Proposal and Study of Model Predictive Control System for Automated Greenhouse Management

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Abstract—**This research explores the possibilities for application of Model Predictive Control (MPC) in greenhouse management to enhance climate precision and energy efficiency. Greenhouses play a crucial role in global food production, but maintaining ideal growing conditions is resource intensive. The study proposes an MPC strategy, empirically validated in a dynamic greenhouse environment, demonstrating its superiority in minimizing energy costs and achieving optimal resource consumption. Emphasizing alignment with Industry 4.0 principles, the research integrates MPC into modern agricultural practices, contributing to low energy consumption and reduced water and pesticide use. An experimental model simulates a commercial growth chamber, providing a platform for comprehensive testing under various scenarios. Despite inherent limitations, the model allows rigorous evaluation of different strategies, highlighting improved temperature control and energy efficiency. The study outlines innovative principles, emphasizing advantages such as intuitiveness, applicability to diverse processes, and robust constraint handling. Challenges, including accurate process modelling, are acknowledged. The findings promise to help revolutionizing greenhouse management, advancing the industry toward a more sustainable and technologically advanced future.**

Index Terms— **Energy Efficiency, Climate Optimization, Model Predictive Control (MPC), Greenhouse Management.**

I. INTRODUCTION

Greenhouses are pivotal for global food production, yet optimizing growing conditions remains resource intensive. The global population is on the rise, yet the availability of cultivable land remains restricted [1]. In regions like South Africa, where only about 11% of the land is deemed suitable for cultivation, this limited resource is gradually diminishing [2, 3]. The severity of the food insecurity issue is evident and presents a substantial challenge [4, 5]. To tackle this problem, there's a growing global adoption of greenhouse cultivation [6]. Greenhouses create an optimal setting for crop growth, shielding plants from adverse weather conditions such as extreme cold, heavy rain, and other challenges. Consequently, crops grown within greenhouses often achieve higher yields compared to those cultivated outdoors [7]. Research points to approximately 5.4 million hectares of global greenhouse cultivation, significantly contributing to 60% of the world's vegetable consumption [8]. This study analyses the possibilities of refining classical greenhouse systems through Model Predictive Control (MPC). Employing rigorously[1] inferred linearized models and a sophisticated generalized predictive control strategy cantered on predefined setpoints, authors study empirical validation of MPC in dynamic greenhouse environments. The research unveils an optimal MPC strategy for climate control, aiming to minimize total energy costs while ensuring adherence to prescribed climatic conditions. The dynamic model, encompassing multiple inputs and outputs, enables precise energy cost calculations. Benchmarking against optimal control strategies reveals the proposed MPC strategy's superior energy efficiency and cost-effectiveness. Beyond immediate applications, the study advocates integrating MPC into modern agriculture, aligning with Industry 4.0 principles and smart farming. Emphasizing technological solutions for real-time monitoring and control, the research meticulously compares traditional and MPC methods, enhancing indoor microclimate conditions. Addressing challenges in warm climates, the study proposes a robust MPC framework integrating an artificial neural network-based model and a production management strategy. Rigorous simulations demonstrate superior temperature control and energy utilization estimation compared to conventional MPC methodologies, contributing to greenhouse automation development. The findings promise transformative impacts on efficiency, sustainability, and precision in greenhouse crop production, signalling a technologically advanced and environmentally sustainable future.

II. EXPERIMENTAL MODEL AND TEST BENCH

To assess the efficacy of the proposed Model Predictive Control (MPC) strategies in enhancing the efficiency and sustainability of greenhouse crop production, a meticulously designed prototype of a production unit was developed. This prototype emulates the dimensions of a standard commercial growth chamber, serving as a realistic and scalable platform for experimental validation. The controlled environment within the prototype integrates seamlessly with an array of sensors and actuators, enabling precise climate control and resource management akin to real agricultural conditions. The inclusion of diverse sensors facilitates comprehensive data collection, providing detailed insights into the dynamic greenhouse conditions.

Strategically positioned actuators in the experimental model exert control over crucial environmental variables, such as temperature, humidity, and resource exchange.

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However, inherent limitations arise from the constraints of these actuators and external environmental influences, particularly the cooling capacity constraints of the thermoelectric cooler, impacting the achievable range of temperature control. Acknowledging these limitations, the experimental model offers a valuable platform for evaluating MPC strategies, demanding a nuanced approach to model predictive control due to controllability constraints.

The network of sensors and actuators forms the backbone of real-time data collection and control within the experimental model. Sensors strategically placed throughout the greenhouse continuously monitor key parameters like temperature, humidity, and carbon dioxide concentration. Actuators, including those governing the thermoelectric cooler, heating systems, and ventilation, respond to MPC algorithms' instructions, ensuring the maintenance of desired environmental conditions.

To comprehensively evaluate the proposed MPC strategies, diverse test scenarios are devised, encompassing varying environmental conditions, disturbances, and external interferences. These scenarios aim to validate the robustness and adaptability of the control strategies under diverse operating conditions. Rigorous data collection and analysis protocols, involving time-series data from sensors and actuators alongside environmental variables, are applied to quantify improvements in performance and energy efficiency resulting from the application of MPC in the greenhouse environment.

III. Advantages of MPC in Greenhouse Management

The advantages of the system can be categorized in:

- Intuitiveness and Ease of Setup: A primary strength of Model Predictive Control (MPC) lies in its inherent intuitiveness, rendering it particularly attractive to individuals with limited control knowledge. Simultaneously, the straightforward setup of MPC algorithms enhances accessibility and applicability, contributing to its widespread adoption.
- Applicability to a Variety of Processes: MPC's versatility is demonstrated by its applicability across a broad spectrum of processes, spanning those characterized by simple dynamics to intricate systems with prolonged delay times, non-minimum phase characteristics, or instabilities. Its innate ability to handle multivariate systems further amplifies its utility, accommodating diverse operational scenarios.
- Dead Time and Disturbance Compensation: MPC inherently addresses dead times in processes and adeptly integrates feedforward control mechanisms to counteract measured disturbances. This feature significantly enhances the controller's adaptability, making it well-suited to contend with real operational challenges encountered in various contexts.
- Implementation of Linear Control Laws: The resultant controller derived from MPC design embodies a linear control law, noted for its efficiency and ease of implementation. This simplicity facilitates the practical application of MPC in the context of greenhouse climate control, emphasizing its viability in real-world scenarios.
- Constraint Handling: MPC excels in handling constraints within management systems. The systematic integration of constraints during the design phase ensures that the controller operates within predefined limits, thereby enhancing overall system stability and robustness.
- Future Reference Considerations: MPC proves especially advantageous when future reference values are known, a circumstance often encountered in applications such as robotics or batch processes. This feature enables a more specific and anticipatory control approach, enhancing precision in controlling dynamic systems.
- Open Methodology with Potential for Future Expansion: Built on fundamental principles, MPC offers an open methodology that accommodates future extensions and adaptations. This inherent flexibility ensures its continued relevance in evolving technology landscapes, positioning MPC as a dynamic and enduring control strategy.

IV. Challenges and Constraints

While the merits of Model Predictive Control (MPC) in regulating greenhouse climates are evident, it is imperative to acknowledge the accompanying challenges. The derivation of the control law, though conceptually straightforward for implementation, necessitates intricate calculations, particularly when considering constraints. The primary challenge resides in the assumption of an accurate process model, as the benefits derived hinge upon the alignment between the actual process and the employed model.

The application of MPC in the realm of greenhouse crop production aligns with the inherent strengths of the methodology. By devising management strategies that minimize an objective function while adhering to time horizon constraints, MPC provides a systematic and anticipatory approach to climate management within greenhouses.

The selection of an appropriate model for MPC in greenhouse crop production presents challenges related to robustness, feasibility, and computational complexity. Striking a delicate balance between capturing the dynamic intricacies of the system and ensuring computational efficiency is pivotal. Various model types, encompassing linear, nonlinear, steady-state, and stochastic models, introduce diverse trade-offs in addressing these challenges.

Subsequent chapters will delineate the application of MPC in the developed experimental model, elucidating specific methodologies, implementation intricacies, and the empirical evaluation of its impact on greenhouse climate control.

V. Study of the Model

The execution and subsequent real-time validation of the model present specific challenges, encompassing aspects such as securing access to an actual installation, establishing an effective communication interface linking the installation and the hardware intended for algorithm execution, and navigating the complexities associated with the hardware itself. The intricacies of conducting real-time tests are underscored by the observation that a review of Model Predictive Control (MPC) systems primarily references theoretical papers, with limited inclusion of applied papers presenting empirical measurement data.

In the prototype implementation of control algorithms, meticulous attention is warranted for selecting an appropriate platform, designing effective communication interfaces interconnecting different systems, and choosing a programming language aligning with the overall system architecture. These considerations significantly impact aspects of control algorithm development, the range of available functionality, and potential constraints imposed on the algorithm. It is imperative to recognize that not all optimizers enjoy universal support across every hardware system or programming language. Additionally, the real-time system's ability to interface with other systems is facilitated by standard network ports or analog and digital signals processed by input/output modules.

Within this model, the main challenge involves determining the future values of variables at the present time, relying on predictions generated by a particular model. At each point in time, a time horizon is computed through a rolling time window that starts at that specific point in time and continues for a fixed duration. Therefore, only the initial values of the optimal control are considered during the optimization process.

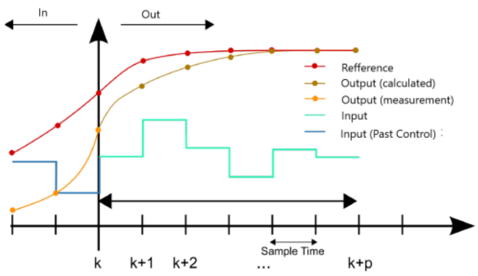

Fig. 1. MPC Diagram

For example, at a given time, within a window with a moving horizon, the standard problem can be expressed by the following mathematical formulation:

$$\min_{u} \frac{1}{2} \sum_{K=0}^{N-1} [x'(k)Qx(k) + u'(k)Ru(k)] + x'(N)Px(N)$$

$$x(k+1) = f\big(x(k), u(k)\big) \; k = 0 \ldots N-1$$

$$u_{min} \le u_k \le u_{max} \; k = 0 \ldots N-1$$

Where:

- Equation 1 is the function expressed as a quadratic function, i.e., the variables represent the deviation from the reference value, which is reported as 0.
- Equation 2 is the function representing the future dynamic behaviour of the system according to a specific theoretical model.
- Equation 3 represents the thresholds constraining management and where:
  - x(k) is a vector of state variables at time k.
  - u(k) is a vector of control variables at time k.
  - Q, P are semi-infinite positive quantities.
  - R is a certain positive number

It is essential to note that the solution of this problem takes place at each time step within the corresponding rolling time horizon. The formulas themselves are not developed by the authors, but adapted according previous researches (available at the end of the paper). Therefore, the solution must be achieved within a reasonable time, ideally shorter than the duration of a time sample. Furthermore, emphasis is placed on applying only (1)u(1), which contributes to the robustness of the solution against potential inaccuracies in the forecast model. Challenges associated with model predictive control (MPC) encompass robustness, feasibility and computational considerations that depend on the chosen model. The overall model for the MPC problem involves striking a reasonable balance between the computational complexity required to solve the optimization problem and the ability to adequately represent the dynamic aspects of the system. The MPC approach, characterized by a quadratic cost function and lack of constraints, can correspond to the linear-quadratic regulator (LQR) problem. Nevertheless, research has shown that the MPC subjected to constraints can be approximated to a constrained LQR controller where the weight matrix Q and R is related to the state and control variables. Therefore, the quadratic program problem can be addressed either by an LQR optimization model or by an MPC.

Essentially, most systems are stochastic and nonlinear in nature. Therefore, the use of a generalized MPC system architecture (or algorithm) does not have the ability to give a sufficiently accurate representation of the full system dynamics. Especially in the case of highly nonlinear dynamics (as is the case for the greenhouse system), a nonlinear representation of the system is unavoidable. For the sake of simplicity, we can adopt the following formulation as a classical nonlinear description of the discrete-time system:

$$x(t+1) = f\big(x(t), u(t), v(t)\big)$$

$$y(t) = h\big(x(t), u(t), v(t)\big)$$

With this nonlinear representation of the system, we obtain the following framework for nonlinear MPC:

$$V_N(x,u) = \sum_{k=0}^{N-1} l(x_k, u_k, r_{k)+V_{f(x_N)}}$$

Subject to:

$$x_{k+1} = f(x_k, u_k)$$

$$y_k = h(x_k, u_k)$$

$$x_0 = x(t)$$

$$u_k \in U$$

$$x_k \in X$$

The algorithm in this case can be described as follows:

- Input: equation of a nonlinear system $f(x(t), u(t), v(t))$ и $x(x(t), u(t), v(t))$ with computed/predicted chorissant N, fringes U and X.
- Initially, the zero (initial) status of x(t) is set.
- Solve the given equation for input parameters $u^* = (u_0^*, \dots, u_{N-1}^*)$
- t gets the value t+1
- we return 1.

To explain, the following simulation experiment is proposed: run two simulations where the algorithm is used to control the greenhouse system. In the first example, the proposed algorithm will be used to track a reference temperature with respect to the air temperature in the greenhouse itself. By means of the second example, the objective will be to increase the yield of the greenhouse crop while maintaining the air temperature in the greenhouse between a set minimum and maximum limit. In both simulations to track the reference temperature and to maximize the yield will be used as the equations of the nonlinear system that are needed in the optimization framework of the proposed algorithm. Subsequently, it is quite possible to use the same algorithms to improve the other variables in the overall system to build full control and synchrony in the conditions (such as irrigation system, humidity, illumination, etc.).

The main factors that influence the greenhouse system are mainly determined by external weather conditions. Therefore, in both simulations conducted in this study, the external inputs were based on the measured meteorological conditions. These meteorological data were obtained from the Food and Agriculture Organization (www.fao.org) and are shown in the figure below. The bottom graph illustrates solar radiation, while the top graph represents outdoor temperature, outdoor absolute humidity, wind speed, outdoor carbon dioxide concentration as well as deep soil temperature. We assume that the signals for outdoor carbon dioxide concentration and deep soil temperature remain constant at 0.1 g/m3 and 10°C, respectively. Furthermore, at each time index, a random variable derived from a standard normal distribution multiplied by 0.01 is added to these constants.

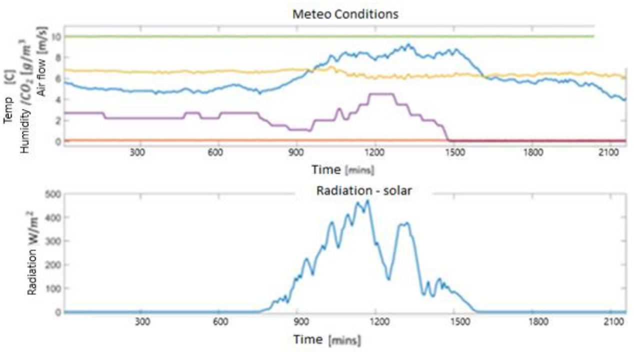

Fig. 2. Meteorological situation

During the experiment, the aim is to follow a reference value for the air temperature in the greenhouse while minimizing the input control. In addition, a limit is set for changes in the control inputs to prevent abrupt changes in the position of the ventilation mechanism or the temperature of the heating system, as such changes can cause fatigue and potential failure of the actuators. Actuator inputs are subject to limitations imposed by the physical constraints of the actuators. Specifically, we assume that the heating agent temperature is limited between 10 °C and 80 °C, while the opening of the ventilation system is limited between 0% and 100%.

$$\min_{u} \sum_{k=0}^{N-1} ||T_{g,k} - r_k||_Q^2 + ||u_k||_R^2 + ||u_k - u_{k-1}||_{R\Delta}^2$$

$$x_{k+1} = f_g(x_k, u_k)y, \quad \forall k \in \{0, \dots, N-1\}$$

$$x_0 = \hat{x}(t)$$

$$u_l \le u_k \le u_u, \quad \forall k \in \{0, \dots, N-1\}$$

In two simulations made for $r_\Delta = 10$ and another with $r_\Delta = 1$ the differences are clearly observed.

The figures graphically illustrate this difference.

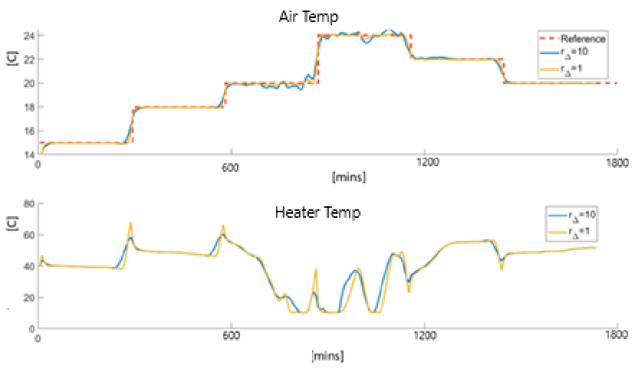

Fig. 3. Temperatures

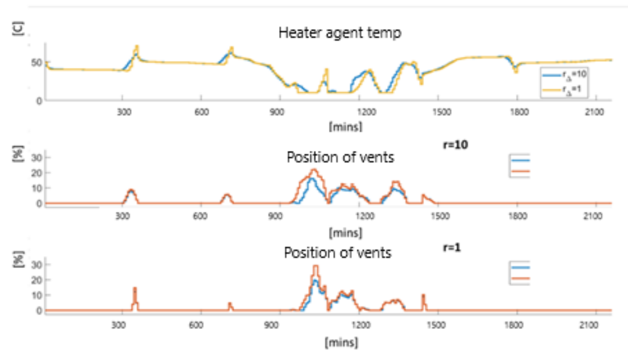

Fig.4. Control Data

Complementing the goal of building a benchmark for optimal temperature control, another capability of MPC may be related to optimizing the crop yield itself. Using climate and crop models, this model can be integrated to maintain an optimal growth environment while balancing input costs and yield enhancement. The main objective is to keep the temperature within certain limits. Constraints are imposed to ensure that the greenhouse air temperature remains within the desired range. However, external signals can push the system outside the desired limits, creating situations where the logic of the built MPC becomes unworkable. In such a case, the optimization algorithm may take the following form:

$$\min_{u} \sum_{k=0}^{N-1} - m_{F,k} + ||\, u_k \,||\, _R^2 + \lambda_{\epsilon} ||\, \epsilon \,||\, _1$$

$$x_{k+1} = f_g(x_k, u_k)y, \ \ \forall k \in \{0, \dots, N-1\}$$

$$x_0 = \hat{x}(t)$$

$$u_l \leq u_k \leq u_u, \ \ \forall k \in \{0, \dots, N-1\}$$

$$x_l - \epsilon \leq x_k^{Temp} \leq x_u + \epsilon \ , \ \ \forall k \in \{0, \dots, N-1\}$$

$$\epsilon \geq 0$$

Here we assume that $m_{F,k}$ expresses the weight of the foetus at time k.

In fact, many plant species have shown very positive effects and high-quality features from CO2 enrichment by increased dry weight, plant height, number of leaves and flowers, and lateral branching [9].

As variables, x_l и x_u are lower and upper bounds also, as r_{co_2} shows the limits of the CO2 in the system. In two different simulations with different levels of r_{co_2} 100 and 500, we observe different readings.

The graphs below also illustrate the result of the study. Subject to temperature limits within requirements (15 to 22 degrees) and two different values of r_{co_2} of 100 and 500 respectively, we observe changes in the productivity readings of the system.

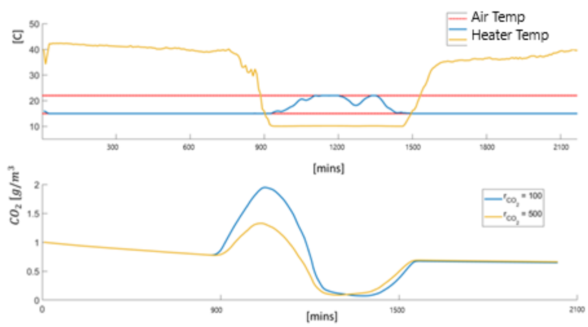

Fig. 5. System Data

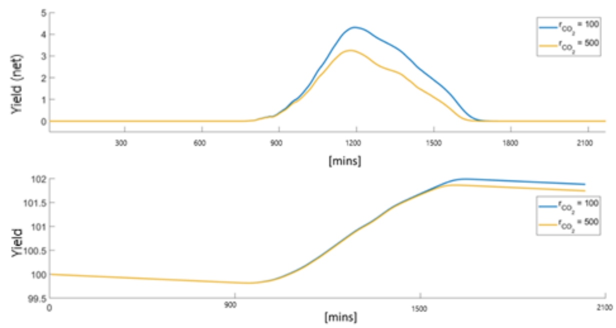

Fig. 6. Yield Data

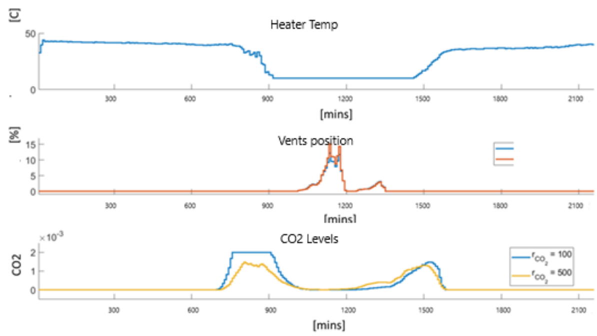

Fig. 7. Control Data

Character	Definition
β	Efficiency of heat absorption
T	Factor of conversion from C to K
C	Heat Capacity
k	Coeff. Of Heat transfer
V	Volume of heater
ζ	Rate of vents
ω	Humidity

VI. Discussion

The contributions of the research outlined in this chapter encompass three principal facets:

1. Development of Generic Models for Open-Source Greenhouse Energy Systems:
- Creation of generic control and emulation models for various greenhouse energy systems, encompassing components such as thermal energy storage, combined heat and power systems, heat pumps, gas boilers, district heating networks, artificial neural networks, and photovoltaics.
- Establishment of these models as generic open-source platforms, facilitating reusability and adaptability to users' specific models.
- Contribution to greenhouse energy system modelling, enabling rapid alignment with users' unique energy systems during simulation and testing in the conceptual design phase.

2. Development of a Detailed Model for Greenhouse Energy System Emulation:
- Presentation of a comprehensive guide outlining the step-by-step development of a detailed emulation model tailored to a specific greenhouse grower.
- Partial validation of the emulation model through benchmarking simulation results against in-situ measurements, assessing model accuracy.
- Provision of recommendations to enhance the fidelity of the emulation model.

3. Demonstration of an Economic Model Predictive Control (MPC) Planning Strategy for Greenhouse Energy Systems:
- Proposal of an economic MPC for greenhouse energy systems based on an energy hub model.
- Objective of minimizing operating costs while meeting thermal and electrical demands of the greenhouse, while respecting physical operating constraints.
- Identification of the flexibility in using diverse

systems through the proposed MPC, demonstrating the potential for economic benefits through strategic dispatch of greenhouse energy systems.
- Confirmation of the feasibility of applying MPC to greenhouse energy planning, underscoring potential economic benefits and contributing to the transition from research simulation to real-world application.

Indeed, by incorporating advanced data processing and intelligent metering technologies, farmers can leverage management systems. These systems facilitate the supervision of energy requirements and the automatic control of the indoor microclimate within greenhouses [10].

The results of this study highlight the transformative potential of the proposed MPC strategies in greenhouse crop production. The economic advantages and efficiency gains make it imperative to recommend the implementation of this new technology, especially given the overwhelming reliance on natural ventilation and manual humidification in current greenhouse management systems. Existing greenhouse control systems relying on manual intervention to set reference values for temperature, heating rate, humidity and fogging rate are error prone. The manual approach not only increases labour costs but also complicates greenhouse management. MPC's proposed strategies provide a reliable alternative by automating the management process and reducing the risks associated with manual interventions.

Given the obvious benefits, sites operating in horticulture are strongly advised to adopt this new technology. Adopting MPC strategies can effectively eliminate errors, reduce labour costs, and streamline the management of greenhouse systems. Moving to automated management is consistent with the principles of efficiency, precision, and resource optimization. The proposed project lays the foundation for future advances in greenhouse management systems. The following recommendations provide a roadmap for extending and implementing the research results:

- Future control systems could explore the integration of multi-objective optimization techniques. This would involve optimizing parameters not only to reduce power consumption, but also to minimize losses in the equipment and simultaneously increase the precision of the actuators. Such a comprehensive approach is consistent with the overarching goal of sustainable and resource-efficient greenhouse management.
- Extending the scope of greenhouse control to include CO_2 regulation represents a significant opportunity for improvement. Incorporating MPC's CO_2 management strategies can contribute to optimizing plant growth conditions, further enhancing the sustainability and productivity of greenhouse crop production.
- The proposed MPC strategies, although rigorously studied in a controlled environment, need to be practically applied in the field. Real-world applications will allow a comprehensive assessment of controller behaviour under a variety of environmental conditions and over an extended period.
- Nevertheless, research indicates that microgrids can attain elevated performance levels by employing advanced control algorithms. These algorithms rely on predicted future conditions, optimize storage device utilization, and prefer optimal approaches over heuristic-based ones [11]. Furthermore, from a control perspective, the power system community suggests the adoption of Model Predictive Control (MPC). MPC is favoured for its foundation on system predictions and its incorporation of feedback mechanisms adept at managing uncertainties and constraints. This makes it particularly appealing for systems reliant on renewable energy forecasts [12].

Although the present study provides a sound basis, it is essential to recognize its limitations. The proposed management strategy was analysed for a limited period in a semi-closed greenhouse, and experimental validation was limited by resource availability. Future studies should address these limitations by extending the analysis to different crops, greenhouses with different configurations, and conduct experiments to validate the proposed MPC strategies. The formulation of the used and proposed formulas is based on deep investigation and adaptation of many existing researches, but mainly studies for Robust Predictive Control and Soft Constraints in MPC [13] [14]. The recommended adoption of MPC strategies in greenhouse crop production implies a paradigm shift towards efficiency, precision, and sustainability. The outlined future extensions and implementations serve as a guide to advance the current state of greenhouse management systems, paving the way for transformative practices in horticulture and agriculture. Ongoing research and practical implementations will contribute to improving and expanding the application of MPC in greenhouse management.

VII. Conclusion

This paper introduces an innovative control strategy, developed through experimentation, tailored for the efficient operation of a microgrid-powered greenhouse. Leveraging Model Predictive Control (MPC), the strategy optimally regulates the microclimate by managing energy and water flows for various greenhouse processes, including irrigation, artificial lighting, CO2 enrichment, dehumidification, ventilation, and heating. Widely applied in greenhouse control, the Model Predictive Control (MPC) strategy is extensively explored. Notably, research in [15] delves into the MPC strategy's application for greenhouse temperature control. In a related study [16], an MPC controller is introduced to effectively regulate indoor temperature. An additional investigation [17] focuses on a robust MPC strategy tailored for greenhouse systems, demonstrating enhanced robustness compared to conventional MPC approaches. The optimization models account for uncertainties in renewable energies, loads, and weather forecasts. Demonstrating the efficacy of the optimization method, the resulting control strategies prove suitable for managing energy in greenhouse devices, adhering to microclimate setpoint signals, and complying with mandatory operating constraints, even in the presence of uncertainty.

To facilitate practical application, considering inherent modelling uncertainties and external disturbances in real-world scenarios, a proposed hierarchical control approach is advocated. This approach operates at different levels, with the top-level defining reference values for environmental factors in the greenhouse. In the lower layer, Model Predictive Control (MPC) controllers efficiently monitor these reference trajectories. This hierarchical structure enhances adaptability and robustness, addressing real-world challenges encountered in greenhouse management.

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