Design and Experimental Evaluation of Non-Cooperative Distributed MPC for a Thermally Coupled System

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***Abstract*—Model Predictive Control (MPC) is widely applied to multivariable systems due to its capability to systematically handle constraints and interactions. However, centralized MPC (CMPC) can become computationally intensive for strongly coupled systems, limiting its real-time applicability. Distributed Model Predictive Control (DMPC) addresses this limitation by decomposing the overall system into smaller subsystems, each controlled by a local MPC. This paper presents the design and experimental evaluation of a non-cooperative DMPC framework for the Temperature Control Laboratory (TCL) system, a thermally coupled two-input two-output process with nonlinear dynamics. In the proposed approach, each subsystem independently solves its local optimization problem while incorporating interaction effects through measured or predicted variables. Both sequential and iterative coordination strategies are implemented to examine the trade-off between computational efficiency and control performance. Experimental results under regulatory and servo conditions demonstrate that DMPC achieves effective disturbance rejection and accurate setpoint tracking with smooth control action. Sequential DMPC shows improved computational efficiency with comparable performance, whereas iterative DMPC enhances coordination at the expense of increased computational effort. These results highlight the practical potential of DMPC as a scalable alternative to centralized control for real-time applications in interconnected multivariable systems.**

***Index Terms*—Model Predictive Control (MPC), Distributed MPC, Non-cooperative DMPC, Sequential DMPC, Iterative DMPC, Temperature Control Laboratory (TCL), Multivariable Systems, Experimental Validation.**

I. Introduction

Model Predictive Control (MPC) is a widely adopted advanced control strategy for multivariable systems due to its capability to explicitly handle constraints, system interactions, and performance objectives via online optimization [1]–[3]. Despite its advantages, CMPC becomes computationally intensive for large-scale or strongly coupled systems, as it requires solving high-dimensional optimization problems at each sampling instant [4], [5]. This limits its scalability and real-time implementation, particularly in complex industrial applications [6]–[8].

Decentralized MPC (dMPC) addresses these challenges by assigning independent controllers to subsystems, improving modularity, reliability, and fault tolerance [9]–[11]. However, ignoring interconnections among subsystems can degrade performance and may lead to instability or constraint violations in strongly coupled systems [12], [13]. Distributed MPC (DMPC) provides an intermediate framework by decomposing the overall system into interacting subsystems, where local controllers incorporate coupling effects through information exchange or predicted interactions [14]–[16].

DMPC approaches are broadly categorized as cooperative and non-cooperative. In non-cooperative DMPC, each controller optimizes a local objective using limited information, treating interactions as disturbances [12], [13], [17]. This reduces computational and communication burden but may result in suboptimal performance compared to CMPC [2], [14]. In contrast, cooperative DMPC employs iterative coordination among controllers to approximate centralized performance while preserving a distributed structure [15], [16]. DMPC can further be implemented using different coordination strategies. In *sequential schemes*, controllers update their decisions in a predefined order using the most recent subsystem information, offering computational efficiency but limited coordination [18], [19]. In *iterative schemes*, controllers repeatedly exchange information within each sampling interval, improving coordination and consistency at the cost of increased computational and communication effort [16], [18], [19].

DMPC has been successfully applied to a variety of large-scale interconnected systems, including smart grids [20], water networks [21], and transportation systems [22]. In the chemical process domain, it has been utilized for complex nonlinear systems such as catalytic reactors [23], [24], reactor–separator systems [25]–[27], and integrated process networks [28], [29], benzene alkylation [30] and multi-tank systems [31], [32].

Despite these developments, experimental validation of DMPC remains relatively limited, with most studies focusing on simulation benchmarks or simplified laboratory setups [33]–[35]. The Temperature Control Laboratory (TCL) system serves as an effective experimental platform due to its nonlinear dynamics, two-input two-output configuration, and strong thermal coupling [36]. It enables evaluation of key control objectives such as setpoint tracking, disturbance rejection, and computational efficiency in a realistic setting.

Motivated by these considerations, this work presents the design and experimental implementation of a non-cooperative DMPC framework for the TCL system. Both sequential and iterative coordination strategies are investigated under servo and regulatory conditions. The main contributions of this work are:

- Development of a non-cooperative DMPC scheme for a thermally coupled two-input two-output system.
- Comparative analysis of sequential and iterative coordination strategies.
- Experimental validation of closed-loop performance and computational efficiency.
- Benchmarking against CMPC to highlight performance–scalability trade-offs.

The remainder of the paper is organized as follows. Section II presents the TCL system modeling and subsystem decomposition. Section III describes the DMPC controller design. Section IV discusses the experimental results and performance evaluation.

II. Temperature Control Laboratory (TCL)

The TCL setup is utilized as an experimental benchmark to validate the effectiveness of the proposed control strategy. This system is commonly adopted in process control research because of its nonlinear dynamics, actuator limitations, and significant interaction between variables. Such features make it well-suited for assessing advanced multivariable control schemes, including DMPC.

A. System Description

The TCL experimental arrangement and its corresponding schematic are illustrated in Fig. 1. The system consists of two heaters whose temperatures are regulated through adjustable power inputs. A fan is incorporated to introduce external disturbances, while thermocouples are employed to measure the surface temperatures of the heaters.

A mechanistic model of the TCL is formulated using fundamental heat transfer laws, primarily based on energy balance equations applied to each heater. Heat transfer mechanisms include convection and radiation between each heater and the environment, as well as thermal interaction between the heaters themselves. This leads to a nonlinear dynamic model that captures the essential behavior of the system.

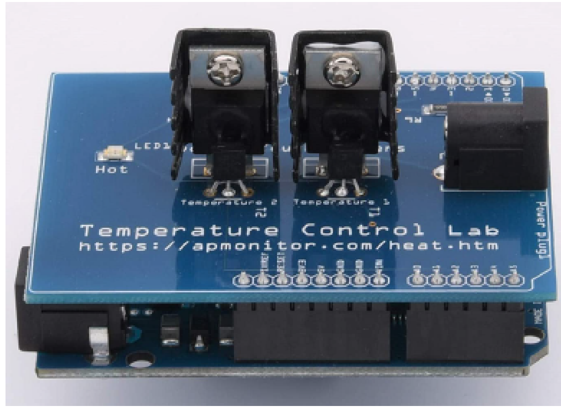
The heat exchange between the heaters is described by

$$Q_{C12} = UA_s(T_2 - T_1), \quad (1)$$
$$Q_{R12} = \epsilon\sigma A(T_2^4 - T_1^4). \quad (2)$$

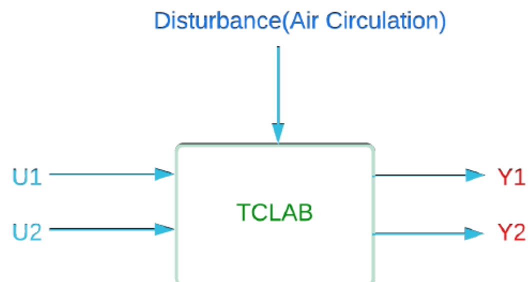
Applying the first law of thermodynamics, the temperature dynamics of the heaters are given by

$$mC_p\frac{dT_1}{dt} = UA(T_\infty - T_1) + \epsilon\sigma A(T_\infty^4 - T_1^4) + Q_{C12} + Q_{R12} + \alpha_1 Q_1, \quad (3)$$
$$mC_p\frac{dT_2}{dt} = UA(T_\infty - T_2) + \epsilon\sigma A(T_\infty^4 - T_2^4) - Q_{C12} - Q_{R12} + \alpha_2 Q_2. \quad (4)$$

where



(a) Experimental setup



(b) Schematic diagram

Fig. 1: Temperature Control Laboratory (TCL)

- T_∞ denotes the ambient temperature,
- Q_1, Q_2 are the heater input powers,
- α_1, α_2 represent heater gain coefficients,
- C_p is the specific heat capacity,
- A is the exposed surface area,
- A_s is the interaction surface area between heaters,
- m is the heater mass,
- U is the heat transfer coefficient,
- ϵ is emissivity, and
- σ is the Stefan–Boltzmann constant.

The nominal parameters of the TCL model are listed in Table I.

TABLE I: Nominal model parameters of the Temperature Control Lab

Parameter	Value	Parameter	Value
Q_1	0–1 W	Q_2	0–0.75 W
C_p	$500\ \mathrm{J\,kg^{-1}K^{-1}}$	A	$1\times10^{-3}\ \mathrm{m^2}$
A_s	$1\times10^{-4}\ \mathrm{m^2}$	m	0.004 kg
ϵ	0.9	σ	$5.67\times10^{-8}\ \mathrm{W\,m^{-2}K^{-4}}$

B. Decomposition of Distributed Control

The TCL process can be characterized as a two-input two-output (TITO) system, where heater powers Q_1 and Q_2 act as manipulated variables and temperatures T_1 and T_2 serve as outputs. Due to heat transfer interactions, each input affects both outputs, resulting in strong coupling.

To enable distributed control implementation, the overall system is divided into two interconnected subsystems. The first subsystem regulates T_1 using Q_1, while considering T_2 as an interacting variable. Similarly, the second subsystem controls T_2 using Q_2, treating T_1 as a coupling variable.

This partitioning allows controller design at the subsystem level, while interaction effects are incorporated either through explicit modeling or information exchange. Such an approach maintains the physical structure of the system and reduces computational requirements compared to centralized control.

C. Decomposition for Non-Cooperative DMPC

For the non-cooperative DMPC formulation, the TCL system is divided into two independent control units:

- Subsystem 1: controls T_1 via Q_1
- Subsystem 2: controls T_2 via Q_2

Each controller treats the influence of the other subsystem as a disturbance or known interaction signal. The optimization problems are solved independently without enforcing a common objective. Interaction is accounted for through shared measurements or predicted trajectories.

This strategy reduces computational effort while preserving essential coupling effects required for satisfactory control.

D. Model Parameter Estimation

Certain TCL parameters can be measured directly; however, parameters such as the heat transfer coefficient (U) and heater gains (α_1, α_2) must be estimated from experimental data.

To achieve this, identification experiments are conducted using pseudo-random binary sequence (PRBS) inputs applied to the heaters. Temperature data are recorded with a sampling time of 4 seconds. The PRBS signal ensures sufficient excitation over a wide operating range, enhancing parameter estimation reliability.

The unknown parameters are obtained by minimizing the error between measured outputs and model predictions using the `fmincon` optimization solver in MATLAB. The estimated values are presented in Table II.

The comparison between experimental data and model predictions is shown in Fig. 2, confirming that the model accurately captures system dynamics.

TABLE II: Estimated model parameters of Temperature Control Lab

Parameter	Unit	Value
U	W/m^2K	3.034
α_1	W (% Heater)	0.0060
α_2	W (% Heater)	0.0025

III. Controller Synthesis

This section outlines the methodology adopted for implementing the DMPC framework. To simplify the controller design and reduce computational burden, a linear MPC formulation is employed. The original nonlinear model of the TCL system is linearized around a chosen steady-state operating condition and then discretized in time.

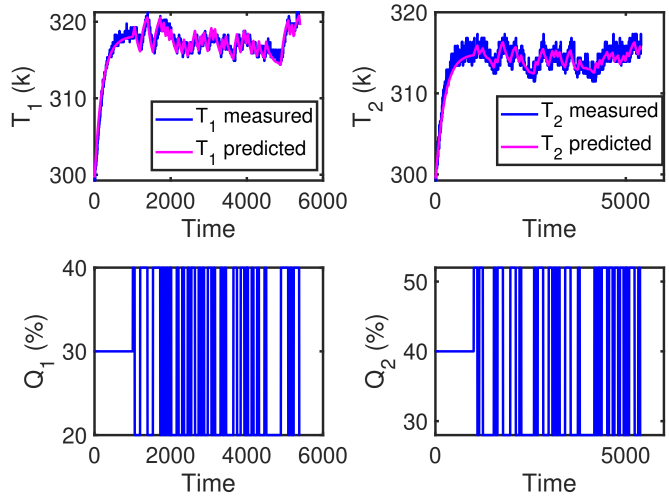


Fig. 2: TCL: Parameter Estimation

The resulting discrete-time state-space model is expressed as

$$\begin{aligned} x_{k+1} &= \Phi x_k + \Gamma u_k, \\ y_k &= C x_k, \end{aligned} \tag{5}$$

where x_k, u_k, and y_k represent the system state, input, and output vectors at the discrete time instant k. The matrices Φ and Γ describe the system dynamics after linearization and discretization, while C is the output matrix.

A. Subsystem Decomposition

To facilitate distributed control, the overall system is divided into M interconnected subsystems. The dynamics of the ith subsystem can be written as

$$\begin{aligned} x_{i,k+1} &= \Phi_{ii} x_{i,k} + \Gamma_{ii} u_{i,k} + L_{p,i} e_{f,k} \\ &\quad + \sum_{j \neq i} \left(\Phi_{ij} x_{j,k} + \Gamma_{ij} u_{j,k} \right), \\ y_{i,k} &= C_{ii} x_{i,k} + e_{f,k}. \end{aligned} \tag{6}$$

Here, Φ_{ii} and Γ_{ii} represent the local dynamics of subsystem i, whereas Φ_{ij} and Γ_{ij} account for interactions with other subsystems. These coupling terms capture the interdependence among subsystems and must be addressed appropriately within the control design.

B. Non-Cooperative DMPC

In the non-cooperative DMPC approach, each subsystem determines its control actions independently by minimizing a local cost function. The influence of other subsystems is incorporated through predicted trajectories, which are treated as known signals. Unlike CMPC, no global optimization objective is enforced.

For subsystem i, the optimization problem at time step k is formulated as

$$
\begin{aligned}
\min_{U_{C_i}} \quad & J_i = e_i^\top W_{e,i} e_i + \bar{U}_{C_i}^\top W_{U,i} \bar{U}_{C_i} \\
& \qquad + \Delta U_{C_i}^\top W_{\Delta U,i} \Delta U_{C_i} \\
\text{s.t.} \quad & \tilde{x}_{C_i,k+1} = \Phi_{ii} \tilde{x}_{C_i,k} + \Gamma_{ii} \tilde{u}_{C_i,k} + L_{p,i} e_{f,C_i,k} \\
& \qquad + \sum_{j \neq i} \left(\Phi_{ij} \hat{x}_{C_j,k} + \Gamma_{ij} \hat{u}_{C_j,k} \right) \\
& \tilde{y}_{C_i,k+1} = C_{C_i} \tilde{x}_{C_i,k+1} + e_{f,C_i,k} \\
& U_{C_i,\min} \leq U_{C_i} \leq U_{C_i,\max} \\
& \Delta U_{C_i,\min} \leq \Delta U_{C_i} \leq \Delta U_{C_i,\max} \\
& y_{C_i,\min} \leq y_{C_i,k} \leq y_{C_i,\max}
\end{aligned} \tag{7}
$$

In this formulation, $e_i = Y_{\text{target},C_i} - Y_{p,C_i}$ denotes the tracking error over the prediction horizon N_p. The term $\bar{U}_{C_i}$ represents the deviation of the control input from its steady-state value, while ΔU_{C_i} corresponds to the change in control input between successive time steps.

The constraints ensure that both the inputs and their rates of change remain within allowable limits. The weighting matrices $W_{e,i}$, $W_{U,i}$, and $W_{\Delta U,i}$ are used to penalize tracking errors, control effort, and input variations, respectively. The variables $\hat{x}_{C_j,k}$ and $\hat{u}_{C_j,k}$ denote predicted states and inputs received from neighboring subsystems.

Since each subsystem solves its optimization problem independently, the resulting control action is locally optimal and may differ from the globally optimal centralized solution.

IV. Performance Evaluation and Comparison

The proposed DMPC strategy is evaluated by comparing its performance with that of a CMPC approach. The comparison is carried out under both regulatory and servo scenarios. Two key metrics are used for assessment: a performance index (PI) to quantify control quality and computation time (CT) to evaluate computational efficiency.

A. Performance Index

The overall control performance is assessed based on both tracking accuracy and control effort. A cumulative cost function is defined over the simulation horizon as

$$
PI = \sum_{k=1}^{N_s} \left(e_k^\top W_e e_k + \bar{u}_k^\top W_U \bar{u}_k + \Delta u_k^\top W_{\Delta U} \Delta u_k \right), \tag{8}
$$

where N_s denotes the total number of sampling instants. The term e_k represents the tracking error, $\bar{u}_k$ denotes the deviation of the control input, and Δu_k corresponds to the input variation.

For comparison purposes, a normalized performance index is defined as

$$
\text{sPI} = \frac{PI_{\text{DMPC}}}{PI_{\text{CMPC}}}. \tag{9}
$$

A value of sPI close to 1 indicates that the distributed controller performs similarly to the centralized approach.

B. Computation Time

In addition to control performance, computational efficiency is an important consideration. The average computation time required to solve the optimization problem at each sampling instant is given by

$$
CT = \frac{1}{N_s} \sum_{k=1}^{N_s} t_k, \tag{10}
$$

where t_k represents the solver execution time at step k.

A normalized metric is defined as

$$
\text{sCT} = \frac{CT_{\text{DMPC}}}{CT_{\text{CMPC}}}. \tag{11}
$$

Together, sPI and sCT provide a comprehensive comparison of control performance and computational cost.

V. Results and Discussion

The closed-loop performance of the TCL system is evaluated under two operating scenarios: disturbance rejection (regulatory control) and setpoint tracking (servo control). In both cases, the performance of CMPC is compared with DMPC strategies.

A. Regulatory Performance

The regulatory study examines the ability of the controllers to maintain the system at its nominal steady-state in the presence of disturbances. To this end, a ceiling fan is activated for one minute at the 1000^{th} sampling instant, introducing additional convective heat loss and perturbing the thermal dynamics.

The resulting output and input responses of the TCL system under CMPC and DMPC strategies are shown in Fig. 3 and Fig. 4, respectively. All control schemes effectively counteract the disturbance and restore the system to its steady-state conditions. During the disturbance period, the manipulated inputs increase in a coordinated manner to compensate for the heat loss, and subsequently return smoothly to their nominal values once the disturbance is removed.

The absence of oscillations and abrupt variations in both the outputs and control inputs indicates stable and well-behaved closed-loop performance. This demonstrates that the controllers achieve effective disturbance rejection while maintaining actuator feasibility and avoiding excessive control effort.

A quantitative comparison is presented in Table III, which reports the scaled performance index (sPI) and scaled computational time (sCT). The results show that both sequential and iterative DMPC schemes provide performance comparable to CMPC, with only marginal differences in sPI. However, this performance is achieved at the expense of increased computational effort, as both DMPC schemes exhibit higher sCT values. In particular, iDMPC requires significantly more computation due to iterative coordination among subsystems. This highlights the trade-off between improved coordination and computational complexity in distributed implementations.

B. Servo Performance

The servo study evaluates the tracking capability of the control strategies under changes in setpoints. A simultaneous step increase of 35% is applied to the temperature setpoints T_1 and T_2 at the 1000^{th} sampling instant, allowing assessment of transient response and tracking accuracy.

The temperature responses under CMPC and DMPC are illustrated in Fig. 5 and corresponding control inputs are shown in

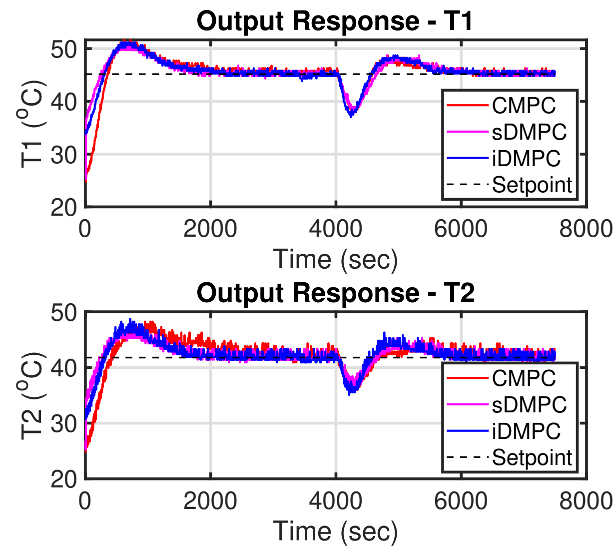


Fig. 3: TCL Regulatory problem: Output response showing temperature variations (T_1 and T_2) under CMPC, sDMPC, and iDMPC strategies.

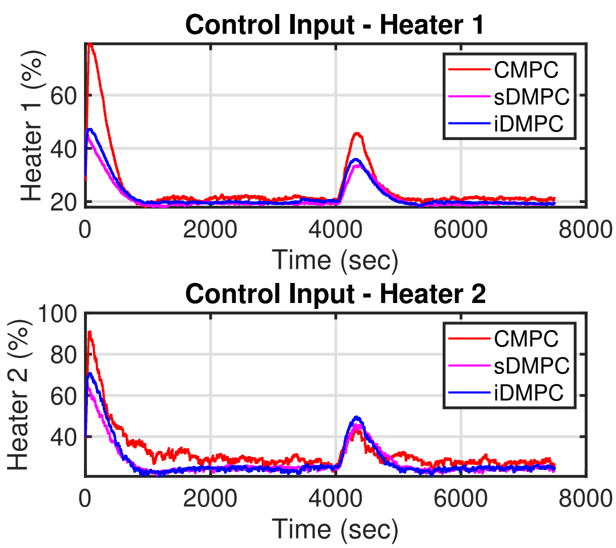


Fig. 4: TCL Regulatory problem: Input response showing manipulated heater inputs (H_1 and H_2) for CMPC, sDMPC, and iDMPC strategies.

Fig.6. All controllers successfully track the new setpoints with smooth and well-damped responses. The absence of overshoot and oscillatory behavior indicates effective handling of subsystem interactions and preservation of closed-loop stability.

The corresponding manipulated inputs, Q_1 and Q_2, adjust gradually following the setpoint change and converge to new steady-state values. This smooth transition confirms that accurate tracking is achieved without aggressive or discontinuous control actions.

Performance metrics reported in Table III further corroborate these observations. Both sequential and iterative DMPC schemes achieve tracking performance close to CMPC, with only minor deviations in sPI. In terms of computational effort, sDMPC demonstrates improved efficiency with lower sCT compared to CMPC, whereas iDMPC incurs higher computational cost due to iterative coordination. These results indicate that DMPC can retain near-centralized performance, while its computational efficiency depends on the chosen coordination strategy.

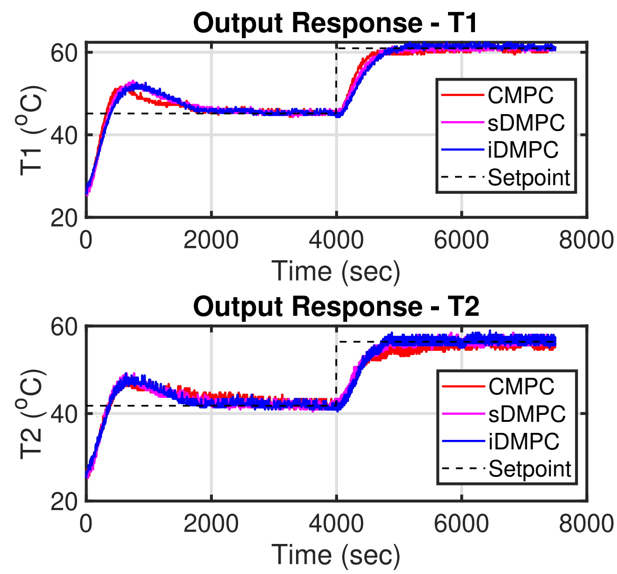


Fig. 5: TCL Servo problem: Output response showing temperature variations (T_1 and T_2) under CMPC, sDMPC, and iDMPC strategies.

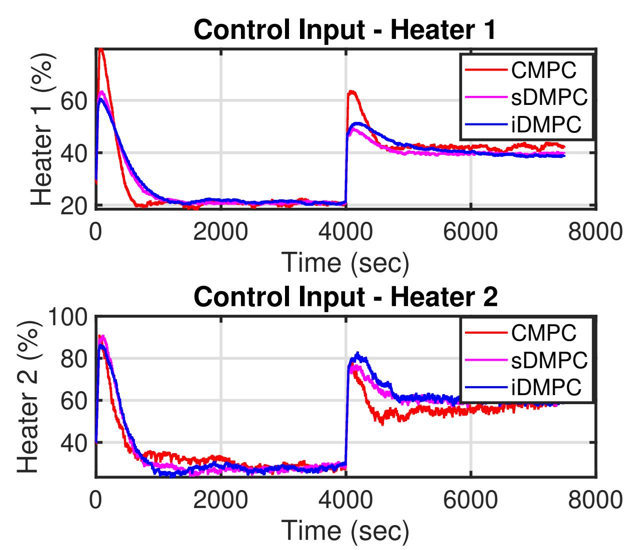


Fig. 6: TCL Servo problem: Input response showing manipulated heater inputs (H_1 and H_2) for CMPC, sDMPC, and iDMPC strategies.

TABLE III: Performance indices and computational time for the TCL system

Control Scheme	Regulatory		Servo	
	sPI	sCT	sPI	sCT
CMPC	1.000	1.000	1.000	1.000
sDMPC	1.015	1.842	1.133	0.744
iDMPC	1.009	3.474	1.105	1.389

VI. Conclusions

This study presented the design and experimental implementation of DMPC strategy for the TCL system. Owing to its nonlinear dynamics and strong thermal interactions, the TCL serves as an effective benchmark for assessing multivariable control methodologies. The experimental results demonstrate that the proposed DMPC framework successfully achieves both disturbance rejection and setpoint tracking, with smooth and well-coordinated control actions. The closed-loop responses confirm stable operation and effective handling of subsystem interactions under both regulatory and servo conditions. While minor deviations in performance are observed when compared to CMPC, the overall control objectives are satisfactorily met. From a computational perspective, the results highlight that the efficiency of DMPC depends on the coordination strategy. In particular, sequential DMPC offers reduced computational effort in certain scenarios, whereas iterative DMPC provides improved coordination at the cost of increased computation. DMPC provides a flexible and scalable alternative to centralized control, making it well-suited for practical implementation in interconnected systems with computational and communication constraints.

References

[1] S. J. Qin and T. A. Badgwell, "A survey of industrial model predictive control technology," *Control Engineering Practice*, vol. 11, no. 7, pp. 733–764, 2003.

[2] J. B. Rawlings and D. Q. Mayne, *Model Predictive Control: Theory and Design*. Madison, WI, USA: Nob Hill Publishing, 2009.

[3] E. F. Camacho and C. Bordons, *Model Predictive Control*. London, UK: Springer, 2nd ed., 2013.

[4] J. B. Rawlings, *Tutorial Overview of Model Predictive Control*. University of Wisconsin, 1999. Technical Report.

[5] J. M. Maciejowski, *Predictive Control with Constraints*. Harlow, UK: Pearson Education, 2002.

[6] F. Allgöwer and A. Zheng, *Nonlinear Model Predictive Control*. Basel, Switzerland: Birkhäuser, 2004.

[7] M. Morari and J. H. Lee, "Model predictive control: Past, present and future," *Computers & Chemical Engineering*, vol. 23, no. 4–5, pp. 667–682, 2000.

[8] G. Pannocchia, "Offset-free tracking mpc: A tutorial review and comparison of different approaches," *Journal of Process Control*, vol. 23, no. 8, pp. 1039–1052, 2013.

[9] S. Cui, S. J. Qin, and T. A. Badgwell, "A survey of industrial model predictive control applications," *AIChE Symposium Series*, vol. 98, no. 326, pp. 1–12, 2002.

[10] N. H. El-Farra and P. D. Christofides, "Bounded robust control of constrained multivariable nonlinear processes," *Chemical Engineering Science*, vol. 60, no. 4, pp. 1129–1150, 2005.

[11] T. Keviczky, F. Borrelli, and G. J. Balas, "Decentralized receding horizon control for large scale dynamically decoupled systems," *Automatica*, vol. 42, no. 12, pp. 2105–2115, 2006.

[12] J. M. Maestre and R. R. Negenborn, *Distributed Model Predictive Control Made Easy*. Dordrecht, Netherlands: Springer, 2014.

[13] A. Richards and J. P. How, "Robust distributed model predictive control," *International Journal of Control*, vol. 80, no. 9, pp. 1517–1531, 2007.

[14] A. N. Venkat, J. B. Rawlings, and S. J. Wright, "Stability and optimality of distributed model predictive control," *Proceedings of the 44th IEEE Conference on Decision and Control*, pp. 6680–6685, 2005.

[15] P. D. Christofides, N. H. El-Farra, and P. D. Daoutidis, *Nonlinear and Robust Control of PDE Systems: Methods and Applications to Transport-Reaction Processes*. Boston, MA, USA: Birkhäuser, 2013.

[16] B. T. Stewart, A. Papachristodoulou, and M. N. Zeilinger, "Distributed model predictive control: A tutorial review and future directions," *Annual Reviews in Control*, vol. 35, no. 2, pp. 210–220, 2011.

[17] E. Camponogara, D. Jia, B. H. Krogh, and S. Talukdar, "Distributed model predictive control," *IEEE Control Systems Magazine*, vol. 22, no. 1, pp. 44–52, 2002.

[18] R. Scattolini, "Architectures for distributed and hierarchical model predictive control—a review," *Journal of Process Control*, vol. 19, no. 5, pp. 723–731, 2009.

[19] H. Chen and F. Allgöwer, "A quasi-infinite horizon nonlinear model predictive control scheme with guaranteed stability," *Automatica*, vol. 34, no. 10, pp. 1205–1217, 1998.

[20] Y. Shi, H. D. Tuan, A. V. Savkin, C.-T. Lin, J. G. Zhu, and H. V. Poor, "Distributed model predictive control for joint coordination of demand response and optimal power flow with renewables in smart grid," *Applied Energy*, vol. 290, p. 116701, 2021.

[21] Z. Zhu, G. Guan, and K. Wang, "Distributed model predictive control based on the alternating direction method of multipliers for branching open canal irrigation systems," *Agricultural Water Management*, vol. 285, p. 108372, 2023.

[22] S. Li, L. Yang, and Z. Gao, "Distributed optimal control for multiple high-speed train movement: An alternating direction method of multipliers," *Automatica*, vol. 112, p. 108646, 2020.

[23] F. Albalawi, H. Durand, and P. D. Christofides, "Distributed economic model predictive control for operational safety of nonlinear processes," *AIChE Journal*, vol. 63, no. 8, pp. 3404–3418, 2017.

[24] T. L. Anderson, M. Ellis, and P. D. Christofides, "Distributed economic model predictive control of a catalytic reactor: Evaluation of sequential and iterative architectures," *IFAC-PapersOnLine*, vol. 48, no. 8, pp. 26–31, 2015.

[25] P. D. Christofides, J. Liu, and D. Muñoz de la Peña, "Networked and distributed predictive control," *Springer*, 2011.

[26] M. J. Tippett and J. Bao, "Distributed model predictive control based on dissipativity," *AIChE Journal*, vol. 59, pp. 787–804, 2013.

[27] D. B. Pourkargar and S. S. Jogwar, "Distributed model predictive control of integrated process networks: Optimal decomposition for varying operating point," *Proceedings of the American Control Conference (ACC)*, pp. 801–807, 2021.

[28] D. B. Pourkargar, A. Almansoori, and P. Daoutidis, "Impact of decomposition on distributed model predictive control: A process network case study," *Industrial & Engineering Chemistry Research*, vol. 56, no. 34, pp. 9606–9616, 2017.

[29] D. B. Pourkargar, A. Almansoori, and P. Daoutidis, "Comprehensive study of decomposition effects on distributed output tracking of an integrated process over a wide operating range," *Chemical Engineering Research and Design*, vol. 134, pp. 553–563, 2018.

[30] J. Liu, X. Chen, D. Muñoz de la Peña, and P. D. Christofides, "Sequential and iterative architectures for distributed model predictive control of nonlinear process systems," *AIChE Journal*, vol. 56, no. 8, pp. 2137–2149, 2010.

[31] P. R. Sukhadeve and S. S. Jogwar, "Model predictive control of interacting systems - effect of control architecture," *2022 Eighth Indian Control Conference (ICC)*, pp. 43–48, 2022.

[32] P. R. Sukhadeve and S. S. Jogwar, "Effect of control structure on the performance of distributed model predictive control," in *IFAC-PapersOnLine*, vol. 57, pp. 262–267, 2024.

[33] M. Mercangöz and S. Skogestad, "Control of a fluid catalytic cracking unit," *Computers & Chemical Engineering*, vol. 31, no. 5–6, pp. 535–549, 2007.

[34] I. Alvarado, G. Stathopoulos, C. N. Jones, and M. Morari, "A fast and practical method for explicit model predictive control," *IEEE Transactions on Control Systems Technology*, vol. 19, no. 5, pp. 1250–1257, 2011.

[35] P. R. Sukhadeve and S. S. Jogwar, "Impact of structure on the performance of distributed model predictive control: Insights from an experimental case study," *Journal of Process Control*, vol. 161, p. 103695, 2026.

[36] J. D. Hedengren and R. Gopaluni, "Temperature control lab (tclab): An arduino-based experiment for process control education," 2014.