouse in southern Algeria (Figure II.4). A comparison was made between two greenhouses: one traditional and the other equipped with the thermal storage system. The results showed an improvement in temperature, with an increase of 0.9°C at night and a decrease of 1.6°C during the day, along with a reduction in relative humidity by 3.4%, leading to an improved plant growth environment. However, the airflow was insufficient to achieve optimal heat distribution, necessitating system development by adding active ventilation [9].

Figure II.4. Storage system based on a rock bed [9]

L. Gourdo et al., (2019) studied a rock-bed heating system in a Canarian-type greenhouse in Agadir (figure II.5). Two identical greenhouses were tested, one with the heating system and one without. Results showed that the heated greenhouse had a 3°C higher nighttime temperature than the unheated one and 4.7°C higher than the outside, while daytime temperatures were 1.9°C lower inside and 3°C lower than outside. The system also improved crop yield by 22% [10].

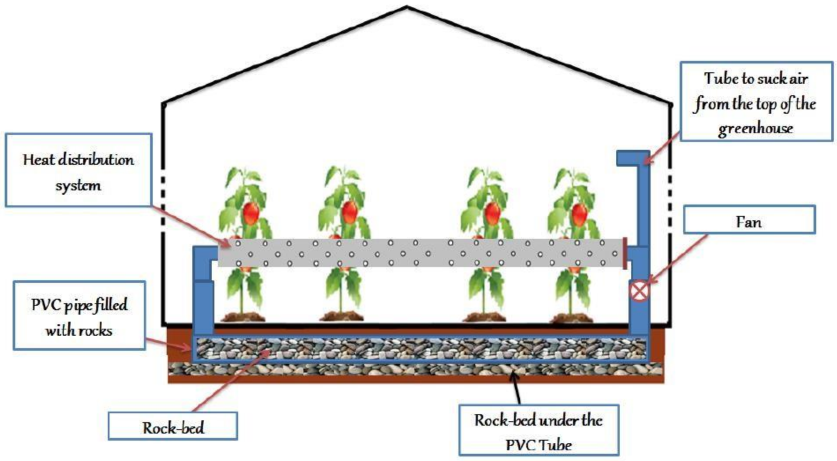

Figure II.5. Greenhouse with rock-bed [10]

A. Bazgaou et al., (2020) evaluated a hybrid heating system for a canarian-type greenhouse in southern Morocco, combining rock bed thermal storage with passive solar energy in water (figure II.6). Compared to an unheated greenhouse, the system increased nighttime air temperature by 3–5°C on clear days and 2–3°C on cloudy days, reduced thermal fluctuations by 24–25%, and lowered nighttime humidity by 10–15%. It also raised soil temperature by 3–4°C, boosting tomato yield by 49% and reducing Tutaabsoluta spread by 64%. Economically, it proved cost-effective, generating an additional profit of 1.02 USD/m². However, further research is needed to enhance its performance in extreme cold [11].

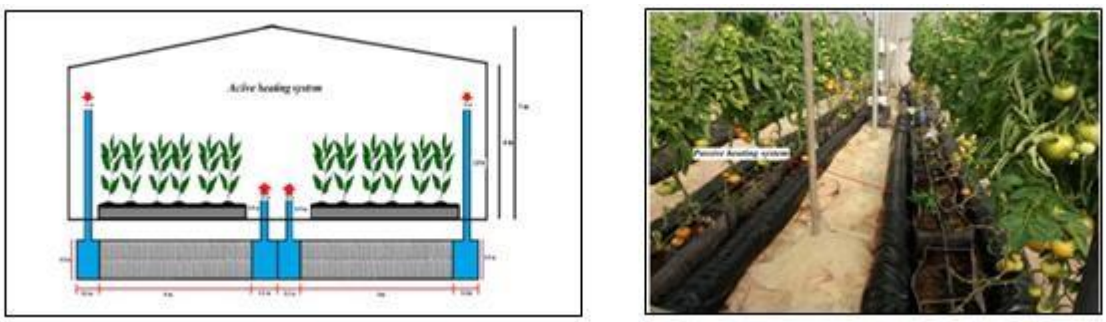

Figure II.6. Description of active heating system and passive heating system [11]

II.2.3 Phase change materials storage system

Phase Change Materials (PCMs) represent an efficient solution for thermal energy storage, offering a higher storage density compared to conventional methods while maintaining temperature stability during heat absorption and release. These materials operate by absorbing a significant amount of heat during their phase transition from solid to liquid and subsequently releasing this stored energy when they solidify [8].

The performance of PCMs is influenced by key factors, including melting temperature, thermal conductivity, and energy storage density. Various enhancements have been introduced to improve their efficiency, such as the incorporation of fins and heat pipes for better heat exchange, micro- and macro-encapsulation techniques for enhanced thermal distribution, and the integration of highly conductive nanoparticles into PCMs, known as nano-enhanced PCMs. Continuous advancements have established PCMs as a promising solution to enhance energy efficiency and sustainability in buildings [12].

S.M. Thaler et al., (2024) studied phase change materials (PCMs) to improve greenhouse heating. Paraffin proved the most effective for stable heat storage. Two protection units were developed for greenhouse roots and fruit trees. Tests showed the PLA unit maintained stable temperatures for 326 minutes, with slight improvement using metal. CFD simulations confirmed the findings, supporting PCMs as a cost-effective, sustainable solution. Further testing and design refinements were recommended [13].

C. Maraveas et al., (2023) analyzed sustainable greenhouse coverings using nanomaterials like nanosilica and zinc oxide to minimize heat loss while allowing light to pass through. They tested polymer films with thermal additives (PLA/ZnO, LDPE/ZnO) for improved insulation and incorporated phase-change materials (PCMs) to stabilize temperatures by storing heat during the day and releasing it at night. Additionally, they explored solar-active materials like graphene to enhance energy efficiency. The study found that these innovations reduce energy consumption, lower carbon emissions, and cut operational costs, making them essential for sustainable agriculture and increased productivity [14].

H. Ling et al., (2014) conducted an experiment to evaluate the thermal storage performance of the Active–Passive Triple Phase Change Material Wall (APTPCMW) in solar greenhouses, aiming to enhance thermal energy efficiency. The study involved a practical experiment to measure heat storage performance in the middle layer of the wall, considering several factors such as the distance between air tunnels, the direction of heated airflow, and the temperature and speed of the supplied air. The results indicated that the system effectively increased heat storage capacity and trapped more heat inside the wall during the day. The optimal operating parameters for maximum efficiency were found to be an air tunnel spacing of 0.4m, a downward direction of heated airflow, a supply air velocity of 0.26 m/s, and a supply air temperature of 60°C [15].

II.2.4. North wall storage system

Greenhouses with a north wall exhibit superior thermal performance compared to other structural components, such as the north and south roofs and the ground, due to the wall's ability to store and release heat consistently. The internal surface structure (ISS) of the north wall enhances solar radiation capture and heat dissemination, improving nighttime thermal performance. For maximum thermal efficiency, the north wall should combine high thermal storage capacity, effective insulation, and structural load-bearing strength [16, 17]. China is a global leader in the implementation of north-wall greenhouses, particularly in cold climates. The advanced design of the north wall increases thermal autonomy and reduces energy consumption, making it a crucial element in modern greenhouse design. The figure II.7 explores development of research on the use of north wall storage in greenhouses.

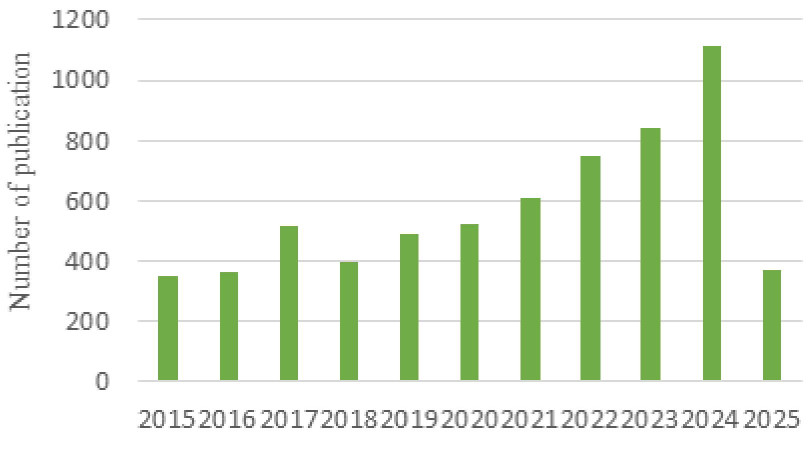

Figure II.7. Development of research on the use of north wall storage in greenhouses

(Source : The authors, 2025)

X. Liu et al., (2019) studied the impact of wall materials on the thermal environment in Chinese solar greenhouses (Figure II.8). They tested three types, all with an outer north wall layer of polystyrene boards but different inner layers: perforated brick, fine coal ash brick, and common clay brick. The fine coal ash brick wall was the most efficient, storing 34.5–130.6 W/m² and releasing -24.15 to -45 W/m² daily, with a heat storage duration of 5–8 hours. It also maintained nighttime temperatures 3–4°C higher, keeping indoor temperatures between 16.7–31.1°C and relative humidity at 29.75%–45% [18].

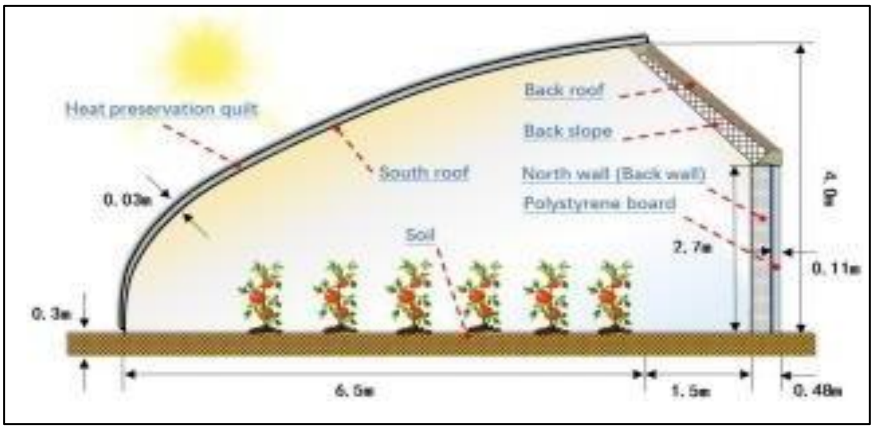

Figure II.8. Structure of the Chinese solar greenhouse [18]

Studies by **F. Berroug et al., (2011)** explored the integration of phase change materials (PCMs) into greenhouse structures to enhance thermal regulation. One notable approach involves the use of $CaCl_2 \cdot 6H_2O$ as a PCM within a north wall storage system in east–west oriented greenhouses. Numerical thermal models, accounting for key greenhouse components and local climatic data, indicate significant night-time temperature gains of 6–12 °C and reduced humidity levels. The results demonstrate that the north wall PCM system effectively moderates internal conditions. These findings highlight the potential of PCM-based storage systems to improve greenhouse microclimates during the winter period [19]

L. Zhao et al., (2024) studied the effect of north wall design on heat storage and humidity in solar greenhouses using Multiphysics modeling. Comparing flat (FW), striped (SW), and Alveolate (AW) walls (Figure II.9), they found solar radiation to be the main factor affecting indoor temperature changes. The honeycombed wall (AW) provided the best heat retention, efficient temperature control, and the lowest humidity on sunny days. On cloudy days, SW and AW performed similarly in heat regulation, but AW maintained more stable humidity. Power spectral density (PSD) analysis confirmed AW's superior heat storage and release, making it the most effective design for greenhouse efficiency [20].

Figure II.9. Illustration of the different internal surface structures of the north wall [20]

(a) Flat wall; b) Striped wall; (c) Alveolate wall

M. Takiet al., (2016) conducted modeling and experimental evaluation of heat and mass transfer processes in a solar greenhouse equipped with a thermal screen and a modified north wall. A semi-solar greenhouse was designed and constructed in the northwest region of Iran. A dynamic heat and mass transfer model was developed to estimate temperatures at six different locations within the greenhouse.The results from using a thermal screen during night-time hours (12 hours) in autumn demonstrated a reduction in fossil fuel consumption of up to 58%, leading to lower operating costs and decreased air pollution. The use of this movable insulation created a temperature difference of approximately 15 °C between the interior and exterior environments, and about 6 °C between the air temperature near the plants and the average air temperature [21].

X. Gao et al., (2017) examined the effect of north wall length on the indoor thermal environment in Lanzhou. They found that the highest shadow rate on the east and west walls occurs at 10:00 AM on the winter solstice, with shadow reduction slowing as the wall approaches 90 meters. On sunny days, heat storage and release are balanced, but when the wall exceeds 90 meters, heat release surpasses storage, leading to lower indoor temperatures the next morning, especially on cloudy days. Based on ventilation and insulation needs, the optimal north wall length is around 90 meters [22].

Other Research has focused on optimizing the indoor thermal environment of solar greenhouses by leveraging the solar thermal storage and release characteristics of the north wall. In a study conducted by **F. Han et al., (2024)** a mathematical model was developed incorporating simplified calculations of the greenhouse's spatial parameters. The model also included a design method for an active–passive ventilation wall with latent heat storage, previously proposed, to evaluate the impact of the north wall's thermal behavior on indoor climate conditions. Experimental results demonstrated that applying active–passive solar heat storage systems to the north wall significantly improved the indoor thermal environment during night-time and increased winter cucumber yields by over 10%. This study provides a valuable reference for optimizing active–passive solar energy utilization in greenhouse design [23].

Table II.1. Comparison of different types of thermal energy storage systems

Facture	North Wall	Rock Bed	Water Tank	PCM Storage
Storage Efficiency	Moderate	Moderate	High	Very High (~80–90%)
Space Requirements	Integrated into wall	Ground space needed	Large volume tanks	Compact, low volume required
Cost	Moderate to High	Low to Moderate	Moderate	High
Heat Capacity	Low to Moderate (depends on material mass)	Medium (~800–1000 J/kg·K depending on rock type)	Very high (~4186 J/kg·K)	Very high (100–150 kWh/m³ or more)
Maintenance	Low	Low	Moderate (leakage/algae)	Moderate (PCM stability)
Thermal Storage Mechanism	Passive insulation / solar mass wall	Sensible heat (air-to-solid medium)	Sensible heat	Latent heat (phase change)

(Source : The authors, 2025)

II.3. Application of ANN to the Prediction of Greenhouse Microclimate

Accurate prediction of the microclimate within greenhouses is crucial for optimizing energy efficiency, enhancing crop yields, and maintaining stable growing conditions. Artificial Neural Networks (ANNs) have emerged as effective tools for modeling the complex, nonlinear interactions between environmental variables such as temperature, humidity, solar radiation, and CO_2 concentration [24, 25]. This review examines the application of ANNs in greenhouse climate prediction, focusing on various network architectures, training algorithms, and input variables.

Artificial intelligence techniques such as artificial neural networks (ANN) have been widely used in the field of greenhouse microclimate control (Figure II.10). ANNs provide reliable models that can reflect nonlinear greenhouse characteristics that are difficult to resolve using traditional techniques. They do not require any prior knowledge of the system and are well-suited for modeling real-time dynamic systems [26, 27].

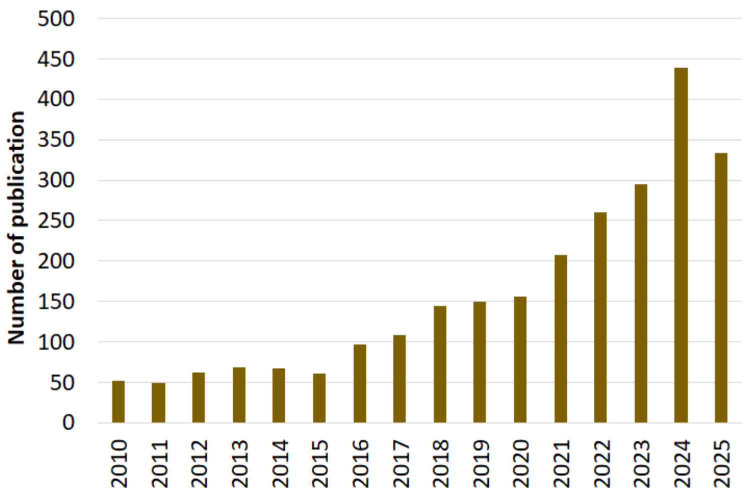

Figure .II.10. Development of research on the use of ANN in greenhouses

(Source : The authors, 2025)

P.M. Ferreira et al., (2002) developed a model to predict indoor temperature in a hydroponic greenhouse, considering factors like relative humidity, outdoor temperature, and solar radiation. They evaluated training methods for a radial basis function neural network, which is simpler to design and train than multilayer perceptrons. The study compared off-line and on-line training, finding that the levenberg-marquardt method provided the best results for on-line training, significantly improving prediction accuracy [28].

A. Dariouchy et al., (2009) employed an Artificial Neural Network (ANN) model to predict greenhouse internal parameters over a 7-day period using real climatic data from a tomato greenhouse in Agadir, Morocco. The model considered key inputs, including external moisture (Mext), total radiation (Rt), wind direction (Dw), wind velocity (Vw), and external temperature (Text). A comparison between the predicted and experimental results confirmed that the ANN model accurately forecasts greenhouse climate conditions, making it a reliable tool for climate prediction in controlled agriculture [29].

E.C. Lachouri et al., (2015) described an Adaptive Neuro-Fuzzy Inference System (ANFIS) to model and predict greenhouse climate conditions for tomato seedlings. The system estimates air temperature, humidity, CO_2 concentration, and internal radiation using ten key meteorological and control parameters. The model was trained over 48 days with a neural network optimized through backpropagation and least squares algorithms (500 iterations). Simulation results demonstrated the efficiency and accuracy of ANFIS, making it a reliable tool for greenhouse climate control in agriculture [30].

H. Yue et al., (2016) utilized an Artificial Neural Network with a radial basis function model to predict air temperature and humidity in Chinese solar greenhouses. Accurate temperature forecasting is essential to prevent crop losses due to extreme weather conditions. This study introduced a novel prediction model using a Least Squares Support Vector Machine optimized by Improved Particle Swarm Optimization (IPSO) with mutation probability. The IPSO method effectively enhanced the selection of LSSVM hyperparameters, improving prediction accuracy. A comparative analysis with traditional models, including standard Support Vector Machines (SVM) and Backpropagation Neural Networks (BPNN), demonstrated that the IPSO-LSSVM model outperformed existing methods, providing more precise temperature predictions. The prediction of maximum and minimum temperatures makes it a reliable and effective tool for forecasting greenhouse temperatures [31].

M. Taki et al., (2016) compared different mathematical models, including Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN), to predict inside air temperature (Ta), roof temperature (Tri), and energy loss in a semi-solar greenhouse in Iran. The study found that MLR was inaccurate, while the Multilayer Perceptron (MLP) neural network model performed best, achieving lower RMSE and MAPE values and higher EF indices. No significant differences were observed between predicted and actual values, confirming the effectiveness of MLP in estimating energy loss. This makes MLP a valuable tool for reducing sensor costs and enhancing greenhouse efficiency [21].

V.K. Singh et al., (2017) developed an Artificial Neural Network model to predict mean air temperature and relative humidity one day in advance for a greenhouse in India's sub-humid subtropical region. The study utilized a Backpropagation neural network, with temperature, humidity, wind speed, and solar radiation as input variables. The network was trained using a hyperbolic tangent activation function in the hidden layer and a linear function in the output layer. Performance was assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient. The BP neural network (6-4-2 model) demonstrated the highest accuracy, with temperature RMSE and MAE of 0.711°C and 0.558°C, and humidity RMSE and MAE of 2.514% and 1.976%, making it a reliable tool for greenhouse climate control [32].

S. Özden et al., (2018) applied an artificial neural network (ANN) model to predict energy consumption for greenhouse temperature control. The model was designed based on key temperature parameters, including indoor temperature, outdoor temperature, and soil temperature. The ANN output represents the energy demand, which is entirely dependent on temperature data, providing an effective approach for optimizing energy use in greenhouse climate management [33].

M.H. Shojaei et al., (2019) used an ANN with a Multiple Linear Regression (MLR) model to predict air temperature. The study tested two models to forecast the air temperature inside a single-sided glass greenhouse one without ventilation and one with an evaporative cooling system. Data analysis was performed using both ANN and regression methods. The results indicated that the ANN model provided more accurate temperature predictions. Moreover, in the absence of ventilation, a 1°C increase in ambient air temperature and a 100 W/m² increase in solar radiation led to a 3°C rise in greenhouse temperature [34].

M.A. Tawfeek et al., (2022) established a research on integrating Adaptive Particle Swarm Optimization (PSO) with Artificial Neural Networks (ANNs) to enhance agricultural decision-making while minimizing costs. The adaptive PSO-ANN model dynamically updates datasets by filtering out irrelevant records and retaining essential ones for classification. A comparative study demonstrated that this approach outperformed existing methods, achieving a high accuracy of 94.8%. A case study on smart olive cultivation using Internet of Things

(IoT) tools validated the model, demonstrating improved crop yield and optimized resource utilization [35].

N. Choab, et al., (2022) carried out a study on the application of an Artificial Neural Network (ANN) model to predict internal temperature and humidity in a greenhouse using external climatic data in a real tomato cultivation scenario in the semi-arid region of Agadir, Morocco. The optimal model featured one hidden layer with six neurons and achieved high prediction accuracy, with Mean Relative Errors (MRE) of 4.23% for internal temperature (Tint) and 3.85% for internal moisture (Mint). A comparison with experimental results showed that the ANN method outperformed traditional regression models in forecasting greenhouse climate, highlighting its effectiveness in addressing complex agricultural challenges [36].

A. Daliran et al., (2023) developed a model to predict temperature and mass of dried mint in a Greenhouse Solar Dryer (GSD) using Artificial Neural Networks (ANN) and Gaussian Process Regression (GPR). Among the tested models, Radial Basis Function (RBF) performed best, achieving high accuracy with minimal error (MAPE: 1.4% and 1.82%). Statistical tests confirmed no significant difference between actual and predicted values, proving the RBF model's reliability for drying process prediction [37].

According to **F. Cletus et al., (2024),** the effectiveness of Bi-LSTM, ANN, GBM, and RF models in predicting microclimatic factors such as temperature, humidity, and CO_2 levels is evaluated. The study also discusses the limitations of applying machine learning models to greenhouse microclimate prediction and suggests directions for future research. The results demonstrate that both ensemble methods (Gradient Boosting Machine and Random Forest) and deep learning architectures (ANN and Bi-LSTM) performed well in the evaluation. These findings support the view that machine learning algorithms are effective predictive tools, offering valuable insights for optimizing greenhouse operations [38].

H. EinGhaderi et al., (2025) explored the design of a system for predicting greenhouse environmental conditions using deep learning techniques. The proposed method was implemented to maintain optimal conditions for tomato crop production in a glass greenhouse. The deep learning-based model accurately predicted key parameters, including temperature, relative humidity, and carbon dioxide concentration. Its performance was notably superior to that of traditional dynamic modeling approaches. These findings suggest that intelligent artificial intelligence methods offer effective solutions for optimal greenhouse control, improving performance and addressing existing limitations [39].

Table II.2 summarizes a significant number of works related to the use of ANNs for Greenhouse Microclimate Prediction. We provide details on the input and output variables and the network architecture in the training process.

Table II.2. Application of artificial neural network models for greenhouse microclimate prediction

Reference	Input	Output	Architecture	Commentary
Eddine, C.et al [29]	• ventilation • heating • shading • artificial light, • CO2 injection • fogging/cooling • external temperature • external humidity • global radiation • wind speed	• Internal temperature • Internal humidity • CO2concentration • Internal radiation	10-40-4	The ANFIS model accurately predicted greenhouse climate during seedling growth, showing strong agreement with experimental data. Training with backpropagation and least-squares methods achieved a 2% error rate
Morteza et al [21]	• Outdoor temperature • external humidity • wind speed • global radiation	• Internal temperature • Internal humidity	3-21-9-9-3	13 types of learning algorithms were tested. It was found that RFBRANN had the lowest errors among the models.

Singh, V. K.et al **[31]**	• maximum temperature • minimum temperature • relative humidity • outside average wind speed • solar radiation	• meantemperature • mean relative humidity	6- 4 -2	ANN based modeling approach in predicating the greenhouse mean temperature and relative humidity.
Özden et al **[32]**	• Inner Temperature • Outdoor temperature • Soil temperature • target temperature	• energyconsumption	4-10-10 -1	ANN to predict energy consumption based on inner, outer, and soil temperatures. The data was collected to aid in temperature control within a greenhouse environmen
A. Daliran et al **[36]**	• Outdoor Temperature • Outdoor Humidity • Global Illuminance	• The mass of dried mint • Temperature of dried mint	3 – 18 -1	The study showed that the RBF model was the mostccurate in predicting the temperature and mass of dried mint.

II.4. Conclusion

This chapter presented a comprehensive review of solar greenhouses, with a particular focus on their thermal performance under local climatic conditions. It explored various thermal energy storage methods—including water, rock beds, north walls, and phase change materials—as well as the application of artificial intelligence, particularly artificial neural networks (ANNs), for predicting key microclimatic parameters such as temperature, solar radiation, and relative humidity.

Despite the technological advancements reported in the literature, significant gaps remain. Most studies are based on simulations or small-scale experiments, with a notable lack of large-scale experimental validation. Furthermore, comparative analyses of different thermal storage methods under uniform climatic conditions are scarce, limiting the ability to generalize findings.

The integration of ANNs with optimization algorithms has emerged as a promising approach to enhance greenhouse control efficiency. However, challenges persist, including the need for real-time adaptability, high-quality datasets, and the development of generalized models applicable across various climatic zones. Additionally, the application of AI techniques to greenhouses equipped with thermal energy storage systems remains underexplored.

Addressing these challenges presents a critical opportunity to advance the automation and efficiency of solar greenhouses. Doing so will not only reduce energy consumption but also contribute to more sustainable and resilient agricultural practices.

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CHAPTER III.

Experimental Study and Predictive Modeling

III.1 Introduction

The semi-arid climate of the Ghardaïa region is characterized by a temperature difference between day and night during the winter season. This characteristic requires the use of greenhouses equipped with thermal storage systems to create a microclimate favorable to plant growth.

This chapter presents the methodology used to investigate the thermal behavior of a greenhouse prototype incorporating a thermal storage wall. The study combines experimental observations with predictive modeling to evaluate how various structural components particularly the north wall and the cover material affect the internal thermal environment of the greenhouse. It begins with a description of the study site and its climatic conditions, which are essential for understanding the context of the heat transfer processes. The experimental setup is then outlined, detailing the configuration of the greenhouse system, the construction of the north wall using locally sourced stones, and the properties of the transparent cover. The instrumentation used for measuring environmental and structural parameters is also described, along with the procedure for experimentally determining the density of the stones employed.

In the modeling phase, an Artificial Neural Network (ANN) is developed to predict the indoor temperature of the greenhouse based on environmental inputs and system characteristics. This approach helps evaluate the influence of design elements on thermal performance.

III.2. Description of site and climate

The work presented in this thesis was carried out at the Applied Research Unit for Renewable Energies (URAER), located approximately 20 km east of Ghardaïa, Algeria (32°38' N latitude, 3°81' E longitude), with an altitude of 469 meters above sea level. The site is situated in a semi-arid region in southern Algeria, about 600 km from the capital city, Algiers.

Ghardaïa is characterized by exceptional solar conditions, with an average annual sunshine duration of around 3000 hours and a mean annual global solar radiation exceeding 6000 Wh/m² on a horizontal surface. These favorable conditions support the development and utilization of solar energy and renewable energy technologies across various sectors.

The region also experiences harsh winter conditions due to cold winds blowing from the snowy highlands. In addition, sandstorms originating from the southwest during late winter can be particularly disruptive.

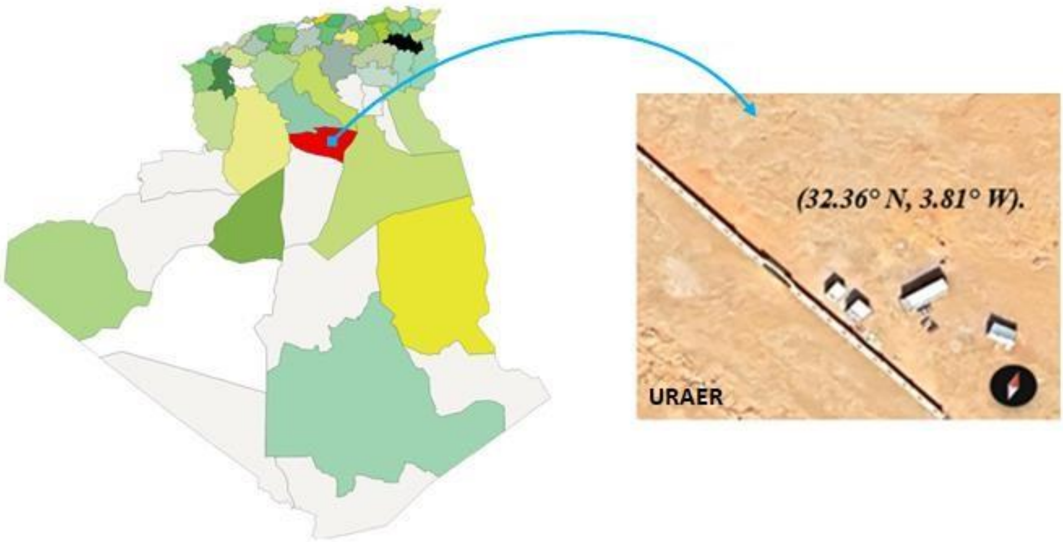


Figure III.1. Experimental study site (Ghardaia)
(Source : The authors, 2025)

In the following section, the annual evolution of solar radiation, temperature, and relative humidity at the Ghardaïa site is illustrated; based on data reported by Bezari et al. [1].

Figure III.2 illustrates the daily average global solar radiation for the entire year of 2017. High solar radiation levels were observed between March 2nd and September 17th, 2017; with the highest daily average of 9080 Wh/m² recorded on June 6th. The annual average daily solar energy input was approximately 21.83 MJ/m²/day, consistent with the values reported in the global solar radiation map [2].

Figure III.3 shows the variation in ambient temperature throughout the 365-day period, reflecting seasonal trends. The maximum temperatures exceeded 40 °C in summer season, while minimum temperatures remained around 25 °C. In contrast, during winter, the average minimum and maximum temperatures were approximately 5 °C and 15 °C, respectively.

Figure III.4 presents the average relative humidity evolution over the year. The relative humidity ranged from 10% to 30% during the summer months (June, July and August). However, maximum relative humidity values reached around 85% in winter.

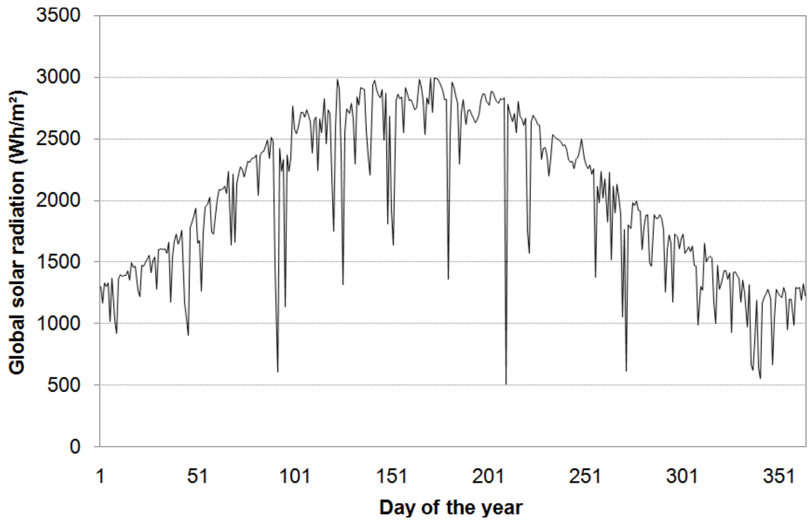


Figure III.2. Variation of global solar radiation

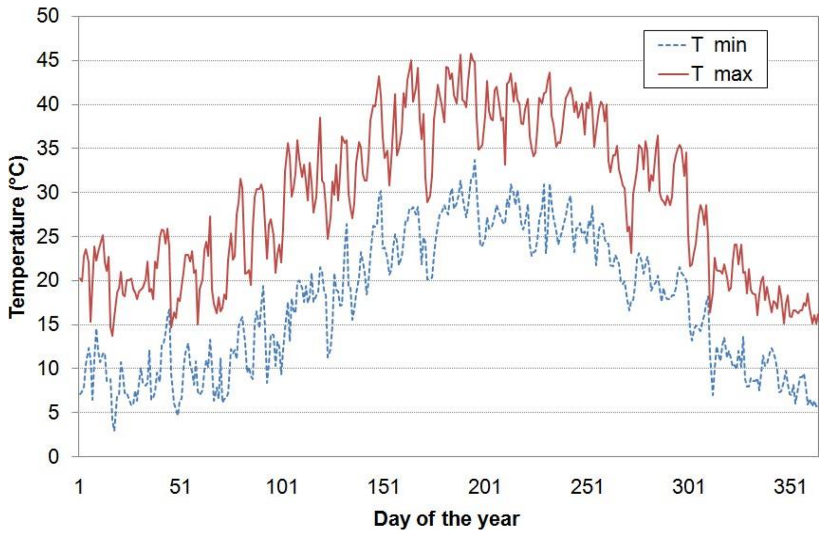


Figure III.3. Variation of air temperature

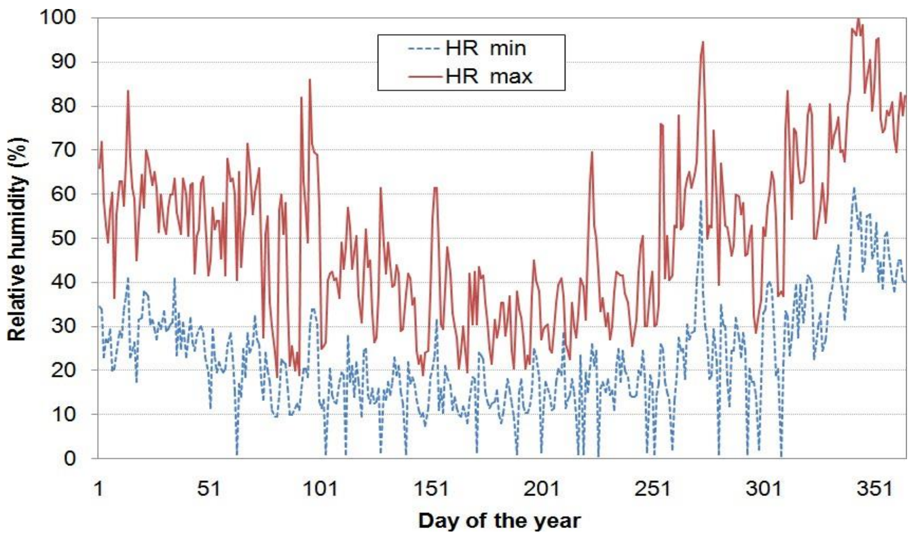


Figure III.4. Variation of the relative humidity

III.3. Experimental setup

III.3.1. Greenhouse system

The greenhouse, initially conceived as a basic shelter to protect plants from unfavorable environmental conditions, has developed into an engineered agro-environmental system designed to optimize plant productivity and quality through precise control of the immediate growing environment. These structures primarily harness solar radiation while aiming to isolate the cultivated crops from external climatic influences, native soil conditions, and seasonal variability. Within this framework, the study and modeling of the greenhouse microclimate key variables such as temperature, humidity, evaporation, condensation, thermal and radiative exchanges, and ventilation are essential for achieving accurate environmental regulation.

- Greenhouse structure design

A comprehensive understanding of greenhouse structural designs and their interaction with external climatic factors is essential for analyzing operational performance and improving efficiency especially in sunny regions with arid or semi-arid climates. After reviewing various greenhouse configurations, this study selects a modern and innovative design, the uneven span, for construction due to its potential advantages under such environmental conditions.

Figure III.5 illustrates a variety of commonly used greenhouse structural designs, including traditional models such as the even span, vinery, semi-solar, arch, and Quonset types, as well as a newly proposed configuration the uneven span design. These structures differ in geometry, which significantly influences their thermal behavior, light distribution, and adaptability to external climatic conditions. The innovative uneven span design, highlighted in this study, was selected for its potential to optimize solar gain and internal climate control, particularly in regions with high solar radiation and arid or semi-arid climates.

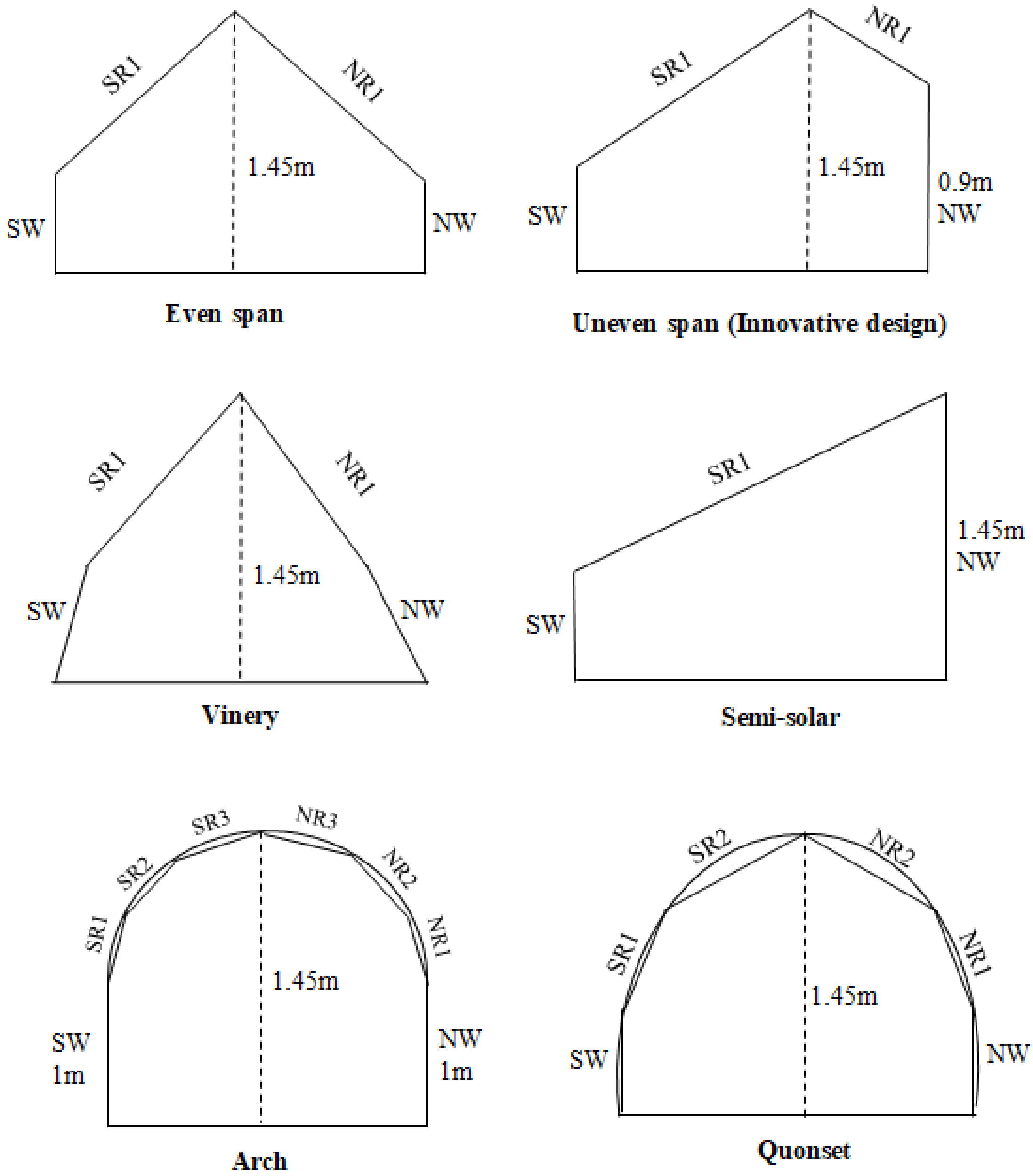


Figure III.5. Common types of greenhouses and innovative structures in the study (SW= South Wall, SR= South Roof, NR= North Roof, NW= North Wall)

- Realization of structure

The figure III 6 illustrates the experimental prototype of the greenhouse under study, designed with a bioclimatic approach to optimize thermal management. This small-scale greenhouse 1.8 m in length and 1.45 m in maximum height) features a north wall made of local stone, functioning as a passive thermal mass. Its compact and functional design is particularly well suited for experiments in arid climates, such as that of the Ghardaïa region, and enables the evaluation of the energy performance of this passive thermal configuration.

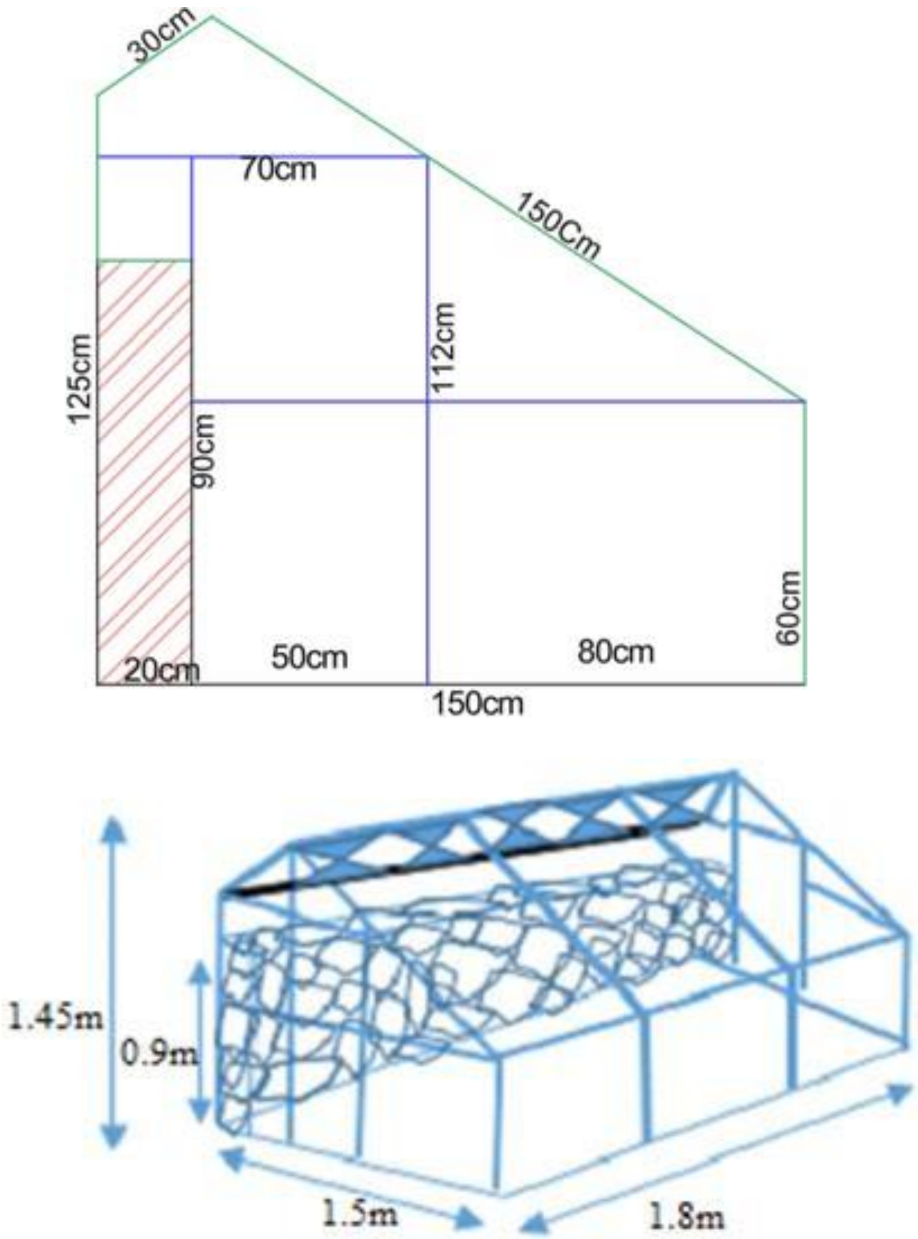


Figure III.6. Design of experimental greenhouse

After completing the design of the greenhouse structure and precisely determining the required dimensions, appropriate steel materials were selected based on their strength and resistance to environmental conditions. The fabrication process began with cutting the steel components according to the engineering specifications, followed by welding the main structural elements to form modular units. Bolts and fasteners were used to ensure mechanical stability, ease of assembly, and potential disassembly. These initial construction activities were carried out in the workshop under controlled conditions to ensure precision and high-quality joints (Figure III. 7). Upon completion of the prefabrication phase, the structure was transported to the installation site, where it was reassembled according to the approved design plans, with careful attention to anchoring and mechanical stability to ensure the structural integrity and operational safety of the greenhouse in its intended environment (Figure III. 8).

Figure III. 7. Greenhouse structure realization in atelier URAER

Figure III.8. Implementation of structure in site experiments

III.3.2. North wall element

The construction process began with the collection of stones directly from the building site. These stones were then subjected to a preparatory phase that included thorough cleaning, washing to remove dust and debris, and air drying to ensure proper adhesion during masonry work. Once dried, the stones were weighed and sorted according to size and mass to facilitate uniform wall construction and load distribution (Figure III.9). The wall was then built by carefully positioning the stones and securing them in place using a cement-based mortar, ensuring structural stability, proper bonding (Figure III.10). The resulting wall serves both structural and thermal functions in the experimental setup.

Figure III.9. Collected and stones preparation :: Cleaning;Drying andWeighing

Figure III.10. On-site construction of the wall for the experimental greenhouse

III.3.3. Cover element

The greenhouse covering process takes into account the areas to be fitted with a transparent cover and those requiring a dark insulating cover. Prior to this, a protective coating was applied to the metal frame to shield it from harmful environmental factors and reduce corrosion caused by humidity and weather conditions.

In the step, sandwich panels were installed as part of the structural insulation (Figure III. 11). They represent a cutting-edge solution for greenhouse envelopes due to their excellent thermal and mechanical properties, which effectively reduce heat loss. This type of envelope significantly enhances durability, impact resistance, and protection against moisture and UV radiation, making it well-suited for long-term outdoor exposure. Their lightweight construction allows for easy installation while maintaining structural stability.

To ensure adequate natural lighting inside the structure, transparent polycarbonate panels known for their high light transmittance and excellent impact resistance were strategically placed (Figure III.12). These properties make them particularly suitable for greenhouse applications.

To achieve airtightness and prevent the infiltration of air or moisture, insulating polyurethane foam was applied to seal the gaps and joints between structural elements. This ensures a stable internal environment, essential for efficient and sustainable protected cultivation.

Figure III 11. Sandwich panel installation

Figure III.12. Polycarbonate sheet installation

III.3.4. Measurement instrumentation

After the greenhouse was completed and its structural components were assembled, a comprehensive monitoring system was installed to assess the local climatic conditions inside and outside. Thermocouples were strategically placed to measure key temperature variables, including the ambient outdoor temperature, indoor air temperature, north-facing wall surface temperature, and incident solar radiation (Figure III.13). The soil temperature inside the greenhouse was also monitored to assess the thermal behavior of the growing medium. These measurements were conducted to analyze the dynamics of heat transfer and storage within the greenhouse environment.

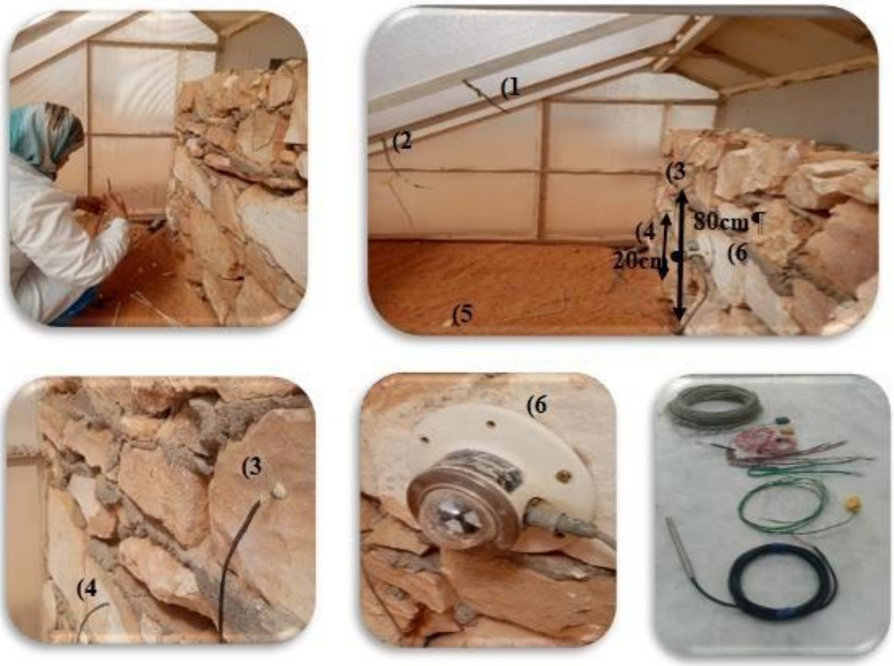


Figure III. 13. Installation of measuring instruments

Table III.1. Sensor accuracy and measurement ranges

Description	Sensors	Measurement range	Accuracy
 **Global solar radiation**	Pyranometer EPPLEY (model 8-48 serial N° 27037	0-2000 W/m² −50 to 80 °C 0–100% RH	Uncertainty Daily Average approx. 1% Level accuracy 0.2°
 **Station radiometric Solys2**	Pyranometer Kipp&zonen CMP11	0-4000 W/m² -40 to 80 °C 0–100% RH	Expected daily accuracy < 2% Level accuracy 0.1°
 **Air temperature**	PT-100	-50 to 200 °C	+/ - 0.3°C
 **Data Acquisition**	Consort T8710	Range , Type J Range , Type K Range , Type T Range , Type E	J: -200°C to 900 °C K : -200°C to 1370 °C T : -200°C to 600°C E : 0°C to 1000°C <1000°C: +/- 0.1°C >999.9°C: +/- 1°C 0.05% +/- 0.5°C
 **Weather station**	Temperature Relative humidity Wind	T (outside): - 29.9°C to + 79.9°C T (inside): 0°C to + 60°C RH : 1-99% U : 0 to 200 km/h	+/- 0.8°C +/- 0.8°C +/- 5% Resolution : 0.1 km/h

The table III.2 shows the thermo-physical properties four materials air, soil, stone, and polycarbonate used in experimental study, each of which plays a unique role in thermal processes.

Table III.2. Thermo-physical properties of the various elements [3]

Elements	Specific heat [J/kg.C°]	Thermal conductivity [W/m.C°]	Density [Kg/m^3]
Air	1003	0.024	1.127
Soil	2100	1.15	1700
Stone (Rocks)	683	2	2166
Polycarbonate	1.2 – 1.3	0.19 – 0.22	1150

Experimental calculation of the density of used stones

To determine the density of the stone samples used in the northern wall of the greenhouse, an electronic balance with an accuracy of 0.01g was used to determine the mass of the samples, and a Beaker 100 ml with accuracy of 0.05 ml was used to measure the volume of water (Figure III.14). The measurements were carried out at the Applied Research Unit for Renewable Energy. A total of 24 samples were prepared.

Figure III.14. Tools used: digital scale, beaker and samples

The volume of water was consistently maintained at 1500 ml in each case, and the stone's volume was determined through the water Archimedes method. Each measurement was repeated three times to ensure accuracy and reliability of the results (Figure III.15).

Figure III.15. Density measurement stages

Subsequently, the Excel application was employed to process the recorded data and compute the average mass and volume for each sample. The density (ρ) of each stone sample was calculated using the following relation:

$$\rho = m / V \qquad (1)$$

Where:

ρ is the density (kg/m^3),

m is the mass (kg),

V is the volume (m^3).

Finally, the average density value for all samples was obtained, which resulted in an overall value of :

ρ =505.384375 \ 233.347222

ρ = 2.1658 g/cm^3 ρ = 2165.8 kg/m^3

Uncertainty calcul

- The uncertainty in mass (Δm) is 0.01 g, because the balance has a precision of 0.01 g.
- The uncertainty in volume (ΔV) is 0.05 ml= 0.05 cm^3
- The following general formula for a function f(x,y) where x and y are the variables with uncertainties:

$$\Delta f = \sqrt{\left(\frac{\partial f}{\partial x}\Delta x\right)^2 + \left(\frac{\partial f}{\partial x}\Delta y\right)^2} \qquad (2)$$

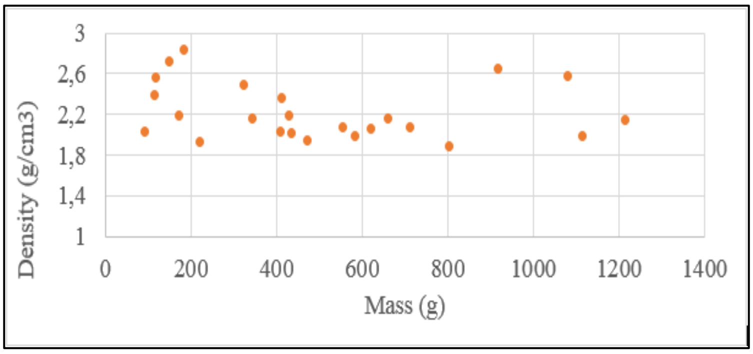
Uncertainties $\Delta\rho$: $$\Delta\rho = \sqrt{\left(\frac{\Delta m}{V}\right)^2 + \left(\frac{m\Delta V}{V^2}\right)^2} \qquad (3)$$

Application: $m_{moy} = 387{,}4465278g$ $V_{moy} = 165{,}0555556m^3$

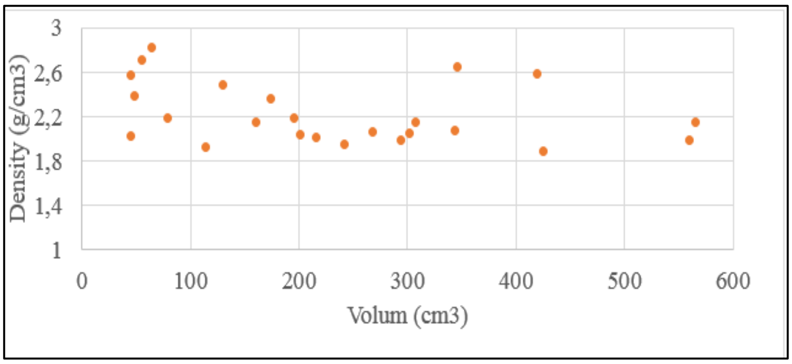
$$\Delta\rho = \sqrt{\left(\frac{0.01}{165.0555556}\right)^2 + \left(\frac{387{,}4465278\ .0.05}{174.3333333^2}\right)^2}$$

$$\Delta\rho = 0.0071 \text{ g/cm}^3$$

ρ =2 .1658 g/cm^3 ρ =2165.8 ± 7.1 kg/m^3



(a) Variation of density as a function of mass



(b) Variation of density as a function of volume

Figure III.16. Experimental values for stone density

Table III.3 displays the uncertainty values associated with each of the 24 samples. The results show a variation in uncertainty, with some samples (e.g., 10 and 24) exhibiting significantly higher uncertainty, indicating potential measurement or consistency issues in those specific cases.

Table III.3. Measurement Uncertainty of density parameter

Sample	M (g)	V (cm^3)	ρ (g/cm^3)	Uncertainty
1	411,683333	174,333	2,361	± 0,014
2	470,933333	242	1,946	± 0,016
3	344,463333	160	2,152	± 0,011
4	408,686667	201	2,033	± 0,0127
5	116,4	45,333	2,567	± 0,029
6	1080,82333	419	2,579	± 0,013
7	323,13	129,667	2,492	± 0,075
8	916,62	346,333	2,646	± 0,013
9	115,4	48,333	2,387	± 0,047
10	150,286667	55,333	2,716	± 0,136
11	219,786667	114,333	1,922	± 0,0856
12	91,145	45	2,025	± 0,101
13	1113,56333	560,333	1,987	± 0,0099
14	582,666667	293,667	1,984	± 0,099
15	435,393333	216	2,015	± 0,097
16	712,136667	344	2,070	± 0,103
17	171,61	78,667	2,181	± 0,109
18	804,243333	425	1,892	± 0,095
19	553,613333	267,667	2,068	± 0,103
20	620,596667	302	2,054	± 0,103
21	1213,67333	565,333	2,146	± 0,107
22	661,3	307	2,154	±0,107
23	429,143333	195,667	2,193	±0,11
24	181,926667	64,333	2,827	±0,141

III.4 Artificial neural network for modeling

Artificial Neural Networks (ANNs) also referred to as neuro-computers, parallel processors, or connectionist systems are computational models composed of a collection of interconnected processing units, often called artificial neurons or simply neurons. These networks are designed to emulate certain functions of the human brain, making them biologically inspired systems. Although typically implemented using electronic components, ANNs can also be simulated in software on conventional digital microcomputers.

III.4.1. Artificial Neural Networks application

ANNs process information by receiving inputs, transforming them through weighted connections, and producing outputs. The strength of these connections, known as synaptic weights, serves as a form of local memory (Figure III.17). These weights determine how input signals are combined and passed through the network, effectively controlling the behavior of the ANN.

Artificial neural networks mirror the human brain in two key ways [4]:

Learning through experience: ANNs acquire knowledge via a learning process governed by specific learning algorithms. These algorithms adjust the synaptic weights systematically to minimize error and achieve the desired performance on a given task.

Memory through connection strength: Information is stored in the network through the values of the synaptic weights. These weights encode the knowledge gained during training, similar to how the brain is believed to store information through the strength of synaptic connections between neurons.

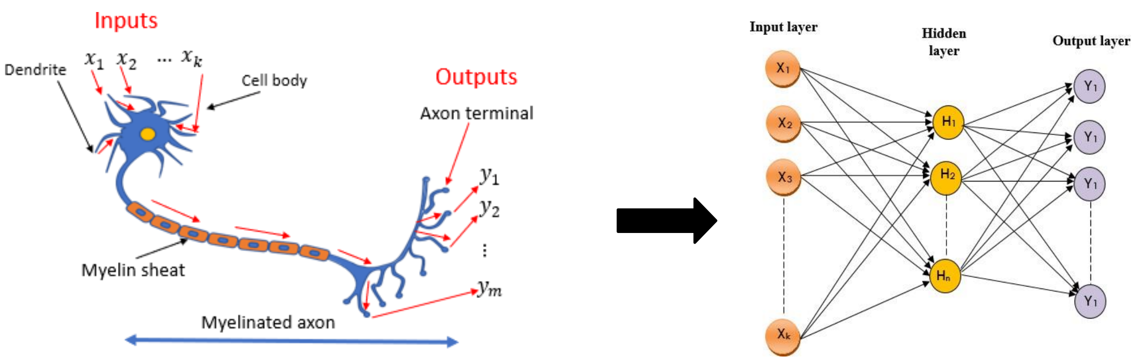


Figure III.17. Biological Neurons(left) and Artificial Neurons(right)

- **Operating principle**

A neural network consists of a layered architecture that includes three main types of layers: the input layer, which receives the initial data; one or more hidden layers, which process the information; and the output layer, which provides the final results. These layers are interconnected through signal channels that are continuously adjusted and refined by training algorithms.

A neuron is the fundamental processing unit within the neural network and serves as the building block of the entire network. The connections between neurons are associated with numerical weights, which represent the "long-term memory" of the network and play a crucial role in its operation. Additionally, a bias is applied to each neuron, influencing the inputs to the activation function. This bias is an essential component of the mathematical operations occurring within each neuron [5].

In artificial neural networks (ANNs), artificial neurons mimic the behavior of biological neurons by receiving input signals in the form of pulses. Neural activity is typically characterized by the rate at which these pulses are generated over time, as well as the average peak generation rate across multiple trials. Each neuron connects to neurons in the previous layer through adaptive synaptic weights, which serve as the primary means of representing knowledge within the network. Initially, these weights are random and carry no meaningful information; however, through the training process, they are systematically modified and become carriers of the acquired knowledge. Information processing within a neuron begins with receiving a set of inputs; each multiplied by its corresponding weight and summed to produce a net input Equation (4). This summed value is then passed through an activation function to determine the neuron's output, which is subsequently propagated to the next layer after being scaled with additional connection weights. In the case of a linear activation function, the output can be represented by Equation (5).

$$\xi = \sum X_i . W_i \qquad (4)$$

$$y = \alpha(wx + b) \qquad (5)$$

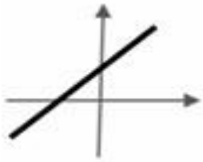
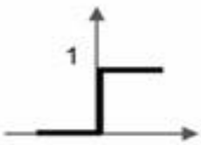
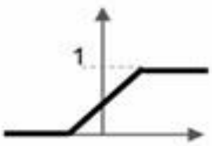
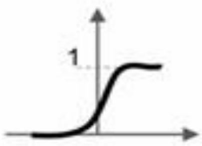
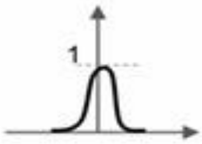
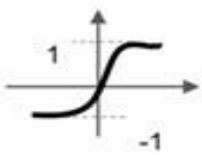
Where:

Learning in artificial neural networks involves presenting input-output pairs to the network and adjusting the connection weights using appropriate learning algorithms, such as backpropagation, to reduce the output error and improve predictive performance [6].

- **Activation Function of an Artificial Neural Network**

The activation function in artificial neural networks is a mathematical function that determines the output of a neuron based on its input. Specifically, it processes the aggregated input signal and generates an output only when the total input exceeds a predefined threshold. The threshold thus plays a critical role in controlling the flow of information through the network, effectively determining whether a neuron should be activated or remain inactive [7]. The most commonly used transfer functions are presented in Table III.4.

Table III.4. Activation functions for layers in artificial neural networks [6]

Name	Graphic	Function	
Linear		$f(\xi) = a \cdot \xi + b$	
Binary step		if $\xi \geq 0$, if $\xi < 0$,	then $f(\xi) = 1$, then $f(\xi) = 0$,
Piecewise linear		if $\xi \geq \xi_{max}$, if $\xi_{min} > \xi > \xi_{max}$, if $\xi \leq \xi_{min}$,	then $f(\xi) = 1$, then $f(\xi) = a \cdot \xi + b$, then $f(\xi) = 0$,
Sigmoid		$f(\xi) = \frac{1}{1 + e^{-b \cdot \xi}}$,	interval (0,1)
Gaussian		$f(\xi) = e^{-\xi^2}$,	interval (0,1]
Hyperbolic tangent		$f(\xi) = \frac{2}{1 + e^{-2 \cdot \xi}} - 1$,	interval [-1,1]

III.4.2. Prediction of indoor air temperature in greenhouse by ANN

The simulation of microclimatic conditions in an experimental greenhouse using Artificial Neural Networks (ANNs) represents a powerful application of artificial intelligence in agriculture. This approach enables accurate prediction of internal climate variables based on environmental data collected from in-situ sensors within the greenhouse.

The modeling process begins with the collection of comprehensive data related to the system under investigation, in order to design an optimal predictive model. Once the data are gathered, the neural network architecture is constructed and subsequently trained using a labeled dataset. This dataset integrates both current and historical environmental conditions along with the corresponding expected outputs.

As training progresses, the ANN iteratively adjusts its weights and biases to minimize prediction error. Upon successful training, the model becomes capable of reliably forecasting future climatic conditions inside the greenhouse, thereby enhancing environmental control and optimizing crop production. Figure III.18 illustrates the steps to follow to predict the greenhouse microclimate.

- **Data Collection**

Following the setup of the greenhouse and the installation of appropriate measurement instruments, the process of collecting experimental data was initiated to support the development of an accurate predictive model. Specialized sensors were employed to monitor key environmental parameters within the greenhouse, including internal air temperature, wind speed, and solar radiation intensity. Additionally, internal temperature was recorded as the primary output variable for use in the modeling phase.

The monitoring campaign was conducted over two consecutive days, specifically on March 21 and 22. Measurements were taken at regular intervals of 10 minutes, resulting in a total of 439 valid data points. This structured data acquisition process enabled the construction of a rich and comprehensive dataset (Figure III.19), serving as a foundational resource for designing and training predictive models based on artificial intelligence techniques. The ultimate goal is to enhance environmental control strategies and operational efficiency within solar greenhouses.

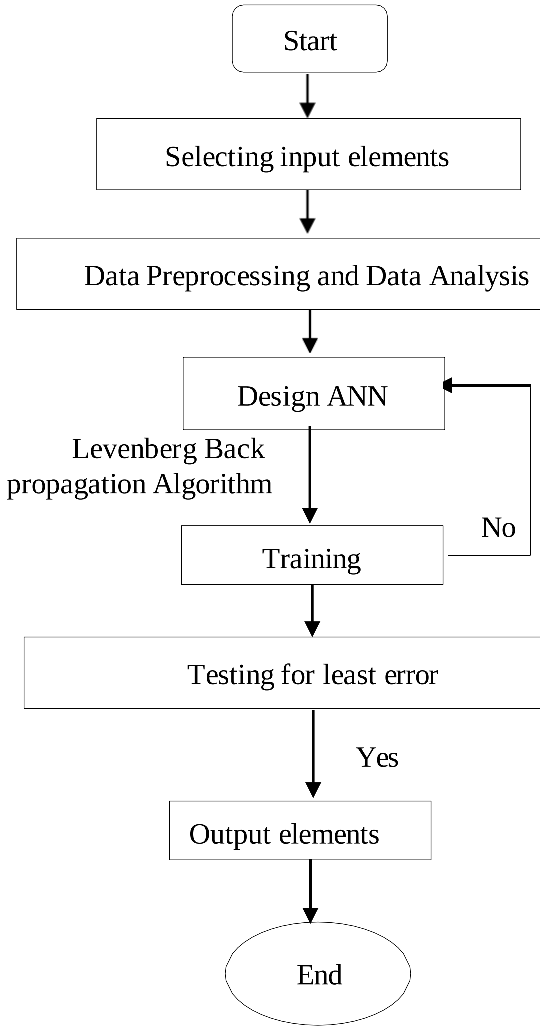


Figure III.18. Flowchart of prediction system

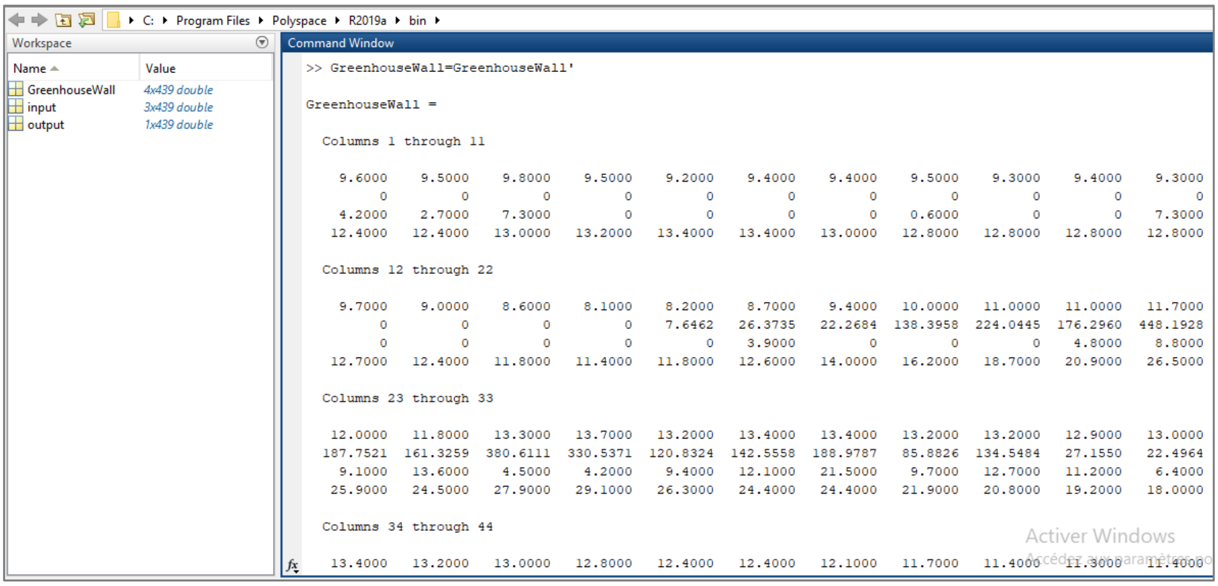


Figure III.19. Data collection

- **Neural network architecture**

After processing the data and entering it into the model, a multi-layered neural network (MLN) was chosen, with three input parameters and one target output the indoor temperature of the greenhouse. Determining the appropriate architecture for the ANN (Figure III.20), particularly the number of neurons in the hidden layer, requires careful consideration, as there is no general rule in previous studies. Therefore, we adopted an empirical approach by varying the number of neurons in the hidden layer and evaluating the model's performance using the regression coefficient (R).

After multiple iterations to determine the optimal configuration, we found that the hidden layer with 23 neurons achieved the highest regression coefficient, indicating the best predictive performance.

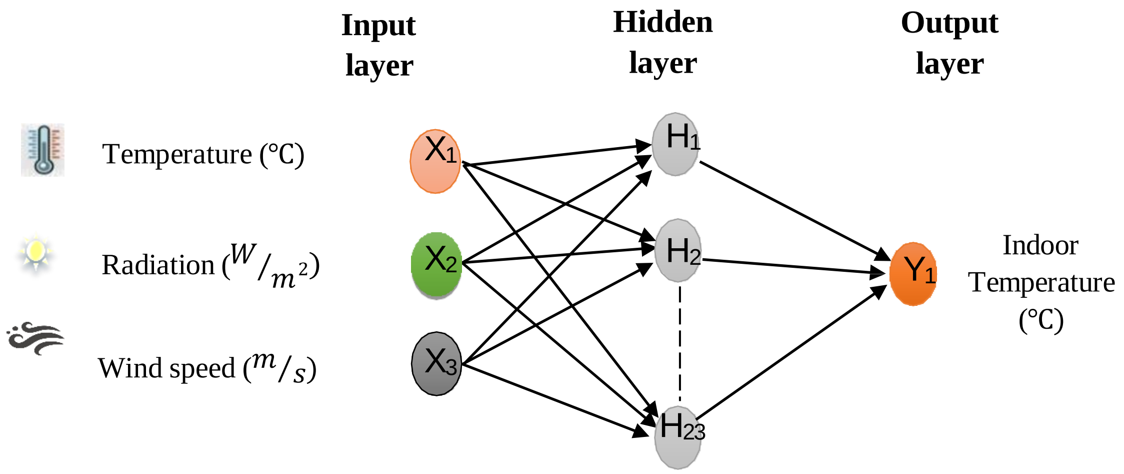


Figure III.20. Schematic of the greenhouse ANN model architecture

The model was trained using a dataset collected from the experimental setup. In this work, the Levenberg-Marquardt learning algorithm was used due to its high convergence speed and ability to produce regression values with steep slopes, typically close to 1, reflecting high predictive accuracy (Figure III.21).

The splitting of the dataset into subsets for training, testing, and validation were optimized through practical experiments. Several splitting ratios were tested, and the one that gave the highest regression performance was finally chosen as the most suitable for our problem (Figure III.22).

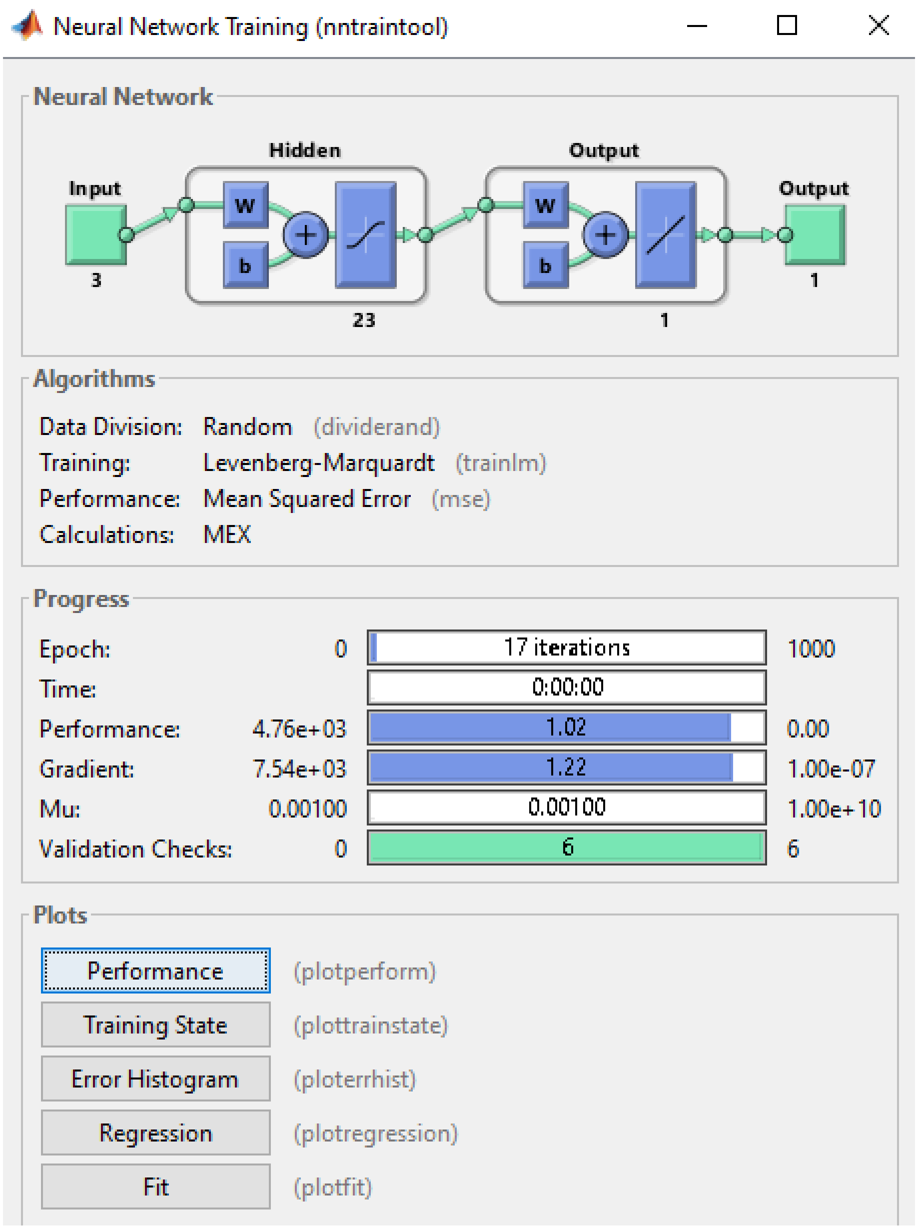


Figure III.21. ANN model structure in MATLAB

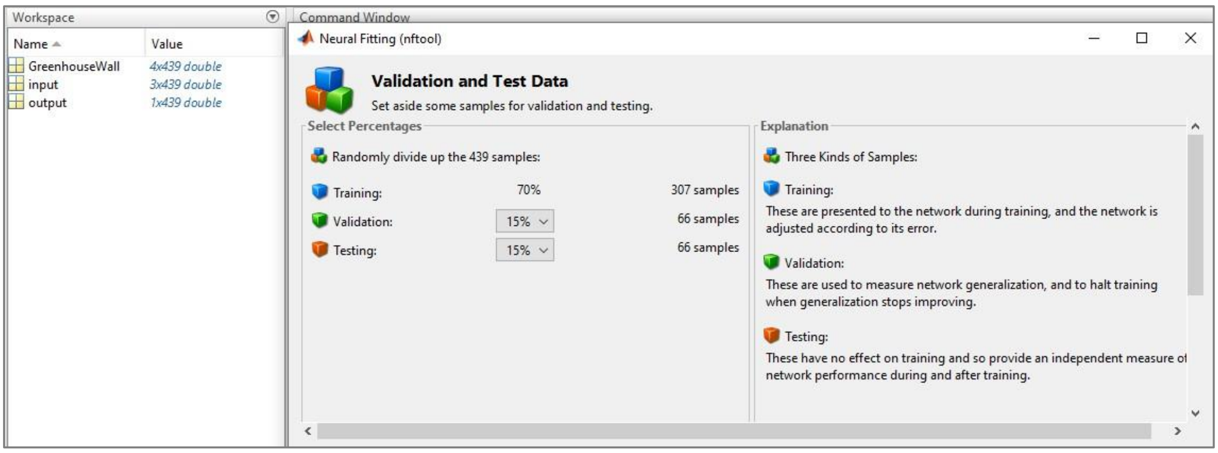


Figure III.22. Data base division

III.5. Conclusion

In this chapter, we begin by describing the geographic and climatic context of the Ghardaia region, including its coordinates and prevailing environmental conditions. We then proceed to the design and construction of the greenhouse, followed by the implementation of the northern thermal storage wall. Finally, we present The RNA structure used to predict the greenhouse's internal temperature, with the goal of improving climate control and energy efficiency.

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CHAPTER IV.

Results and discussion

IV.1 Introduction

The design and construction of the experimental greenhouse equipped with a north wall serving as a sensible heat storage system, was described in the previous chapter, this step focuses on determining the input parameters and the optimal architecture of the artificial neural network (ANN). We present the experimental results concerning the temperature of key greenhouse components: the soil, the north wall, and the indoor air. These data allow us to analyze and interpret the complex physical phenomena that define the greenhouse microclimate. Additionally, we introduce the simulation and prediction results of indoor temperature using ANN, followed by a discussion and interpretation of the findings.

IV.2. Analysis of experimental results

In this experiment, solar irradiance was measured over two consecutive days March 21 and 22 to analyze variations in light transmittance due to weather conditions (Figure IV.1). The collected data showed a distinct daily pattern in solar irradiance, with irradiance values increasing in the morning, peaking at midday, and then declining with sunset. On March 21, the maximum recorded irradiance was approximately 862.76 W/m² at 1:30 p.m., indicating partial cloud cover that limited solar energy reaching the surface. In contrast, on March 22, the maximum irradiance was much higher, at 954.35 W/m², and occurred earlier, at 1:00 p.m., indicating clearer weather conditions. Nevertheless, the values still indicate a region with significant solar radiation.

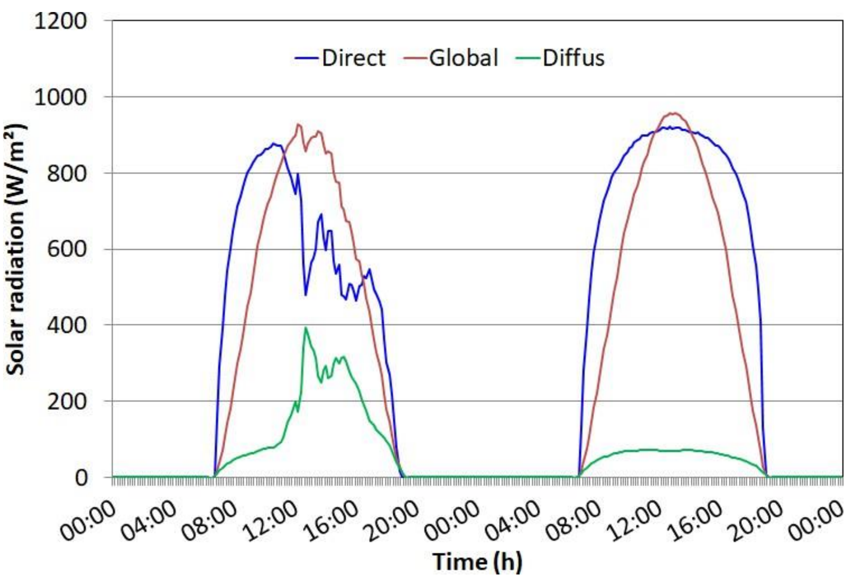


Figure IV.1. Variation of solar radiation: direct; diffuse and global

In an experiment designed to evaluate the thermal performance of the greenhouse structure, temperature sensors were installed inside and outside the greenhouse to monitor nighttime conditions (Figure IV.2). The goal was to evaluate the effectiveness of the north wall in storing and retaining heat. Over a series of nights, the data showed a difference between indoor and outdoor temperatures that reached a maximum of 20°C during the afternoon, while decreasing significantly during the night. This temperature difference indicates that the north wall plays a critical role in thermal storage, absorbing solar energy during the day and gradually releasing it at night to maintain a warmer indoor environment. These results demonstrate the wall's effectiveness in enhancing the greenhouse's passive heating capabilities, reducing the need for external heating sources during cold periods.

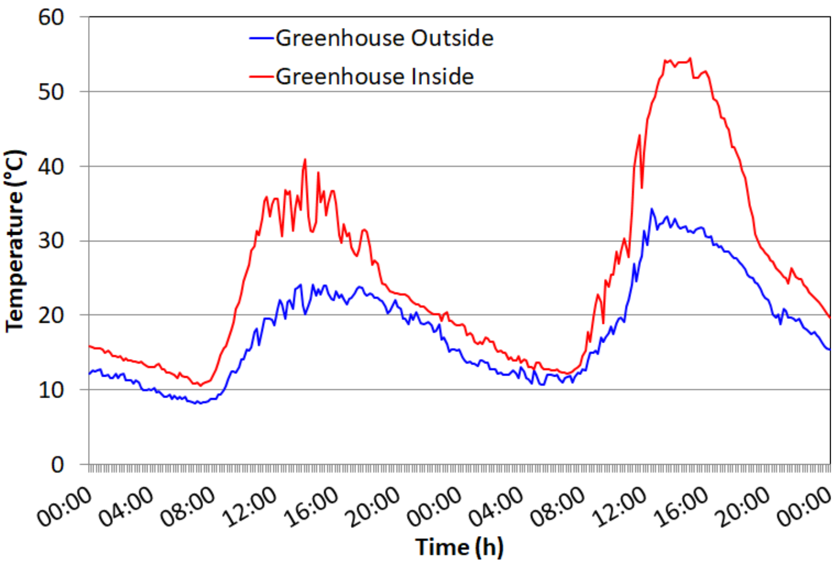


Figure IV.2. Variation in the internal and external temperature of the greenhouse

In this study, temperature fluctuations on the north-facing wall were monitored over two consecutive days to analyze its thermal behavior in response to environmental conditions (Figure IV.3). On the first day, the peak temperature was recorded at 1:00 PM, reaching 38.1°C, while on the second day, the peak occurred later, at 4:20 PM, with a much higher value of 47.3°C. The lowest temperatures were recorded at 7:50 AM, reaching 17.1°C on the first day and 19.6°C on the second day. These variations reflect the wall's ability to store heat, specifically its ability to absorb and retain heat throughout the day. This is essential during cold periods, as the retained heat can contribute to maintaining indoor thermal comfort range (18–24°C), thereby reducing heating requirements.

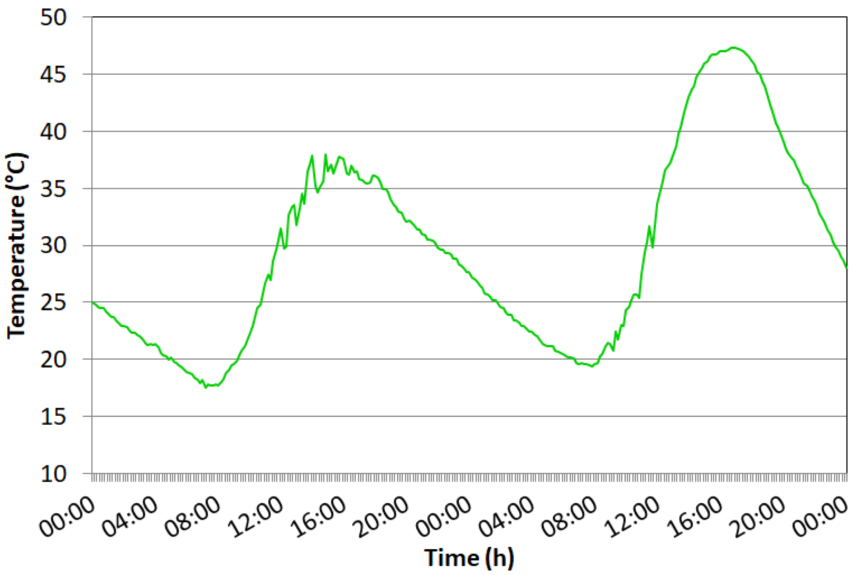


Figure IV.3. Temperature evolution of the north wall over time

Thermal monitoring of soil temperatures inside the greenhouse over two consecutive days revealed significant variation between the daily minimum and maximum temperatures (see Figure IV.4).

On the first day, the peak soil temperature was recorded at 2:22 p.m., reaching 45.1°C. On the second day, the maximum temperature was significantly higher, reaching 54.4°C at 3:50 p.m. In contrast, the minimum temperatures on both days were recorded at 7:40 a.m., reaching 21.0°C on the first day and 21.6°C on the second day.

We note that these soil temperature fluctuations are closely related to the intensity of solar radiation throughout the day. As solar radiation increases, especially during the afternoon hours, heat builds up inside the greenhouse, leading to higher soil temperatures. The later timing of the daily maximum on the second day may reflect a longer duration or greater intensity of sun exposure. Conversely, constant minimum readings in the early morning coincide with the period of minimum solar input, following heat loss during the night.

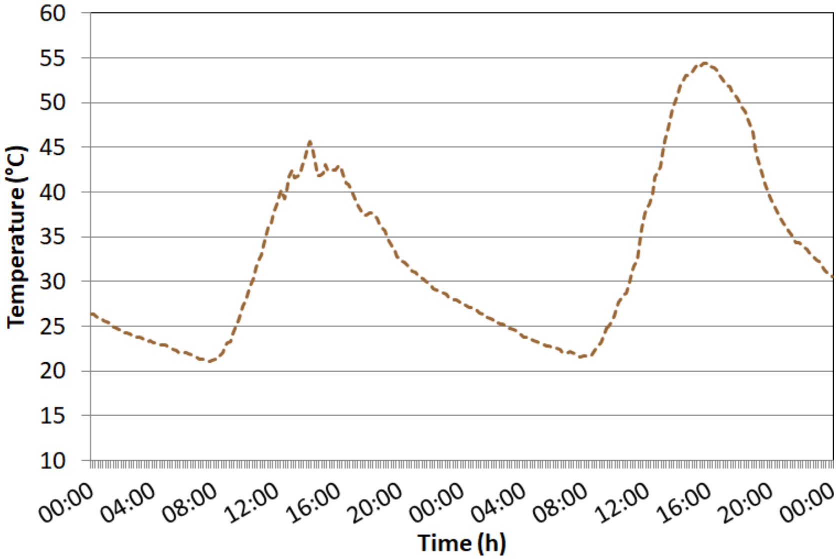


Figure IV.4. Temporal variation of the soil temperature

IV.3. Analysis of the modeling results

In this study, an MLP neural network was used to predict the temperature inside a greenhouse. To find the best architecture, specifically the number of nodes in the hidden layer, the model was trained and tested for the corresponding periods mentioned in Chapter III (Section III.4.2). After running the process for a different number of nodes each time (from 10 to 25), and based on the statistical indices MAE, RMSE, R^2, and maximum error, the best neural network architecture was found to be 3-23-1, which provided the most reliable results for the test period. Based on the specific neural network architecture, the following graphs were drawn to compare the predicted and predicted values of the two variables.

The model training process was completed after 42 epochs (Figure IV.5), where the validation mean square error (MSE) increased 6 times in a row. The number of epochs was selected to be 36 where the validation error presented its minimum value, which was equal to approximately 3,6163. This value was obtained through the normalized input and output variables and presents the best performance of the model.

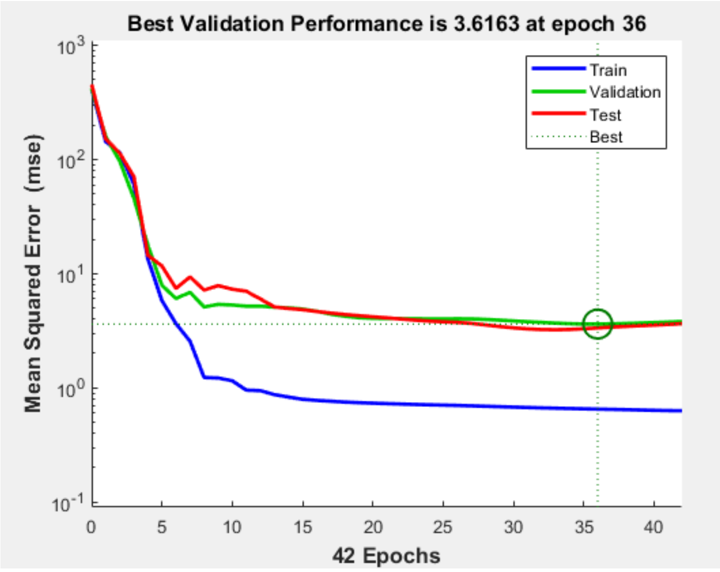
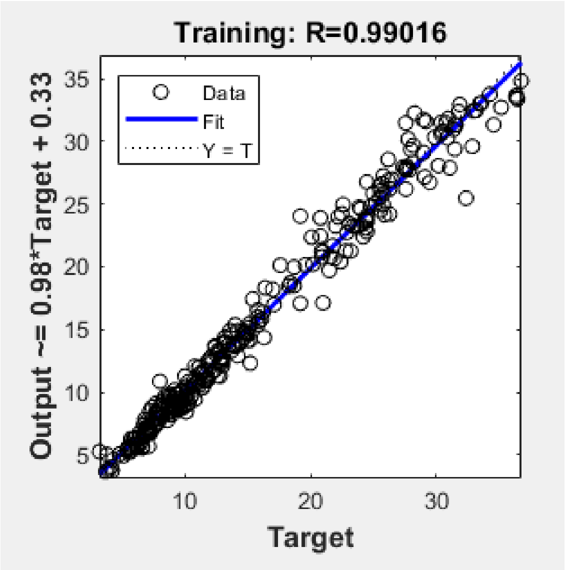
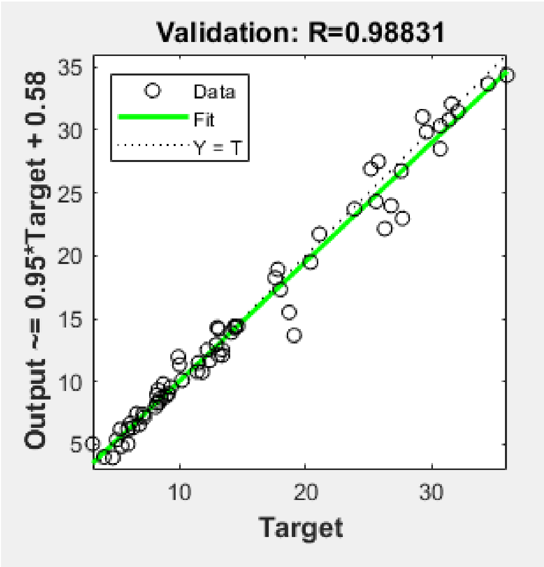


Figure IV.5. Mean squared error value vs epochs

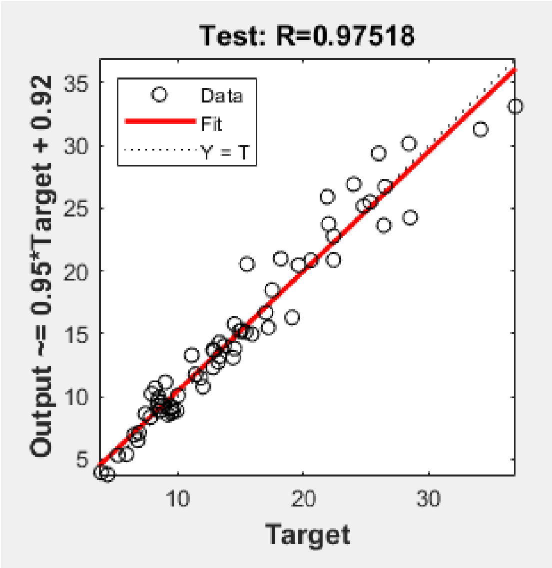
Figure IV.6 presents the coefficient of determination (R^2) obtained from the comparison between observed and simulated data in the substrate across the four key evaluation phases: (a) training, (b) validation, (c) testing, and (d) overall (global).The R^2 values serve as a measure of how well the predictive model replicates the actual data. A value closer to 1 indicates a stronger correlation and better model performance. Training Phase (a): The model demonstrates excellent performance during training, with an R^2 value exceeding 0.99. This indicates that the model successfully learned the underlying patterns in the training dataset. Validation Phase (b): The validation results show a high R^2 value above 0.97, confirming the model's strong generalization ability to unseen data and indicating minimal overfitting. Test Phase (c): Similarly, the R^2 value during the test phase remains high (>0.99), validating the model’s reliability and accuracy when applied to independent data. Global Evaluation (d): The overall performance, combining all data sets, also yields a coefficient above 0.99, confirming the model’s robustness and consistency across different phases.


Training: R=0.99016
Output ~= 0.98*Target + 0.33
Target
Data
Fit
Y = T
5
10
15
20
25
30
35
10
20
30

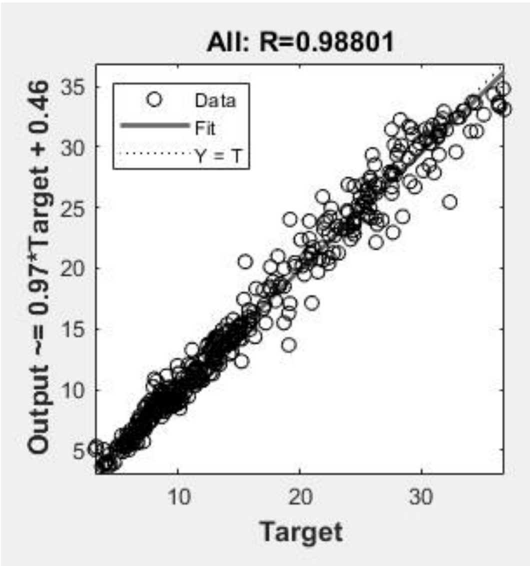
(a)


Validation: R=0.98831
Output ~= 0.95*Target + 0.58
Target
Data
Fit
Y = T
5
10
15
20
25
30
35
10
20
30

(b)



(c)



(d)

Figure IV.6. Results of the coefficient of determination

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

Figure IV.7 shows a comparison between the measured and calculated temperature curves, and Figure IV.8 illustrates the relationship between the measured and calculated values. From the results observed in the two previous figures, we see that the predicted values are in good agreement with the measured values.

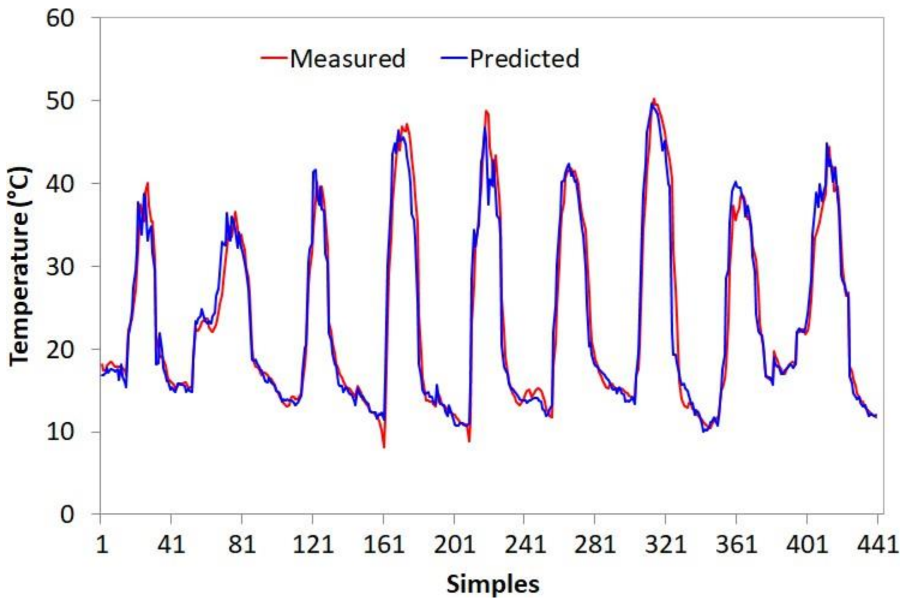


Figure IV.7. Comparison of actual and predicted results

Analyzing the graph (Figure IV.8), a comparison of the time series of measured and predicted global warming temperatures reveals high model accuracy. The predicted values closely follow the experimental data, with the largest deviations occurring during daylight hours, when temperature changes are most rapid and pronounced. These discrepancies are likely a result of limited training data under harsh conditions. Nevertheless, the overall agreement confirms the robustness and reliability of the model. Enhancing the training dataset and incorporating advanced modeling techniques may reduce prediction errors and improve performance in dynamic environments.

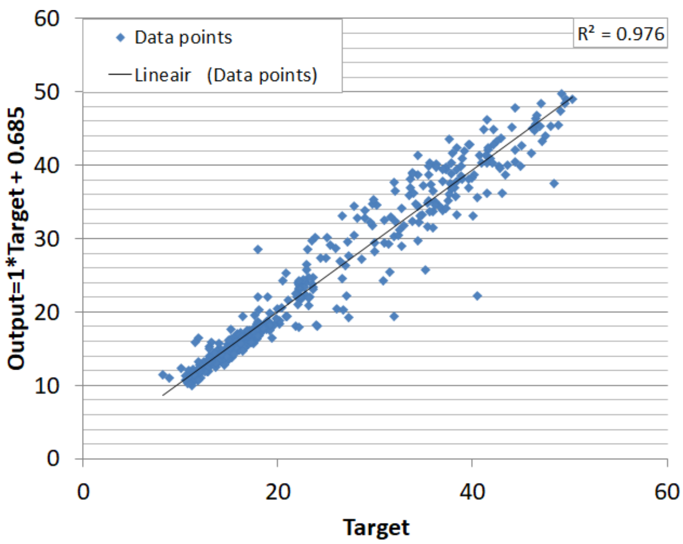


Figure IV.8. Relationship between measured and estimated values

The mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) were calculated by Equations (1), (2) and (3). The maximum error is a critical value for a decision support system, which will activate various system management devices based on the model results.

$$\mathrm{MAE}=\frac{1}{N}\sum_{i=1}^{N}|y_{pred.}-y_{obs.}| \quad (1)$$

$$\mathrm{RMSE}=\sqrt{\sum_{i=1}^{N}\left[\frac{(y_{pred.}-y_{obs.})^2}{N}\right]} \quad (2)$$

$$R^2=1-\frac{\sum_{i=1}^{N}[(y_{obs.}-y_{pred.})^2]}{\sum_{i=1}^{N}[(y_{obs.}-\bar{y}_{\overline{obs.}})^2]} \quad (3)$$

TableIV.1 : Performance indicators

Hidden neurons	Structure ANN	RMSE (°C)	MAE (°C)	R^2
		Indoor temperature		
23	3-23-1	2.59	1.64	0.976

IV.4. Conclusion

The results obtained from the experimental campaigns confirm the effectiveness of the solar greenhouse design incorporating a north-facing thermal storage wall in enhancing thermal stability under semi-arid climate conditions such as those in Ghardaïa. The integration of a thermal energy storage system successfully reduced the temperature fluctuations between day and night, thereby supporting improved greenhouse microclimate. Additionally, the developed Artificial Neural Network (ANN) model demonstrated a high accuracy in predicting indoor temperature, validating its potential as a reliable tool for enhancing smart climate control strategies.

GENERAL CONCLUSION

General Conclusion

As part of our master's project, we presented a contribution to the study of the microclimate in greenhouse equipped with thermal storage north wall. Study investigates the thermal performance and climate optimization of a chapel-type greenhouse specifically designed to withstand the extreme diurnal temperature fluctuations typical of the Ghardaia region in southern Algeria.

An experimental study has been conducted on a new type of greenhouse equipped with a solar thermal storage system through a north-facing wall using local pebbles. A compact greenhouse structure, covered with a polyethylene film, was constructed and integrated with a passive solar thermal energy storage system. The thermal mass, embedded within a north wall made of locally sourced stones, absorbs solar energy during the day and gradually releases it at night, mitigating temperature fluctuations. Field experiments were conducted to monitor key climatic parameters, including indoor and outdoor air temperatures and solar radiation.

The results demonstrated the system's effectiveness in improving the indoor environment of the greenhouse. It should be noted that the nighttime temperature difference between the indoor and outdoor environments was approximately 2.7 °C. In the second phase of the research, an artificial neural network (ANN)-based predictive model was developed to estimate indoor greenhouse temperatures. The model demonstrated high predictive accuracy and strong correlation with observed data with a correlation coefficient of 0.98, confirming its reliability as a tool to support smart environmental control strategies in protected agriculture.

This study highlights the potential of integrating passive thermal storage systems with advanced data-driven modeling approaches to improve the performance and sustainability of greenhouse operations in arid and semi-arid climates.

Finally, this project will enable the implementation of innovative, large-scale and more efficient processes for agriculture, meeting quality and yield requirements, being more energy-efficient and more acceptable from the point of view of environmental preservation.

Future work should focus on expanding the dataset to include extreme weather conditions and assessing the impact of different crop types on greenhouse thermal dynamics.

To build upon the current findings, future research could focus on the following aspects:

- Long-term Monitoring: Extend the monitoring period to cover different seasons and climatic conditions to better assess the year-round performance of the system.
- Integration with Renewable Energy: Investigate the integration of renewable energy sources, such as photovoltaic panels or solar thermal collectors, to enhance the energy efficiency and sustainability of the greenhouse system.
- Control Strategies: Develop and test advanced control algorithms for ventilation, heating, and cooling systems to optimize the indoor environment based on real-time data.

SCIENTIFIC VALORIZATION

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

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CERTIFICATE

OF PARTICIPATION

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S. Tahar Chaouch

in oral and technical presentation recognition and appreciation of research contributions to

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"Artificial Intelligence Trends: Theory to Practice"
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with the paper entitled

APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO THE PREDICTION OF GREENHOUSE MICROCLIMATE: A COMPREHENSIVE ANALYSIS

Harpreet Kaur

Prof. Dr. Harpreet Kaur
PrincipaL, Mata Sundri CoLLege for Women, University of DeLhi

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with the paper entitled

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كلية العلوم والتكنولوجيا
قسم التعليم المشترك في العلوم والتكنولوجيا

غرداية في : ...2025

إذن بالطباعة (مذكرة ماستر)

بعد الاطلاع على التصحيحات المطلوبة على محتوى المذكرة المنجزة من طرف الطلبة التالية أسماؤهم:

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2. الطالب (ة) : طاهر شاوش سهام TAHAR CHAOUCH Sihem

تخصص : فيزياء طاقوية وطاقات متجددة

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اللقب و الاسم	الرتبة – الجامعة الأصلية	الصفة	الامضاء
قدور عبد المجيد	مدير بحث – وحدة البحث التطبيقي في الطاقات المتجددة	مصحح (1)	
عكرمي فوزي	استاذ مساعد أ – جامعة غرداية	مصحح (2)	
صالح بزاري	استاذ بحث أ – وحدة البحث التطبيقي في الطاقات المتجددة	مؤطر	

الإذن بطباعة النسخة النهائية لمذكرة ماستر الموسومة بعنوان :

Contribution to the study of the microclimate in greenhouse equipped with thermal storage north wall

إمضاء رئيس القسم

رئيس قسم التعليم المشترك العلوم والتكنولوجيا
بنويسة فيصل

جامعة غرداية - قسم التعليم المشترك في العلوم والتكنولوجيا - كلية العلوم و التكنولوجيا