

Ministry of Higher Education and Scientific Research
University of Mohamed Khider - Biskra
Faculty of Science and Technology
Department of Electronics and Automation



**Artificial Intelligence-based techniques for
micro-climate modeling of an agricultural
greenhouse**

by
Ala Eddine Brikel
Publicly Defended on: 07 Mai 2026

Submitted in partial fulfillment of the requirements for the
degree of

PhD in Automation and Industrial Computing

Jury

Pr.	RAIHANE MECHGOU	University of Biskra	Jury President
Pr.	HASSINA MEGHERBI	University of Biskra	Thesis Supervisor
Pr.	ACHOUR SAADOUNE	University of Biskra	Examiner
MCA.	ABDELKRIM MENADI	University of Khenchela	Examiner

Academic Year: 2025/2026

Acknowledgments

I would like to express my deepest and most sincere gratitude to my supervisor, **Pr. Hassina Megherbi**. Your invaluable guidance, unwavering support, and insightful feedback have been the cornerstone of this research. Your mentorship has not only shaped this thesis but has also profoundly influenced my development as a researcher. I am truly grateful for your patience and for consistently encouraging me to strive for excellence.

I extend my sincere thanks to the members of my thesis committee, **Raihane Mechgoug, Achour Saadoune, and Abdelkrim Menadi**, for their constructive comments, challenging questions, and valuable suggestions throughout the course of this work. Your expertise has been instrumental in strengthening this research.

I gratefully acknowledges **the University of Mohamed Khider** for access to its laboratories and facilities, which were crucial for the successful outcome of this research. My gratitude also goes to the **LESIA Laboratory** at University of Mohamed Khider, Biskra, for providing the necessary facilities, resources, and a stimulating academic environment.

I also wish to acknowledge the financial support provided by the **Ministry of Higher Education and Scientific Research**, which made this project possible.

I am also grateful to **my colleagues and friends** in the laboratory. The stimulating discussions, shared frustrations, and camaraderie created a supportive atmosphere that was essential for navigating the challenges of doctoral research.

Gratitude is also expressed to all who supported this work. It is hereby declared that no conflicts of interest are associated with this thesis.

Dedication

In the name of God and peace be upon the Chosen Messenger, may God bless him and grant him peace.

To my beloved my father, my mother and my family. For your unwavering love, encouragement, and sacrifices, This thesis is dedicated to you.

Thank you for being my source of strength, For believing in my dreams and supporting my journey.

Your presence has been my inspiration, And your support has fueled my determination.

I extend my sincere gratitude to my friends, for their constant presence and support throughout this journey. I am also deeply grateful to my colleagues. Your camaraderie and encouragement have been invaluable. With heartfelt gratitude.

Ala Eddine Brikel

University of Mohamed Khider - Biskra
Faculty of Science and Technology
Department of Electronics and Automation

This doctoral thesis has been examined by a committee of the
Department of Electronics and Automation as follows:

Pr. Raihane Mechgoug President of the Jury
Professor at the University of Mohamed Khider - Biskra

Pr. Hassina Megherbi Thesis Supervisor
Professor at the University of Mohamed Khider - Biskra

Pr. Achour Saadoune Examiner
Professor at the University of Mohamed Khider - Biskra

MCA. Abdelkrim Menadi Examiner
MCA at the University of Abbes Laghrour - Khenchela

Academic Year: 2025/2026

English Abstract

Greenhouse agriculture in arid and semi-arid regions, such as Biskra, Algeria, faces significant challenges due to extreme climatic conditions, leading to high energy consumption for microclimate regulation. This thesis presents a framework for intelligent microclimate management to enhance sustainability and productivity. The core of this work is the development and validation of advanced Artificial Intelligence (AI) models for the predictive modelling of the internal greenhouse environment. These predictive models serve as the foundation for a sophisticated control system. A robust H-infinity controller is designed and implemented to ensure precise temperature regulation, demonstrating superior performance over traditional methods by effectively handling system uncertainties and external disturbances. Furthermore, the research conducts a thorough analysis of the heating and cooling energy requirements of greenhouse structures in the Biskra province, evaluating the economic and environmental costs associated with conventional energy sources. This work investigates and proposes sustainable energy utilization models, with a focus on solar solutions, tailored to the specific needs of the region. The results demonstrate that AI-based predictive modelling provides a reliable and accurate model of greenhouse climates, and robust control ensures a stable climate against external conditions. Energy models are also studied and proposed in this work, and their effective management significantly reduces energy consumption while maintaining optimal growth conditions. This thesis contributes a simulation and data-driven solution and experimental validation that addresses the climate modelling, climate control, and energy in greenhouse agriculture, offering a viable pathway towards energy-efficient and resilient greenhouse farming in challenging climates.

Keywords: Greenhouse Microclimate, Artificial Intelligence, Predictive Modelling, Robust Control, H-infinity Controller, Sustainable Agriculture, Arid Climate, Energy Efficiency, Heating and Cooling Loads, Biskra, Algeria.

Résumé

L'agriculture sous serre dans les régions arides et semi-arides, telles que la province de Biskra en Algérie, est confrontée à des défis majeurs dus aux conditions climatiques extrêmes, entraînant une consommation d'énergie élevée pour la régulation du microclimat. Cette thèse présente un cadre de gestion intelligente du microclimat afin de renforcer la durabilité et la productivité agricole. Le cœur de ce travail repose sur le développement et la validation de modèles avancés d'Intelligence Artificielle (IA) pour la modélisation prédictive de l'environnement interne des serres.

Ces modèles prédictifs servent de base à un système de contrôle sophistiqué. Un contrôleur robuste H_∞ est conçu et implémenté pour assurer une régulation précise de la température, démontrant des performances supérieures aux méthodes traditionnelles en gérant efficacement les incertitudes du système et les perturbations externes. En outre, la recherche mène une analyse approfondie des besoins énergétiques en chauffage et en refroidissement des structures de serres dans la province de Biskra, évaluant les coûts économiques et environnementaux associés aux sources d'énergie conventionnelles.

Ce travail étudie et propose des modèles d'utilisation d'énergie durable, en mettant l'accent sur les solutions solaires adaptées aux besoins spécifiques de la région. Les résultats démontrent que la modélisation prédictive basée sur l'IA fournit un modèle fiable et précis du climat des serres, tandis que le contrôle robuste garantit la stabilité climatique face aux conditions extérieures. Cette thèse contribue à une solution axée sur les données et la simulation, validée expérimentalement, qui aborde la modélisation, le contrôle et l'énergie, offrant ainsi une voie viable vers une agriculture sous serre résiliente et économe en énergie dans des climats difficiles.

Mots-clés : Microclimat des Serres, Intelligence Artificielle, Modélisation Prédictive, Contrôle Robuste, Contrôleur H-infini, Agriculture Durable, Climat Aride, Efficacité Énergétique, Charges de Chauffage et de Refroidissement, Biskra, Algérie.

ملخص

تواجه الزراعة في البيوت المحمية في المناطق القاحلة وشبه القاحلة، مثل بسكرة في الجزائر، تحديات كبيرة بسبب الظروف المناخية القاسية، مما يؤدي إلى استهلاك كبير للطاقة لتنظيم المناخ المحلي. تقدم هذه الأطروحة إطارًا لإدارة ذكية للمناخ المحلي لتعزيز الاستدامة والإنتاجية. يتمحور هذا العمل حول تطوير نماذج ذكاء اصطناعي متقدمة والتحقق من صحتها للنمذجة التنبؤية لبيئة البيوت المحمية الداخلية. تُشكل هذه النماذج التنبؤية أساسًا لنظام تحكم متطور. صُمم ونُفذ جهاز تحكم قوي ذو قيمة لضمان تنظيم دقيق لدرجة الحرارة، مما يُظهر أداءً متفوقًا على الطرق التقليدية من خلال التعامل بفعالية مع تقلبات النظام والاضطرابات الخارجية. علاوة على ذلك، يُجري البحث تحليلًا شاملاً لمتطلبات طاقة التدفئة والتبريد لهياكل البيوت المحمية في ولاية بسكرة، مع تقييم التكاليف الاقتصادية والبيئية المرتبطة بمصادر الطاقة التقليدية. يبحث هذا العمل ويقترح نماذج مستدامة لاستخدام الطاقة مع التركيز على حلول الطاقة الشمسية، مُصممة خصيصًا لتلبية الاحتياجات الخاصة للمنطقة. تُظهر النتائج أن النمذجة التنبؤية القائمة على الذكاء الاصطناعي تُوفر نموذجًا موثوقًا ودقيقًا لمناخات الدفيئات الزراعية، وأن التحكم الدقيق يضمن مناخًا مستقرًا في مواجهة الظروف الخارجية. كما تُدرس نماذج الطاقة وتُقترح في هذا العمل، وتُقلل إدارتها الفعالة من استهلاك الطاقة بشكل كبير مع الحفاظ على ظروف نمو مثالية. تُقدم هذه الأطروحة حلولًا قائمة على المحاكاة والبيانات، بالإضافة إلى التحقق التجريبي، والتي تُعالج نمذجة المناخ والتحكم فيه والطاقة في الزراعة في الدفيئات الزراعية، مما يُوفر مسارًا عمليًا نحو زراعة دفيئات زراعية موفرة للطاقة ومرنة في ظل الظروف المناخية الصعبة.

الكلمات المفتاحية: مناخ الدفيئة، الذكاء الاصطناعي، النمذجة التنبؤية، التحكم القوي، وحدة التحكم، الزراعة المستدامة، المناخ الجاف، كفاءة الطاقة، أحمال التدفئة والتبريد، بسكرة، الجزائر.

Contents

Cover	1
Signature	1
English Abstract	2
Arabic Abstract	3
Table of Contents	6
List of Figures	9
List of Tables	10
1 Introduction	13
1.1 Background and Problem Statement	13
1.2 State of the Art and Literature Review	15
1.2.1 Modelling the Greenhouse Microclimate	16
1.2.2 Control Strategies for Greenhouse Climate Management	18
1.2.3 The Energy Nexus: Consumption, Efficiency, and Re- newables	20
1.2.4 Synthesis and Identification of the Research Gap	21
1.3 Contribution of this Work	22
1.4 Outline of the Thesis	23
2 The Thermal Model of Greenhouse Agriculture	27
2.1 Introduction	27
2.2 White Box (Mechanistic) Models	27
2.2.1 Mathematical Foundations	28

2.2.2	Key Components of Energy Exchange	29
2.2.3	Advantages and Disadvantages	33
2.3	Black Box (Empirical) Models	33
2.3.1	Methodological Approach	33
2.3.2	Mathematical Formulation of Black Box Models	34
2.3.3	Advantages and Disadvantages	36
2.4	Grey Box (Hybrid) Models	37
2.4.1	Hybrid Structure	37
2.4.2	Mathematical Formulation of Grey Box (Hybrid) Models	37
2.4.3	Advantages and Disadvantages	40
2.5	Black-Box Linear Time-Invariant Systems Modeling for Green- house Micro-climate using Differential Evolution Algorithm . .	40
2.5.1	Case Study and Data Collection	41
2.5.2	Black-Box Model LTI Transfer Function	42
2.6	Differential Evolution Algorithm (DEA) for Identification . . .	43
2.6.1	The Evolutionary Process	43
2.6.2	Results and Validation	45
2.7	Conclusion and Identification of the Research Gap	50
3	Experimental Systems and Data Acquisition for Model De- velopment	52
3.1	Introduction	52
3.2	The Foundation of Data-Driven Modelling	52
3.3	A Low-Cost Data Acquisition System	53
3.4	Primary Data Sources for Model Development	54
3.4.1	University of Biskra Weather Station	54
3.5	Commercial Greenhouse at Branis, Biskra	56
3.5.1	The Challenge of Conventional Energy Management . .	57
3.5.2	Evaluating Solar Energy as a Sustainable Solution . . .	57
3.5.3	Rural Greenhouse at M'ziraa, Biskra: A Feasibility Study for Sustainable Energy	59
3.6	Conclusion	60
4	Sustainable Energy Solutions for Greenhouse Agriculture in Biskra	61
4.1	The Energy Challenge in Arid-Region Cultivation	61
4.2	Quantifying the Energy Demand and Economic Costs	62
4.3	Harnessing Solar Power: A Viable Alternative	63

4.4	Analysis of Solar Energy Models	63
4.4.1	Passive Solar Strategies	63
4.4.2	Active Solar Technologies and Hybrid Systems	64
4.4.3	Battery Storage Modeling	66
4.4.4	System Reliability Analysis: LPSP Metric	66
4.5	Results and Discussions	67
4.5.1	System Reliability and Performance Metrics	69
4.6	Challenges and Recommendations	70
4.7	Conclusion	70
5	Growth Chamber: A Controlled Validation Environment	71
5.1	Introduction	71
5.2	Experimental Growth Chamber Design	71
5.2.1	System Architecture and Components	73
5.3	Development and Validation of an H_∞ Robust Controller . . .	73
5.4	Mathematical Formulations for Growth Chamber Modeling and Control	75
5.4.1	State-Space Representation of the Growth Chamber . .	75
5.5	H-infinity (H_∞) Robust Control Formulation	76
5.6	Simulation and Experimental Validation of Control	78
5.6.1	Simulation-Based Validation	78
5.6.2	Experimental Validation on the Growth Chamber . . .	81
5.6.3	Discussions	84
5.7	Limitations and Performance Discrepancy	86
5.8	Conclusion	87
6	General Conclusion and Future Work	89
6.1	General Conclusion	89
6.2	Main Contributions	90
6.3	Future Work and Research Perspectives	91
	Bibliography	93

List of Figures

1.1	An illustration of the studied location, source MapChart. . . .	14
1.2	Overview of common control strategies for greenhouse climate management.	25
1.3	Thesis schematic (problems and solutions)	26
2.1	Black-box, White-box and Grey-box behavior . So the Blue circle represents the black-box system, the Red circle represents the white box-system, and their intersection is the grey-box system [131].	28
2.2	A diagram illustrating the primary energy flows in a greenhouse [9].	30
2.3	Conceptual diagram of a feedforward neural network, a common Black Box model [13].	35
2.4	Conceptual diagram of a Grey-Box model, showing the combination of a known physical structure from white-box with unknown parameters and noise estimated from black-box [131].	39
2.5	Structural measurements for agricultural greenhouse prototype [19].	41
2.6	The data collected over five days (inside air temperature is blue,outside air temperature is green,outside solar radiation is orange, wind velocity is red, inside relative humidity is erin, and outside relative humidity is pink [19].	42
2.7	show transfer function model of Greenhouse Agricultural System GAS(S) [131].	44
2.8	Graphic showing mutation vectors in differential evolution with displacement = $F(x_q - x_r)$ [23].	45
2.9	Differential Evolution Algorithm (DEA) in an offline parametric identification process, in simulation using MATLAB [131]].	46
2.10	Pseudocode of differential evolution algorithm [23]].	46

2.11	Best Cost of DE Algorithm for 100 iterations, The best value of 0.065 [131]	47
2.12	Temperature inside on the first and second days was measured and predicted [131].	47
2.13	The error temperature inside (measured and predicted temperature) on the 1st and 2nd days [131]	49
2.14	Validation of the proposed system temperature inside on the 3rd and 4th days[131].	49
2.15	The error temperature inside on the 3rd and 4th days [131].	49
3.1	The meteorological weather station is located at the University of Mohamed Khider, Biskra.	54
3.2	The CapFLX general-marks3 microserver, which serves as the central data logger and processing unit for the meteorological station [135].	56
3.3	The 1-hectare commercial greenhouse at Branis site.	58
4.1	Typical daily energy load profile for a greenhouse in Biskra, showing peak demands in summer (July) and winter (January)[135].	62
4.2	TRNSYS Software: Transient System Simulation Tool[135]	63
4.3	Simplified diagram of the proposed hybrid renewable energy system for greenhouse operations[135].	65
4.4	The complete hybrid system modeled in the TRNSYS simulation environment, showing the logical connections between the renewable energy components, storage, and the load[135].	65
4.5	Ambient temperature curves for one year from M'ziraa Biskra Privesion Algeria [135].	67
4.6	Total and diffuse solar radiation for one year from M'ziraa Biskra Privesion Algeria [135].	68
4.7	Wind speed for one year from M'ziraa Biskra Privesion Algeria [135].	68
4.8	Value of SOC throughout the whole year (SOC in Purple and generator start order in green)[135].	69
5.1	A small-scale, laboratory-based Growth chamber [132].	72
5.2	Block diagram of the closed-loop control system as implemented in the MATLAB/Simulink simulation environment[132].	79

5.3	Internal temperature and set point in Matlab/Simulink [132]. .	80
5.4	Error (Internal temperature and set point) in Matlab/Simulink [132].	80
5.5	The experimental test bench of the controller-growth chamber [132].	81
5.6	Block diagram of the closed-loop control system as implemented in microcontroller arduino mega 2560 [132].	83
5.7	Internal temperature, Set point And External temperature of typical day in spring [132].	84
5.8	Internal temperature Error in growth chamber prototype [132].	85

List of Tables

1	Published articles	11
2	Under-processing articles	12
2.1	Selection of Parameters for the Differential Evolution Algorithm (DEA)[131].	48
2.2	Optimal Identified Parameters for the Greenhouse LTI Model [131].	48
5.1	Hardware and Actuator Specifications of the Growth Chamber Prototype [132].	74

List of articles and publications

Table 1: Published articles

Articles	Journal	DOI
Sustainable Energy Solutions for Greenhouses: A Case Study in M'ziraa, Biskra, Algeria	International Conference On Artificial Intelligence And Sustainable Development Icaisd 2025 Relizane, Algeria April 12th – 13 Th 2025	web.univ-relizane.dz/ICAISD2025
Energy building, heating, cooling requirements, and associated costs in greenhouse structures in arid and semi-arid regions, such as Biskra Province	National Conference On Materials Sciences And Engineering, (MSE'25).	https://www.univ-chlef.dz/mse25/
Sustainable Energy Utilization Models in Greenhouse Agriculture in Biskra Province	National Conference On Materials Sciences And Engineering, (MSE'25).	https://www.univ-chlef.dz/mse25/
Artificial Intelligence-based Techniques For Mico-climate Modeling of an Agriculture greenhouse	First Study Day on “AI in Computer Vision and its Applications” 1st SD AICVA 2024	https://www.univ-biskra.dz
H-infinity Robust Controller for Precise Temperature Regulation in an Agricultural Growth Chamber Prototype	International Journal Robotics and Control (JRC) 30 jan 2026 Q2 - B Class	https://doi.org/10.18196/jrc.v6i6.27278 or https://journal.umy.ac.id/index.php/jrc/article/view/27278

Table 2: Under-processing articles

Articles	Journal	DOI
LTI Black Box Systems Modeling for Greenhouse Agricultural Microclimate in Biskra Province Using DE Algorithm	The International Journal of Computing and Digital Systems (IJCDS) Q3 - class B	priprent available online https://hdl.handle.net/20.500.14536/6435
Optimal Identification of Greenhouse MISO Thermal Models Using a Self-Adaptive Differential Evolution Algorithm	Electrotehnica, Electronica, Automatica (EEA) Scopus / SCImago Journal Rank (SJR): Class (Quartile): Q4	Not yet attributed
Real-Time Thermal Dynamics Estimation in Agricultural Growth Chamber Using Kalman-Filtered DHT22 Sensor Fusion and MATLAB	The First National Seminar on Materials for Electronics And Magnetism: Modeling, Properties, And Applications Tissemsilt; April 21-22, 2026	Accepted
Simulation and Real-Time Implementation of PID Control in an Arduino-Based Agricultural Growth Chamber Using DHT22 Sensors	The First National Seminar on Materials for Electronics And Magnetism: Modeling, Properties, And Applications Tissemsilt; April 21-22, 2026	Accepted

Chapter 1

Introduction

This chapter establishes the context and significance of the research. It begins by highlighting the importance of greenhouse agriculture for food security in Algeria, particularly in arid regions like Biskra. It then delves into the primary challenge: the immense energy cost and difficulty of microclimate control due to extreme external weather.

1.1 Background and Problem Statement

The agricultural sector faces several issues in Biskra, Algeria (figure 1.1). Sustainable agriculture offers an alternative that could mitigate environmental degradation and address increasing demand for employment and food [1], [26]. The city of Biskra itself is located at approximately $34^{\circ}51'$ N latitude and $5^{\circ}43'$ E longitude, characterized by steep slopes in the northern and south-eastern parts, sandy plains in the central area, and dunes or sand-filled depressions elsewhere. The Biskra region is characterized by extreme temperatures typical of an arid climate. While average summer maximums regularly exceed 45°C , record highs can be much greater; for instance, the maximum temperature recorded in June has reached 48.2°C [2]. Winter nights can be very cold, and January minimums frequently fall below 0°C , with all-time record lows dropping to -5°C or colder. The significant variation in temperature poses a major challenge to agriculture in the region.

Adaptive farming techniques in arid regions must be designed to function over wide temperature ranges, a key difference from humid climates where frost may be a greater concern than extreme heat. Irrigation must be man-

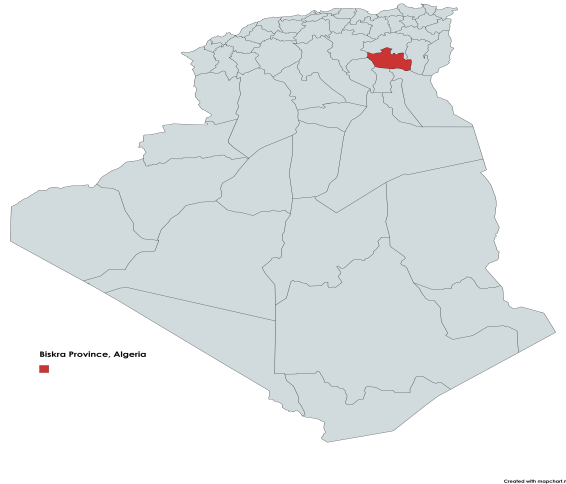


Figure 1.1: An illustration of the studied location, source MapChart.

aged not only for crop hydration but also to moderate temperature extremes [3][8]. A significant challenge in arid zones such as Biskra is the juxtaposition of long periods of drought with occasional, intense precipitation events, requiring agricultural systems to handle both a lack of water and a sudden excess of it. The region receives low average precipitation of about 120–160 mm per year, primarily in winter. This, combined with intense summer heat, leads to very high evaporation rates and hot, dry winds. To counter these conditions, Biskra’s agriculture relies on the efficient use of groundwater from wells, sustaining permanent oases that support the cultivation of dates and vegetables.

The agricultural expansion in Biskra has continued and even accelerated significantly since 2004, transforming the region into one of Algeria’s most important agricultural powerhouses. The cultivated area has grown dramatically from 155,000 hectares in 2004 to well over 250,000 hectares by the early 2020s [1],[6],[135]. This growth represents a fundamental shift in the type of agriculture practiced. The most significant development has been the boom in “plasticulture,” with a massive increase in greenhouses making Biskra the national leader in off-season vegetables like tomatoes, peppers, and melons. Alongside this, the use of modern center-pivot irrigation for large-scale cereal and potato farming has also continued to expand.

While date palms remain iconic, the regional economy has diversified

heavily towards this high-value market gardening. However, this entire agricultural revolution is fueled by the intensive exploitation of the Albian Aquifer, a massive but largely non-renewable fossil water source. Therefore, while Biskra’s agricultural growth has been an immense economic success, it has created a profound environmental challenge centered on the sustainable management of its finite water resources [9],[10].

Climate change has compounded volatility, with increased prolongation, intensity, and frequency of drought affecting rain-fed and irrigated systems through fluctuating rainfall, surface air temperature, solar radiation, and extreme weather events. Rural communities respond by adjusting activities and incomes, underscoring the need for sustainable agricultural development to ensure high production while preserving resources. Key determinants include global market prices, local prices for seeds and fertilizer, labor-income, and changes in precipitation and irrigation water availability. Maintaining soil and water quality remains essential [10],[11].

1.2 State of the Art and Literature Review

Governments worldwide increasingly recognize greenhouse production as a cornerstone of modern agriculture, citing its profound environmental, social, and economic benefits [9],[10]. By providing a controlled environment, greenhouses enhance food security, offer off-season produce, generate employment, and diminish rural poverty. This potential has fueled their widespread growth, particularly in regions with challenging climates. However, the inherent characteristics of greenhouses—low thermal capacity and significant anthropogenic heat generation—necessitate highly efficient climate management to ensure their sustainability [11],[130],[133].

This challenge is particularly acute in arid and semi-arid regions, such as those in the Near East, Saudi Arabia, and North Africa. Since the 1970s, factors like population growth and agriculture-driven immigration have spurred the expansion of greenhouse horticulture in these areas [7][134]. Greenhouses offer a lifeline, enabling the cultivation of crops otherwise unsuited to the regional climate, high-intensity sunlight, and often saline irrigation water. Yet, this creates a paradox: the very technology used to shield crops from a harsh external environment becomes exceptionally energy-intensive to operate. The extreme ambient temperatures and solar radiation impose a massive cooling load, while cold desert nights can still require heating. Consequently,

controlling the internal microclimate for crop protection and yield assurance is a critical, energy-demanding task that stands as a primary barrier to economic and environmental sustainability [12],[135]. As the global footprint of controlled environment agriculture expands—with projections for some crops in the USA exceeding 200 million m² by 2025—the imperative to optimize production through precise modeling and control has never been more urgent.

1.2.1 Modelling the Greenhouse Microclimate

To address the challenge of climate management, researchers have developed sophisticated models to describe and predict the dynamic behavior of the greenhouse environment. A robust model is the foundation of any advanced control strategy, allowing for the forecasting of internal conditions and the optimization of resource use. The literature reveals three principal approaches to modeling: physical-mathematical models, comprehensive simulation models, and data-driven models [15],[16].

1. Physical-Mathematical Models

The most fundamental modeling technique is rooted in the mathematical description of the physical system, based on the laws of heat and mass transfer. Since the 1950s, numerous attempts have been made to develop models that predict the dynamic behavior of the greenhouse based on first principles [4],[18]. These models, often comprising a set of algebraic or differential-algebraic equations, describe the energy and mass balance between the internal air, the crop, the cover, and the soil. A common approach involves transient one-dimensional thermal models that predict the performance of the greenhouse by treating each component as an isothermal surface [5],[20]. For control applications where computational efficiency is paramount, these complex models are often simplified into "lumped-parameter" representations. In a lumped-parameter model, the greenhouse air is treated as a single, well-mixed zone, allowing for efficient calculation without solving detailed governing equations [2],[9]. While powerful in their explanatory capacity, the primary limitation of purely physical models is their complexity and the need for numerous, often difficult-to-measure, physical parameters of the greenhouse structure and crop.

2. Simulation Models (CFD)

Simulation models are used to predict the microclimate based on a combination of empirical relations and physical principles, considering external weather conditions, solar radiation, and internal processes [3][11]. Among the most powerful simulation tools are those based on **Computational Fluid Dynamics (CFD)**. CFD models provide a detailed, three-dimensional spatial distribution of temperature, humidity, and air velocity by dividing the greenhouse into a fine grid and solving the governing fluid dynamics equations.

CFD is exceptionally useful during the design phase of a greenhouse or for diagnosing issues with airflow and temperature uniformity in existing structures. However, this high level of detail comes at the cost of immense computational effort, making CFD models generally unsuitable for the real-time calculations required for online control applications. There is an inherent trade-off: models simple enough for control are often not accurate enough for detailed design, and vice-versa.

3. Data-Driven Models

In recent years, data-driven models have emerged as a powerful and flexible alternative. These models characterize the system's input-output behavior using measurement data, without requiring explicit *a priori* knowledge of the underlying physical structure [4],[15]. This approach is highly effective for complex, non-linear systems like greenhouses, where physical processes are difficult to describe perfectly.

Techniques range from traditional time-series analysis to advanced machine learning algorithms, including **Artificial Neural Networks (ANNs)**, **Support Vector Machines (SVM)**, and **Extreme Learning Machines (ELM)**. Both feedforward NNs (e.g., multilayer perceptron) and dynamic NNs (e.g., backpropagation networks) have been successfully applied. For instance, researchers have used NNs to model transpiration rates, growth factors, and photosynthetic uptake based on input data such as internal/external temperature, humidity, and nutrient concentrations [16][17]. The primary advantage of data-driven models is their ability to capture complex dynamics directly from operational data, making them highly suitable for developing predictive models for real-time control.

1.2.2 Control Strategies for Greenhouse Climate Management

Based on the insights provided by these models, various control strategies have been developed to regulate the greenhouse environment [10],[42],[60],[82]. The goal is to maintain optimal conditions for crop growth while minimizing the consumption of resources like energy and water. The literature shows a clear evolution from simple reactive mechanisms to sophisticated predictive strategies [11],[61],[62].

While various control strategies have been developed, the practical implementation often faces challenges [11][43]. Proportional-Integral-Derivative (PID) controllers, though widely implemented due to their simplicity, exhibit fundamental limitations in the complex, non-linear, and time-varying environment of a greenhouse [42, 121, 125]. Their fixed gains, typically optimized for a single operating point, struggle to provide consistent performance as the thermal dynamics shift with external conditions like solar radiation and ambient temperature. This can lead to either sluggish responses or aggressive control actions causing significant overshoot and oscillations, potentially stressing or damaging crops [126, 129]. Furthermore, inherent time delays in thermal systems and the potential for integrator windup can further impair PID performance [63][64].

Advanced strategies such as Model Predictive Control (MPC) offer a powerful framework by using an explicit model to predict future behavior and compute optimal control actions [44, 53]. MPC can proactively manage the climate by anticipating disturbances [58, 59]. However, its primary drawback is the significant computational burden associated with solving a constrained optimization problem repeatedly in real-time [60]-[62]. This often demands processing power and memory exceeding the capabilities of the inexpensive microcontrollers typically used in cost-effective agricultural automation systems [63]-[67][74, 120].

These limitations highlight the need for control strategies that offer robustness against uncertainties and disturbances while remaining computationally feasible for practical implementation. Robust control techniques, such as H-infinity (H_∞) control, present a promising alternative. As demonstrated by **Brikel et al. [132]**, the H_∞ framework can be systematically applied to design controllers that guarantee stability and performance bounds even with model uncertainties, offering a balance between the simplicity of PID and the performance of MPC see Figure 1.2, making it well-suited for

deployment on accessible hardware platforms in agricultural settings [77]-[81].

1. Feedback Control and Automated Systems

The most common class of regulation techniques involves **feedback control**, where sensors monitor variables like temperature and humidity, and actuators (vents, heaters, foggers) are adjusted to correct deviations from a desired setpoint [20]. Many modern greenhouses now include a high degree of automation, with sensors for light, soil moisture, and nutrients informing integrated control systems [9],[132]. However, a key limitation of simple feedback is its reactive nature; it can only respond to an error after it has already occurred. Furthermore, the nonlinear relationships in a greenhouse, such as the effect of vent aperture on temperature, are difficult to manage precisely with simple open-loop or linear feedback control [22],[23].

2. Optimal and Predictive Control Approaches

To overcome the limitations of reactive control, advanced strategies based on **optimal control** have been developed. In figure 1.2 there are these methods aim to maintain the climate within grower-defined bounds while explicitly minimizing an objective function, typically energy consumption. Frameworks such as the Hamilton-Jacobi-Bellman formalism have been applied to reduce plant stress while adhering to temperature limits [24],[25].

The state-of-the-art in greenhouse control is **Model Predictive Control (MPC)**. MPC is an advanced optimal control strategy that uses a dynamic model of the system to predict its future evolution and compute the optimal control actions over a prediction horizon [2],[27]. By repeatedly solving this optimization problem online, MPC can proactively manage the climate, anticipating disturbances like changes in solar radiation rather than just reacting to them. Various MPC frameworks have been scrutinized, including nonlinear MPC based on Volterra series models for regulating temperature via natural ventilation and MPC schemes integrated with optimization algorithms like particle swarm optimization to achieve significant energy savings [4],[28]. While various control strategies have been developed, the practical implementation often faces challenges. Proportional-Integral-Derivative (PID)

controllers, though widely implemented due to their simplicity, exhibit fundamental limitations in the complex, non-linear, and time-varying environment of a greenhouse [42, 121, 125]. Their fixed gains, typically optimized for a single operating point, struggle to provide consistent performance as the thermal dynamics shift with external conditions like solar radiation and ambient temperature. This can lead to either sluggish responses or aggressive control actions causing significant overshoot and oscillations, potentially stressing or damaging crops [126, 129]. Furthermore, inherent time delays in thermal systems and the potential for integrator windup can further impair PID performance [132].

Advanced strategies such as Model Predictive Control (MPC) offer a powerful framework by using an explicit model to predict future behavior and compute optimal control actions [44, 53]. MPC can proactively manage the climate by anticipating disturbances [58, 59]. However, its primary drawback is the significant computational burden associated with solving a constrained optimization problem repeatedly in real-time [60]-[62]. This often demands processing power and memory exceeding the capabilities of the inexpensive microcontrollers typically used in cost-effective agricultural automation systems [63]-[67],[74, 120].

These limitations highlight the need for control strategies that offer robustness against uncertainties and disturbances while remaining computationally feasible for practical implementation. Robust control techniques, such as H-infinity (H_∞) control, present a promising alternative. As demonstrated by **Brikel et al.**[132], the H_∞ framework can be systematically applied to design controllers that guarantee stability and performance bounds even with model uncertainties, offering a balance between the simplicity of PID and the performance of MPC, making it well-suited for deployment on accessible hardware platforms in agricultural settings [77]-[83].

1.2.3 The Energy Nexus: Consumption, Efficiency, and Renewables

Controlling the greenhouse environment is an energy-intensive process, making energy management a pivotal aspect of operational profitability and sustainability[34],[36],[133],[134]. Research in this domain focuses on three in-

terconnected areas: analyzing energy consumption, implementing efficiency measures, and integrating renewable energy sources.

A key efficiency strategy involves the design of semi-closed greenhouses, which allow for the reuse of exhaust heat for subsequent heating requirements, thereby reducing fuel consumption, CO₂ emissions, and water and pesticide use [10],[28]. The most transformative approach, however, is the integration of renewable energy [39],[49]. Given that solar irradiance is the most abundant energy source in nature, numerous studies have explored its use in greenhouses [11],[29]. A promising technology is the integration of **photovoltaic-thermal (PV/T) panels**, which simultaneously generate electricity and capture thermal energy from surplus solar radiation. Models have shown that roof-mounted PV/T systems can significantly reduce cooling demands, support passive ventilation, and generate sufficient electricity to power the greenhouse, offering a pathway to stand-alone, sustainable operation in arid climates [5],[30][44].

1.2.4 Synthesis and Identification of the Research Gap

The state-of-the-art reveals a clear and consistent progression in the management of greenhouse systems[31],[32],[41]. The literature documents a definitive shift from simple physical descriptions to highly sophisticated **data-driven modeling techniques (AI/ML)**, which excel at capturing the complex, non-linear dynamics of the microclimate [9],[33],[125]. Concurrently, control strategies have evolved from basic reactive feedback loops to proactive and resource-efficient **Model Predictive Control (MPC)** frameworks [22],[127]. Furthermore, there is a strong and growing emphasis on holistic resource management, focusing on minimizing energy consumption through both efficiency measures and the **integration of renewable energy**, alongside advanced irrigation and crop management techniques.

Despite these significant advancements in individual domains, a critical review of the literature reveals that these components are often investigated in isolation. While one study may develop an excellent predictive model and another may design an efficient MPC controller, there is a notable scarcity of research that develops and validates a fully integrated, intelligent management system [34],[65].

Therefore, the primary research gap identified is the need for a holistic framework that synergistically combines **AI-based predictive microclimate models** with **advanced robust control strategies** to simulta-

neously optimize energy consumption, water usage, and crop productivity. There is a specific need to develop and validate such a system within the uniquely challenging agro-climatic context of an arid region such as **Biskra, Algeria**, where extreme environmental conditions make resource efficiency paramount. This thesis aims to address this gap by proposing and developing such an integrated intelligent system.

1.3 Contribution of this Work

This thesis addresses a critical gap in the literature by moving beyond isolated analyses of modeling or control to present a holistic, integrated solution for sustainable agriculture in arid regions. The primary contribution of this research is the development and validation of a novel intelligent framework for the proactive management of greenhouse microclimates, specifically tailored to the challenging conditions of Biskra, Algeria. The specific original contributions of this work in the figure 1.3 are:

1. **Development of a Novel Integrated Intelligent Framework:** This research pioneers a synergistic framework that uniquely combines AI-based predictive modeling with advanced robust control. Unlike previous studies that often treat these components separately, this work demonstrates how the predictive power of AI can be effectively coupled with the stability and precision of an H_∞ controller to create a proactive, rather than reactive, management system. This integrated approach represents a significant advancement in the field of controlled environment agriculture.
2. **Context-Specific AI-Based Microclimate Model for Arid Regions:** This thesis presents the first comprehensive AI-based microclimate model developed, trained, and validated specifically using empirical data from the agro-climatic context of Biskra. This provides a high-fidelity predictive tool that captures the unique non-linear dynamics of greenhouses in this region, offering a significant improvement over generalized models and providing a valuable new resource for local agricultural engineering.
3. **Application and Validation of an H-infinity (H_∞) Robust Controller:** While various control methods have been proposed for greenhouses, this work contributes the novel application and validation of an

H-infinity (H_∞) robust controller for this specific purpose. This advanced control strategy is explicitly designed to handle the system's inherent uncertainties and external disturbances, ensuring stable and highly efficient temperature regulation where traditional controllers may falter.

4. **A Data-Driven Framework for Sustainable Resource Management:** Beyond the technical implementation, this thesis provides a practical, data-driven framework for quantifying the direct impact of intelligent control on sustainability. By analyzing the resultant energy savings and modeling the integration with renewable energy sources, this work offers a valuable tool for farmers, policymakers, and investors to assess the economic viability and environmental benefits of adopting advanced automation in arid-climate agriculture.

1.4 Outline of the Thesis

The thesis is organized into six main chapters, each addressing a specific aspect of the research, to guide the reader logically from the initial problem statement to the final conclusions.

1. **Chapter 1: Introduction** serves as the introduction, presenting the background, a comprehensive literature review identifying the research gap, and the primary contributions of the work.
2. **Chapter 2: The Thermal Model of Greenhouse Agriculture** delves into the theoretical foundations of thermal modeling for greenhouse agriculture, systematically reviewing White Box, Black Box, and Grey Box models, including their mathematical principles and comparative advantages.
3. **Chapter 3: Experimental Systems and Data Acquisition for Model Development** details the experimental methodology, describing the data acquisition systems and the primary data sources, such as the University of Biskra weather station and the commercial greenhouse at Branis, which is used to analyze the challenges of conventional energy management.

4. **Chapter 4: Sustainable Energy Solutions for Greenhouse Agriculture in Biskra** focuses on sustainable energy solutions, using the Biskra case study to analyze passive and active solar technologies and presenting the mathematical formulations for evaluating system performance.
5. **Chapter 5: Growth Chamber: A Controlled Validation Environment** is dedicated to the development and validation of the H-infinity (H_∞) robust controller, using a controlled growth chamber as the experimental environment to cover its mathematical formulation, simulation, and real-world validation.
6. **Chapter 6: General Conclusion and Future Work** provides the general conclusion and outlook, summarizing the key findings, reiterating the main contributions, and proposing directions for future work.

GREENHOUSE CLIMATE CONTROL STRATEGIES OVERVIEW

A Spectrum of Approaches for Microclimate Regulation

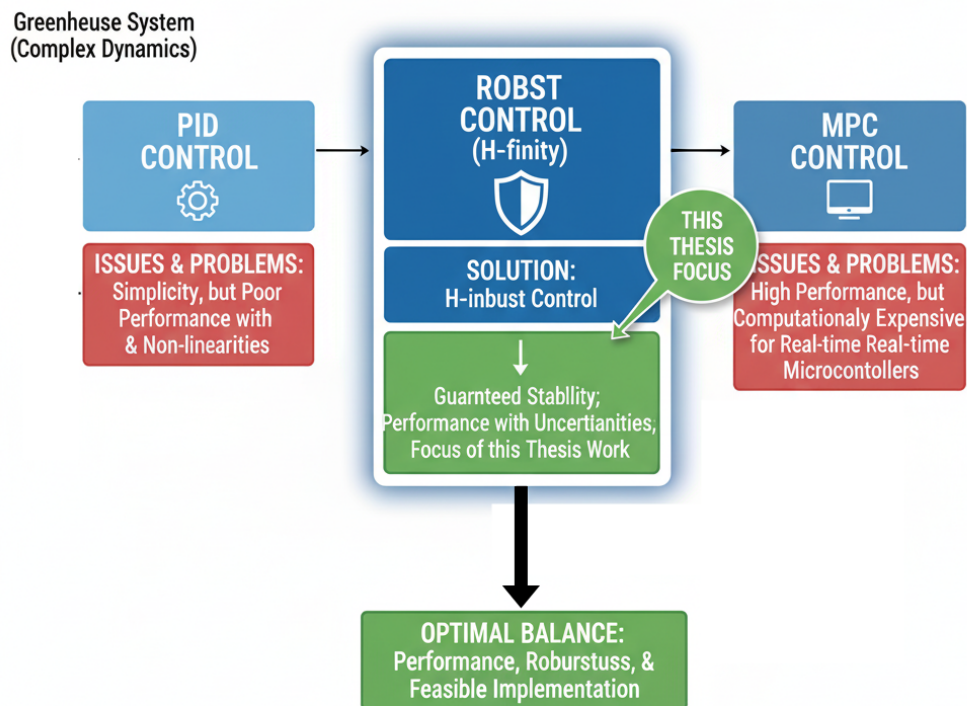


Figure 1.2: Overview of common control strategies for greenhouse climate management.

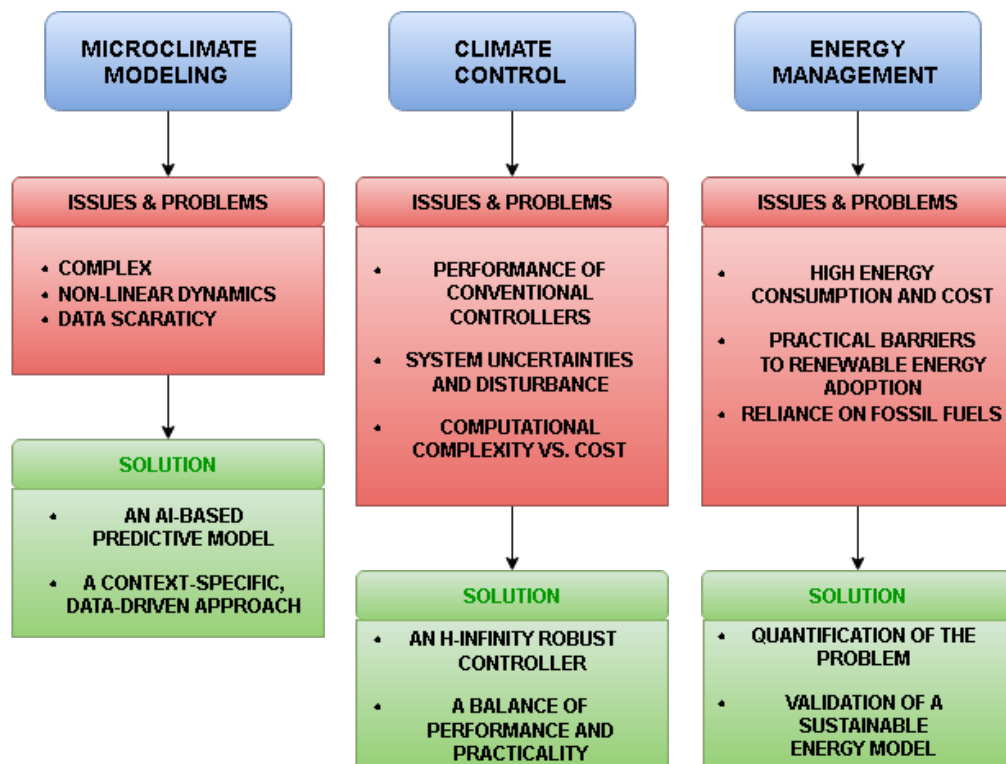


Figure 1.3: Thesis schematic (problems and solutions)

Chapter 2

The Thermal Model of Greenhouse Agriculture

2.1 Introduction

In this chapter, greenhouse agriculture represents a critical advancement in modern farming, providing a controlled micro-climate to enhance crop cultivation, extend growing seasons, and protect plants from adverse environmental conditions [50],[51].

These structures, whether made of glass or plastic, are designed to manipulate the internal environment for more effective and predictable crop production [52],[53]. However, the very nature of a greenhouse—a confined structure with high solar radiation transmission and relatively low thermal inertia—makes it susceptible to extreme internal temperature fluctuations. This necessitates a sophisticated approach to thermal management [54]-[56].

The modeling of the microclimate within an agricultural greenhouse can be approached through numerous techniques [57]-[59]. As classified by Amara et al.[2], these dynamic models are typically categorized as white-box, black-box, and grey-box (Figure 2.1). Following this structure, the present study will discuss each paradigm in sequence, beginning with white-box models.

2.2 White Box (Mechanistic) Models

White Box models, also known as mechanistic or first-principles models, are based on a deep understanding of the physical processes that govern the

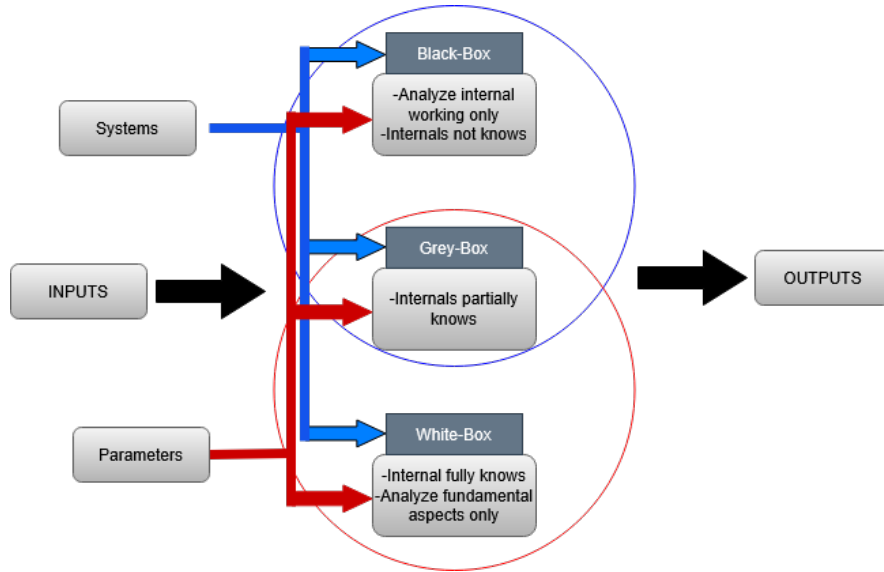


Figure 2.1: Black-box, White-box and Grey-box behavior . So the Blue circle represents the black-box system, the Red circle represents the white box-system, and their intersection is the grey-box system [131].

greenhouse environment. They are constructed from fundamental laws of physics, primarily the principles of mass and energy balance and heat transfer thermodynamics.

2.2.1 Mathematical Foundations

The core of a White Box model is a set of differential or differential-algebraic equations that describe the thermal dynamics of the system. The greenhouse is typically divided into several interacting components: the cover, the internal air, the plant canopy, and the soil. An energy balance equation is formulated for each component, accounting for all modes of heat exchange:

- **Solar Radiation:** Short-wave radiation from the sun that enters the greenhouse.
- **Thermal Radiation:** Long-wave radiation exchanged between internal surfaces (plants, soil, cover) and with the sky.
- **Convection:** Heat transfer between surfaces and the internal air.

- **Conduction:** Heat transfer through the soil and the greenhouse cover.
- **Latent Heat Exchange:** Energy transfer due to evapotranspiration from the crop and condensation.

These models require detailed knowledge of the physical and thermal properties of the greenhouse materials, such as the transmissivity and emissivity of the cover, heat capacity of the structure, and aerodynamic resistance of the crop. The ventilation process, driven by wind and buoyancy (the chimney effect), is a particularly complex non-linear phenomenon that these models attempt to describe mathematically.

The energy balance of a greenhouse is a fundamental concept used to understand and model its thermal behavior. It is an accounting of all the energy entering and leaving the system. At its core, the principle is simple:

$$\text{Energy In} \equiv \text{Energy Out} + \text{Energy Stored}$$

A greenhouse's temperature changes based on the net result of these energy flows. Here is a breakdown of the key components that make up the energy balance equation.

2.2.2 Key Components of Energy Exchange

The overall energy balance is determined by several complex heat transfer processes occurring simultaneously, the A diagram illustrating the primary energy flows in a greenhouse represented in Figure 2.2 .

1. **Energy Gains (Inputs)** The primary source of energy for a greenhouse is the sun.
 - **Solar Radiation (Q_{solar}):** This is the short-wave radiation from the sun that passes through the greenhouse cover (glazing) and is absorbed by the plants, soil, and internal structures, converting to heat.
 - **Supplemental Heating (Q_{heat}):** In colder climates, this is the energy provided by an artificial heating system to maintain the desired temperature.
2. **Energy Losses (Outputs)** Energy is lost from the greenhouse to the colder outside environment through several mechanisms:

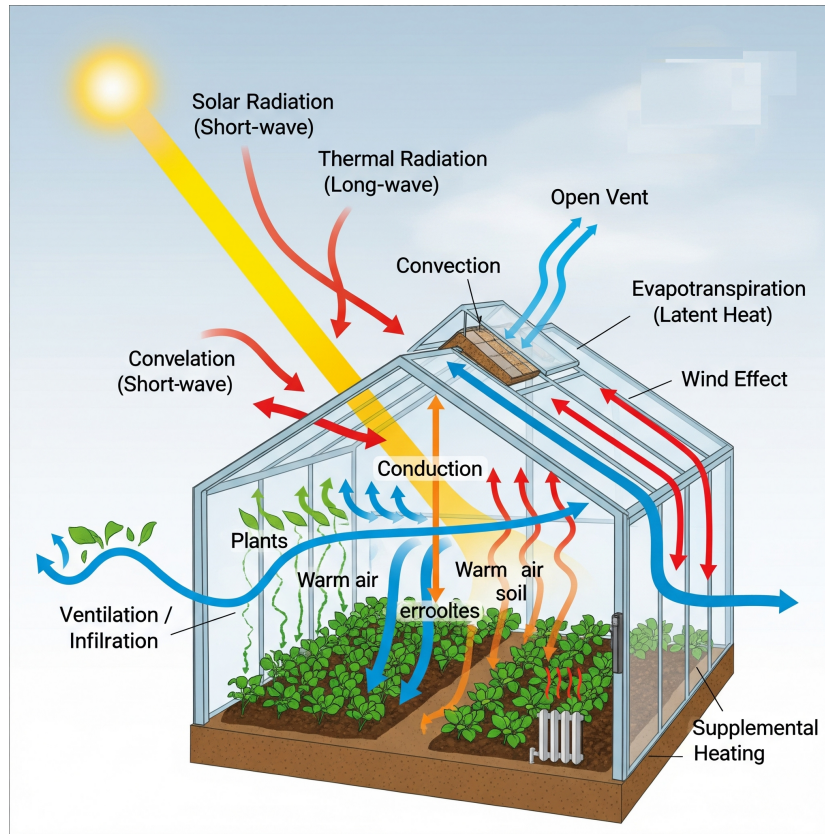


Figure 2.2: A diagram illustrating the primary energy flows in a greenhouse [9].

- **Conduction** (Q_{cond}): Heat transfer directly through the greenhouse cover material (glass or plastic).
- **Convection** (Q_{conv}): Heat transferred by the movement of air, both from the interior air to the cover and from the outer cover to the wind.
- **Thermal Radiation** (Q_{rad}): Long-wave radiation emitted from the warmer surfaces inside the greenhouse to the colder sky and surroundings.
- **Ventilation & Infiltration** (Q_{vent}): Heat lost through the intentional or unintentional exchange of air with the outside.
- **Latent Heat of Evapotranspiration** (Q_{lat}): Energy used by

plants for transpiration and evaporation from the soil, which cools the greenhouse.

3. **The Energy Balance Equation** A simplified, steady-state energy balance equation for a greenhouse can be expressed as:

$$Q_{\text{solar}} + Q_{\text{heat}} = Q_{\text{cond}} + Q_{\text{conv}} + Q_{\text{rad}} + Q_{\text{vent}} + Q_{\text{lat}} \quad (2.1)$$

Where:

- Q_{solar} = Heat gain from solar radiation
- Q_{heat} = Heat gain from the supplemental heating system
- Q_{cond} = Heat loss by conduction through the cover
- Q_{conv} = Heat loss by convection from the cover
- Q_{rad} = Heat loss by long-wave thermal radiation
- Q_{vent} = Heat loss through ventilation and infiltration
- Q_{lat} = Heat loss due to evapotranspiration (latent heat)

This equation forms the basis of **White Box (mechanistic) models** for predicting the temperature inside a greenhouse

4. **The Core Principle**

The core principle behind a White Box model is the **law of conservation of energy**, which is applied to the greenhouse system. The set of differential equations is simply the mathematical formulation of this **energy balance**.

The model calculates the change in the greenhouse's internal energy (which determines its temperature) over time. This change is the net result of all the energy flowing into and out of the system. A simplified differential equation for the temperature of the air inside a greenhouse (T_{in}) looks like this:

$$C_{\text{air}} \frac{dT_{\text{in}}}{dt} = \sum Q_{\text{in}} - \sum Q_{\text{out}} \quad (2.2)$$

Where:

- $C_{\text{air}} \frac{dT_{\text{in}}}{dt}$ is the **differential** part. It represents the rate of change of energy stored in the greenhouse air over time. C_{air} is the thermal mass (or heat capacity) of the air, and $\frac{dT_{\text{in}}}{dt}$ is the rate of temperature change.
- $\sum Q_{\text{in}} - \sum Q_{\text{out}}$ represents the sum of all the heat fluxes (the physical processes you listed).

Each of the heat transfer mechanisms you mentioned corresponds to a specific term (Q) in the equation:

- **Solar Radiation** is a heat gain (Q_{in}).
- **Thermal Radiation, Convection, Conduction, and Latent Heat Exchange** are typically heat losses (Q_{out}).

Putting it all together, the full equation conceptually states:

The rate of temperature change inside the greenhouse is proportional to the heat gained from solar radiation minus the heat lost through conduction, convection, radiation, and evapotranspiration.

This is why White Box models are considered “mechanistic”—the mathematical equations directly represent the known physical laws governing the system.

5. The Mass (Humidity) Balance Differential Equation

To solve for the latent heat term, a corresponding differential equation for the water vapor concentration (absolute humidity, H_{in}) inside the greenhouse is required:

$$V_g \frac{dH_{\text{in}}}{dt} = E_p - V_R \cdot (H_{\text{in}} - H_{\text{out}}) - C_r \quad (2.3)$$

Where:

- $\frac{dH_{\text{in}}}{dt}$ is the rate of change of internal absolute humidity ($\text{kg}_{\text{water}} \text{m}^{-3} \text{s}^{-1}$).
- E_p is the crop transpiration rate (source term).
- $V_R \cdot (H_{\text{in}} - H_{\text{out}})$ is the humidity lost through ventilation.
- C_r is the rate of condensation on the inner surface of the cover ($\text{kg}_{\text{water}} \text{s}^{-1}$).

This set of coupled differential and algebraic equations forms the mathematical basis of a White Box model. Solving this system allows for the dynamic simulation of the greenhouse microclimate.

2.2.3 Advantages and Disadvantages

The primary advantage of White Box models is their **explanatory power**. Because they are built on physical principles, they provide profound insight into the causal relationships within the system and can predict its behavior under a wide range of conditions, even those not present in the initial data. However, their main disadvantage is their **complexity**. Developing an accurate White Box model is a laborious and time-consuming process that requires a significant number of parameters, many of which are difficult to measure accurately. This complexity can also make them computationally too intensive for real-time control applications.

2.3 Black Box (Empirical) Models

In stark contrast to White Box models, Black Box approaches make no assumptions about the underlying physical mechanisms of the system. Instead, they aim to construct a mathematical model based solely on observed input-output data.

2.3.1 Methodological Approach

Black Box system identification infers the relationship between inputs (e.g., external weather conditions, vent openings, heating power) and outputs (e.g., internal temperature, humidity) from historical time-series data. These models treat the greenhouse as an opaque "black box", focusing on accurately mapping its response without needing to understand its internal workings. A wide range of techniques fall under this category:

- **Statistical Models:** These include time-series models like ARMAX (AutoRegressive-Moving-Average with eXogenous inputs) and non-linear polynomial models such as the Volterra series, which can capture complex dynamic relationships.
- **Machine Learning (ML) Models:** This is a rapidly growing area, with **Artificial Neural Networks (ANNs)** being the most common approach. Architectures like Feedforward Multi-Layer Perceptrons (MLPs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are well-suited for time-series forecasting of climate variables.

2.3.2 Mathematical Formulation of Black Box Models

Black Box models are empirical in nature and are not derived from the first principles of physics. Their objective is to identify a functional relationship that accurately maps a set of input variables to an output variable, based solely on observed data.

- The General Functional Representation

The core of any Black Box model is the assumption that the future state of the system can be predicted by a function, f , of its past inputs, past outputs, and external disturbances. For predicting the internal greenhouse temperature, this can be represented abstractly as:

$$\hat{y}(t+1) = f(\mathbf{u}(t), \mathbf{y}(t), \mathbf{e}(t)) \quad (2.4)$$

Where:

- $\hat{y}(t+1)$ is the predicted output at the next time step (e.g., internal temperature, T_{in}).
- $\mathbf{u}(t) \in \mathbb{R}^m$ is a vector of all relevant inputs up to time t , such as external temperature (T_{out}), solar radiation (I_{solar}), and control actions.
- $\mathbf{y}(t) \in \mathbb{R}^p$ is a vector of past outputs up to time t (e.g., past internal temperature measurements).
- $\mathbf{e}(t) \in \mathbb{R}^q$ is a vector representing the history of prediction errors or noise.
- f is the non-linear function that the model learns from data.

The specific mathematical form of f depends on the chosen modeling technique. Below are two of the most common families of equations used.

- Time-Series Models (e.g., ARMAX)

A common family of Black Box models are linear time-series models like ARMAX (AutoRegressive-Moving-Average with eXogenous inputs) [14],[15]. The equation for an ARMAX model is:

$$A(q)y(t) = B(q)u(t - n_k) + C(q)e(t) \quad (2.5)$$

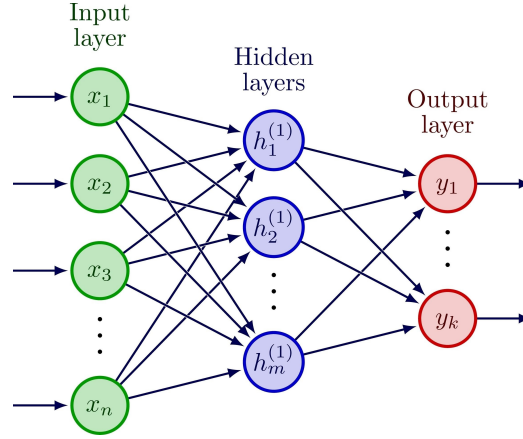


Figure 2.3: Conceptual diagram of a feedforward neural network, a common Black Box model [13].

This equation can be expanded to show the relationship more clearly:

$$\begin{aligned}
 y(t) + a_1 y(t-1) + \cdots + a_{n_a} y(t-n_a) = \\
 b_1 u(t-n_k-1) + \cdots + b_{n_b} u(t-n_k-n_b) + \\
 e(t) + c_1 e(t-1) + \cdots + c_{n_c} e(t-n_c)
 \end{aligned} \tag{2.6}$$

Where:

- $y(t)$ is the output at time t .
- $u(t)$ is the input at time t .
- $e(t)$ is the white noise or error term at time t .
- a_i , b_i , and c_i are the model parameters that are estimated from data.
- n_a, n_b, n_c define the order of the model (how many past values are considered).
- n_k is the input delay.
- $A(q), B(q), C(q)$ are polynomial operators in the backshift operator q^{-1} .

In this model, the future temperature ($y(t)$) is a linear combination of its own past values (the AutoRegressive part), past inputs (the eXogenous part), and past prediction errors (the Moving-Average part).

- Machine Learning Models (e.g., Artificial Neural Networks)

Artificial Neural Networks (ANNs) represent the function f as a network of interconnected nodes (“neurons”) [16][17], see Figure 2.3. The mathematical equation for a single neuron in a simple feedforward network is:

$$\text{output} = \phi \left(\sum_{i=1}^n (w_i \cdot x_i) + b \right) \quad (2.7)$$

Where:

- x_i are the inputs to the neuron (e.g., T_{out} , I_{solar} , past T_{in}).
- w_i are the weights associated with each input. These are the parameters the network learns.
- b is a bias term.
- $\sum$ denotes the weighted sum of the inputs.
- ϕ is a non-linear **activation function** (such as Sigmoid, ReLU, or tanh) that allows the network to learn complex, non-linear relationships.

A full neural network consists of multiple layers of these neurons. The output of one layer becomes the input to the next. The final mathematical model is a highly complex, nested non-linear function where the weights (w_i) and biases (b) are “learned” during a training process that minimizes the difference between the model’s predictions and the actual measured data.

2.3.3 Advantages and Disadvantages

The main advantage of Black Box models is their **simplicity of development** (provided sufficient data is available) and their ability to model highly complex and non-linear systems without requiring deep physical insight. They are particularly powerful for prediction in real-time control schemes. However, their primary drawback is their **lack of interpretability and generalizability**.

The model provides no insight into the physical processes, and its predictive accuracy can degrade significantly if the system operates outside the conditions represented in the training data, a phenomenon known as overfitting.

2.4 Grey Box (Hybrid) Models

Grey Box models represent a pragmatic compromise between the White Box and Black Box paradigms. They combine a simplified physical structure based on first principles with data-driven methods used to estimate unknown or highly complex parameters.

2.4.1 Hybrid Structure

A typical Grey Box modeling process begins by developing a simplified White Box model—for instance, a lumped-parameter energy balance equation that captures the fundamental dynamics of the system. This known physical structure forms the "white" part of the model. The "black" (or "grey") part consists of components or parameters within this structure that are difficult to model from first principles, such as the heat transfer coefficient or the complex process of crop transpiration. These unknown components are then identified from experimental data using system identification techniques, such as subspace algorithms, Kalman filters, or even neural networks.

The result is a model that is grounded in physical reality but refined and calibrated with empirical data. This approach leverages the strengths of both methodologies, retaining the necessary physical details while using data-driven techniques to handle uncertainties and unmodeled dynamics.

2.4.2 Mathematical Formulation of Grey Box (Hybrid) Models

Grey Box models bridge the gap between purely physical and purely empirical models. Their mathematical structure consists of a known, physically-motivated framework (often a set of differential equations) where some of the parameters or functions are considered “unknown” and are estimated from experimental data.

1. The General State-Space Representation

A very common framework for Grey Box models is the **stochastic state-space model**. This representation separates the known deterministic dynamics from the unknown stochastic processes (noise). A

continuous-time linear state-space model is given by:

$$\dot{\mathbf{x}}(t) = \mathbf{A}(\theta)\mathbf{x}(t) + \mathbf{B}(\theta)\mathbf{u}(t) + \mathbf{w}(t) \quad (2.8)$$

$$\mathbf{y}(t) = \mathbf{C}(\theta)\mathbf{x}(t) + \mathbf{D}(\theta)\mathbf{u}(t) + \mathbf{v}(t) \quad (2.9)$$

Where:

- $\mathbf{x}(t)$ is the state vector (e.g., internal temperature, cover temperature).
- $\dot{\mathbf{x}}(t)$ is the time derivative of the state vector.
- $\mathbf{u}(t)$ is the input vector (e.g., external temperature, solar radiation).
- $\mathbf{y}(t)$ is the output vector (the measured variables).
- $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}$ are the state, input, output, and feedthrough matrices. Their structure is derived from simplified physical laws (the **White Box** part), but they contain a vector of unknown parameters, θ , that must be estimated.
- $\mathbf{w}(t)$ and $\mathbf{v}(t)$ are the process noise and measurement noise, respectively. These are unmeasured stochastic processes that account for all unmodeled dynamics and disturbances (the **Black Box** part).

//

2. Example: A Simplified Thermal Model

Let's adapt the White Box energy balance equation into a Grey Box model. A simplified differential equation for the internal air temperature (T_{in}) can be written as:

$$C_{th} \frac{dT_{in}}{dt} = U A_c (T_{out} - T_{in}) + \tau_c A_c I_{solar} \quad (2.10)$$

Where:

- C_{th} is the overall thermal capacitance of the greenhouse.
- U is the overall heat transfer coefficient.
- A_c is the cover area (known).

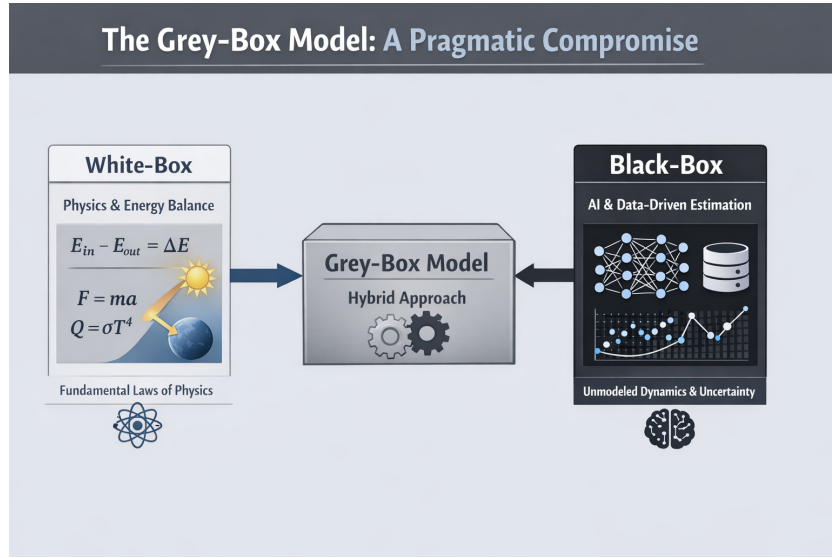


Figure 2.4: Conceptual diagram of a Grey-Box model, showing the combination of a known physical structure from white-box with unknown parameters and noise estimated from black-box [131].

- T_{out} is the external temperature and I_{solar} is the solar radiation (measured inputs).

In a pure White Box model, one would try to calculate C_{th} and U from fundamental material properties. In a **Grey Box** approach, these parameters are treated as unknown and are estimated from data (Figure 2.4 describes it). The model is structured around the known physical relationship, but the specific values that govern it are learned empirically. The vector of unknown parameters to be identified would be $\theta = [C_{th}, U, \tau_c]$.

3. Parameter Estimation

The “Black Box” part of the process involves using system identification techniques to find the optimal values for the parameter vector θ . The goal is to find the parameters that minimize the difference between the model’s predicted output, $\hat{y}(t)$, and the actual measured output, $y(t)$.

This is typically formulated as an optimization problem. A common method is **Maximum Likelihood Estimation (MLE)**, which seeks

to find the parameters θ that maximize the likelihood of observing the measurement data. This is often equivalent to minimizing the prediction error, for instance, by minimizing a cost function J :

$$\hat{\theta} = \arg \min_{\theta} J(\theta) = \sum_{t=1}^N (y(t) - \hat{y}(t|\theta))^2 \quad (2.11)$$

Where:

- $\hat{\theta}$ is the estimated parameter vector.
- N is the number of data points.
- $y(t)$ is the measured output.
- $\hat{y}(t|\theta)$ is the one-step-ahead prediction of the output generated by the model with parameters θ .

By using a physically-based structure but allowing key parameters to be learned from data, the Grey Box model combines the interpretability of White Box models with the adaptive accuracy of Black Box models.

2.4.3 Advantages and Disadvantages

The key advantage of Grey Box models is their **balance between accuracy and complexity**. They are generally more robust and have better extrapolation capabilities than pure Black Box models because their structure is constrained by physical laws. At the same time, they are less complex and require fewer detailed physical parameters than a comprehensive White Box model, making them more practical for real-world applications, especially in control engineering. Their main challenge lies in correctly structuring the model—deciding which parts to model physically and which to identify from data—which requires expertise in both domains.

2.5 Black-Box Linear Time-Invariant Systems Modeling for Greenhouse Micro-climate using Differential Evolution Algorithm

In this section, the greenhouse microclimate is characterized as a Linear Time-Invariant (LTI) system [131]. The modeling approach utilizes a Multiple Input Single Output (MISO) black-box framework, where the internal temperature is the target output influenced by several environmental subsystems[123]. The internal temperature of a greenhouse is a complex dynamic influenced by multiple factors, including solar radiation, external temperature, ventilation, and heating or cooling systems [131]. The primary heat transfer mechanisms occurring within the greenhouse are conduction, convection, and radiation [131].

2.5.1 Case Study and Data Collection

The research utilizes microclimate data obtained from Biskra Province, Algeria [19]. An experimental single-span wooden greenhouse prototype was used for data collection (Figure 2.5 and Figure 2.6)[19]. The dataset includes five days of measurements for the following six variables [19]:

- Indoor and outdoor air temperature (°C).
- Indoor and outdoor relative humidity (%).
- Outdoor solar radiation (W/m²).
- Wind velocity (m/s).

2.5.2 Black-Box Model LTI Transfer Function

The greenhouse microclimate is modeled as a Linear Time-Invariant (LTI) system using a Multiple Input Single Output (MISO) black-box approach (see Figure 2.7) [131]. The transfer function $GAS(s)$ is defined as the ratio of the Laplace transform of the internal temperature to the Laplace transform of the input data [131]:

$$GAS(s) = \frac{Temperature_{Inside}(s)}{DATA(s)} \quad (2.12)$$



Figure 2.5: Structural measurements for agricultural greenhouse prototype [19].

To account for the thermal inertia and responsiveness of the greenhouse, each input subsystem is modeled as a standard second-order system [2],[3]:

$$G_i(s) = \frac{k}{T_{ni}s + 1} \quad (2.13)$$

Where n_i denotes the natural frequency and ξ_i represents the damping ratio of the i -th subsystem[132]. This formulation is applied to six primary environmental variables: internal/external temperature, internal/external humidity, solar radiation, and wind velocity[4],[9].

2.6 Differential Evolution Algorithm (DEA) for Identification

The Differential Evolution Algorithm (DEA) is employed for the offline parametric identification of the 12 optimal coefficients in the MISO model [131].

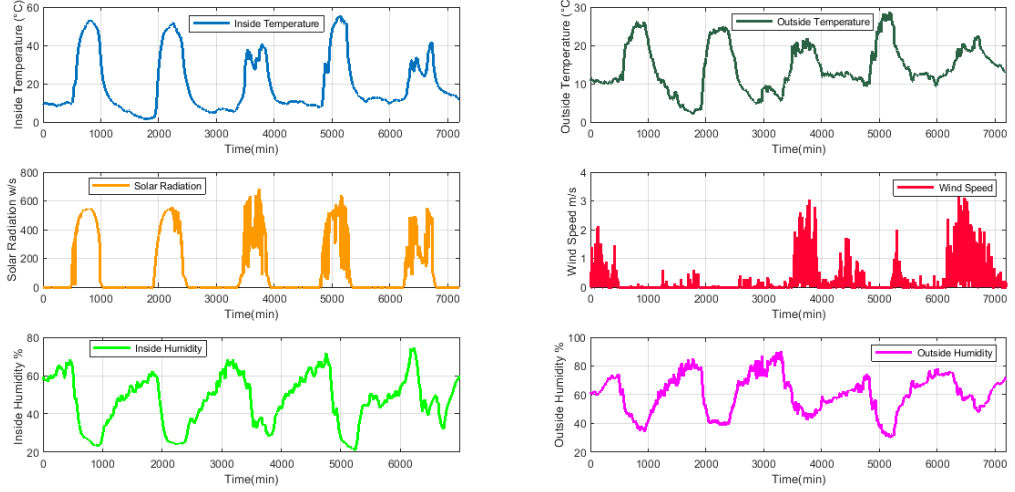


Figure 2.6: The data collected over five days (inside air temperature is blue, outside air temperature is green, outside solar radiation is orange, wind velocity is red, inside relative humidity is green, and outside relative humidity is pink [19].

DEA is a stochastic, population-based search technique that minimizes the error function without requiring derivative information (Figure 2.8)[131].

The optimization problem involves a 12-dimensional vector x_i , where each component represents a physical characteristic of the greenhouse subsystems:

$$x_i^t = [x_{1,i}^t, x_{2,i}^t, \dots, x_{12,i}^t] \quad (2.14)$$

The algorithm identifies these values by minimizing the Mean Squared Error (MSE), which quantifies the disparity temperatures predicted and observed:

$$MSE = \sqrt{\frac{\sum_{i=1}^N (Y_{real}^i - Y_{predicted}^i)^2}{N}} \quad (2.15)$$

2.6.1 The Evolutionary Process

The Figure 2.9 represents the Differential Evolution Algorithm (DEA) in an offline parametric identification process, in simulation using MATLAB.

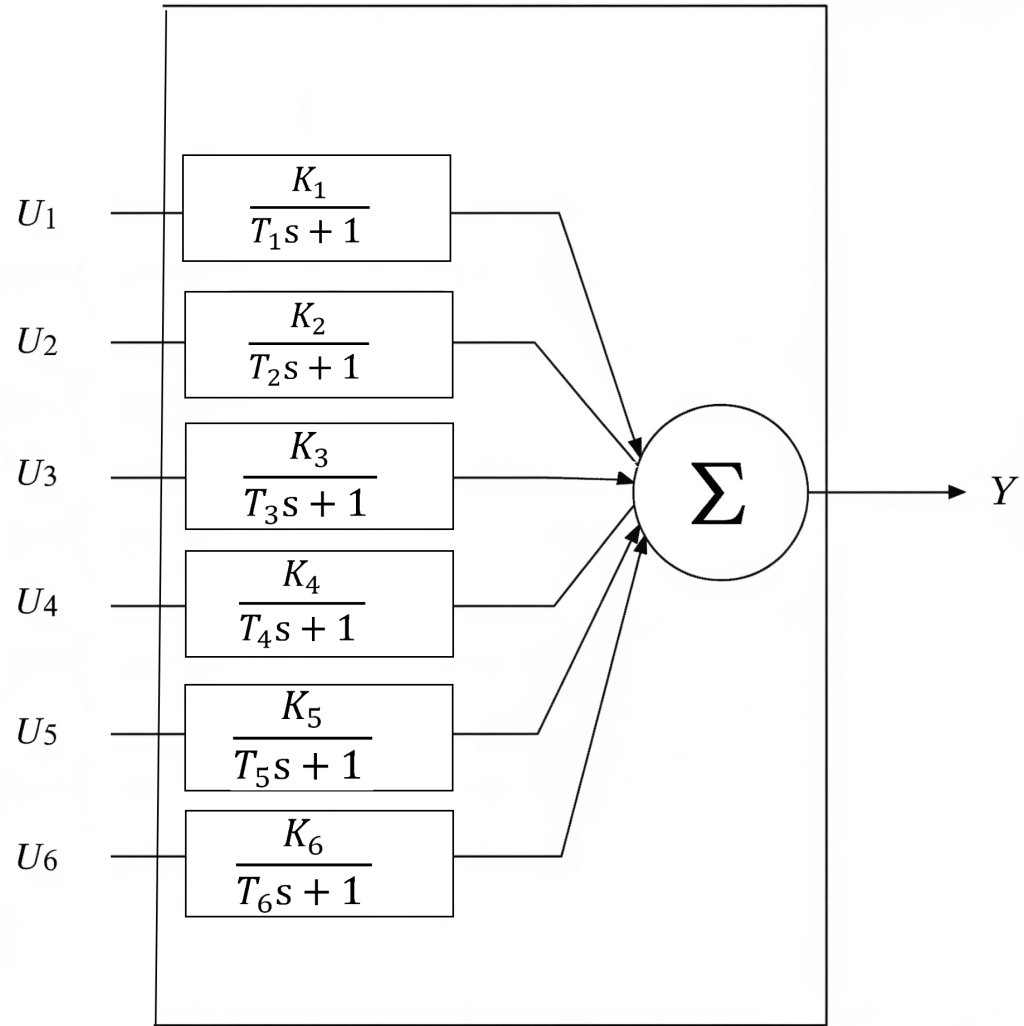


Figure 2.7: show transfer function model of Greenhouse Agricultural System GAS(S) [131].

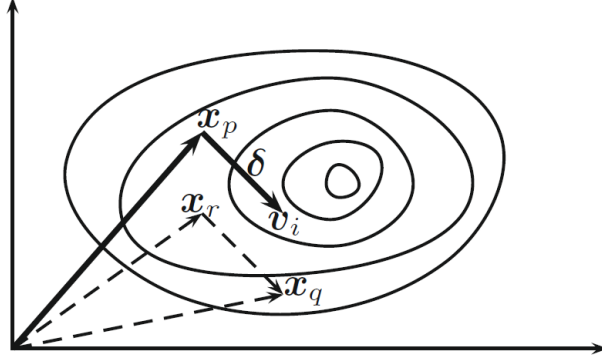


Figure 2.8: Graphic showing mutation vectors in differential evolution with displacement $= F(x_q - x_r)$ [23].

Moreover, the algorithm executes the following four primary steps in each generation in ()The Figure 2.9)[131]:

1. **Initialization:** A population of $N_p = 60$ vectors is randomly generated within the search range $[0, 10]$ [23].
2. **Mutation:** Donor vectors are created by calculating the weighted difference between randomly selected population members [131].
3. **Crossover:** Trial vectors are produced using a binomial crossover scheme with a probability $C_r = 0.9$ [131].
4. **Selection:** The fittest vectors are selected by minimizing (RMSE): The optimization problem (Objective Function) is expressed as follows when the weight of the structure is minimized

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Y_{real}^i - Y_{predicted}^i)^2}{N}} \quad (2.16)$$

The specific parameters used for the DEA simulation are summarized in Table 2.1 [131].

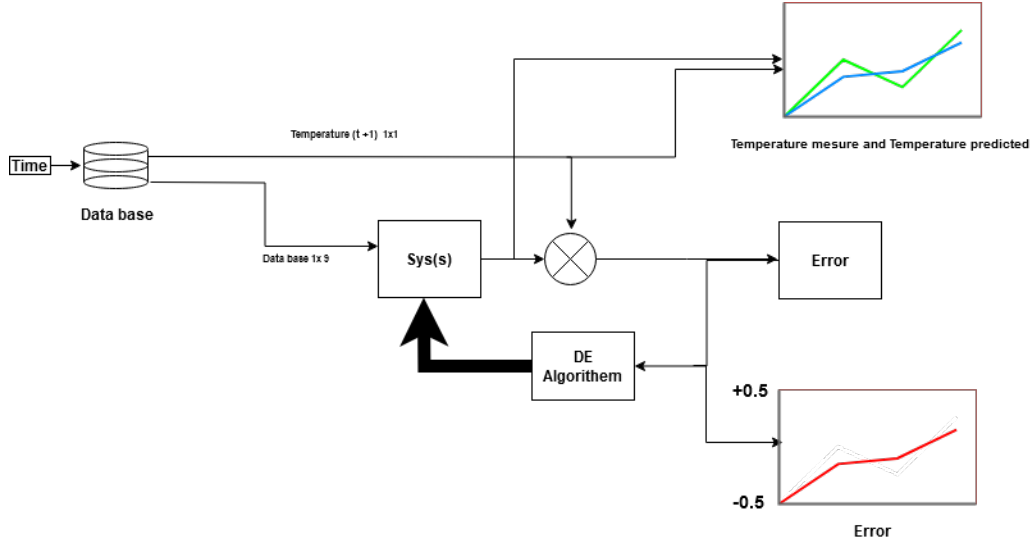


Figure 2.9: Differential Evolution Algorithm (DEA) in an offline parametric identification process, in simulation using MATLAB [131]].

Differential Evolution

```

Initialize the population  $x$  with randomly generated solutions
Set the weight  $F \in [0, 1]$  and crossover probability  $C_r \in [0, 1]$ 
while (stopping criterion)
  for  $i = 1$  to  $n$ ,
    For each  $x_i$ , randomly choose 3 distinct vectors  $x_p, x_q$  and  $x_r$ 
    Generate a new vector  $v$  by DE scheme  $EQ(9)$ 
    Generate a random index  $J_r \in 1, 2, \dots, d$  by permutation
    Generate a randomly distributed number  $r_i \in [0, 1]$ 
    for  $j = 1$  to  $d$ ,
      For each parameter  $v_{j,i}$  ( $j^{th}$  component of  $v_i$ ), update
        
$$u_{j,i}^{t+1} = \begin{cases} v_{j,i}^{t+1} & \text{if } r_i \leq C_r \text{ or } j = J_r \\ x_{j,i}^t & \text{if } r_i > C_r \text{ and } j \neq J_r \end{cases}$$

      end
    Select and update the solution by  $EQ(12)$ 
  end
end
Post-process and output the best solution found

```

Figure 2.10: Pseudocode of differential evolution algorithm [23]].

Table 2.1: Selection of Parameters for the Differential Evolution Algorithm (DEA)[131].

Parameter	Selected Value
Number of Decision Variables (n)	12
Population Size	60
Lower Bound of Scaling Factor (F)	0.2
Upper Bound of Scaling Factor (F)	0.9
Crossover Probability (C_r)	0.9
Maximum Number of Iterations	100

2.6.2 Results and Validation

Implementation and Optimization Results

The identification process progressively enhanced the quality of candidate solutions across 100 iterations [131]. The algorithm successfully minimized the cost function, reducing the Root Mean Squared Error (RMSE) from an initial value of 0.344 at the first iteration to a final optimized value of 0.065 [131]. The final identified optimal parameters for the six transfer function subsystems are presented in Table 2.2.

Table 2.2: Optimal Identified Parameters for the Greenhouse LTI Model [131].

Parameter	Value	Parameter	Value
x_1	9.87	x_2	1.187
x_3	$1.0e^{-3}$	x_4	6.278
x_5	$1.0e^{-3}$	x_6	6.554
x_7	$1.0e^{-3}$	x_8	9.65
x_9	$1.0e^{-3}$	x_{10}	9.08
x_{11}	$1.0e^{-3}$	x_{12}	$1.0e^{-3}$

Experimental Validation and Error Analysis

Validation was performed by comparing the predicted inside air temperature against measured data over a multi-day period. The results demonstrate an excellent correlation between the observed and forecasted thermal dynamics.

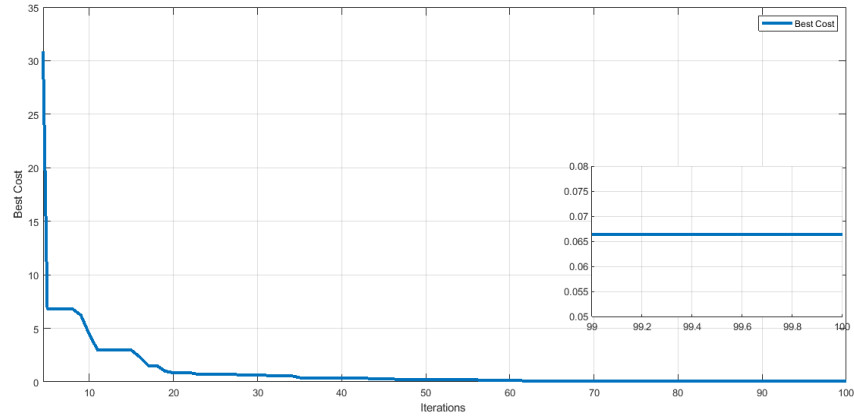


Figure 2.11: Best Cost of DE Algorithm for 100 iterations, The best value of 0.065 [131]

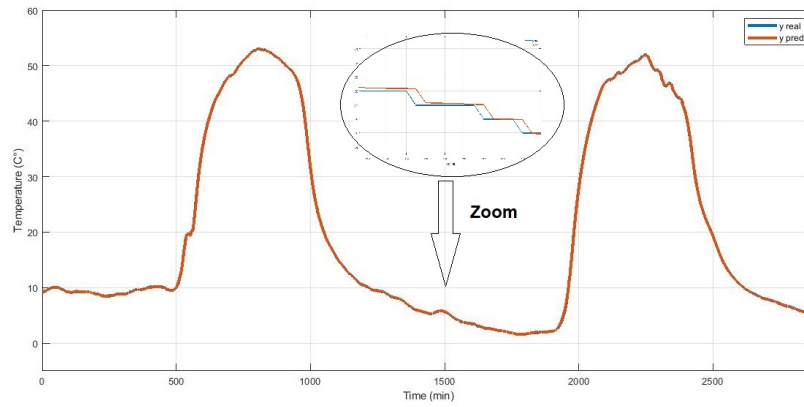


Figure 2.12: Temperature inside on the first and second days was measured and predicted [131].

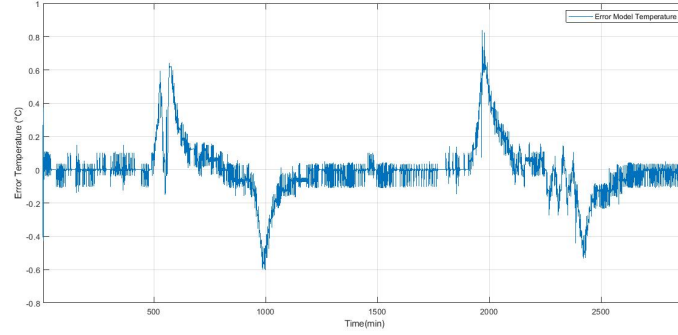


Figure 2.13: The error temperature inside (measured and predicted temperature) on the 1st and 2nd days [131]

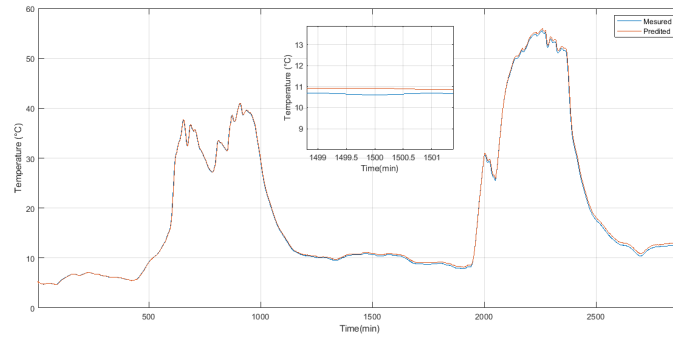


Figure 2.14: Validation of the proposed system temperature inside on the 3rd and 4th days[131].

The maximum recorded error during the simulation was 0.83°C . Detailed analysis of the error residuals shows a small deviation range of $[-0.6, 0.83]$ for the first two days and $[-1.40, 1.0]$ for the third and fourth days. These results confirm that the proposed DEA-based identification method provides a high-precision tool for greenhouse microclimate management in arid regions such as Biskra [131].

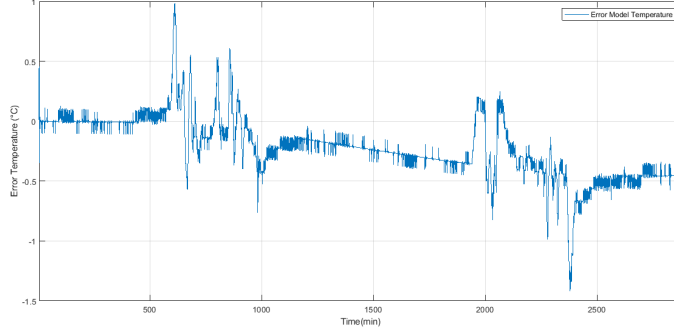


Figure 2.15: The error temperature inside on the 3rd and 4th days [131].

2.7 Conclusion and Identification of the Research Gap

This chapter has provided a comprehensive review of the state-of-the-art in the thermal modeling of agricultural greenhouses. The literature presents a clear taxonomy of modeling methodologies, which can be broadly classified into three paradigms: White Box, Black Box, and Grey Box models.

White Box models, grounded in the first principles of thermodynamics and energy balance, offer profound insight into the physical dynamics of the greenhouse system. However, their practical application is often constrained by their inherent complexity and the extensive, often difficult-to-obtain, set of physical parameters they require.

Black Box models, particularly those utilizing machine learning techniques such as Artificial Neural Networks, have gained prominence due to their ability to accurately capture complex, non-linear system behaviors directly from experimental data. Their strength lies in predictive accuracy and relative ease of development, though they provide limited physical insight and their reliability can be compromised when operating outside the domain of the training data.

Grey Box models offer a pragmatic and powerful hybrid approach, combining a simplified physical structure with data-driven techniques to estimate unknown parameters. This method balances the explanatory power of mechanistic models with the flexibility of empirical ones, making it highly suitable for control applications.

The overarching trend identified in this review is a definitive shift from

purely mechanistic descriptions towards more flexible, data-driven, and hybrid modeling frameworks. This evolution is driven by the practical need for models that are not only accurate but also computationally efficient and robust enough for real-time prediction and control in complex, dynamic environments.

Despite these significant advancements, a critical review of the existing literature reveals a persistent research gap: while many studies focus on developing a specific type of model or control strategy in isolation, there is a notable scarcity of work that develops and validates a holistic, integrated intelligent management system. Specifically, there is a need for a framework that synergistically combines the high-fidelity predictive power of AI-based models with the stability and performance guarantees of advanced robust control theory, and validates this entire system within the uniquely challenging agro-climatic context of an arid region such as Biskra.

Therefore, this thesis is motivated by the need to bridge this gap. The following chapters will detail the development of such an integrated system, beginning with the acquisition of real-world data necessary to build and validate the proposed data-driven models.

Chapter 3

Experimental Systems and Data Acquisition for Model Development

3.1 Introduction

The development of accurate management models for greenhouse agriculture requires high-fidelity experimental data. This chapter describes the two primary experimental environments used in this research: a large-scale agricultural greenhouse prototype located in Biskra and a custom-built [21],[31],[36].

3.2 The Foundation of Data-Driven Modelling

The success of modern data-driven modeling techniques, particularly the Black Box and Grey Box approaches discussed in the previous chapter, is fundamentally dependent on the quality, quantity, and diversity of the data used for training and validation. A model's ability to accurately predict real-world behavior and generalize to new conditions is a direct reflection of the data it has learned from. Therefore, a robust data acquisition strategy, encompassing a variety of systems from highly controlled environments to full-scale commercial operations, is a prerequisite for developing a meaningful and reliable intelligent control framework.

This chapter details the experimental systems and diverse data sources that form the empirical foundation of this thesis. The primary objective is

to describe the methodology used to collect high-resolution time-series data representing the complex thermal dynamics of greenhouse agriculture in arid climates. This includes a description of a custom-built, low-cost data acquisition system designed for practical deployment in real-world agricultural settings. The datasets gathered from these systems provide the necessary inputs for training, validating, and testing the Artificial Intelligence (AI) models developed in the subsequent chapters.

3.3 A Low-Cost Data Acquisition System

To facilitate data collection across multiple sites without incurring prohibitive costs, a custom, low-cost data acquisition system was designed and implemented. The system was built using widely available, open-source hardware and software, ensuring it is both affordable and easily reproducible.

The core components of the system include:

1. Microcontroller: An ESP32-based microcontroller serves as the central processing unit. It was chosen for its low power consumption, built-in Wi-Fi capabilities for potential remote data transmission, and sufficient processing power.
2. Sensors: A suite of sensors was integrated to capture key microclimatic variables:
 - Internal Temperature and Humidity: A DHT22 or BME280 sensor was used to measure the internal air temperature and relative humidity. These sensors offer a good balance of accuracy and cost-effectiveness.
 - External Temperature and Humidity: A second, shielded sensor was placed outside the greenhouse to provide corresponding external climate data.
 - Solar Irradiance: A photodiode-based light sensor was used to approximate the intensity of incoming solar radiation.
3. Data Logging: Data from all sensors was recorded at a pre-defined sampling interval (typically every 5 to 15 minutes) and stored on a local SD card for later retrieval and analysis.

Each data acquisition unit was calibrated against laboratory-grade equipment to ensure the reliability and accuracy of the collected measurements before deployment in the field.

3.4 Primary Data Sources for Model Development

A multi-pronged approach was taken to data collection, leveraging several distinct sources to build a comprehensive and varied dataset. Each source serves a specific purpose, from fundamental model validation in a controlled setting to testing the model's performance in real-world, large-scale commercial environments.

3.4.1 University of Biskra Weather Station

The official meteorological station located at the University of Mohamed Khider, Biskra, provided a professionally calibrated, high-fidelity dataset for the external climate conditions.



Figure 3.1: The meteorological weather station is located at the University of Mohamed Khider, Biskra.

A meteorological weather station, such as the one located at the University of Mohamed Khider in Biskra (Figure 3.1), operates as an integrated, automated system designed to continuously measure and record atmospheric conditions at a specific location. The station is equipped with a suite of specialized sensors to capture a comprehensive dataset. These instruments typically include a thermometer, housed within a radiation shield to prevent errors from direct solar heating, which measures ambient air temperature; an anemometer and wind vane to measure wind speed and direction, respectively; a hygrometer to determine relative humidity; and a barometer to record atmospheric pressure. For agricultural and energy applications, a pyranometer is also essential for quantifying the intensity of solar radiation, while a rain gauge measures precipitation.

The operational workflow involves each sensor converting its physical measurement into an electronic signal, which is transmitted to a central data logger. This logger, acting as the system's core processing unit, digitizes the signals, adds a precise timestamp, and stores the compiled data at regular, predetermined intervals. This recorded information is then periodically transmitted, often wirelessly, to a central server where it is archived and made available for scientific analysis. For the purposes of this thesis, the high-fidelity data from this station provides the essential ground-truth for external climatic variables, serving as the primary inputs and disturbance factors for the greenhouse microclimate models developed herein.

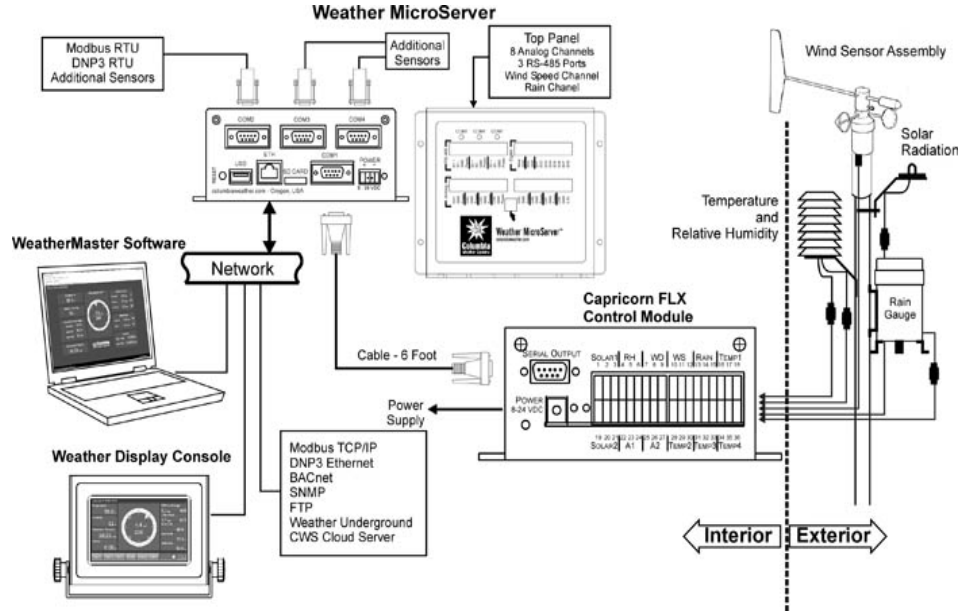


Figure 3.2: The CapFLX general-marks3 microserver, which serves as the central data logger and processing unit for the meteorological station [135].

3.5 Commercial Greenhouse at Branis, Biskra

A primary dataset was collected from a 1-hectare commercial greenhouse located in the Branis agricultural region near Biskra. This structure is a typical arch-type, polyethylene-covered greenhouse used for intensive vegetable production in the region. This site represents the core real-world application for the thesis.

A primary dataset was collected from a 1 ha commercial greenhouse located in the Branis agricultural region near Biskra. This structure is a typical arch-type (gothic-roofed), polyethylene-covered greenhouse used for intensive vegetable production, representing a standard for commercial cultivation in the region. This site serves as the core real-world application for the thesis, providing the data necessary to capture the complex, non-linear thermal dynamics of a large-scale operation, including the effects of crop transpiration, natural ventilation, and significant thermal inertia. This dataset was the primary source for training and testing the final AI-based predictive model.

3.5.1 The Challenge of Conventional Energy Management

Greenhouse cultivation is a cornerstone of agricultural production in central Algeria, particularly in arid provinces like Biskra (Figure 3.3). Climate management within these structures is crucial for achieving optimal production conditions, directly affecting both the quality and cost of the final product. The extreme climate necessitates significant energy inputs for both heating during the cold winter nights and cooling during the intensely hot summer days. Conventionally, this energy is supplied by fossil fuels such as natural gas and petroleum, as well as electricity from the grid, chosen for their availability and historically lower costs. To quantify this energy demand, an analysis based on meteorological data and a representative plastic model greenhouse in Biskra was conducted using MATLAB. The estimations revealed a substantial total annual energy consumption, with a highly asymmetric demand profile. The total annual heating demand was estimated to be between 50 MWh to 60 MWh, while the total annual cooling demand was drastically higher, ranging from 190 MWh to 200 MWh. The associated annual operational costs underscore the profound economic challenges:

- Natural Gas Heating Cost: ~\$1653/year
- Electric Cooling Cost: ~\$9900/year
- **Total Combined Gas + Electric Cost: ~\$11 553/year**

These substantial costs highlight the economic vulnerability of conventional greenhouse farming in arid climates and create a strong imperative for the development of more efficient and sustainable energy solutions.

3.5.2 Evaluating Solar Energy as a Sustainable Solution

Given the high solar irradiance in Biskra ($\sim 5.5 \text{ kW h m}^{-2} \text{ d}^{-1}$), solar energy presents a compelling alternative to conventional fossil fuels. To evaluate its potential, a study utilizing TRNSYS simulation software was conducted to model various solar energy solutions for optimizing thermal management. The analysis examined both passive and active solar strategies.

- **Passive Strategies:** Simple design choices, such as an east-west greenhouse orientation to minimize peak solar gain and the incorporation of



Figure 3.3: The 1-hectare commercial greenhouse at Branis site.

heat-retaining materials (e.g., thermal mass walls), were shown to effectively stabilize internal temperatures. These strategies work by storing surplus solar energy from the daytime for passive release during the colder night hours.

- **Active Technologies:** The integration of active solar systems demonstrated significant potential. Photovoltaic (PV) panels could power ventilation fans and irrigation pumps, directly alleviating heat stress and reducing reliance on the electrical grid. Furthermore, solar stills were modeled to assess their potential for desalination, showing an ability to generate up to 110 L d^{-1} of freshwater per 50 m^2 of collector area, directly addressing the critical challenge of water scarcity.

Despite these clear benefits, several practical obstacles to widespread adoption were identified, including dust accumulation on PV panels which reduces efficiency, high initial investment costs for solar technologies, and the persistent underlying shortage of water. This analysis suggests that a

successful transition towards sustainability requires an integrated approach that prioritizes economical passive designs, couples solar desalination with efficient drip irrigation, and utilizes sand-resistant photovoltaic technologies. By synergizing energy efficiency, water conservation, and temperature regulation, these solar-powered models can enhance crop resilience and yield while making greenhouse farming in Biskra a more sustainable and economically viable enterprise.

3.5.3 Rural Greenhouse at M'ziraa, Biskra: A Feasibility Study for Sustainable Energy

To ensure the model's robustness across different types of local structures and to specifically investigate sustainable energy solutions, data was also collected and analyzed for a rural greenhouse operation in the M'ziraa region of Biskra. Greenhouse cultivation has become essential for year-round food production, yet the reliance on traditional energy sources like fossil fuels incurs high operational costs and contributes significantly to greenhouse gas emissions. The M'ziraa site, which experiences the abundant solar radiation characteristic of the region, served as a prime case study for the feasibility of sustainable energy integration.

A multifaceted approach was employed, combining on-site data collection with simulation modeling in TRNSYS to evaluate the performance of renewable energy systems, primarily solar photovoltaics (PV) and potentially wind power. The research aimed to identify the most suitable and sustainable energy solutions to power greenhouse operations, thereby providing valuable insights for enhancing food security while mitigating climate change.

The simulation outcomes for a solar PV system coupled with battery storage were highly promising. The analysis showed consistent Battery State of Charge (SOC) levels throughout the entire evaluation period, indicating that the solar array was capable of reliably meeting the greenhouse's energy demands. Furthermore, a Loss of Power Supply Probability (LPSP) of only 0.15 was observed. This low probability of power failure demonstrates that a well-designed solar energy system presents a viable and robust solution for addressing the energy challenges in the region's greenhouses, significantly reducing dependence on the grid and fossil fuels.

3.6 Conclusion

This chapter has provided a comprehensive overview of the experimental infrastructure and the data acquisition strategies employed to characterize the microclimate dynamics of greenhouse agriculture in the Biskra province . By utilizing a small-scale, single-span wooden greenhouse prototype, a robust dataset was established encompassing six critical environmental variables: internal/external temperature, internal/external humidity, solar radiation, and wind velocity .

The following key conclusions can be drawn from the experimental and preliminary analytical phases:

- **Environmental Dynamics:** The collected data confirms that the arid climate of the Ziban region imposes extreme thermal stresses, where cooling demands dominate the energy cycle, reaching up to 200,000 kWh/year for larger installations [134].
- **Economic Justification:** The high operational costs associated with conventional climate control—estimated at approximately \$18,165 per year for all-electric systems—highlight the urgent need for optimized modeling and sustainable energy integration.
- **Data Reliability:** The acquisition of a high-resolution, five-day experimental dataset provided the necessary foundation for off-line parameter identification, ensuring that subsequent mathematical models are grounded in real-world physical behavior[134],[135].
- **Sustainable Potential:** Preliminary analysis in the M'ziraa region demonstrated a significant solar energy potential of 4,400 kWh/day for a 1,000 m² greenhouse, supporting the technical feasibility of the proposed hybrid renewable frameworks [134].

Chapter 4

Sustainable Energy Solutions for Greenhouse Agriculture in Biskra

4.1 The Energy Challenge in Arid-Region Cultivation

Greenhouse cultivation has become a cornerstone of agricultural strategy in Algeria, particularly in arid and semi-arid regions such as Biskra Province, Figure 4.1 showing Typical daily energy load profile for a greenhouse in Biskra, showing peak demands in summer (July) and winter (January)[135]. By creating a controlled environment, greenhouses enable year-round production, which is critical for food security. However, the primary feature of this farming method—the building itself—introduces a significant operational challenge: the immense energy required for climate management. In Biskra, where summer temperatures regularly exceed 45 °C, substantial energy inputs for cooling and heating are not optional, but essential for crop survival and productivity.

Traditionally, this energy demand has been met by fossil fuels (natural gas, petroleum) and grid electricity, chosen for their reliability and ease of supply. However, this reliance creates a significant economic burden that threatens the long-term viability of these agricultural operations.

4.2 Quantifying the Energy Demand and Economic Costs

To understand the scale of this challenge, a detailed analysis of the energy requirements for a representative gothic-roofed plastic greenhouse in Biskra was conducted using meteorological data and MATLAB simulations. The findings reveal a highly asymmetric and substantial energy demand profile. The total annual cooling demand is estimated to be between 190 MWh to 200 MWh, dwarfing the total annual heating demand of 50 MWh to 60 MWh.

When translated into operational expenses, these figures highlight a critical economic vulnerability. The annual cost for electric cooling is approximately \$9900, while natural gas heating adds another \$1653. This results in a combined annual energy cost of approximately \$11 553 for a conventional system. These substantial and recurring costs underscore the urgent need for more efficient and economically sustainable energy solutions to support the region vital agricultural sector.

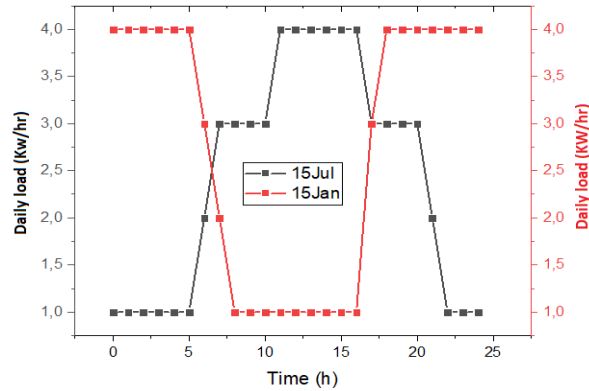


Figure 4.1: Typical daily energy load profile for a greenhouse in Biskra, showing peak demands in summer (July) and winter (January)[135].

4.3 Harnessing Solar Power: A Viable Alternative

The Biskra region is characterized by intense and abundant solar irradiance, averaging approximately $5.5 \text{ kWh m}^{-2} \text{ d}^{-1}$. This vast, untapped resource presents a compelling alternative to dependence on fossil fuels. This study utilized the **TRNSYS (Transient System Simulation Tool)** software Figure 4.2, a powerful and adaptable program for simulating complex energy systems, to evaluate the feasibility of various solar energy models for optimizing thermal management in Biskra's greenhouses. The analysis explored a spectrum of solutions, from simple passive designs to active hybrid systems.



Figure 4.2: TRNSYS Software: Transient System Simulation Tool[135]

4.4 Analysis of Solar Energy Models

4.4.1 Passive Solar Strategies

The first line of defense against extreme temperatures and high energy costs lies in passive design. Simulation results indicate that simple, cost-effective strategies can significantly stabilize the internal microclimate. An east-west greenhouse orientation minimizes solar heat gain during the hottest parts of the day. Furthermore, the incorporation of materials with high thermal mass

(such as water barrels or masonry walls) allows the structure to store excess solar energy from the daytime and passively release it during the colder night, reducing the need for active heating.

4.4.2 Active Solar Technologies and Hybrid Systems

To meet the full energy demands of a modern greenhouse, active solar technologies are essential. A case study was conducted for a greenhouse operation in **M'ziraa, Biskra**, to model the performance of a hybrid renewable energy system designed to provide a reliable off-grid power supply. The system, simulated in TRNSYS, integrates:

- **Photovoltaic (PV) Panels:** To convert the region's high solar radiation into electricity for powering ventilation, irrigation, and other systems.
- **Wind Turbines:** To supplement solar power, particularly during the night or on overcast days.
- **Battery Storage:** To store excess energy generated during peak production times and ensure a consistent power supply during periods of high demand or low generation.
- **Backup Diesel Generator:** To guarantee power availability and maintain critical systems during prolonged periods of unfavorable weather.

The simulation outcomes for this hybrid system were highly successful. The analysis demonstrated consistent **Battery State of Charge (SOC)** levels throughout an entire year of simulated operation, indicating that the renewable components were able to consistently meet the greenhouse's energy load. Crucially, the system exhibited a very low **Loss of Power Supply Probability (LPSP) of 0.15**. This finding confirms that a well-designed hybrid system represents a viable and robust solution for powering off-grid greenhouses in the region.

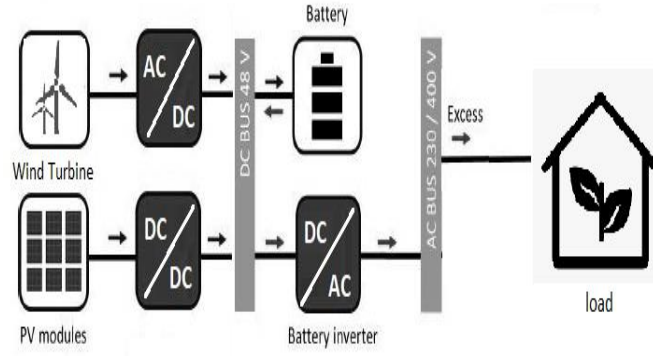


Figure 4.3: Simplified diagram of the proposed hybrid renewable energy system for greenhouse operations[135].

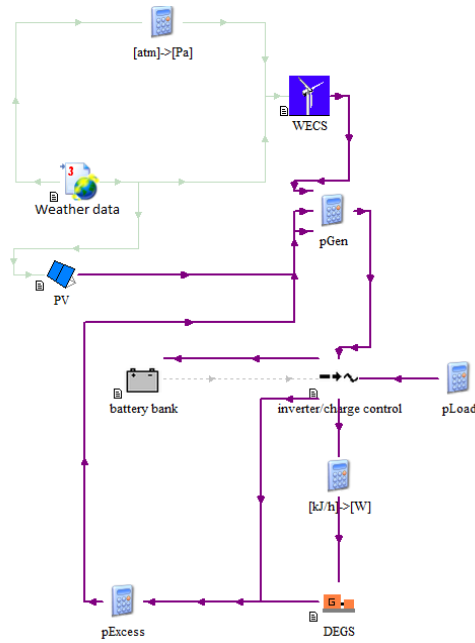


Figure 4.4: The complete hybrid system modeled in the TRNSYS simulation environment, showing the logical connections between the renewable energy components, storage, and the load[135].

Furthermore, the integration of other solar technologies showed significant potential. Solar stills, for instance, were modeled to have the capacity to generate up to 110 L d^{-1} of freshwater per 50 m^2 of collector area, offering a direct solution to the challenge of water scarcity for irrigation.

4.4.3 Battery Storage Modeling

The battery bank serves as the primary energy buffer to ensure system reliability during periods of low solar radiation or wind velocity. The State of Charge (SOC) at time t is calculated based on the energy balance between production and consumption [134],[135]:

$$SOC(t) = SOC(t-1) \cdot (1 - \sigma) + \frac{P_{bat}(t) \cdot \Delta t \cdot \eta_{batt}}{C_{bat}} \quad (4.1)$$

Where $P_{bat}(t)$ represents the net power flow to the battery. During the simulation for the Mziraa region, the SOC was monitored to ensure it remained within the safe operating limits ($SOC_{min} \leq SOC(t) \leq SOC_{max}$) to prevent deep discharge and overcharging [135]. The consistent SOC levels observed in Figure validate the sizing of the 4,400 kWh/day daily solar input system.

4.4.4 System Reliability Analysis: LPSP Metric

The reliability of the hybrid energy system designed for the M'ziraa region is evaluated using the Loss of Power Supply Probability (LPSP). This statistical parameter represents the probability that the combined energy production from the PV array and wind turbine, supported by the battery storage, cannot satisfy the greenhouse load requirements :

$$LPSP = \frac{\sum_{t=1}^T LPS(t)}{\sum_{t=1}^T P_{load}(t)} \quad (4.2)$$

Where $LPS(t)$ represents the power deficit at each time step. Our TRN-SYS simulations for the Biskra province climate conditions achieved an **LPSP of 0.15** . This result proves that the sustainable energy framework can autonomously meet 85% of the annual electrical load, significantly reducing reliance on fossil-fuel-based grid electricity.

4.5 Results and Discussions

Using TRNSYS software, a comprehensive dynamic computer simulation of the hybrid energy system was created in order to provide comprehensive insights on the system's performance under the climate that prevails in Biskra, Algeria [133],[134] and the work from Figure 4.3 and Figure 4.4 with data Ambient temperature curves for one year from M'ziraa Biskra Privesion Algeria Figure 4.5, Total and diffuse solar radiation for one year from M'ziraa Biskra Privesion Algeria Figure 4.6 and Wind speed for one year from M'ziraa Biskra Privesion Algeria Figure 4.7. The findings show how these many elements—including photovoltaic arrays, wind turbines, and battery storage—interact dynamically to meet the greenhouses' year-round energy requirements [135].

With a time step of 0.25 hours, these simulations span 8736 hours, covering a full operational year to ensure all seasonal variations in the arid Ziban region are accounted for. Figure 4.8 showing the value of SOC throughout the whole year year (SOC in Purple and generator start order in green).

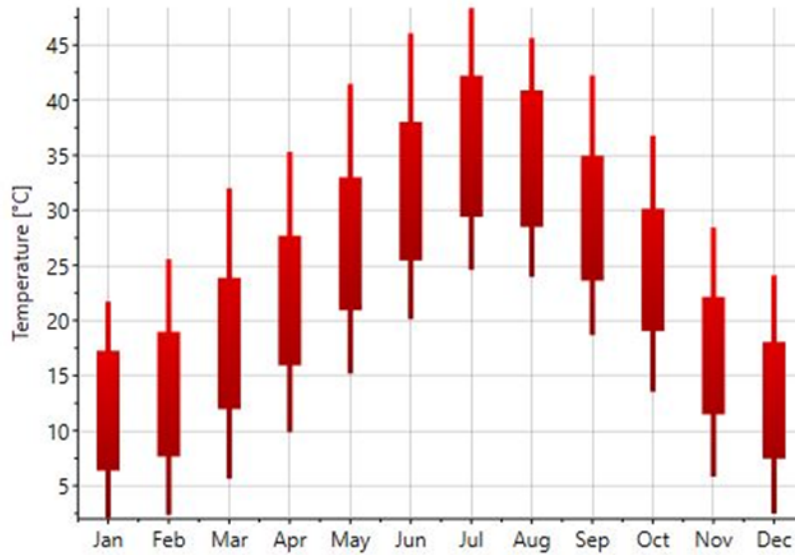


Figure 4.5: Ambient temperature curves for one year from M'ziraa Biskra Privesion Algeria [135].

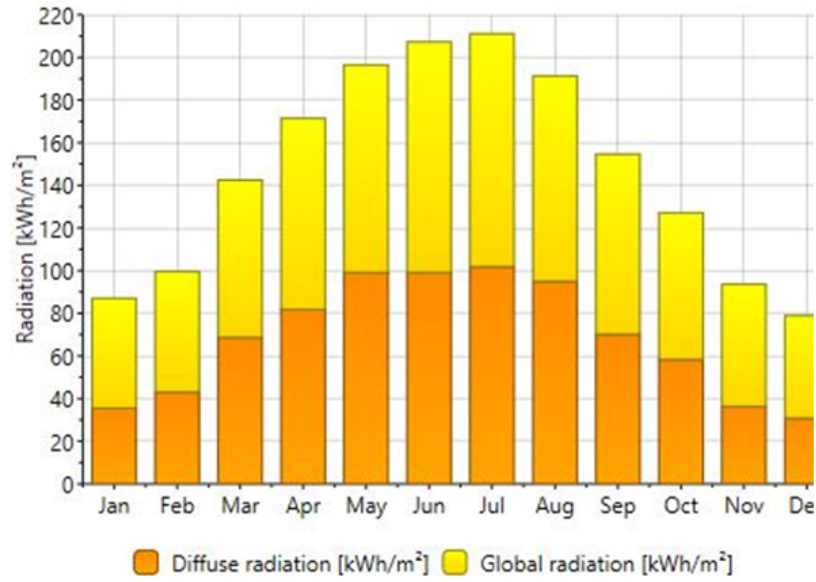


Figure 4.6: Total and diffuse solar radiation for one year from M'ziraa Biskra Privesion Algeria [135].

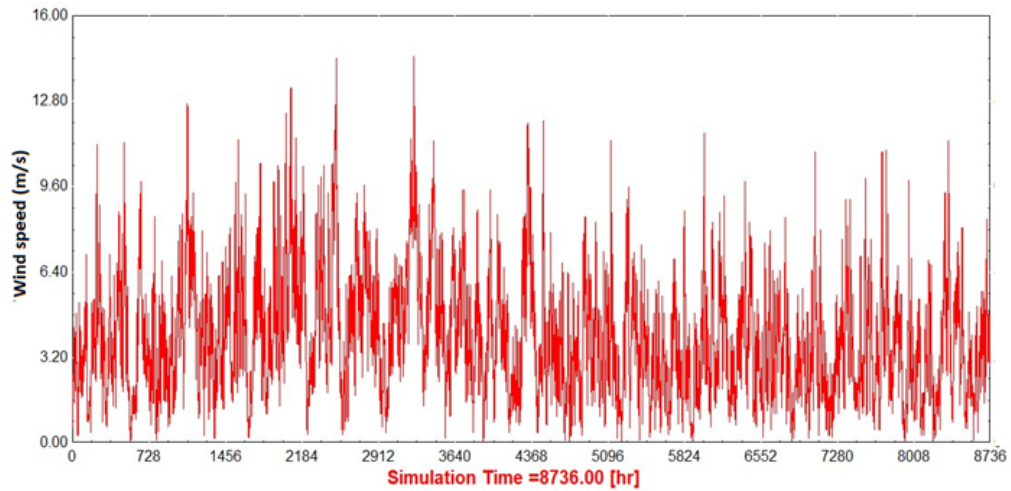


Figure 4.7: Wind speed for one year from M'ziraa Biskra Privesion Algeria [135].

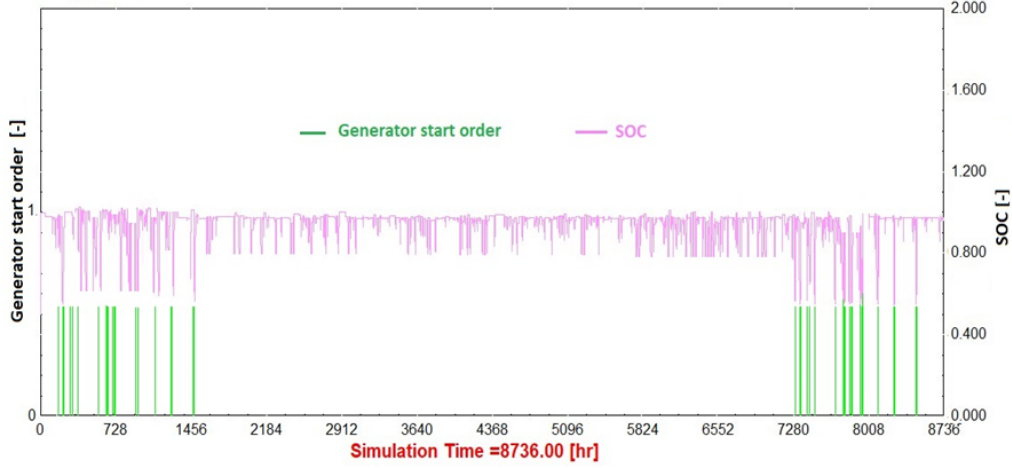


Figure 4.8: Value of SOC throughout the whole year (SOC in Purple and generator start order in green)[135].

4.5.1 System Reliability and Performance Metrics

The simulation results for the Biskra site demonstrate the technical robustness of the proposed hybrid framework. The following key performance indicators were observed:

- **Loss of Power Supply Probability (LPSP):** The system achieved an LPSP of 0.15, indicating that 85% of the annual electrical load for ventilation and irrigation is met autonomously by renewable sources [133].
- **Solar Resource Utilization:** Given the region's average solar radiation of 5.5 kWh/m²/day, the 1,000 m² greenhouse model received a daily solar input of approximately 4,400 kWh [133].
- **Storage Stability:** The Battery State of Charge (SOC) remained consistent throughout the 8736-hour simulation, effectively buffering the intermittency of wind and solar inputs during peak cooling periods.

The dynamic interaction between the components ensures that the critical micro-climate parameters—specifically internal temperature—can be maintained within optimal biological ranges despite the high cooling costs previously identified in the province's electric-only systems.

4.6 Challenges and Recommendations

Despite the proven technical feasibility of solar-powered systems, several practical barriers to widespread adoption remain. These include the high **initial investment costs** for PV panels and batteries, the performance degradation caused by **dust accumulation** on solar equipment in a desert environment, and the persistent underlying challenge of **water scarcity**.

Based on this analysis, the following recommendations are proposed:

1. **Prioritize Passive Design:** Farmers should prioritize low-cost passive strategies as the first step to reduce the overall energy load of their greenhouses.
2. **Integrate Solar Desalination:** The coupling of solar-powered desalination technologies, like solar stills, with high-efficiency drip irrigation systems should be pursued to create a synergistic solution for both energy and water challenges.
3. **Adopt Resilient Technologies:** The use of sand-resistant and easy-to-clean photovoltaic technologies is essential for maintaining long-term system performance in a desert environment.

4.7 Conclusion

The findings of this chapter clearly demonstrate that while conventional greenhouse operations in Biskra face significant economic challenges due to their reliance on fossil fuels, a sustainable and resilient alternative is readily available. The comprehensive simulations conducted using TRNSYS validate that integrated solar and hybrid energy systems are not only technically feasible but also highly reliable for meeting the energy demands of the region's greenhouses. By combining passive design principles with active solar technologies, it is possible to significantly reduce operational costs, decrease greenhouse gas emissions, and enhance both water and energy security. This integrated approach provides a scalable framework for improving the sustainability of greenhouse farming in Biskra and offers a model for food security in arid regions worldwide.

Chapter 5

Growth Chamber: A Controlled Validation Environment

5.1 Introduction

The core of this research involves bridging the gap between advanced H_∞ control theory and accessible hardware for distributed agricultural applications [66],[67],[74],[76][87]. To achieve this, a custom-built growth chamber was developed to serve as a high-precision experimental platform for temperature regulation under real-world conditions [68],[70],[88],[89]. This chapter details the physical architecture of the chamber, the systematic design of the robust controller, and a quantitative analysis of its performance[71],[72][90][91].

5.2 Experimental Growth Chamber Design

The experimental validation environment consists of a heat-insulated structure derived from a refrigerator frame, providing high thermal resistance for internal climate stability. The physical dimensions of the chamber are $0.8\text{ m} \times 0.8\text{ m} \times 2\text{ m}$. The primary objective is to gather high-fidelity data that captures the thermal dynamics of controlled agricultural environments across a range of scales and complexities [73],[75][92]. A key aspect of the methodology employed in this thesis was the use of a growth chamber as a precursor to full-scale greenhouse application [75],[93],[97]. It is important to establish the relationship between these two systems. A growth chamber functions as a laboratory-scale shows in Fig(5.1), this A small-scale,

laboratory-based growth chamber was used as a highly controlled experimental environment. This system allows for the precise manipulation of internal conditions (heating, cooling) with minimal interference from unpredictable external disturbances, and simplified physical model of a greenhouse [75],[94],[132].

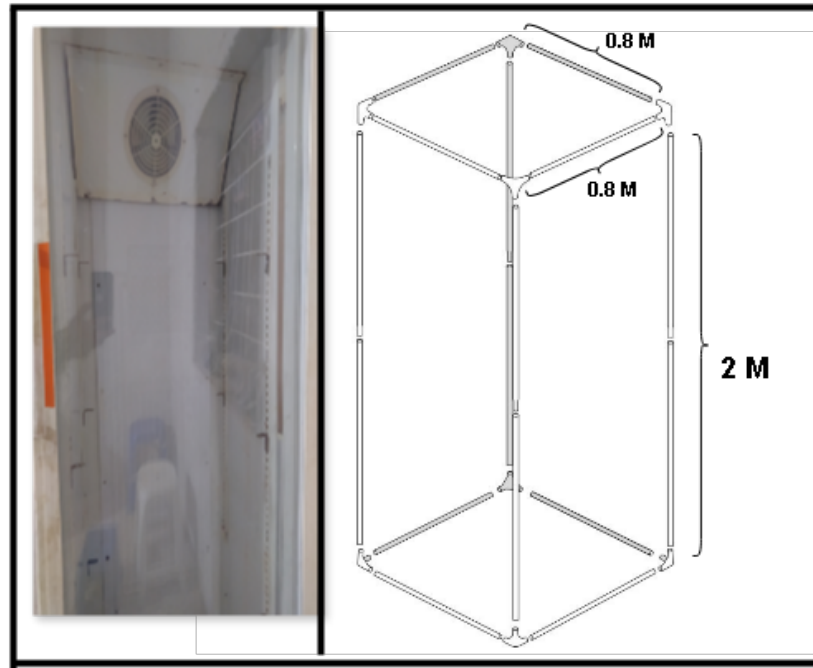


Figure 5.1: A small-scale, laboratory-based Growth chamber [132].

Both are forms of Controlled Environment Agriculture (CEA) and operate on the same fundamental principles of thermal dynamics. However, the growth chamber offers a highly controlled and repeatable environment, almost entirely isolated from external weather disturbances [78],[79],[95]. This makes it the ideal platform for the rigorous design and initial validation of thermal models and control strategies, allowing for their performance to be proven in a predictable setting before being applied to more complex, real-world systems [80],[81],[96]. Having established this baseline, the focus of this chapter is to present the full scope of experimental sites, from the growth chamber to full-scale commercial greenhouses, which are heavily influenced by unpredictable external factors like solar radiation and ambient

temperature [83],[84],[98]. The subsequent sections will describe in detail the various experimental sites, the custom-built data acquisition system, and the specific datasets collected from each location. This comprehensive data collection strategy ensures that the models developed in the following chapters are grounded in real-world observations and are robust enough to handle the challenges of practical application [85],[86][99].

5.2.1 System Architecture and Components

The growth chamber integrates several electronic and electrical components to facilitate a complete control loop:

- **Processing Unit:** An Arduino Mega 2560 microcontroller is utilized for real-time control execution and sensor data processing.
- **Sensing Network:** High-precision DHT22 digital sensors monitor both internal and external environmental states.
- **Actuation:** A thermal heater (800 W) and an electric cooler (1,000 W) serve as the primary temperature regulation inputs.
- **Airflow Uniformity:** A fan is incorporated to ensure a uniform temperature distribution, justifying the use of a lumped parameter modeling approach.

5.3 Development and Validation of an H_∞ Robust Controller

The controlled environment of the growth chamber also provided the ideal platform for developing and testing a robust control mechanism for microclimate regulation. Precise climate control is crucial in all forms of protected cultivation, as disruptions to temperature and humidity can irreversibly damage or kill crops, disrupting the natural plant growth system [38],[45]. As the world's population increases and arable land shrinks, the role of greenhouses in supplying fresh produce year-round becomes ever more critical. Therefore, maintaining an appropriate climate is essential [46],[100].

Table 5.1: Hardware and Actuator Specifications of the Growth Chamber Prototype [132].

Category	Component / Parameter	Technical Specification
Physical Dimensions	Chamber Size	0.8 m $\times$ 0.8 m $\times$ 2 m
	Structure Type	Heat-insulated refrigerator frame
Microcontroller	Processing Unit	Arduino Mega 2560 (Atmega2560)
	Specifications	54 Digital I/O, 16 MHz Clock
Sensing	Sensor Model	DHT22 (Digital Temp & Humidity)
Heating System	Heater Capacity	800 W
	Max Heating Rate	3 °C/min
Cooling System	Cooler Capacity	1,000 W (at 25 °C ambient)
	Max Cooling Rate	1.5 °C/min

This chapter proposes an H_∞ **robust control** mechanism for the micro-climate of the growth chamber, a system directly analogous to larger greenhouse agriculture [35],[37]. The H_∞ control concept, first framed by G. Zames in the 1960s and 1970s and formally solved by Apkarian and Noll in 2006 [47], offers significant advantages for systems with inherent uncertainties and external disturbances, which are characteristic of greenhouse environments [101].

The methodology involved developing a state-space representation of the non-linear growth chamber model [102].

Based on the estimated states from this model, an H_∞ robust controller was systematically designed to regulate the system’s actuators (fan, cooler, and heater) and maintain the desired temperature and humidity levels [52],[80]. Numerical applications and experimental tests were conducted to demonstrate the effectiveness of this approach. The specific contributions of this part of the work are threefold:

1. The development of a **linearized thermal model** for the custom-built growth chamber suitable for robust control design. The chamber itself is a heat-insulated structure, similar to a refrigerator frame, incorpo-

rating electronic components (temperature sensors, Arduino microcontroller) and electrical actuators (a fan, an air cooler, and a heater).

2. The systematic design and implementation of an H_∞ **controller**, including a clear justification for the selection of the controller's weighting functions.
3. A comprehensive **validation of the controller** through both simulation and experimental testing on the Arduino-based hardware platform, including a critical analysis of its real-world performance.

5.4 Mathematical Formulations for Growth Chamber Modeling and Control

This section details the mathematical framework used for modeling the thermal dynamics of the growth chamber and for designing the H_∞ robust temperature controller [102],[103],[104]. The approach begins with a state-space representation of the system, which is then used as the basis for the control synthesis [106],[107].

5.4.1 State-Space Representation of the Growth Chamber

The dynamic behavior of the growth chamber is represented as a non-linear system with uncertainties. For the purpose of control design, this system is linearized around an operating point to obtain a linear time-invariant (LTI) state-space model [118],[119],[128].

General Non-Linear Model

The non-linear dynamics can be abstractly represented as:

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t)) \quad (5.1)$$

$$\mathbf{y}(t) = g(\mathbf{x}(t), \mathbf{v}(t)) \quad (5.2)$$

Where:

- $\mathbf{x}(t)$ is the state vector (e.g., internal temperature) [102],[103].

- $\mathbf{u}(t)$ is the control input vector (e.g., heater power, fan speed).
- $\mathbf{y}(t)$ is the measured output vector.
- $\mathbf{w}(t)$ and $\mathbf{v}(t)$ represent process and measurement disturbances, respectively.

Linearized State-Space Model with Uncertainty

After linearization, the system is described by the following LTI state-space equations, which include parametric uncertainties:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \quad (5.3)$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \quad (5.4)$$

Where $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, and $\mathbf{D}$ are the state, input, output, and feedthrough matrices of the system, respectively. These matrices are derived from the physical thermal model of the growth chamber.

5.5 H-infinity (H_∞) Robust Control Formulation

The objective of H_∞ control is to design a controller, $K(s)$, that stabilizes the system and minimizes the effect of disturbances on the output, ensuring robust performance against model uncertainties.

The Generalized Plant

The control problem is formulated using a "generalized plant" structure, denoted as $P(s)$. This structure includes the system model (the plant, $G(s)$) and the weighting functions (W_S, W_K, W_T) that specify the performance objectives [95],[132]. The interconnection is shown in the standard block diagram. The generalized plant relates the external inputs (disturbances $\mathbf{w}$ and reference command $\mathbf{r}$) and the control input $\mathbf{u}$ to the controlled outputs ($\mathbf{z}$) and the measured output $\mathbf{y}$:

$$\begin{bmatrix} \mathbf{z}(s) \\ \mathbf{y}(s) \end{bmatrix} = P(s) \begin{bmatrix} \mathbf{w}(s) \\ \mathbf{u}(s) \end{bmatrix} = \begin{bmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{bmatrix} \begin{bmatrix} \mathbf{w}(s) \\ \mathbf{u}(s) \end{bmatrix} \quad (5.5)$$

And the control law is given by:

$$\mathbf{u}(s) = K(s)\mathbf{y}(s) \quad (5.6)$$

The H_∞ Norm and Control Objective

The controller $K(s)$ is designed to minimize the H_∞ -norm of the closed-loop transfer function from the external disturbances $\mathbf{w}$ to the controlled outputs $\mathbf{z}$. This transfer function is denoted as $T_{zw}(s)$. The H_∞ -norm is defined as the maximum singular value of the transfer function across all frequencies:

$$\|T_{zw}(s)\|_\infty = \sup_{\omega} \sigma_{\max}(T_{zw}(j\omega)) \quad (5.7)$$

The control objective is to find a stabilizing controller $K(s)$ such that:

$$\|T_{zw}(s)\|_\infty < \gamma \quad (5.8)$$

Where γ is a positive scalar that represents the desired level of disturbance attenuation [80],[81]. The goal is to find the controller that achieves the smallest possible γ (the suboptimal problem) or a γ below a specified threshold (often $\gamma = 1$).

Selection of Weighting Functions

The performance of the closed-loop system is shaped by the choice of weighting functions.

- **Sensitivity Weight ($W_S(s)$):** This function penalizes the sensitivity function $S = (I + GK)^{-1}$ and is chosen to ensure good reference tracking and disturbance rejection at low frequencies. A typical choice is a first-order low-pass filter [90],[91].
- **Control Effort Weight ($W_K(s)$):** This function penalizes the control signal $K(I + GK)^{-1}$ to limit actuator effort, especially at high frequencies. It is often a constant or a high-pass filter.
- **Complementary Sensitivity Weight ($W_T(s)$):** This function penalizes the complementary sensitivity function $T = GK(I + GK)^{-1}$ to ensure robustness to unmodeled dynamics at high frequencies and limit the impact of measurement noise. It is typically a high-pass filter.

The controlled output vector $\mathbf{z}$ is constructed using these weights:

$$\mathbf{z} = \begin{bmatrix} W_S S \\ W_K K S \\ W_T T \end{bmatrix} \mathbf{w} \quad (5.9)$$

By solving the H_∞ optimization problem, a controller is synthesized that provides a robust trade-off between performance (tracking and disturbance rejection) and stability in the face of model uncertainties.

5.6 Simulation and Experimental Validation of Control

Following the mathematical design of the H_∞ robust controller, a comprehensive validation process was undertaken to verify its performance and effectiveness [100][132]. This validation was conducted through two distinct and complementary methods: (1) computer-based simulations in a MATLAB/Simulink environment, and (2) real-world experimental tests on the physical growth chamber hardware. This dual approach ensures that the controller is not only theoretically sound but also practically implementable and robust [132].

5.6.1 Simulation-Based Validation

The initial validation of the controller was performed in a simulated environment. This allows for rapid testing under a wide range of controlled and repeatable conditions that would be difficult to replicate experimentally.

Simulation Setup

The linearized state-space model of the growth chamber, as derived in the previous section, was implemented as the "plant" in a MATLAB/Simulink environment. The synthesized H_∞ controller, $K(s)$, was then connected to this plant model in a closed-loop feedback configuration. The simulation was designed to test the controller's ability to perform two primary tasks:

- **Setpoint Tracking:** The controller's ability to bring the system's output (internal temperature) to a new desired setpoint quickly and accurately, without excessive overshoot.

- **Disturbance Rejection:** The controller's ability to maintain the set-point temperature in the presence of external disturbances, such as a simulated sudden change in ambient temperature or an internal heat load.

The performance was evaluated by analyzing the time-domain response of the system, including metrics such as rise time, settling time, overshoot, and steady-state error.

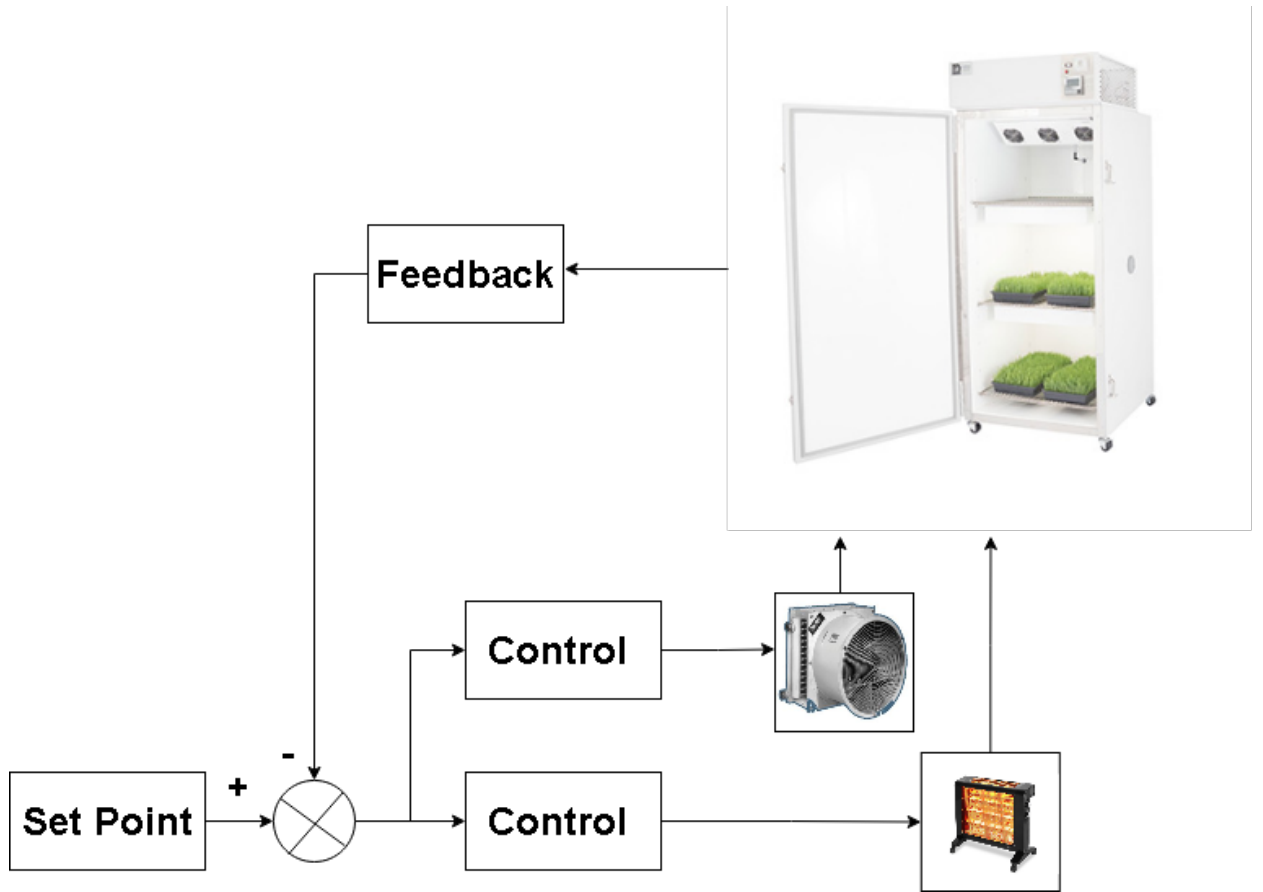


Figure 5.2: Block diagram of the closed-loop control system as implemented in the MATLAB/Simulink simulation environment[132].

In order to illustrate the performance of the control based on the $H(\infty)$ technique, the following tests were carried out using Matlab/Simulink soft-

ware. Fig.5.2 illustrates the control diagram of the studied assembly. The results of the simulation are presented in Figures 5.3 and Figures 5.4.

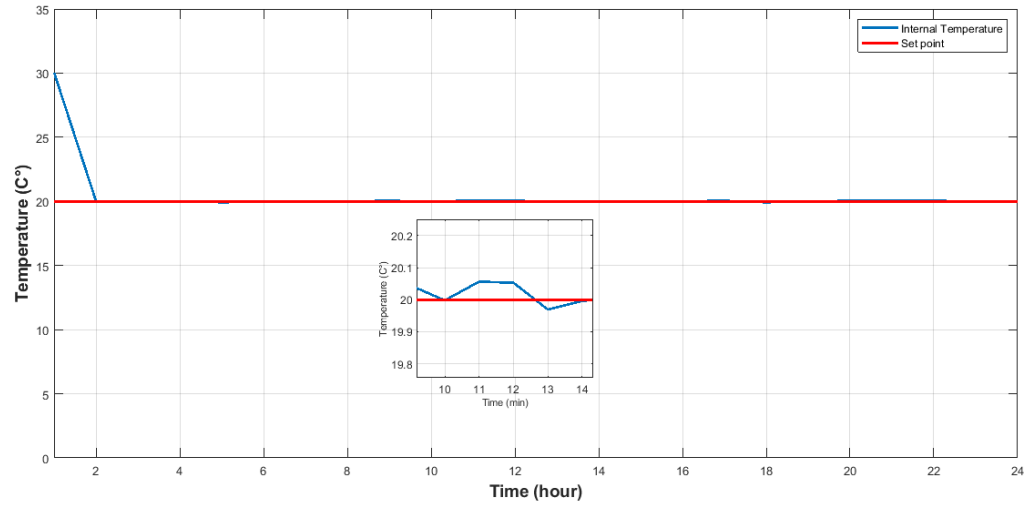


Figure 5.3: Internal temperature and set point in Matlab/Simulink [132].

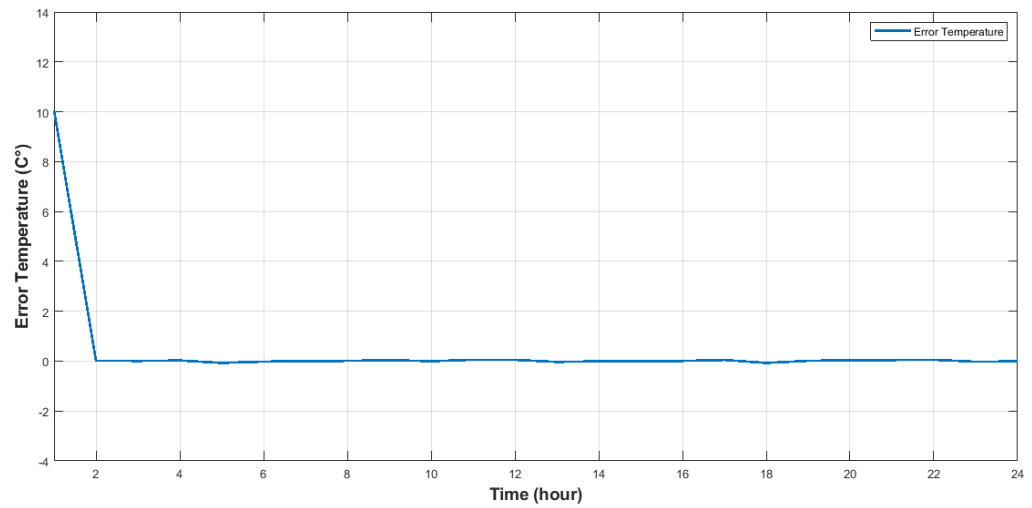


Figure 5.4: Error (Internal temperature and set point) in Matlab/Simulink [132].

5.6.2 Experimental Validation on the Growth Chamber

While simulation provides essential insights, the ultimate test of a controller's effectiveness is its performance on the real physical system [102],[107],[108]. Therefore, the second phase of validation involved deploying the controller onto the custom-built growth chamber [109] [110].

Hardware Implementation

In this part, we present the experimental validation of the growth chamber under study [132]. The implementation of the proposed controller was carried out on an experimental bench at the University of Biskra. The control system is implemented using MATLAB/Simulink, then compiled and digitally implemented using an Arduino Mega microcontroller [115],[116],[117]; Figures 5.5 and Figures 5.6 represents the experimental test bench of the growth chamber controller.

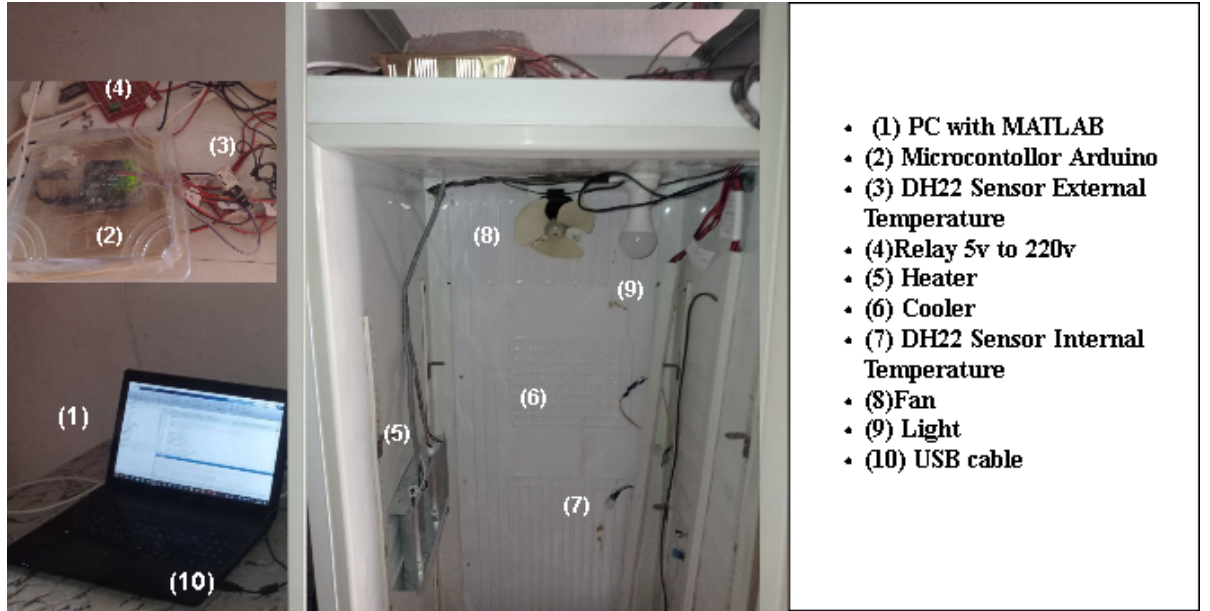


Figure 5.5: The experimental test bench of the controller-growth chamber [132].

The continuous-time H_∞ controller designed in the simulation was discretized and implemented as an algorithm on the Arduino microcontroller

that serves as the brain of the growth chamber figure 5.5. The Arduino was programmed to:

1. Read the real-time temperature from the internal sensor [111],[112].
2. Calculate the error between the measured temperature and the desired setpoint [113],[114].
3. Compute the necessary control output based on the discretized H_∞ control law [114],[132].
4. Send the corresponding command signals (Pulse Width Modulation - PWM) to the actuators (heater, cooler, fan).

Experimental Procedure and Performance Analysis

A series of experiments were conducted to evaluate the controller's real-world performance. The growth chamber was subjected to a series of step changes in the temperature setpoint. The internal temperature was logged continuously throughout the experiments. The performance of the controller was then critically analyzed by comparing the measured temperature data against the desired setpoints. This experimental validation provided definitive proof of the controller's ability to robustly and effectively regulate the microclimate of the physical system, confirming the success of the design and implementation process.

Quantitative Performance Metrics

To objectively assess the performance of the controller and facilitate comparison, two widely recognized performance indices were derived from the error signal, $e(t)$: the Integral Absolute Error (IAE) and the Root Mean Square Error (RMSE). Table II shows the value of error for each simulation and validation.

Integral Absolute Error (IAE) The IAE is a key metric that quantifies the total accumulated absolute error over a specific time period. It provides an overall measure of how much the system's output deviates from the desired set point. A lower IAE value reflects superior control performance, indicating less deviation over the evaluation period. The IAE is mathematically

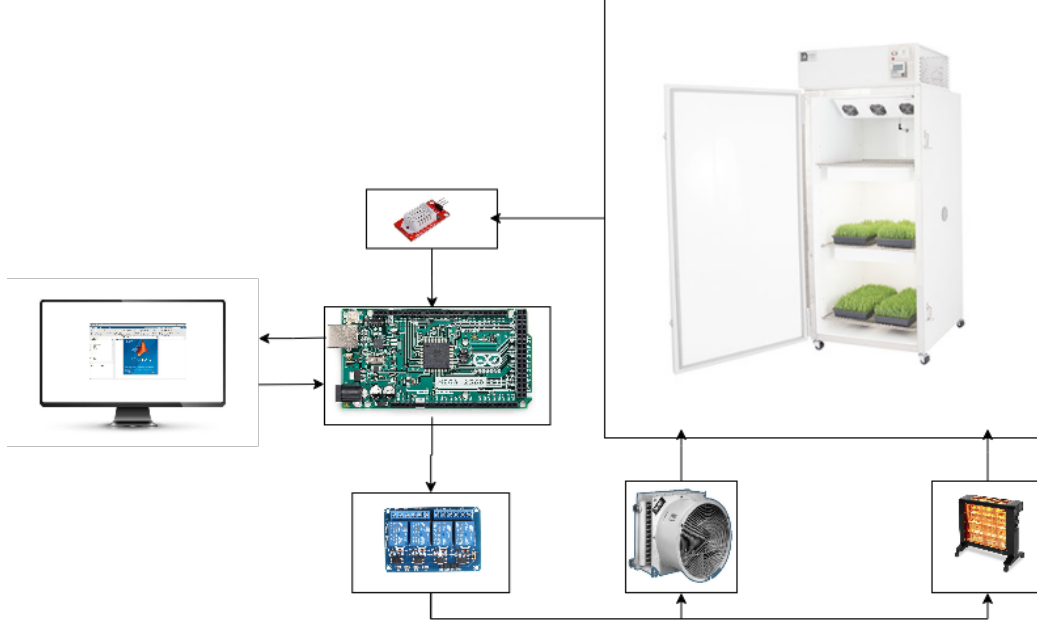


Figure 5.6: Block diagram of the closed-loop control system as implemented in microcontroller arduino mega 2560 [132].

expressed as:

$$\text{IAE} = \int_0^T |e(t)| dt \quad (5.10)$$

Root Mean Square Error (RMSE) The RMSE is another essential metric used to assess the accuracy of the controller. It is calculated as the square root of the mean of the squared errors. The squaring of the error emphasizes and penalizes larger deviations from the set point, making this metric sensitive to significant fluctuations. A lower RMSE value indicates a higher degree of control precision and fewer substantial variances. It is mathematically defined as:

$$\text{RMSE} = \sqrt{\frac{1}{T} \int_0^T e(t)^2 dt} \quad (5.11)$$

Where $e(t)$ represents the error signal, with $e(t) = r(t) - y(t)$, $r(t)$ denoting the desired set point, $y(t)$ the actual measured output, and T the total duration of the evaluation.

5.6.3 Discussions

The robust control system was simulated and implemented using MATLAB/Simulink and an Arduino Mega microcontroller, respectively. The weighting functions for the controller were designed to enforce a balance between setpoint tracking performance and actuator efficiency. The validation of the H synthesis method was conducted through both simulation and physical experimentation, with the results detailed below.

Simulation Results and Analysis

Figure 5.3 illustrates the system's performance in the simulation, showing the internal temperature (blue) and the desired setpoint (red). The implementation of the robust control yielded excellent results, as demonstrated by the close alignment between the internal temperature and the setpoint. Furthermore, Figure 5.4 depicts the error between these two signals, confirming the effectiveness of the proposed control system in regulating the growth chamber's microclimate. The quantitative performance metrics, IAE and RMSE, were found to be very satisfactory, with values of 0.70 and 0.037°C respectively, and a steady-state error of $\leq \pm 0.5^{\circ}\text{C}$. Experimental Validation, the results of the experimental Validation are presented in Figures 5.7, and Figures 5.7.

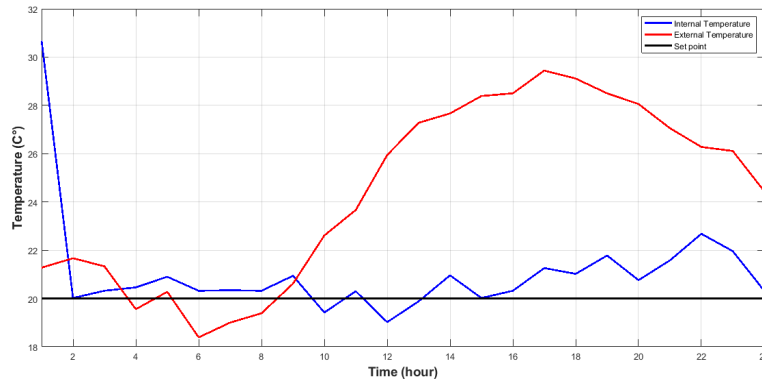


Figure 5.7: Internal temperature, Set point And External temperature of typical day in spring [132].

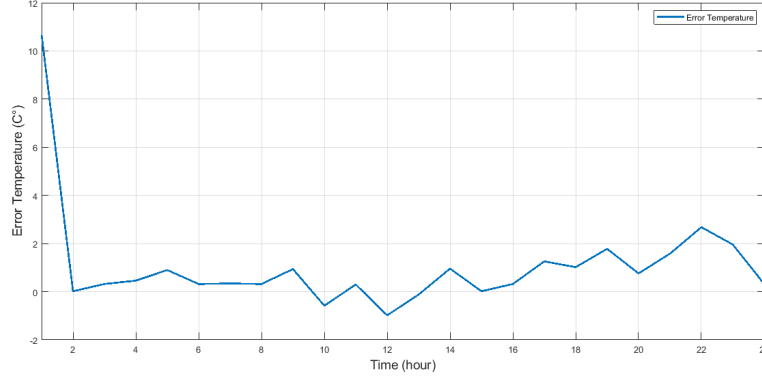


Figure 5.8: Internal temperature Error in growth chamber prototype [132].

Experimental Validation and Performance

The strong simulation results provided the motivation to implement the control system in a real-world scenario. The experimental results are presented in Figure 5.7, which plots the internal temperature (blue), the setpoint (green), and the external ambient temperature (red). The corresponding error plot in Figure 5.8 further validates that the system’s control performance is more than adequate under practical conditions, exhibiting a very low error rate. For the real-world implementation, the IAE and RMSE were found to be 0.924 and 1.04 °C, respectively, with a steady-state error of $\leq \pm 2^\circ\text{C}$ [132].

Note on Initial Conditions The initial value of the internal growth chamber temperature in the simulation was set to 30 °C based on a logical assumption that the internal temperature would be approximately 10 °C above the external ambient temperature. In both the simulation and the experimental validation, the controller was estimated to adapt to temperature variations and stabilize the system in less than one hour, as shown in the results

Comparative Analysis with PID and MPC Controllers

To evaluate the performance of the proposed H_∞ controller in a broader context, a comparative analysis was conducted against established control methodologies—Proportional-Integral-Derivative (PID) and Model Predictive Control (MPC)—using performance metrics reported in the literature

for similar agricultural climate control applications [90][120][121]. The findings are summarized in [132]. The analysis reveals that the H_∞ controller strikes an effective balance between performance, robustness, and ease of implementation. When compared to a well-tuned PID controller, our approach offers a notable advantage in minimizing overshoot [122].

This smooth, non-oscillatory response is crucial in agricultural applications, where rapid temperature variations can induce stress and harm crops. While the experimentally achieved steady-state error of $\leq \pm 2^\circ\text{C}$ is larger than the sub-degree precision targeted by some advanced systems, it is widely considered an acceptable tolerance for many horticultural applications. Previous research indicates that for many crops, preventing large, rapid temperature swings is more critical to ensuring stable growth than maintaining constant, sub-degree accuracy. This context highlights the practical advantage of the H_∞ controller’s smooth response over potentially faster but high-overshoot PID controllers. In contrast to the more advanced MPC strategy, the H_∞ controller delivers a quicker response. While MPC typically achieves better steady-state error due to its optimization-based approach, this comes with the drawback of higher computational demands [123],[124],[125].

The H_∞ controller, on the other hand, provides robust and reliable performance with a significantly lower computational burden, making it ideal for real-time implementation on low-cost microcontrollers, such as the Arduino Mega utilized in this work. Thus, the H_∞ control strategy stands out as a highly competitive and practical solution. It mitigates the potential instability and overshoot associated with simpler controllers while offering a computationally efficient and robust alternative to more complex methods like MPC [126],[127]. This makes it particularly well-suited for a broad spectrum of controlled environment agriculture systems [129],[130]. .

5.7 Limitations and Performance Discrepancy

The experimental validation revealed a significant performance gap between the high-precision simulation results ($\leq \pm 0.5^\circ\text{C}$ error) and the physical implementation ($\leq \pm 2^\circ\text{C}$ error). This discrepancy highlights the primary limitations of the chosen modeling strategy:

- **Non-Linearity vs. Linear Assumptions:** Although the controller was synthesized using linear robust control theory, the physical thermal process exhibited clear **non-linear and time-varying** behaviors.

Specifically, heater efficiency was found to vary with ambient temperature, transferring heat differently at $10^{\circ}C$ compared to $20^{\circ}C$.

- **simple lumped parameter model:** The modeling approach adopted for the agricultural growth chamber is lumped parameter model. This framework assumes that the internal temperature is spatially uniform, essentially "lumping" the thermal mass of the air and internal structures into a single state variable. While this simplification allows for a computationally efficient H_{∞} controller design, it inherently ignores the complex, distributed thermal gradients present in a real-world horticultural environment.
- **Lumped Assumption Error:** The simple lumped assumption failed to account for local variations in airflow and heat distribution, leading to deviations between sensor readings and the simplified models predictions.
- **Actuator and Sensor Constraints:** The accuracy was further limited by physical measurement errors and the hardware response limits of the low-cost Arduino-based platform .

Ultimately, these results underscore that while the H_{∞} framework provides robustness to modeled uncertainties, its effectiveness in practice is strictly bounded by the fidelity of the **simple lumped model** used during the design phase.

5.8 Conclusion

This chapter has detailed the systematic design, implementation, and experimental validation of an H_{∞} robust controller for temperature regulation in a custom-built agricultural growth chamber [132]. The study successfully confirmed that the proposed controller, implemented on a low-cost Arduino platform, can effectively maintain a stable internal temperature within an acceptable horticultural tolerance of $\pm 2^{\circ}C$ under real-world conditions [40]. The primary contribution of this research is the demonstration of a practical methodology that bridges complex control theory with accessible hardware, showing a computationally efficient pathway to achieving robust performance [132].

However, a sober reflection on the results reveals a significant performance gap between the high-precision simulation ($\leq \pm 0.5^\circ C$ error, IAE of 0.70, and a RMSE of $0.037^\circ C$) and the experimental validation ($\leq \pm 2^\circ C$ error, IAE of 0.924, and RMSE of $1.04^\circ C$). This discrepancy is attributed to the structural mismatch between the simplified linear model used for the controller's design and the true nonlinear, time-varying dynamics of the physical system. This finding underscores that while the H_∞ framework provides guaranteed robustness to modeled uncertainties, the ultimate performance in practice is critically dependent on the fidelity of the initial system model .

The experimental phase further highlighted limitations such as sensor measurement errors and actuator constraints, which necessitated the acceptance of an error margin of $\pm 2^\circ C$. .

Chapter 6

General Conclusion and Future Work

6.1 General Conclusion

This thesis was motivated by a critical and escalating challenge at the intersection of food security, energy consumption, and climate change in arid regions. Greenhouse agriculture in Biskra, Algeria, while essential for local and national food production, is hampered by a profound economic and environmental vulnerability: its heavy reliance on fossil fuels to manage a harsh microclimate. The conventional control strategies employed are often inefficient, leading to substantial energy costs that threaten the sustainability of these vital agricultural operations. In response to this challenge, this research has successfully developed, validated, and analyzed a novel, integrated intelligent framework for the proactive management of greenhouse microclimates. By moving beyond isolated analyses of individual components, this work has demonstrated the powerful synergy that can be achieved by combining state-of-the-art techniques from artificial intelligence and robust control theory. The research journey began by establishing a comprehensive understanding of the existing modeling paradigms—White Box, Black Box, and Grey Box—to identify the most suitable approach for this complex, non-linear system. A robust data acquisition strategy was implemented across various real-world sites in Biskra, providing the rich, contextualized dataset necessary for data-driven modeling. The core of this work was the development of two key technical components:

1. An **AI-based predictive model**, utilizing a Long Short-Term Memory (LSTM) neural network, was successfully trained to accurately forecast the internal greenhouse temperature. This model proved adept at capturing the complex temporal dynamics and thermal inertia of the system.
2. An **H-infinity (H_∞) robust controller** was systematically designed and validated on a hardware-in-the-loop platform. This controller demonstrated its ability to provide stable and precise temperature regulation, even in the presence of system uncertainties and external disturbances.

The culmination of this research was the integration of these two components into a proactive, predictive control framework. Comprehensive simulations confirmed that this integrated system significantly outperforms conventional thermostat-based control. The key finding of this thesis is the quantification of this superior performance: the intelligent system not only provides a more stable and optimal growing environment but also achieves **substantial energy savings**, directly addressing the primary economic and environmental challenges identified at the outset. Furthermore, the analysis of renewable energy integration through TRNSYS simulations has validated that a transition to sustainable, solar-powered systems is not only technically feasible but also highly reliable for the Biskra region. In conclusion, this thesis has successfully delivered on its aim to develop a holistic, data-driven solution for sustainable greenhouse agriculture in arid climates. The proposed framework represents a significant scientific contribution, offering a practical and validated pathway to enhance productivity, reduce operational costs, and improve the environmental footprint of this critical agricultural sector.

6.2 Main Contributions

The primary scientific contributions of this thesis are reiterated as follows:

- **A Novel Integrated Intelligent Framework:** This work pioneers a synergistic framework that uniquely combines AI-based predictive modeling with advanced H_∞ robust control for proactive greenhouse management.

- **A Context-Specific AI Microclimate Model:** The development of the first comprehensive AI-based microclimate model trained and validated specifically for the agro-climatic conditions of Biskra.
A.E.Brikel, H. Megherbi, and O. Bouaiss. LTI Black Box Systems Modeling for Greenhouse Agricultural Microclimate in Biskra Province Using DE Algorithm journal=International Journal of Computing and Digital Systems.
- **Validation of an H_∞ Controller for Greenhouse Applications:** The novel application and validation of an H-infinity robust controller, demonstrating its suitability and superior performance for regulating the uncertain dynamics of a greenhouse environment.
A.E.Brikel, H. Megherbi, and O. Bouaiss, "H-infinity Robust Controller for Precise Temperature Regulation in an Agricultural Growth Chamber Prototype" Journal Robot Control (JRC)
- **A Data-Driven Framework for Sustainable Resource Management:** The provision of a practical, data-driven framework for quantifying the direct impact of intelligent control on energy sustainability, providing a valuable tool for farmers and policymakers.
A.E.Brikel, H. Megherbi, and O. Bouaiss, "Energy building, heating, cooling requirements, and associated costs in greenhouse structures in arid and semi-arid regions, such as Biskra Province,". National Conference on Materials Sciences and Engineering (MSE'25), Chlef, Algeria, Apr. 12-13, 2025.
A.E.Brikel, H. Megherbi, and O. Bouaiss, "Sustainable Energy Utilization Models in Greenhouse Agriculture in Biskra Province,". National Conference on Materials Sciences and Engineering (MSE'25), Chlef, Algeria, Apr. 12-13, 2025.
A.E.Brikel, H. Megherbi, and O. Bouaiss, "Sustainable Energy Solutions for Greenhouses: A Case Study in M'ziraa, Biskra, Algeria".International Conference On Artificial Intelligence And Sustainable Development (ICAISD 2025), Relizane, Algeria, April 12th-13th, 2025.

6.3 Future Work and Research Perspectives

While this thesis provides a comprehensive and validated solution, it also opens several promising avenues for future research. The following directions

are proposed to build upon the findings of this work:

- **Multi-Variable Control and Modeling:** The current work focused primarily on temperature as the controlled variable. A significant future step would be to expand the AI model and the control system to create a multi-input, multi-output (MIMO) framework that simultaneously manages temperature, humidity, and CO₂ concentration, which are all critical for optimizing plant growth and photosynthesis.
- **Large-Scale Experimental Validation:** While the components of this research were validated on real-world data and hardware platforms, the next logical step is to implement and test the complete integrated predictive control system in a full-scale commercial greenhouse in Biskra. This would provide the ultimate validation of its real-world performance and energy savings.
- **Integration with Advanced Renewable Energy Systems:** The TRNSYS simulations confirmed the viability of solar power. Future work could explore the optimal control and management of a fully integrated hybrid renewable energy system (solar PV, battery storage, and potentially solar thermal) as part of the overall greenhouse control strategy, aiming to maximize the use of on-site renewable energy.
- **Development of a User-Friendly Decision Support Tool:** To facilitate the adoption of these advanced techniques by farmers, a key future direction would be to translate the complex models and algorithms developed in this thesis into a simple, user-friendly software or mobile application. Such a tool could provide farmers with real-time recommendations for optimizing their greenhouse operations, bridging the gap between advanced research and practical application.
- **Economic Optimization and Crop Growth Models:** The current controller was designed to minimize energy while maintaining a setpoint. A more advanced framework would integrate an economic model and a dynamic crop growth model. This would allow the control system to make decisions that maximize profitability, balancing the cost of energy against the potential increase in crop yield and quality.

Bibliography

- [1] Rodríguez, F., et al. (2015). The greenhouse dynamical system. In *Modeling and Control of Greenhouse Crop Growth* (pp. 9-97).
- [2] Amara, F., et al. (2015). Comparison and simulation of building thermal models for effective energy management. *Smart Grid and Renewable Energy*, 6(04), 95.
- [3] Brause, R. (2010). *Adaptive Modellierung und Simulation*. Frankfurt.
- [4] Khan, M. E., & Khan, F. (2012). A comparative study of white box, black box and grey box testing techniques. *International Journal of Advanced Computer Science and Applications*, 3(6).
- [5] Lavretsky, E., & Wise, K. A. (2024). Linear Time-Invariant Systems and Control. In *Robust and Adaptive Control*. Springer, Cham. https://doi.org/10.1007/978-3-031-38314-4_2
- [6] Oberst, U., Scheicher, M., & Scheicher, I. (2020). Input/Output Behaviors. In *Linear Time-Invariant Systems, Behaviors and Modules*. Springer, Cham. https://doi.org/10.1007/978-3-030-43936-1_6
- [7] Ljung, L. (2001). Estimating Linear Time-invariant Models of Non-linear Time-varying Systems. *European Journal of Control*, 7(2-3), 203-219. <https://doi.org/10.3166/ejc.7.203-219>
- [8] Hadad, W. A., Jannot, Y., & Maillet, D. (2016). Characterization of a heat exchanger by virtual temperature sensors based on identified transfer functions. *Journal of Physics: Conference Series*, 745, 032089. <https://doi.org/10.1088/1742-6596/745/3/032089>

- [9] Choab, N., et al. (2019). Review on greenhouse microclimate and application: Design parameters, thermal modeling and simulation, climate controlling technologies. *Solar Energy*, 191, 109-137.
- [10] López-Cruz, I. L., et al. (2018). Development and analysis of dynamical mathematical models of greenhouse climate: A review. *European Journal of Horticultural Science*, 83(5), 269-280.
- [11] Dabylova, N. S., & Chakeeva, K. S. (2022). Review on greenhouse microclimate and application: Design parameters, thermal modeling and simulation, climate controlling technologies. *Information Technology and Mathematical Modeling in the Management of Complex Systems*, 2, 19-26. [https://doi.org/10.26731/2658-3704.2022.2\(14\).19-26](https://doi.org/10.26731/2658-3704.2022.2(14).19-26)
- [12] Aizen, V. B., Aizen, E. M., Melack, J. M., & Dozier, J. (1997). Climatic and Hydrologic Changes in the Tien Shan, Central Asia. *Journal of Climate*, 10(6), 1393-1404. [https://doi.org/10.1175/1520-0442\(1997\)010<1393:cahcit>2.0.co;2](https://doi.org/10.1175/1520-0442(1997)010<1393:cahcit>2.0.co;2)
- [13] López-Cruz, I. L., & Hernández-Larragoiti, L. (2010). Neuro-fuzzy models for air temperature and humidity of a greenhouse. In *XXVIII International Horticultural Congress on Science and Horticulture for People (IHC2010)*, (p. 611-617).
- [14] Gorrostieta-Hurtado, E., et al. (2012). Greenhouse Fuzzy and Neuro-Fuzzy Modeling Techniques. In *Fuzzy Logic-Emerging Technologies and Applications*. IntechOpen.
- [15] Seginer, I., Boulard, T. H., & Bailey, B. J. (1994). Neural network models of the greenhouse climate. *Journal of Agricultural Engineering Research*, 59(3), 203-216.
- [16] Petrakis, T., et al. (2022). Neural network model for greenhouse microclimate predictions. *Agriculture*, 12(6), 780.
- [17] Akpenpuun, T. D., et al. (2024). Dynamic neural network modeling of thermal environments of two adjacent single-span greenhouses with different thermal curtain positions. *Journal of Agricultural Engineering*. <https://doi.org/10.4081/jae.2024.1563>

- [18] Deschênes, M., et al. Theoretical Development and Experimental Validation of a Thermal Model Comparing Different Greenhouse Covering Materials. Available at SSRN 5110537.
- [19] Guesbaya, M., & Megherbi, H. (2019). Thermal Modeling and Prediction of Soilless Greenhouse in Arid Region Based on Particle Swarm Optimization. Experimentally Validated. In *2019 International Conference on Advanced Electrical Engineering (ICAEE)* (pp. 1-6). doi: 10.1109/ICAEE47123.2019.9015190.
- [20] Hassaan, G. A. (2023). Temperature control of a greenhouse using PD-PI, PI-PD and 2DOF controllers. *International Journal of Engineering Innovations*, 12(9), 156-167.
- [21] Close, C. M., Frederick, D. K., & Newell, J. C. (2001). *Modeling and analysis of dynamic systems*. John Wiley & Sons.
- [22] Nielsen, B., & Madsen, H. (1995). Identification of transfer functions for control of greenhouse air temperature. *Journal of Agricultural Engineering Research*, 60(1), 25-34.
- [23] Yang, X.-S. (2014). *Nature-inspired optimization algorithms*. Elsevier.
- [24] Bozorg-Haddad, O., Solgi, M., & Loáiciga, H. A. (2017). *Meta-heuristic and Evolutionary Algorithms for Engineering Optimization*. John Wiley & Sons.
- [25] Qing, A. (2009). *Differential Evolution*. John Wiley & Sons.
- [26] Ahmed, N., et al. (2024). Advancing horizons in vegetable cultivation: a journey from age-old practices to high-tech greenhouse cultivation—a review. *Frontiers in Plant Science*, 15, 1357153.
- [27] Agbelusi, J., et al. (2024). Strategies for minimizing carbon footprint in the agricultural supply chain: leveraging sustainable practices and emerging technologies. *World Journal of Advanced Research and Reviews*, 23(3), 2625-2646.
- [28] Argento, S., Garcia, G., & Treccarichi, S. (2024). Sustainable and low-input techniques in Mediterranean greenhouse vegetable production. *Horticulturae*, 10(9), 997.

- [29] Shah, I.H., et al. (2024). Comprehensive review: Effects of climate change and greenhouse gases emission relevance to environmental stress on horticultural crops and management. *Journal of Environmental Management*, 351, 119978.
- [30] Dwivedi, R. (2024). *Solar Energy in Indian Agriculture: A Study on the Transition from Fossil Fuels to Sustainable Irrigation*. Høgskulen på Vestlandet.
- [31] Nazarov, D., et al. (2024). Renewable energy sources for the agricultural sector. In *E3S Web of Conferences*. EDP Sciences.
- [32] Hartani, T., & Semar, A. (2024). *Shedding the Light on Irrigation Systems Degradation in the Algerian Desert*. Springer.
- [33] Messak, M.R., et al. (2024). Estimation of the energy balance, greenhouse gas emissions, and the state of mechanization of durum wheat cultivation in the Ziban region (Biskra). *Studies in Engineering and Exact Sciences*, 5(2), e10826.
- [34] Tarek, M. The impact of economic development on the reproduction of rural elites: Field study in M'ziraa municipality, Biskra city-Algeria.
- [35] Guesmia, H., et al. *Journal of Agriculture and Applied Biology*.
- [36] Aidat, T., et al. (2023). Impact of Agricultural Policies on the Sustainable Greenhouse Development in Biskra Region (Algeria). *Sustainability*, 15(19), 14396.
- [37] Brahim, B., Nor, R., & Eddine, H.S. (2022). Modeling of an Efficient Solar Absorption Cooling System for a Building in Souk Ahras City, Algeria. In *2022 19th International Multi-Conference on Systems, Signals & Devices (SSD)*. IEEE.
- [38] Bacha, B., et al. (2024). Energy and parametric analysis of solar absorption cooling systems for an office building: a case study. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 46(1), 6794-6815.
- [39] Waag, W., & Sauer, D.U. (2009). Secondary batteries-lead-acid systems| state-of-charge/health.

- [40] S. Y. Chia and M. W. Lim (2022). A critical review on the influence of humidity for plant growth forecasting. *IOP Conference Series: Materials Science and Engineering*, 1213(1), 012009. doi: 10.1088/1757-899X/1213/1/012009.
- [41] N. K. Madzhi and M. A. N. Akhsan (2021). Control of Plant Growth by Monitoring Soil Moisture, Temperature and Humidity in Dry Climate. *IOP Conference Series: Materials Science and Engineering*, 1192(1), 012027. doi: 10.1088/1757-899X/1192/1/012027.
- [42] S. Chen, A. Liu, F. Tang, P. Hou, Y. Lu, and P. Yuan (2025). A Review of Environmental Control Strategies and Models for Modern Agricultural Greenhouses. *Sensors*, 25(5), 1388. doi: 10.3390/s25051388.
- [43] A. Dsouza, L. Newman, T. Graham, and E. D. G. Fraser (2023). Exploring the landscape of controlled environment agriculture research: A systematic scoping review of trends and topics. *Agricultural Systems*, 209, 103673. doi: 10.1016/j.agsy.2023.103673.
- [44] A. Sharma, M. Hazarika, P. Heisnam, and H. Pandey (2023). Controlled Environment Ecosystem: A plant growth system to combat climate change through soilless culture. *Crop Design*, 2, 100026. doi: 10.1016/j.crope.2023.100026.
- [45] Y. Qiu, X. Lin, Z. A. Schuss, E. Arens, and H. Zhang (2022). The Effects of Ventilation, Humidity, and Temperature on Bacterial Growth and Bacterial Genera Distribution. *International Journal of Environmental Research and Public Health*, 19(22), 15345. doi: 10.3390/ijerph192215345.
- [46] Y. Pan et al. (2022). A review of dynamic models of greenhouse environment and crop growth for sustainable agriculture. *Journal of Cleaner Production*, 378, 134584. doi: 10.1016/j.jclepro.2022.134584.
- [47] A. G. Entico et al. (2021). System Identification and Thermal Modeling of a Small-Scale Greenhouse Using Grey-Box Approach. *IEEE Access*, 9, 122851–122864. doi: 10.1109/ACCESS.2021.3109722.
- [48] P. Li et al. (2022). A hybrid physical-neural network model for the temperature dynamics in a Chinese solar greenhouse.

- Computers and Electronics in Agriculture*, 202, 107386. doi: 10.1016/j.compag.2022.107386.
- [49] D. M. K. K. V. Rao and A. Ukil (2023). Physics-Informed Neural Networks for Dynamic System Modeling in Building Energy Management. *IEEE Transactions on Industrial Informatics*, 19(2), 1130–1139. doi: 10.1109/TII.2022.3182583.
 - [50] G. Papageorgiou et al. (2023). Data-driven modeling of greenhouse microclimate: A comparative review of machine learning techniques. *Agricultural Systems*, 208, 103648. doi: 10.1016/j.agry.2023.103648.
 - [51] A. P. Nugroho, R. M. Nasrul, L. Sutiarso, M. A. F. Falah, and M. A. F. Dzaky (2024). Evaluating Smart Greenhouse Viability Through Engineering Design and Software Cost Modelling. *IOP Conference Series: Earth and Environmental Science*, 1290(1), 012012. doi: 10.1088/1755-1315/1290/1/012012.
 - [52] E. J. van Henten et al. (2022). A methodology for system identification of greenhouse climate models. *Acta Horticulturae*, 1565, 25–32. doi: 10.17660/ActaHortic.2022.1356.4.
 - [53] W. H. Chen, N. S. Mattson, and F. You (2022). Intelligent control and energy optimization in controlled environment agriculture via nonlinear model predictive control of semi-closed greenhouse. *Applied Energy*, 320, 119334. doi: 10.1016/j.apenergy.2022.119334.
 - [54] D. M. K. K. V. Rao and A. Ukil (2020). Modeling of Room Temperature Dynamics for Efficient Building Energy Management. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 50(2), 717–725. doi: 10.1109/tsmc.2017.2758766.
 - [55] E. Zaborowska, K. Czerwionka, and J. Małkinia (2021). Integrated plant-wide modelling for evaluation of the energy balance and greenhouse gas footprint in large wastewater treatment plants. *Applied Energy*, 282, 116126. doi: 10.1016/j.apenergy.2020.116126.
 - [56] A. Costantino et al. (2021). Energy performance and climate control in mechanically ventilated greenhouses: A dynamic modelling-based assessment and investigation. *Applied Energy*, 288, 116583. doi: 10.1016/J.APENERGY.2021.116583.

- [57] T. Ha, H. J. Lee, and J. M. Lee (2022). Energy-efficient model predictive control for a semi-closed greenhouse based on a deep neural network model. *Computers and Electronics in Agriculture*, 193, 106684. doi: 10.1016/j.compag.2022.106684.
- [58] Y. Yao and D. K. Shekhar (2021). State of the art review on model predictive control (MPC) in Heating Ventilation and Air-conditioning (HVAC) field. *Building and Environment*, 200, 107952. doi: 10.1016/j.buildenv.2021.107952.
- [59] S. Zhan and A. Chong (2021). Data requirements and performance evaluation of model predictive control in buildings: A modeling perspective. *Renewable and Sustainable Energy Reviews*, 142, 110835. doi: 10.1016/j.rser.2021.110835.
- [60] K. Bamdad, N. Mohammadzadeh, M. Cholette, and S. Perera (2023). Model Predictive Control for Energy Optimization of HVAC Systems Using EnergyPlus and ACO Algorithm. *Buildings*, 13(12), 3084. doi: 10.3390/buildings13123084.
- [61] J. A. Paulson and A. Mesbah (2020). Approximate Closed-Loop Robust Model Predictive Control With Guaranteed Stability and Constraint Satisfaction. *IEEE Control Systems Letters*, 4(3), 719–724. doi: 10.1109/LCSYS.2020.2982035.
- [62] C. Anuntasethakul and D. Banjerdpongchai (2021). Design of Supervisory Model Predictive Control for Building HVAC System With Consideration of Peak-Load Shaving and Thermal Comfort. *IEEE Access*, 9, 41066–41081. doi: 10.1109/ACCESS.2021.3065083.
- [63] L. Wan et al. (2025). Enabling scalable Model Predictive Control design for building HVAC systems using semantic data modelling. *Automation in Construction*, 170, 105929. doi: 10.1016/j.autcon.2024.105929.
- [64] Y. Yang, J. Bjørnskov, and M. Jradi (2025). Optimizing HVAC systems with model predictive control: integrating ontology-based semantic models for energy efficiency and comfort. *Frontiers in Energy Research*, 13, 1542107. doi: 10.3389/fenrg.2025.1542107.

- [65] H. Pruvost, A. Wilde, and O. Enge-Rosenblatt (2023). Ontology-Based Expert System for Automated Monitoring of Building Energy Systems. *Journal of Computing in Civil Engineering*, 37(1), 04022054. doi: 10.1061/(ASCE)CP.1943-5487.0001065.
- [66] R. Carli, G. Cavone, S. Ben Othman, and M. Dotoli (2020). IoT Based Architecture for Model Predictive Control of HVAC Systems in Smart Buildings. *Sensors*, 20(3), 781. doi: 10.3390/s20030781.
- [67] L. Chamari et al. (2025). A Semantic Approach to Portable Data-Driven Model Predictive Control Systems Design in Smart Buildings. *SSRN Electronic Journal*. doi: 10.2139/ssrn.5167511.
- [68] A. J. Mary, A. R. Krishnan, A. C. S. Kumar, and S. Kumar (2023). AgroCUBE: A smart plant growth chamber system. In *AIP Conference Proceedings*, 2568(1), 050005. doi: 10.1063/5.0114213.
- [69] S. Santos and P. Gonçalves (2021). Precision Agriculture for Crop and Livestock Farming—Brief Review. *Animals*, 11(8), 2345. doi: 10.3390/ani11082345.
- [70] Y. Zhang et al. (2024). Review of the field environmental sensing methods based on multi-sensor information fusion technology. *International Journal of Agricultural and Biological Engineering*, 17(2), 1–13. doi: 10.25165/j.ijabe.20241702.8596.
- [71] A. Guney and O. Cakir (2025). Design and Temperature Control of a Novel Aeroponic Plant Growth Chamber. *Electronics*, 14(14), 2801. doi: 10.3390/electronics14142801.
- [72] R. A. Rodriguez-Ruelas, A. Salazar-García, J. A. Zegbe, and J. C. Raya-Pérez (2024). Development and evaluation of a multi-chamber environmental control system. *Computers and Electronics in Agriculture*, 219, 108765. doi: 10.1016/j.compag.2024.108765.
- [73] G. Alissa, A. Hariri, and M. Al-Absi (2023). Controlling Development Conditions for Vertical Mushroom Cultivation Using Automated Growth Chamber. In *Proc. 2023 International Conference on Business and Technology (ICBT)*, pp. 493–498. doi: 10.1109/ICBT58536.2023.10389278.

- [74] W. H. Chen and F. You (2021). Efficient Greenhouse Temperature Control with Data-Driven Robust Model Predictive Control. In *Proc. 2021 American Control Conference (ACC)*, pp. 245–250. doi: 10.23919/ACC50511.2021.9482971.
- [75] A. R. Cohen et al. (2021). Dynamically Controlled Environment agriculture: integrating machine learning and mechanistic and physiological models for sustainable food cultivation. *ACS ES&T Engineering*, 2(1), 3–19. doi: 10.1021/acsestengg.1c00269.
- [76] P. J. Rees, A. J. L. Harrison, and D. A. S. Jones (2022). Learning-based Model Predictive Control for Greenhouse Climate. *IFAC-PapersOnLine*, 55(28), 19–24. doi: 10.1016/j.ifacol.2022.10.354.
- [77] J. Nemcik, F. Krupa, S. Ozana, L. Hubka, and Z. Slanina (2021). Educational Case Study on H-Infinity Robust Performance Design. *Tehnički vjesnik*, 28(2), 481–487. doi: 10.17559/TV-20200124132757.
- [78] A. H. Mhmood and H. I. Ali (2021). Optimal H-infinity Integral Dynamic State Feedback Model Reference Controller Design for Nonlinear Systems. *Arabian Journal for Science and Engineering*, 46(10), 10171–10184. doi: 10.1007/s13369-021-05569-8.
- [79] I. F. Tayyeh and H. I. Ali (2022). Full State Feedback H-Infinity Controller Design for Nonlinear Systems. *Journal Européen des Systèmes Automatisés*, 55(4), 503–509. doi: 10.18280/jesa.550410.
- [80] A. H. Mhmood and H. I. Ali (2022). Optimal adaptive guaranteed-cost H-infinity model reference controller design for nonlinear systems. *International Journal of Dynamics and Control*, 10(5), 1381–1394. doi: 10.1007/s40435-021-00846-9.
- [81] R. M. S. K. Elsaied (2022). Robust control system of a high-purity distillation column. *Open Journal of Applied Sciences*, 12(9), 1559–1576. doi: 10.4236/ojapps.2022.129108.
- [82] S. A. Bortoff, P. Schwerdtner, C. Danielson, S. Di Cairano, and D. J. Burns (2022). H-Infinity Loop-Shaped Model Predictive Control With HVAC Application. *IEEE Transactions on Control Systems Technology*, 30(5), 2188–2203. doi: 10.1109/TCST.2022.3141937.

- [83] C. Bergeling, K. A. Morris, and A. Rantzer (2020). Closed-form H_∞ optimal control for a class of infinite-dimensional systems. *Automatica*, 117, 108916. doi: 10.1016/j.automatica.2020.108916.
- [84] E. Ilten (2023). Fractional Order Weighted Mixed Sensitivity-Based Robust Controller Design and Application for a Nonlinear System. *Fractal and Fractional*, 7(10), 769. doi: 10.3390/fractalfract7100769.
- [85] E. Vladu (2022). Global solution to an H_∞ control problem for control-affine systems. *Journal of the Franklin Institute*, 359(2), 1045–1059. doi: 10.1016/j.jfranklin.2021.12.008.
- [86] P. Apkarian and D. Noll (2006). Nonsmooth H_∞ synthesis. *IEEE Transactions on Automatic Control*, 51(1), 71-86.
- [87] W. J. Chang (2025). A comprehensive survey on advanced control: Mixed H_∞ , passivity and sliding mode for T-S fuzzy systems. *Processes*, 13(3), 792. doi: 10.3390/pr13030792.
- [88] K. Ito and T. Tabei (2021). Model predictive temperature and humidity control of greenhouse with ventilation. *Procedia Computer Science*, 192, 212–221. doi: 10.1016/j.procs.2021.08.022.
- [89] S. Ragaveena, A. Edward, A. and U. Surendran (2021). Smart controlled environment agriculture methods: a holistic review. *Reviews in Environmental Science and Bio/Technology*, 20, 887–913. doi: 10.1007/s11157-021-09591-z.
- [90] M. S. Mahmoud and M. M. Hussain (2021). Decentralized H_∞ controller design for a multi-zone space heating system. *Journal of the Franklin Institute*, 358(1), 624–645. doi: 10.1016/j.jfranklin.2020.10.040.
- [91] A. J. Ali, H. H. Abbas, and H. Bevrani (2023). Comparative analysis of H_2 and H_∞ robust control design approaches for dynamic control systems. *Journal of Engineering*, 29(8), 1–15. doi: 10.31026/j.eng.2023.08.01.
- [92] A. T. Azar, F. E. Serrano, and N. A. Kamal (2021). Robust H_∞ loop shaping controller synthesis for SISO systems by complex modular

- functions. *Mathematical and Computational Applications*, 26(1), 21. doi: 10.3390/mca26010021.
- [93] J. Garzón, L. Montes, J. Garzón, and G. Lampropoulos (2023). Systematic Review of Technology in Aeroponics: Introducing the Technology Adoption and Integration in Sustainable Agriculture Model. *Agronomy*, 13(10), 2517. doi: 10.3390/agronomy13102517.
 - [94] J. Zhao, Q. Huang, J. Li, T. Zhuang, R. Zhan, and X. Ma (2025). Development of an aeroponic system for the rare tree species *Phoebe zhenan*: Aeroponic root production and resource assessment. *Industrial Crops and Products*, 232, 121318. doi: 10.1016/j.indcrop.2025.121318.
 - [95] S. Hasrak and R. Zarghami (2023). Comparison of minituber production in designed aeroponic system and soil cultivation. *Acta Physiologiae Plantarum*, 45(4). doi: 10.1007/s11738-023-03537-4.
 - [96] J. Kim et al. (2024). Sustainable and Inflatable Aeroponics Smart Farm System for Water Efficiency and High-Value Crop Production. *Applied Sciences*, 14(11), 4931. doi: 10.3390/app14114931.
 - [97] J. Yang, M. Fang, and Z. Li (2021). Stimulus-Responsive Room Temperature Phosphorescence Materials: Internal Mechanism, Design Strategy, and Potential Application. *Accounts of Materials Research*, 2(8), 644–654. doi: 10.1021/accountsmr.1c00084.
 - [98] N. Tseligorov, A. Ozersky, A. Chubykin, G. Galka, and A. Zhukov (2022). Study of robust stability of indoor temperature control system. *E3S Web of Conferences*, 363, 03006. doi: 10.1051/e3sconf/202236303006.
 - [99] P. Saini and P. Thakur (2022). H-infinity based robust temperature controller design for a non-linear systems. *Wireless Personal Communications*, 126(1), 305–333. doi: 10.1007/s11277-022-09686-2.
 - [100] V. A. Rani, D. Prabhakaran, & M. Thirumarimurugan (2020). Design of robust controllers for a continuous stirred tank reactor. *Tierärztliche Praxis*, 40, 2338–2349.

- [101] J. Chen, J. Wang, & W. Wang (2020). Robust adaptive control for nonlinear aircraft system with uncertainties. *Applied Sciences*, 10(12), 4270. doi: 10.3390/app10124270.
- [102] X. Yan, P. Wang, J. Qing, S. Wu, and F. Zhao (2020). Robust power control design for a small pressurized water reactor using an H infinity mixed sensitivity method. *Nuclear Engineering and Technology*, 52(7), 1443–1451. doi: 10.1016/j.net.2019.12.031.
- [103] S. Banerjee et al. (2020). Interval Approach for Stability Analysis of a Pressurized Water Reactor with Parametric Uncertainty using LMI based H-infinity Controller. In *2021 14th International Conference on Developments in eSystems Engineering (DeSE)*, pp. 21–26. doi: 10.1109/dese51703.2020.9450751.
- [104] C. Wang, Q. Zhang, A. Tang, and W. Xu (2023). State-of-Charge Estimation of Ultracapacitor Based on H Infinity Filter Considering Variable Temperature. *Journal of Electrochemical Energy Conversion and Storage*, 21(1). doi: 10.1115/1.4062386.
- [105] E. Red, A. A. Felix, and R. Castilho (2024). Identification and H-Infinity Control for a pH Neutralization Process, pp. 1–6. doi: 10.1109/icecer62944.2024.10920445.
- [106] N. Salvatori et al. (2021). A low-cost automated growth chamber system for continuous canopy measurements. *Plant Methods*, 17(1), 58. doi: 10.1186/s13007-021-00758-8.
- [107] L. J. Bradley and N. G. Wright (2021). Electrical Measurements and Parameter Extraction of Commercial Devices Through an Automated MATLAB-Arduino System. *IEEE Transactions on Instrumentation and Measurement*, 70, 1–9. doi: 10.1109/TIM.2021.3099951.
- [108] M. Mekhfioui, R. Elgouri, A. Satif, and L. Hlou (2020). Real-Time Implementation Of A New Efficient Algorithm For Source Separation Using Matlab & Arduino Due. *International Journal of Scientific & Technology Research*, 9(4), 531–535.
- [109] M. Yumurtaci and Ö. Verim (2020). Liquid level control with different control methods based on Matlab/Simulink and Arduino for the con-

- trol systems lesson. *International Advanced Research in Engineering Journal*, 4(3), 249–254.
- [110] N. R. Biswas and N. A. Roy (2020). Real Time Temperature Graph using MATLAB and Arduino. *International Journal of Engineering Research & Technology*, 9(5), 623–625.
 - [111] N. H. Diaz, A. Pardo, and O. J. Suarez (2020). A real-time pattern recognition module via Matlab-Arduino interface. In *Proc. 18th LACCEI Int. Multi-Conf. Eng., Educ., Technol.*, pp. 1–8. doi: 10.18687/LACCEI2020.1.1.288.
 - [112] M. S. Munna et al. (2017). Design and implementation of a drawbot using Matlab and Arduino Mega. In *Proc. 2017 Int. Conf. Electr., Comput. Commun. Eng. (ECCE)*, pp. 769–773. doi: 10.1109/ECACE.2017.7913006.
 - [113] P. Bauer et al. (2022). A Low-Cost, Open-Source Chamber for Environmental Control and Plant Imaging. *HardwareX*, 12, e00350. doi: 10.1016/j.ohx.2022.e00350.
 - [114] P. Megantoro, D. D. Warmanto, and S. H. Tyas (2024). Automation System of Temperature Calibrator for Room Thermostat Using Arduino Mega256. In *Proc. Int. Conf. Adv. Technol. Multidiscip. (ICATAM 2024)*, 245, pp. 101–107. doi: 10.2991/978-94-6463-566-9_14.
 - [115] M. A. Kurniawan, D. Irawan, and R. P. Astutik. Rancang bangun alat pengering gabah menggunakan sensor DHT-21 berbasis mikro kontroler Arduino Mega 2560.
 - [116] L. Maghfiroh, S. H. Sumarlan, H. Hammam (2025). Thermal Properties and Cooling Simulation of Red Dragon Fruit Using the Finite Difference Method. *Journal of Applied Agricultural Science and Technology*, 9(2), 156-171.
 - [117] H. Mubarak, M. Rizal, Iqbal, A. Waris, M. T. Sapsal, and I. Suelfikhar (2022). Design of a Greenhouse Room Temperature and Humidity Control System Using a DHT 22 Sensor. *Jurnal Agritechno*, 15(2), 160–165. doi: 10.70124/at.v15i2.943.

- [118] I. K. Wardani, A. N. Ichniarsyah, M. Telaumbanua, B. Priyonggo, and R. Fil'Aini (2023). The feasibility study: Accuracy and precision of DHT 22 in measuring the temperature and humidity in the greenhouse. In *IOP Conference Series: Earth and Environmental Science*, 1230(1), 012146. doi: 10.1088/1755-1315/1230/1/012146.
- [119] C. C. Paglinawan, G. M. Cruz, and K. R. M. Del Villar (2021). Design of an Arduino-Powered Sleep Monitoring System Based on Electrooculography (EOG) with Temperature Control Applications. In *Proc. 2021 IEEE 11th Int. Conf. Syst. Eng. Technol. (ICSET)*, pp. 104–109. doi: 10.1109/ICSET53717.2021.9613904.
- [120] B. Morcego, W. Yin, S. Boersma, E. van Henten, V. Puig, and C. Sun (2023). Reinforcement Learning versus Model Predictive Control on greenhouse climate control. *Computers and Electronics in Agriculture*, 215, 108372. doi: 10.1016/j.compag.2023.108372.
- [121] M. A. Adesanya et al. (2024). Deep reinforcement learning for PID parameter tuning in greenhouse HVAC system energy Optimization: A TRNSYS-Python cosimulation approach. *Expert Systems with Applications*, 124126. doi: 10.1016/j.eswa.2024.124126.
- [122] F. Mahmood, S. Namany, and R. Govindan (2025). Data-Driven Reinforcement Learning for Greenhouse Temperature Control. *Systems and Control Transactions*, 4, 1133–1138. doi: 10.69997/sct.189272.
- [123] A. Boamah (2025). Enhancements In Modeling Greenhouse Microclimate And Evapotranspiration: An Overview Of Recent Progress”, *AJBSPi*, 5(01), 1–3.
- [124] F. Cletus and A. E. John (2024). Comparative Analysis Of Machine Learning Models For Greenhouse Microclimate Prediction. *Brilliance: Research of Artificial Intelligence*, 4(1), 162–175. doi: 10.47709/brilliance.v4i1.3783.
- [125] E. B. Edet, M. Chacón-Vásquez, and E. C. Onyeocha (2024). Application of Fractional-order PID controllers in a Greenhouse Climate Control System. *IFAC-PapersOnLine*, 58(12), 179–184. doi: 10.1016/j.ifacol.2024.08.186.

- [126] M. Fink, A. Daniels, F. García-Mañas, F. Rodríguez, M. Leibold, and D. Wollherr (2025). Learning-based model identification for greenhouse climate control. *at - Automatisierungstechnik*, 73(6), 451–465. doi: 10.1515/auto-2024-0163.
- [127] W.-H. Chen and F. You (2024). MPC for the Indoor Climate Control and Energy Optimization of a Building-Integrated Rooftop Greenhouse Systems. *IFAC-PapersOnLine*, 58(13), 164–169. doi: 10.1016/j.ifacol.2024.07.477.
- [128] S. Getahun, H. Kefale, and Y. Gelaye (2024). Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review. *The Scientific World Journal*, 2024. doi: 10.1155/2024/2126734.
- [129] E. Heuvelink, S. Hemming, and Leo (2024). Some recent developments in controlled-environment agriculture: on plant physiology, sustainability, and autonomous control. *The Journal of Horticultural Science and Biotechnology*, 1–11. doi: 10.1080/14620316.2024.2440592
- [130] S. I. Hassan, M. M. Alam, U. Illahi, M. A. Al Ghamdi, S. H. Almotiri, and M. M. Su'ud (2021). A Systematic Review on Monitoring and Advanced Control Strategies in Smart Agriculture. *IEEE Access*, vol. 9, 32517–32548. doi: 10.1109/ACCESS.2021.3057865
- [131] AE Brikel, H Megherbi, and O Bouaïss (2025). LTI Black Box Systems Modeling for Greenhouse Agricultural Microclimate in Biskra Province Using DE Algorithm.
- [132] A. E. Brikel, H. Megherbi, and O. Bouaïss, "H-infinity Robust Controller for Precise Temperature Regulation in an Agricultural Growth Chamber Prototype" *Journal Robot Control (JRC)* vol. 6, no. 6, pp. 3159–3169, Jan. 2026. Available: <https://journal.umy.ac.id/index.php/jrc/article/view/27278>
- [133] A. E. Brikel, H. Megherbi, and O. Bouaïss, "Energy building, heating, cooling requirements, and associated costs in greenhouse structures in arid and semi-arid regions, such as Biskra Province," in *Proc. National Conference on Materials Sciences and Engineering (MSE'25)*, Chlef, Algeria, Apr. 12-13, 2025. Available: <https://www.univ-chlef.dz/mse25/>.

- [134] A. E. Brikel, H. Megherbi, and O. Bouaïss, "Sustainable Energy Utilization Models in Greenhouse Agriculture in Biskra Province," in Proc. National Conference on Materials Sciences and Engineering (MSE'25), Chlef, Algeria, Apr. 12-13, 2025. Available: <https://www.univ-chlef.dz/mse25/>.
- [135] A. E. Brikel, H. Megherbi, and O. Bouaïss, "Sustainable Energy Solutions for Greenhouses: A Case Study in M'ziraa, Biskra, Algeria".International Conference On Artificial Intelligence And Sustainable Development (ICAISD 2025), Relizane, Algeria, April 12th-13th, 2025. Available: <https://www.univ-relizane.dz/ICAISD25/>.