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Automated Temperature Control System for a Multi-Point Airflow Channel Using PID and MPC Controllers

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1. Introduction

Air temperature control plays a pivotal role in modern HVAC systems, and is widely employed in industrFial, residential, and commercial applications. In today's dynamic environments, temperature management is essential to ensure comfortable living and working conditions, while simultaneously minimizing energy consumption and environmental impact [1]. The precise control of air temperature not only enhances human comfort but also contributes significantly to the optimal functioning of machinery, preservation of sensitive materials, and overall energy efficiency [2]. Automatic air temperature control aims to maintain a specific temperature within a space or process by automatically adjusting the heating or cooling source based on real-time temperature measurements and a predefined setpoint [3]. In this study, the term multi-point refers to temperature measurements at three positions along the air channel, using sensors placed at different distances to capture how the temperature changes along the flow. This involves continuous monitoring and feedback mechanisms that ensure stability and quick responses to external and internal disturbances.

Maintaining consistent temperatures is particularly critical in industries such as pharmaceuticals, food processing, and electronics, where even slight variations can compromise product quality or operational integrity. Advanced control methods, such as Proportional-Integral-Derivative (PID) control, have been widely adopted to address these limitations [4]. Model Predictive Control (MPC) has emerged as a robust and versatile approach for temperature regulation in modern control systems, due to its ability to handle multivariable processes and constraints effectively. Unlike traditional controllers, MPC predicts future system behavior using a mathematical model, which allows it to optimize control actions over a specified horizon. Several studies have explored its application in various domains and demonstrated its advantages over traditional control methods such as PID [5].

For example, MPC has been extensively applied in heating, ventilation, and air conditioning (HVAC) systems [6], to optimize energy consumption while maintaining thermal comfort. Oldewurtel et al. [7] implemented MPC in building climate control; they highlighted its capability to predict and adjust operations based on forecasted environmental changes, thereby reducing energy costs. Their study emphasized the role of predictive capabilities in minimizing energy usage during peak demand periods; this contributes to overall system efficiency. Similarly, Zhang et al. [8] presented an MPC-based framework for dynamic thermal systems, focusing on processes with delayed responses. Their results showed that MPC outperformed PID in maintaining temperature stability under variable conditions, particularly in processes with significant thermal inertia [9]. Qin and Badgwell [10] provided a comprehensive review of MPC applications in energy systems, which emphasized its potential to manage trade-offs between energy efficiency and performance. Their findings indicate that MPC is well suited for applications where precise temperature regulation is critical for minimizing waste and maximizing sustainability. The flexibility of MPC makes it an ideal choice for systems with multiple interacting variables, such as those found in large-scale HVAC installations.

Recent advancements in IoT and machine learning have further enhanced MPC's utility. Kamalapurkar et al. [11] developed an MPC algorithm integrated with real-time sensor networks for multi-zone temperature control; this achieved superior adaptability and performance in dynamic and unpredictable environments. The integration of predictive analytics with real-time data allows a more responsive and efficient control system, which paves the way for smarter and more sustainable solutions.

This approach ensures precise and efficient regulation of temperature and thus addresses the growing demand for energy-efficient and environmentally friendly climate control solutions in modern applications. By leveraging advanced control strategies such as MPC, industries can achieve greater operational efficiency, reduced energy consumption, and improved environmental sustainability, in order to meet the challenges of contemporary climate control requirements.

2. Mathematical Modeling of Air Temperature Control in Steady-State Systems

To describe this process mathematically, we can use the first law of thermodynamics, which states that energy cannot be created or destroyed, only transferred or converted from one form to another. In the context of air temperature control, this principle is applied to analyze how electrical energy is converted into thermal energy and how this energy is transferred to the air. Below is an expanded mathematical model that captures the essential dynamics of the process. The electrical power supplied P_{elec} is entirely converted into thermal power $Q_{thermal}$ during steady-state operation

$$P_{elec} = Q_{thermal} . \quad (1)$$

The thermal power transferred to the air, $Q_{thermal}$ is determined by several key factors that define the energy required to heat the moving air. These factors include the mass flow rate of the air, $\dot{m}$ which represents the amount of air passing through the system; the specific heat capacity c_p, a material property of air that quantifies the amount of energy needed to raise the temperature of one kilogram of air by one degree Kelvin; and the temperature difference $T_{out}–T_{in}$, which measures the change in temperature between the air entering and leaving the system

$$Q_{thermal} = \dot{m}c_p(T_{out} - T_{in}) \,. \tag{2}$$

The mass flow rate of air $\dot{m}$ represents the amount of air moving through the system and is a crucial parameter in thermal systems, as it directly influences the energy transfer rate. It is calculated based on two primary factors: the volumetric flow rate $\dot{V}$, which measures the volume of air passing through the system, and the air density ρ, which quantifies the mass of air per unit volume (in kilograms per cubic meter)

$$\dot{m} = \rho\dot{V} \,. \tag{3}$$

Here, ρ depends on the air's temperature and pressure, as it is affected by the ideal gas law. For most practical applications, air density is assumed to be constant for small temperature and pressure variations, to simplify the calculation. However, for systems with significant environmental changes, ρ may need to be dynamically adjusted. This formula underscores the importance of airflow and environmental conditions in determining the mass flow rate, which in turn governs the amount of energy required for heating or cooling. By accurately calculating $\dot{m}$, engineers can design more efficient HVAC systems and ensure effective thermal management [12].

The electrical power supplied to the system, P_{elec} represents the rate at which electrical energy is delivered and subsequently converted into thermal energy for temperature control. It is determined by the product of the voltage, V, which is the electrical potential difference across the system (measured in volts), and the current I, which represents the flow of electric charge through the circuit (measured in amperes).

$$P_{elec} = VI \,. \tag{4}$$

In this equation, P_{elec} is measured in watts (W), where one watt equals one joule of energy per second. The voltage depends on the power supply characteristics, while the current varies with the electrical resistance and the operational conditions of the heating or cooling elements in the system. For systems with alternating current (AC), the power calculation may also involve the power factor $cos\phi$, which accounts for phase differences between voltage and current.

$$P_{elec,AC} = V_{rms} I_{rms} \cos\phi \,. \tag{5}$$

V_{rms} and I_{rms} are the root mean square values of voltage and current, respectively, and $cos\phi$ reflects the efficiency of energy transfer. Understanding this relationship is fundamental for designing energy-efficient systems, as it directly links electrical energy consumption to the system's operating parameters. Proper control of V and I ensures optimal performance while minimizing energy waste and operational costs. The efficiency η of the system quantifies how effectively electrical energy is converted into useful thermal energy.

The efficiency of the system is a critical parameter that quantifies the system's performance by measuring how effectively the supplied electrical energy is converted into useful thermal energy for heating or cooling purposes. Efficiency is expressed as a ratio of the output energy to the input energy, often presented as a percentage.

$$\eta = \frac{Q_{thermal}}{P_{elec}} \,. \tag{6}$$

This formula provides a direct measure of the system's capability to minimize energy losses during operation. A high efficiency indicates that most of the electrical energy is effectively used for thermal processes, with minimal losses due to factors such as heat dissipation, electrical resistance, or mechanical inefficiencies.

- Inefficient insulation or unwanted heat transfer to the surroundings can reduce the amount of thermal energy effectively delivered to the intended area.
- Resistive losses in electrical components such as wires, heating elements, or transformers can reduce the energy available for heating.
- The choice of materials, component alignment, and control strategies (e.g., PID or MPC controllers) influence the system's ability to convert and distribute energy efficiently.

For modern HVAC systems, improving efficiency is a primary design objective, driven by the need to reduce energy consumption and environmental impact. Advanced control algorithms such as MPC can further optimize system efficiency by dynamically adjusting operations based on real-time feedback and predicted conditions. As shown below in Fig. 1, the thermal power depends on the air volume and the temperature difference.

$$W_{th} = c_L \gamma_L V_v \upsilon \,, \tag{7}$$

where the variables are as follows:

- W_{th} is a thermal power transferred to the air W,
- c_L is a specific heat capacity of air at constant pressure J/(kgK),
- γ_L is a density of air kg/m^3,
- V_v is a volume of air being heated m^3/s,
- υ is an increase in air temperature °C.

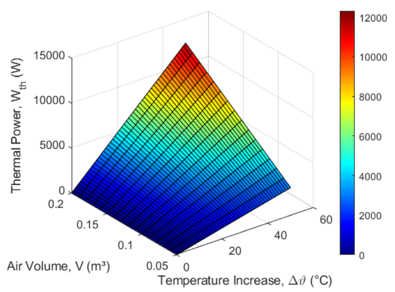

Fig. 1 Thermal power as a function of volume and temperature

An air duct system is used to distribute conditioned or fresh air to a specified space. To build the mathematical model of this system, the dynamics of air flow, energy losses, and variations in temperature and pressure are typically considered. As illustrated in Fig. 2, the velocity exhibits a sudden change around 7 m due to a localized disturbance in the model, leading to a non-uniform flow behavior.

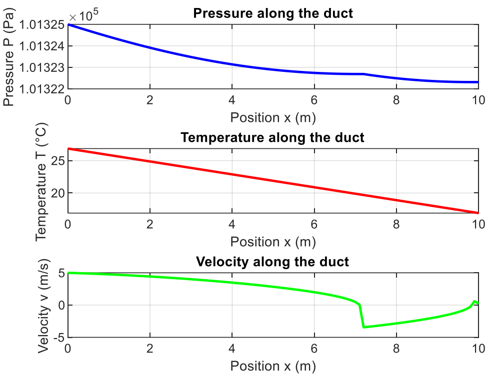

Fig. 2 Pressure, temperature and velocity profiles along the channel

Before the supplied electrical energy can be completely converted into thermal energy, the heating element must first be heated. Additionally, the warm air must travel to the location where the temperature is measured. If the heating element is considered a homogeneous body with thermal capacity C_H and surface temperature υ, then the energy stored in the heating element can be determined as follows

$$E_H = C_H \upsilon . \tag{8}$$

If it is necessary to integrate energy as a function of time to obtain a dynamic response, the differential equation for heat transfer can be used

$$\frac{dE_H}{dt} = P - Q . \tag{9}$$

where P is the electrical power supplied to the heating element. Q is the energy lost through heat transfer to the environment.

The dynamic response refers to how a system reacts to a change in input, such as a change in a set parameter, a load, or other operating conditions. Therefore, this section provides the analysis of the system's behavior over time, until it reaches a new equilibrium or stability state. The dynamic response is critical for evaluating the performance of control systems and their design, to ensure they are fast and stable

$$W_H = C_H v_H = -\int (P_{el} - P_{th})\, dt . \tag{10}$$

By differentiating with respect to time, we obtain

$$C_H \frac{v_H}{dt} = P_{el} - P_{th}, P_{el} = c_L \gamma_L A_v v_H + C_H \frac{v_H}{dt} . \tag{11}$$

If we have a constant flow rate and take the electrical power P_{elec} as the input variable and the temperature v_H as the output variable, then we obtain the first-order linear differential equation as follows

$$v_H(t) \frac{v_H}{c_L \gamma_L A_v} \frac{dv_H(t)}{dt} = \frac{1}{c_L \gamma_L A_v} P_{el}(t) . \tag{12}$$

By performing the Laplace transform, we obtain the follow ing expression for the frequency domain.

$$v_H(s) \frac{v_H}{c_L \gamma_L A_v} s v_H(s) = \frac{1}{c_L \gamma_L A_v} P_{el}(s) . \tag{13}$$

If a time constant $T_s = \dfrac{c_H}{c_L \gamma_L A_v}$ and a proportional coefficient $K_s = \dfrac{1}{c_L \gamma_L A_v}$ are introduced, the transfer function of the heating element can be described as

$$G_H(\mathrm{s}) = \frac{v_H(\mathrm{s})}{P_{el}(\mathrm{s})} = K_s \frac{1}{1 + sT_s} . \tag{14}$$

For the transfer function of the system controlled with a constant volumetric air flow rate, we obtain.

$$G_H(\mathrm{s}) = \frac{v(\mathrm{s})}{v_H(\mathrm{s})} = K_s \frac{1}{1 + sT_s} e^{-T_t(\mathrm{s})} . \tag{15}$$

From the differentiation, it can be concluded that we are dealing with a PT1T-type controlled system. During this derivation, several simplifications have been made. Furthermore, certain variables are difficult to determine.

For this reason, it must be assumed that some system parameters can only approximate the real response under certain conditions. For the controlled system we have considered, it is not the power but the voltage that is preset. Therefore, the response of the controlled system is nonlinear.

However, if a working point with minimal fluctuations around it is considered, it can be assumed that the system's response is linear. Alternatively, the controlled system can also be considered as a black box, with the research limited to the input and output variables. In this case, physical relationships are no longer important. With the help of the step response, it is possible to describe the controlled system's response and convert it into a mathematical model.

The Value Iteration Algorithm is an optimization technique used to compute the optimal control input for a given system over a predictive horizon.

In the context of MPC [13], this algorithm iterates through a series of steps to minimize a predefined cost function, subject to system constraints, while predicting the future behavior of the system.

Algorithm 1: Value Iteration Algorithm

1. **The dynamic model of the system**

The system is modeled with a linear model in the form:

$x(t+1) = A \cdot x(t) + Bu(t)$

2. **Prediction in the steps** N_P

For a future time of N_P steps, MPC predicts the system's behavior using the above model and simulates the behavior for different values of $u(t+k)$.

3. **Cost function** J

$$J = \sum_{k=1}^{N_p} \left\| T_{setpoint} - y(t+k) \right\|^2 + \lambda \cdot \left\| \Delta u(t+k) \right\|^2$$

The cost function measures the deviation from the desired temperature and has a significant impact on the system's control.

- $\left\| T_{setpoint} - y(t+k) \right\|^2$, gives the error between the desired temperature and the predicted temperature.
- λ, is the coefficient that calculates the deviation for the control input change of the system.
- $\Delta u(t+k) = u(t+k) - u(t+k\text{ - }1)$, the change in parameters.

4. **Optimization**
   $u_{min} \le u(t+k) \le u_{max}$
5. **return**
6. **end**

MPC will be employed to minimize deviations from desired objectives, such as maintaining stable pressure or a constant temperature, by optimizing parameters over a defined time horizon.

This control strategy uses a predictive model of the system to anticipate future behavior and determine the control inputs that will minimize the cost function, which typically includes terms for tracking errors and control effort. The optimization process considers system dynamics, constraints, and disturbances, to ensure that the system operates efficiently and remains within the desired operating conditions. By continually updating predictions and control actions at each time step, MPC ensures that the system adapts to changing conditions and thus provides an effective means of achieving long-term performance goals.

The updated graph in Fig. 3 illustrates the parameters controlled by MPC, highlighted in red to distinctly emphasize the influence of the MPC algorithm. This is contrasted with the nonlinear behavior, which is represented by dashed lines. The red lines clearly show the optimal control adjustments made by the MPC algorithm, demonstrating its effectiveness in regulating the system's parameters. The dashed lines, representing the system's natural nonlinear behavior without MPC, provide a baseline for comparison, to highlight the improvements achieved through MPC in terms of stability and accuracy. As shown in Fig. 2, the pressure, temperature, and velocity vary along the channel. The change in velocity around 8 m is caused by a local disturbance in the model, resulting in a non-uniform flow behavior.

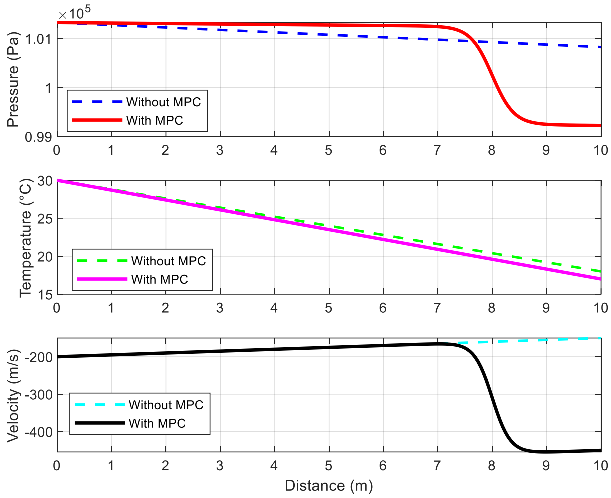

Fig. 3 The updated graph shows the parameters controlled by Model Predictive Control in red to clearly highlight the impact of the MPC algorithm compared to the nonlinear behavior (represented by dashed lines)

3. Heat Transfer in Air

Heat transfer in air is a physical process that involves the transfer of thermal energy from a hotter object to cooler air, or vice versa. This process is fundamental to many natural and technological phenomena, including space heating and cooling, ventilation and air conditioning systems, and thermal circulation in the atmosphere. Heat transfer in air occurs primarily through three main modes, conduction, convection, and radiation.

Conduction is the transfer of thermal energy from hotter molecules to cooler ones through direct contact, as in the case of air. Conduction occurs through molecular collisions, as the hotter air molecules transfer kinetic energy to the cooler molecules. Air, being a gas, is a poor conductor of heat due to its low density and large molecular distances.

Convection is the most common method of heat transfer in air and occurs through the movement of air masses. Natural Convection, where movement occurs due to density differences. Hotter air becomes lighter and rises, while colder, denser air sinks, creating a circulation pattern. Forced Convection, where the movement of air is induced by mechanical devices such as fans or pumps.

Radiation is the transfer of heat through the emission of electromagnetic waves, without the need for a medium. In the case of air, air itself is not a strong absorber or emitter of infrared radiation, but gases such as water vapor and carbon dioxide significantly contribute to heat transfer. Radiation from a hot surface can heat the surrounding air. Heat transfer in air is governed by these mechanisms and is crucial for understanding and designing efficient thermal systems in various applications. A first-order differential equation describing the temperature dynamics of a heating element is commonly used to model the change in temperature over time, depending on parameters such as supplied power and heat losses

$$P_{output} = hA\left(\nu - \nu_{air}\right), \tag{16}$$

where h is a heat transfer coefficient, W/(m^{2}K) and represents the rate of heat transfer per unit area and per unit temperature difference. It depends on the properties of the air, the surface characteristics, and the flow conditions. A is a s urface area of the heating element, m^2; the total area through which heat is exchanged between the heating element and the surrounding air. $\nu - \nu_{air}$ is an air temperature at the mea surement location, °C; it indicates the temperature of the ai r in the vicinity of the heating element or at a specified poin t of interest.

As shown in Fig. 4, the temperature of the heating element increases over time and stabilizes, while the air and ambient temperatures remain constant.

The time constant τ represents the response time

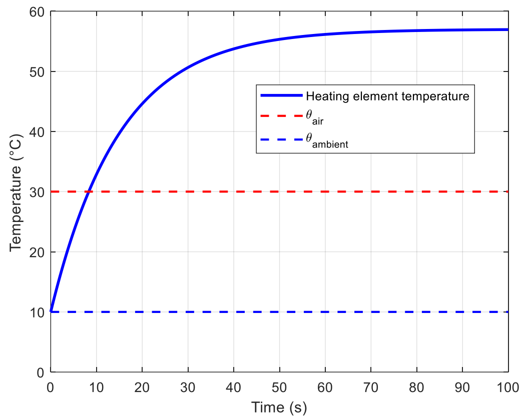

Fig. 4 The updated graph shows the parameters controlled by Model Predictive Control in red, to clearly highlight the impact of the MPC algorithm compared to the nonlinear behavior (represented by dashed lines)

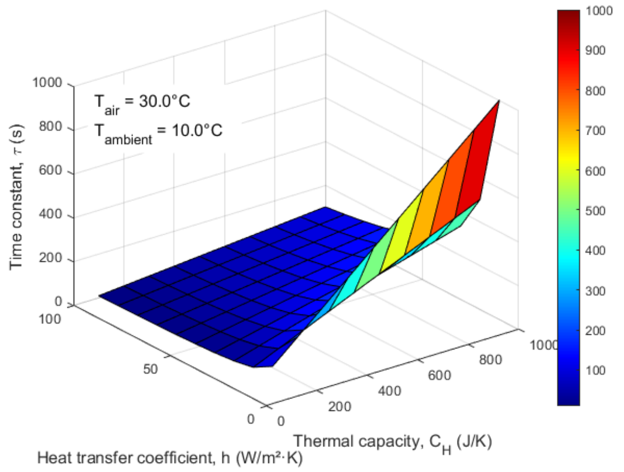

Fig. 5 Air heat transfer coefficient

of the heating system and is influenced by the thermal capacity and heat transfer properties of the system. This parameter is critical in determining how quickly a system can reach thermal equilibrium or respond to changes in operating conditions. A larger time constant indicates a slower response and is often associated with systems having high thermal mass or low heat transfer efficiency. Conversely, a smaller time constant reflects a faster response, typical of systems with low thermal capacity or efficient heat transfer mechanisms. Understanding the time constant is essential for designing and optimizing heating systems to achieve precise temperature control and energy efficiency

$$\tau = \frac{C_H}{hA}. \tag{17}$$

Fig. 5 illustrate key thermal properties in the air heat transfer process. The figure shows the variability of the air heat transfer coefficient with parameters such as air velocity and thermal properties, emphasizing its role in efficient heat exchange.

These results are further complemented by the relationship between thermal capacity and the heat transfer coefficient, demonstrating their combined impact on the system's thermal dynamics. Together, they provide insights into how these properties influence the time constants and efficiency of heat transfer systems. A larger thermal capacity or a lower heat transfer coefficient increases the response time of the system. These factors cause the system to store more energy or dissipate heat less efficiently, resulting in slower adjustments to changes in temperature. Such characteristics are typical of systems with substantial thermal inertia, where significant time is required to reach thermal equilibrium after a disturbance. Understanding these relationships is crucial for optimizing system performance, particularly in applications that require precise and rapid temperature control. The air travel delay t_{travel} representing the time it takes for the heated air to reach the measurement location, depends on the airflow velocity v and the distance L. Mathematically, it can be expressed as

$$t_{travel} = \frac{L}{\upsilon}. \tag{18}$$

The transient response and steady state describe the heating element's behavior as it transitions from an initial state to a stable operating condition. Initially, the heating element undergoes a transient phase, during which its temperature rises as it absorbs energy from the heat source. Over time, the temperature gradually approaches a steady-state value, where the heat input balances the heat losses, and no further significant changes in temperature occur. The transient response is characterized by the time it takes for the temperature to reach approximately 38% of its final value, representing a key measure of the system's dynamic characteristics. Factors such as the thermal capacity of the element, the heat transfer coefficient, and external conditions influence this behavior. In the steady state, the system achieves thermal equilibrium, where the rate of heat supplied equals the rate of heat dissipated to the surroundings. This stable temperature depends on the input power, heat transfer efficiency, and environmental conditions. Understanding both phases is crucial in designing systems that require precise temperature control, to ensure rapid stabilization and efficient operation.

The Fig. 6 illustrates the dynamic behavior of temperature and airflow when controlled by MPC. The graph highlights how MPC effectively regulates these parameters to achieve the desired setpoints, while minimizing deviations caused by external disturbances or system nonlineari-

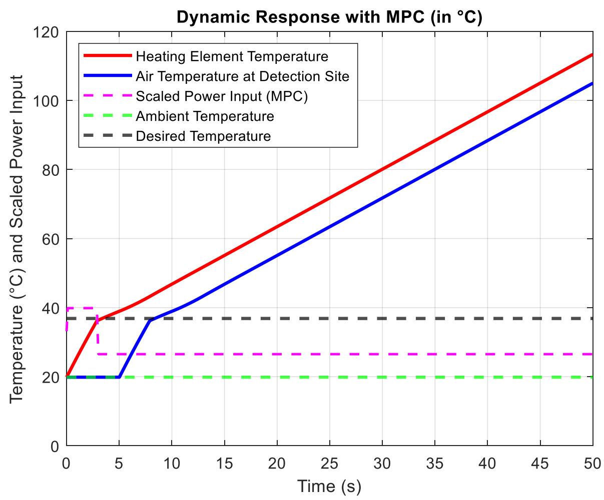

Fig. 6 Temperature and dynamic flow with MPC

ties. The smooth transition of the curves demonstrates the algorithm's ability to optimize performance and ensure system stability over time.

4. Experimental Set-Up of Hardware-In-The-Loop

In Fig. 7, the system of the temperature and airflow channel is presented, which includes a controller for communication with a PC. This system is designed to monitor and analyze various parameters of temperature and airflow in real time, while providing high accuracy and complete control over the process. The channel consists of three distinct measurement positions, strategically placed along the airflow path. Each position is equipped with sensitive sensors that measure temperature and flow parameters with high speed and precision.

Through these measurement points, it is possible to detect minor changes in temperature and airflow that occur during the process. The controller, which is the central component of the system, utilizes advanced communication protocols to connect with the PC. This connection ensures that the data collected by the sensors is transferred quickly and efficiently for further analysis. On the PC, the data is processed and displayed graphically, thus facilitating the interpretation of results and real-time decision-making. The presented system offers an integrated and flexible solution for monitoring and controlling processes that are dependent on temperature and airflow parameters.

The use of this system can be applied in various fields, including scientific laboratories, industrial production lines, and other engineering applications. With the help of three measurement positions and the advanced communication controller, this system ensures stable and optimized control for processes that require high precision.

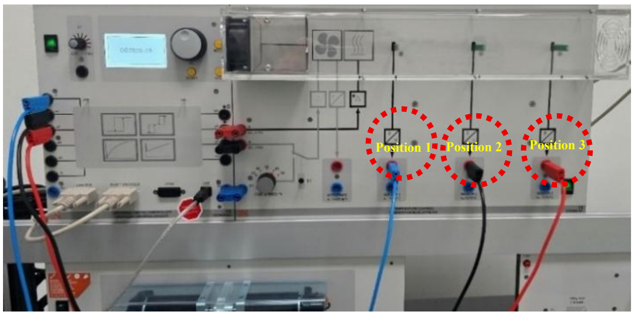

Fig. 7 The measuring device and controller in the Mechatronics Laboratory at FME during real testing

4.1. Steps for conducting the experiment

Gradually adjust the value of the manipulated variable (e.g., fan power or reference temperature) to predefined increments. Record the temperature or amplitude corresponding to each value of the manipulated variable once the system has reached a steady-state condition. The static response (steady-state behavior) of a controlled system is analyzed by examining the relationship between manipulated variables and the system's output. To do this, the value of the manipulated variable, such as fan power or reference temperature, is gradually adjusted in predefined increments. After each adjustment, the system is allowed to stabilize and reach a steady-state condition.

Once stabilized, the corresponding output response, such as temperature or amplitude, is recorded. This process ensures that the data accurately represents the system's steady-state behavior. To evaluate the system's sensitivity, or gain, the changes in the manipulated variable Δu and the resulting output response Δy are measured. The system gain K, is calculated using the formula

$$K = \frac{\Delta y}{\Delta u}, \tag{18}$$

where K is the system gain, Δy is the change in the output response, and Δu is the change in the manipulated input. This calculation provides a clear understanding of how variations in input influence the output response [14].

Fig. 8 provides a detailed representation of the measurements recorded at Position 1. It illustrates the heater temperature, which indicates the thermal output of the heating element during operation, as well as the measured temperature, which is the actual temperature observed at this position. Additionally, the figure highlights the desired temperature limit along the channel; this represents the target value set to achieve optimal system performance. This limit serves as a benchmark for evaluating the system's accuracy and stability.

Fig. 9 provides a detailed representation of the measurements recorded at Position 1. It illustrates the heater temperature, which indicates the thermal output of the heating element during operation, as well as the measured temperature, which is the actual temperature observed at this position.

A crucial aspect depicted in the Fig. 12 is the error

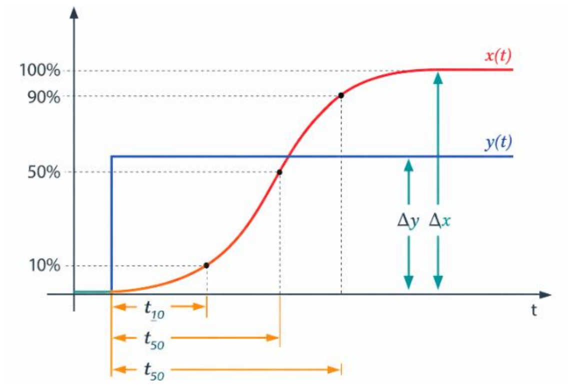

Fig. 8 Based on the step-by-step measured response, the values t_{10}, t_{50} and t_{90} are obtained, along with Δx and Δy

Table 1

Synchronized parameters prior to device testing

Controller	Controller Cycle Time	1, ms
Reference point of variables	Filtering	Without filtering
Controlled variables	Analog [x], Scaling, Filtering	Scale division
Adjusted variables	Limitation – Range (±100%): Indicates that the input or output values can vary between -100% and +100%. Scaling – Offset (0%): Indicates that no offset is applied; the starting point of the measurement remains unchanged. Output – Delay (0 ms): Indicates that there is no time delay in the output signal.	

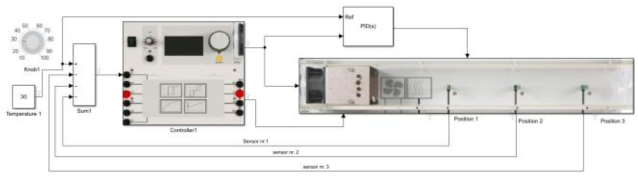

Fig. 9 Implementation of temperature measurement and control using the PID algorithm

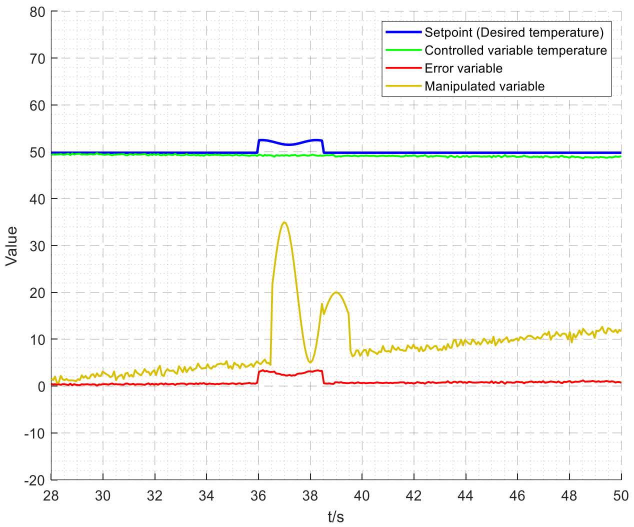

Fig. 10 Presents the real measurement data for Position 1 using PID

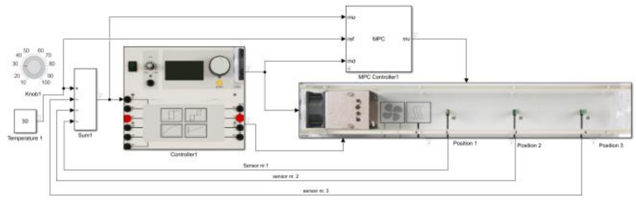

Fig. 11 Implementation of temperature measurement and control using the MPC

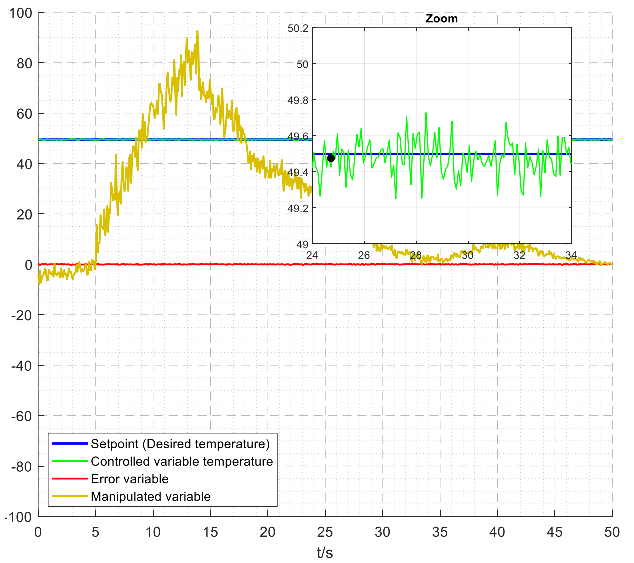

Fig. 12 The real measurement data for Position 1 using MPC control

between the measured temperature and the setpoint. This error quantifies the deviation of the actual temperature from the target value, and provides insight into the system's precision and responsiveness.

By analyzing these measurements, it is possible to assess the performance of the temperature regulation process, identify potential discrepancies, and determine areas for optimization. The data presented in Fig.11 is critical for ensuring that the system operates within the desired parameters, while maintaining efficiency and reliability. for handling complex temperature control systems, compared to traditional methods. In Fig. 12 shows the real measurement data at Position 1 under MPC control, where the system response follows the setpoint with a transient deviation before stabilizing.

6. Conclusions

This study examined the use of MPC for temperature control and compared it with PI and PID controllers. The results show that PI and PID work well for simpler systems and provide stable control, but MPC performs better when the system becomes more complex and the temperature behavior is more dynamic.

MPC stands out because it handles constraints effectively, responds quickly to disturbances such as changes in airflow, and tracks setpoint changes with high accuracy. It maintains stability while reducing overshoot, oscillations, and unnecessary energy use.

The experiments carried out in the Mechatronics Laboratory confirmed these advantages. MPC managed variations in air speed and external influences more reliably than traditional controllers, while keeping the temperature within the required limits.

For future work, the air channel model can be improved by including turbulent effects and energy losses to better reflect real conditions. The approach can also be extended to larger and more complex applications, such as HVAC systems and industrial temperature control processes.

The comparison between Fig. 10 and Fig. 12 shows clear performance differences. PID presents a large overshoot 80-90°C and slow settling 30-40 s, while MPC limits overshoot to about 5-7% and settles much faster 3-5 s. Overall, MPC provides better stability, accuracy, and smoother control behaviour.

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AUTOMATED TEMPERATURE CONTROL SYSTEM FOR A MULTI-POINT AIRFLOW CHANNEL USING PID AND MPC CONTROLLERS

S u mm a r y

This study compares MPC with PI and PID controllers for temperature control. While PI and PID are effective for simple and stable systems, MPC shows better performance in complex and dynamic conditions. Laboratory experiments confirm that MPC handles disturbances, airflow variations, and setpoint changes more accurately, with improved stability and reduced overshoot. The results highlight MPC as a more efficient and reliable solution for advanced temperature control applications, with strong potential for use in larger industrial systems.

Keywords: model predictive control, temperature control, PID controller, dynamic systems.

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