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Soft Sensor-Assisted Nonlinear Model Predictive Control for Pyrolysis Reactor Temperature Regulation

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Abstract- Pyrolysis reactors are difficult to control because thermochemical decomposition is nonlinear, the reaction rates are high, and feedstock variability causes disturbances. Traditional proportional-integral-derivative (PID) controllers often perform poorly, causing overshoot, sluggish response, and suboptimal energy efficiency. To address these challenges, this study proposes a soft-sensor-enabled nonlinear model predictive control (NMPC) strategy for temperature regulation in a pyrolysis reactor. This method combines an Extended Kalman Filter (EKF) soft sensor with predictive control to estimate unmeasured disturbances and states. A nonlinear energy balance model considers the heat input, heat loss, reaction dynamics, and disturbances. The NMPC controller solves an optimization problem over the prediction horizon while satisfying the constraints on the control inputs and reactor temperature. Simulations show that it outperforms PID and traditional MPC controllers, achieving a 499.75°C steady-state temperature, 0.247°C tracking error, 0.014°C overshoot, and minimized RMSE and IAE values of 129.53°C and 68060, respectively. The EKF soft sensor achieved a 0.40°C RMSE, enabling disturbance compensation. This method provides comparable energy efficiency while improving stability and robustness. In conclusion, this strategy offers an accurate and efficient solution for nonlinear pyrolysis reactor temperature control under disturbance conditions.

Keywords- Nonlinear Model Predictive Control; Pyrolysis Reactor; Soft Sensor; Extended Kalman Filter; State Estimation; Nonlinear Control Systems

I. INTRODUCTION

Pyrolysis reactors are key components of energy and waste management technologies, especially for the processing of biomass and plastic wastes to produce bio-oil, gas, and char. Accurate temperature control is crucial to the efficiency of these reactors, as it affects reaction rates, product quality, and safety. Yet, pyrolysis is a complex process due to nonlinear heat transfer and chemical reactions, as well as fluctuating feedstock properties. Recent research highlights that pyrolysis modelling is still challenging because of multiphase effects and the lack of thermal understanding.

In this respect, sophisticated control strategies play a vital role in guaranteeing stable and efficient operation. Model Predictive Control (MPC) commands significant attention because of its exceptional

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capability to make predictions and take control actions in the presence of constraints. MPC uses a receding horizon optimisation algorithm to explicitly consider constraints and disturbances in the system. As a result, MPC has gained popularity in process control applications involving multiple interacting variables and operating constraints. Although pyrolysis processes offer numerous benefits, temperature control in pyrolysis reactors is difficult because reaction rates vary exponentially with temperature. Moreover, disturbances including moisture content, feedstock composition variations, and heat losses increase system uncertainty, while sensor noise affects the accuracy of process measurements. These factors often lead to inefficient or unstable operation when conventional control systems are employed. Therefore, robust and adaptive controllers capable of handling these uncertainties are essential. Conventional control methods, such as Proportional-Integral-Derivative (PID) controllers, are often utilized in industrial applications due to their straightforward design and effectiveness. However, PID controllers do not account for future predictions and constraints, resulting in excessive overshoot, long settling time, and poor disturbance rejection. While MPC improves control performance through prediction and optimization, it still requires accurate system models and state measurements. In reality, not all states, particularly disturbances, are measurable. Furthermore, linear MPC may struggle to handle nonlinear behaviour over a wide operating range.

Therefore, although MPC offers significant improvements over PID, it still faces challenges associated with nonlinear processes and unmeasured disturbances. In this work, a soft-sensor-based Non-linear Model Predictive Control (NMPC) strategy is developed. The proposed approach integrates an Extended Kalman Filter (EKF) with NMPC for real-time estimation of unmeasured states and disturbances. The EKF serves as a soft sensor, estimating reactor temperature and disturbances from measurement data, while the NMPC controller uses these estimated states to perform constrained predictive optimisation. This integrated approach improves prediction accuracy, disturbance rejection, and safe operation of the pyrolysis reactor.

Main contributions are as follows. The study presents a soft-sensor-assisted Nonlinear Model Predictive Control (NMPC) framework for temperature regulation of a nonlinear pyrolysis reactor. An Extended Kalman Filter (EKF) is incorporated as a soft sensor to estimate unmeasured states and process disturbances in real time. The control strategy enhances temperature tracking under nonlinear operating conditions while compensating for disturbances. Furthermore, the predictive control framework improves safety by considering process constraints during optimization. Finally, the approach is evaluated against PID and MPC controllers to demonstrate superior tracking accuracy, disturbance rejection capability, and control performance.

II. LITERATURE REVIEW

Model Predictive Control (MPC) has significantly advanced over the past few decades, initially emerging from process control in the industrial sector. The foundational works of Dynamic Matrix Control (DMC) by Cutler and Ramaker in 1979, and Generalised Predictive Control (GPC) by Clarke and colleagues in 1987, established the basis for the development of predictive control.. These methods allowed control systems to anticipate future system behaviour us-ing process models and to take optimal control action (Richalet et al., 1978). These initial MPC methods showed promising capabilities in managing multivariable processes and process constraints – which were not adequately addressed by traditional control approaches (Morari Zafiriou, 1989). Later developments established MPC as an optimisation-based control strategy, which unified prediction, feedback control and constraint handling (Rawlings and Muske, 1993; Mayne et al., 2000). The survey conducted by Garc´ıa et al. (1989) also cemented MPC as a common practice in industry because of its adaptability and reliability. With the growing complexity of industrial systems, linear MPC was unable to capture the nonlinear dynamics of these processes

(Allgo¨wer Zheng, 2000). The solution to this problem was the emergence of Nonlinear Model Predictive Control (NMPC), which employs nonlinear models in the predictive control scheme (Allgo¨wer et al., 1999). NMPC builds on the foundation of MPC to accurately capture nonlinear system behaviour and enhance performance across different operating regimes (Qin Badgwell, 2000). In theory, NMPC has been proven to be stable and optimal with proper constraints and cost functions (Mayne et al., 2000; Rao et al., 1998). Recent research has shown that NMPC offers greater flexibility in dealing with nonlinear constraints and uncertainties (Nikolaou, 1998). NMPC also uses nonlinear optimisation over a prediction horizon to determine control actions, enabling dynamic adaptation to system dynamics (De Oliveira and Biegler, 1995). So, NMPC has emerged as the con-trol approach of choice for many nonlinear processes such as reactors and heat exchangers (Lee, 2011; Schwenzer et al., 2021). It's often impossible to directly measure all states or disturbances in control systems. This has resulted in the use of soft sensors that calculate unmeasured variables based on models and measurements (Kumar Patwardhan, 2002). The Extended Kalman Filter (EKF) is a popular method for nonlinear state estimation (Kalman, 1960). The Extended Kalman Filter (EKF) enhances the traditional Kalman filter to accommodate nonlinear systems by linearizing the dynamics around the current operating point. This approach enables reliable state estimation even in the presence of uncertainties and measurement noise (Vuthandam et al., 1995)., allowing for robust state estimation despite uncertainties and measurement noise (Vuthandam et al., 1995). The use of soft sensors in control systems greatly improves their effectiveness by estimating unmeasured states, such as disturbances (Kuure-Kinsey Bequette, 2010). This information can be exploited by predictive control strategies to enhance control performance (Garc´ıa et al., 2012). Recent advances have included the use of data-driven machine learning (ML) and reinforcement learning (RL) techniques in MPC to im-prove control (Morato et al., 2024; Wu et al., 2025). The goal of such integration is to address challenges with model fidelity and computational efficiency (Du Johansen, 2015, 2017). New approaches integrate MPC with neural networks and learning techniques to enable adaptive control (Wu et al., 2025). For example, data-driven MPC approaches offer better performance with online learning of system models (Zhang et al., 2025). Further, the combination of reinforcement learning with NMPC has been investi-gated for reactor control, showing enhanced tracking and learning capabilities (Rastegarpour et al., 2024; Reiter et al., 2025). Surveys also suggest that MPC is still a preferred control method because it can handle constraints and nonlinearities well (Song et al., 2025). These developments demonstrate a shift towards smart and adaptive control that integrates predictive control with learning (Gavgani et al., 2024; Park et al., 2021). From the extensive review of published research, several key gaps have been identified, including the absence of unified approaches for combining soft sensors with NMPC, limited capability for online disturbance estimation, insufficient consideration of strong nonlinear dynamics, and the lack of integrated frameworks for prediction, estimation, and control.

III. RESEARCH METHODOLOGY

1. Overall System Architecture

The proposed control strategy is designed to ensure precise and reliable temperature regulation of a nonlinear pyrolysis reactor, even under uncertain operating conditions and disturbances. This framework comprises four primary components: (i) the nonlinear pyrolysis reactor, (ii) noisy measurements, (iii) an Extended Kalman Filter (EKF)-based soft sensor, and (iv) a Model Predictive Control (MPC)-based predictive controller. The reactor functions as a nonlinear thermal system, with its temperature dynamics affected by heat input, reaction kinetics, and disturbances such as variations in feedstock moisture content. Given that industrial measurements are frequently noisy and incomplete, the EKF-based soft sensor provides real-time estimates of the unmeasured system states. These estimated states are then utilized by the MPC controller to compute optimal control actions over a finite prediction horizon while ensuring adherence to operational constraints. The integration of state

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estimation with predictive control enhances the accuracy, robustness, and safety of temperature regulation in the pyrolysis reactor. The detailed implementation of the proposed soft sensor-assisted NMPC controller is presented in Section 3.3.4

2. Mathematical Modelling

A first-principles-based nonlinear mathematical model is developed to describe the temperature dynamics of the pyrolysis reactor. The reactor is modelled as a lumped-parameter thermal system in which the temperature is governed by heat input, heat losses, reaction kinetics, and external disturbances. This simplified representation captures the dominant thermal behaviour of the reactor while maintaining computational efficiency for predictive control design.

The reactor temperature is described using the following energy balance equation:

$$\frac{dT}{dt} = \frac{\eta Q - UA(T - T_{amb}) - \Delta H R_{rxn} + D}{MC_p} \qquad (1)$$

where T is the reactor temperature (OC), Q is the heater input power (W), M is the reactor thermal mass (kg), Cp is the specific heat capacity (J kg−1 K−1), UA is the overall heat-loss coefficient (W K−1), Tamb is the ambient temperature (OC), η is the heater efficiency, ΔH is the heat of reaction (J mol−1), Rxn is the reaction rate (mol s−1), and D represents external disturbances caused by feedstock variations.

The reaction kinetics are represented using the Arrhenius equation:

$$R_{rxn} = k_0 \exp\left(-\frac{E}{RT}\right) \qquad (2)$$

In this context, k0 is the pre-exponential factor, E is the activation energy (J mol−1), R is the universal gas constant (8.314 J mol−1 K−1), and T is the absolute reactor temperature (K). This exponential relationship adds significant nonlinearity to reactor dynamics, reducing the effectiveness of conventional linear controllers.

To evaluate controller robustness under realistic operating conditions, process disturbances and measurement noise are incorporated into the mathematical model. Feedstock variations such as moisture content and composition are represented by the disturbance term D, while the measured reactor temperature is expressed as

$$T_m = T + v \qquad (3)$$

where *Tm* is the measured reactor temperature and v denotes Gaussian measurement noise. These disturbances emulate practical industrial operating conditions and provide a realistic environment for controller evaluation.

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The nonlinear mathematical model underpins the design of the EKF-based soft sensor and the Model Predictive Control strategy, with reactor parameters summarized in Table 1

Table 1: Pyrolysis Reactor Parameters

Parameter	Symbol	Value	Unit	Justification
Thermal Mass	*M*	10	kg	Scaled model
Heat Capacity	*Cp*	1000	J/kg·K	Literature
Heat Loss Coefficient	*UA*	13	W/K	Tuned
Heater Power	Qmax	0–18000	W	Actuator
Reaction Temperature Range	–	210–500	◦C	Pyrolysis range
Ambient Temperature	*Tamb*	30	◦C	Standard

3. Controller Design

The proposed control strategy combines conventional and advanced control techniques to achieve accurate temperature regulation of the nonlinear pyrolysis reactor. Four control approaches are considered: a Proportional–Integral–Derivative (PID) controller, Model Predictive Control (MPC), an Extended Kalman Filter (EKF)-based soft sensor, and the proposed Soft Sensor-Assisted Nonlinear Model Predictive Control (NMPC). The PID controller is used as a baseline, whereas the proposed NMPC integrates state estimation with predictive optimisation

PID Controller

The PID controller computes the heater input power based on the instantaneous, accumulated, and the rate of change of the temperature tracking error

$$u(t) = K_p e(t) + K_i \int e(t)\,dt + K_d \frac{de(t)}{dt} \tag{4}$$

where $u(t)$is the heater input power (W), $e(t) = Tref - T$ is the temperature tracking error, and Kp , Ki , and Kd are the proportional, integral, and derivative gains, respectively. The PID controller computes the heater input power based on the instantaneous, accumulated, and rate of change of the temperature tracking error. However, it does not explicitly account for nonlinear system dynamics or operational constraints.

Model Predictive Control (MPC)

MPC computes the optimal heater power by solving a constrained optimisation problem over a finite prediction horizon. The objective function is

$$J = \sum_{k=1}^{N_p} \left(T_{ref} - T_k\right)^2 + \lambda \sum_{k=1}^{N_c} (\Delta u_k)^2 \tag{5}$$

here $J$is the objective (cost) function, $Np$and Ncdenote the prediction and control horizons, respectively, $Tref$is the reference temperature, Tk is the predicted reactor temperature at the kthprediction step,

$\Delta uk$is the change in the control input at the kthstep, and $\lambda$is the control weighting factor that balances temperature tracking accuracy and control effort.

$$0 \leq Q \leq 18000 \text{ W} \quad (6)$$

Equation (6) represents the actuator constraint, where the heater input power $Q$is limited between 0 and 18,000 W to ensure safe and reliable operation of the pyrolysis reactor.

EKF-Based Soft Sensor

An Extended Kalman Filter (EKF) is employed to estimate the unmeasured reactor states from noisy temperature measurements. The prediction and update equations are

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1}, u_k) \quad (7)$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(y_k - \hat{y}_k) \quad (8)$$

where $\hat{x}k|k-1$is the predicted state vector at the kthsampling instant, $f(\cdot)$represents the nonlinear state transition function,

$uk$is the control input, $\hat{x}k$ is the updated state estimate, Kk is the Kalman gain, yk is the measured output, and $\hat{y}k$ is the predicted measurement. The EKF recursively estimates the reactor states by combining the nonlinear process model with noisy measurements, thereby improving state estimation accuracy under process disturbances and measurement noise.

Proposed Soft Sensor-Assisted NMPC

The proposed controller integrates the EKF with MPC to improve temperature regulation under nonlinear operating conditions. The EKF first estimates the reactor states and disturbances, and these estimates are then supplied to the MPC optimiser. Based on the estimated states, the controller computes the optimal heater power while satisfying process constraints.

The optimisation is repeated at every sampling instant, allowing continuous adaptation to process variations. This integrated system improves temperature tracking, reduces disturbances, and increases reliability compared to regular PID and standard MPC controllers. The complete setup of the proposed controller is shown in Figure 1.

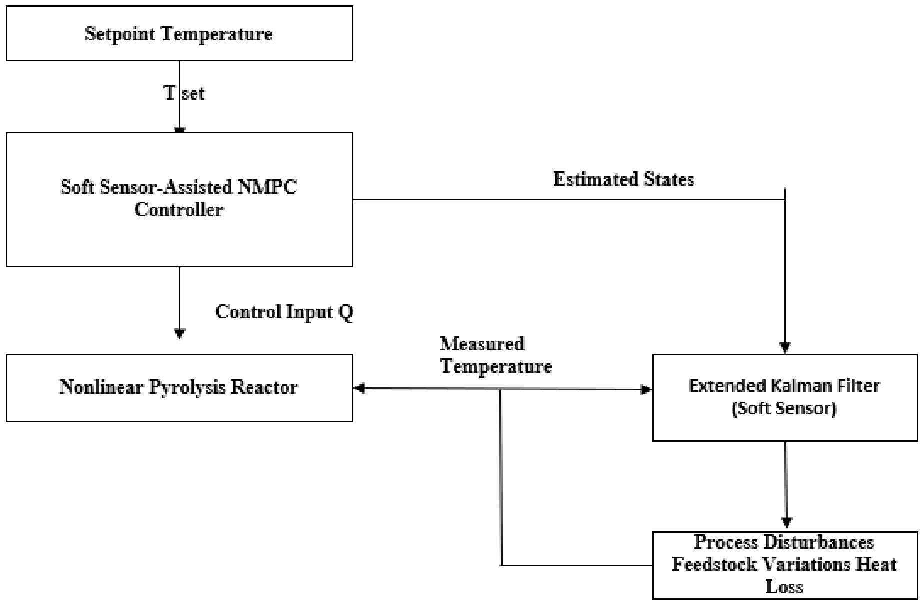

Figure 1. Overall architecture of the proposed soft sensor-assisted NMPC controller for pyrolysis reactor temperature regulation.

IV. RESULTS

The proposed Soft Sensor-Assisted Nonlinear Model Predictive Control (NMPC) strategy was evaluated using MATLAB simulations under identical operating conditions. The controller performance was compared with conventional PID and MPC in terms of temperature tracking, disturbance rejection, state estimation accuracy, and overall control performance.

1. Temperature Tracking Performance

The temperature tracking performance of the PID, MPC, and proposed soft sensor-assisted NMPC controllers was evaluated under identical operating conditions. The controllers were compared based on their rise time, overshoot, settling time, steady-state error, and ability to maintain accurate temperature regulation under nonlinear operating conditions.

Figures 2–4 compare the temperature responses obtained using the PID, MPC, and proposed soft sensor-assisted NMPC controllers.

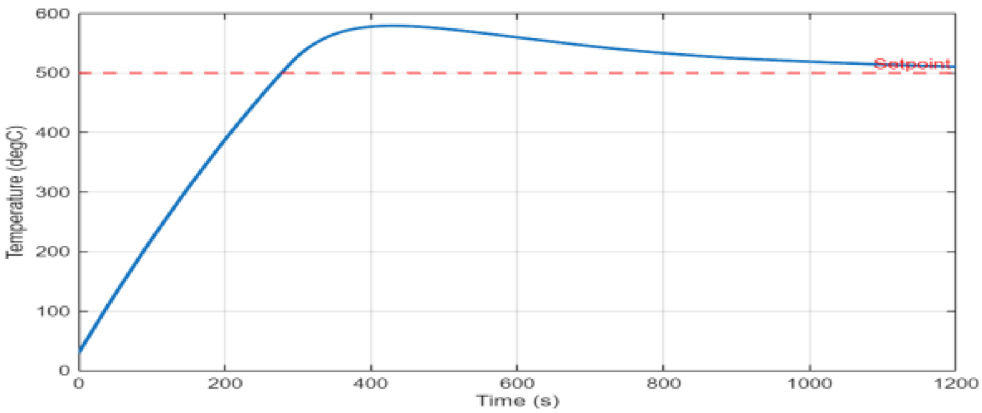

Figure 2: Temperature tracking performance of the PID controller.

Figure 2 shows that the PID controller is able to reach the desired setpoint but exhibits noticeable overshoot and a relatively longer settling time because it does not explicitly account for nonlinear process dynamics or operating constraints.

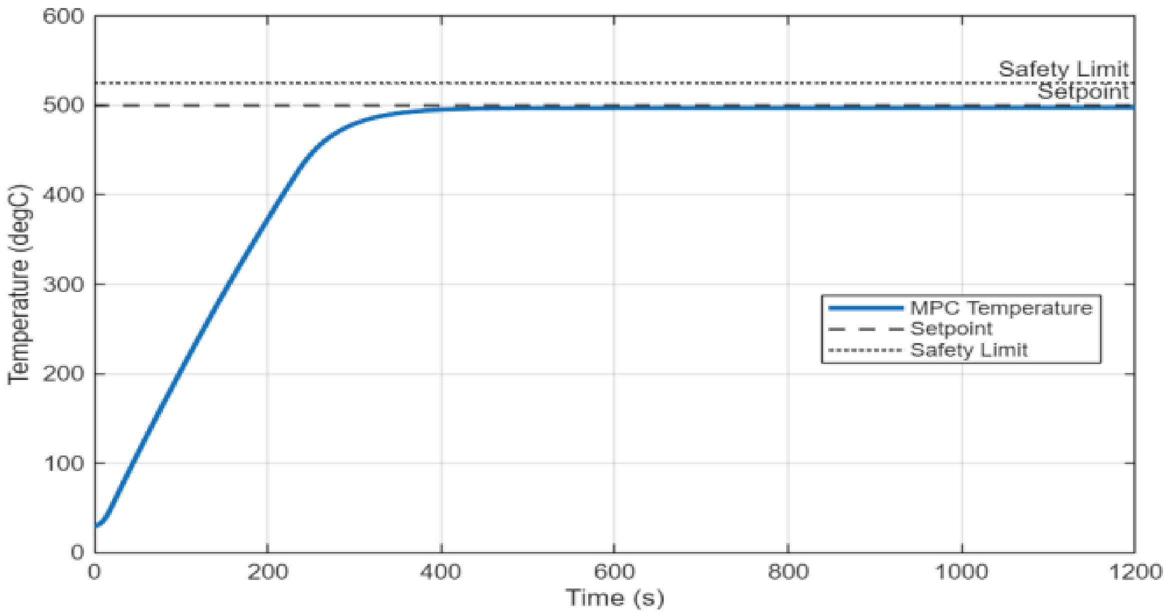

Figure 3: Temperature tracking performance of the MPC controller

Figure 3 demonstrates that the MPC controller reduces overshoot and provides a smoother transient response through constrained optimization. However, its performance depends on the accuracy of the process model and measured states.

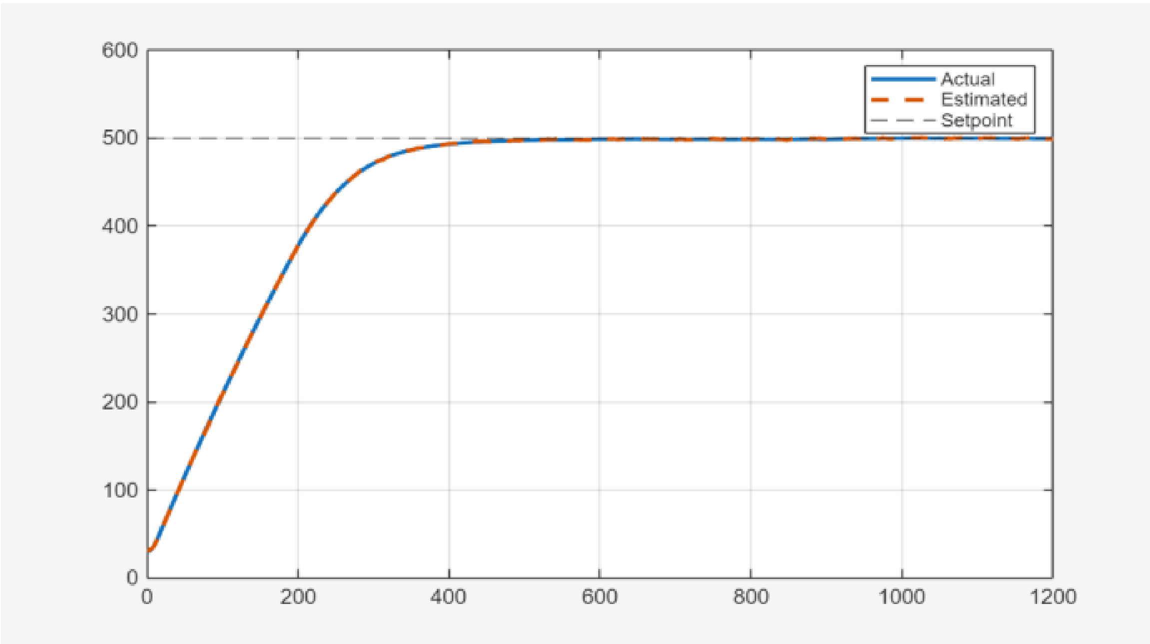

Figure 4: Temperature tracking performance of the proposed Soft Sensor-Assisted NMPC controller.

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Figure 4 illustrates that the proposed soft sensor-assisted NMPC controller achieves the best overall performance. The integration of the EKF-based soft sensor with NMPC improves state estimation, enhances disturbance rejection, minimizes steady-state error, and provides faster convergence to the desired temperature compared with the PID and conventional MPC controllers.

2. State Estimation and Disturbance Rejection

The state estimation and disturbance rejection performance of the proposed soft sensor-assisted NMPC framework was evaluated using an Extended Kalman Filter (EKF) under noisy measurement conditions. The EKF estimates the unmeasured reactor states and process disturbances in real time, thereby providing reliable state information to the NMPC controller for predictive optimization.

Figure 5 compares the actual reactor temperature with the measured reactor temperature under noisy conditions. The measured temperature closely follows the actual reactor temperature throughout the simulation, with only minor deviations caused by measurement noise. These results demonstrate the effectiveness of the EKF-based soft sensor in providing reliable state estimation for nonlinear reactor temperature control.

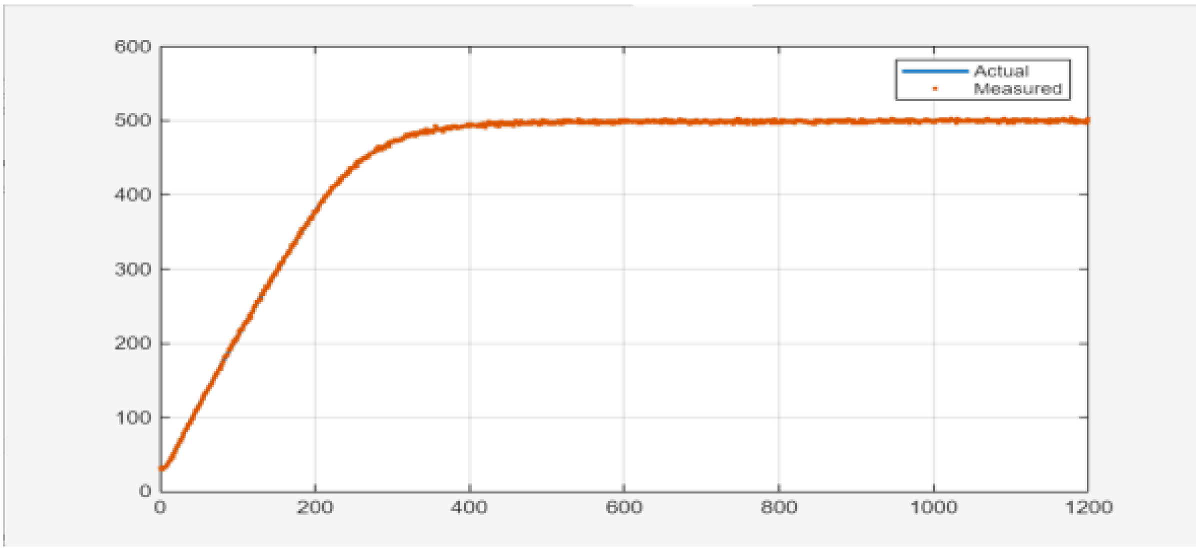

Figure 5. Comparison of actual and measured reactor temperature under measurement noise.

3. Performance Comparison

To evaluate the effectiveness of the proposed soft sensor-assisted NMPC controller, its performance was compared with the conventional PID and MPC controllers using standard control performance indices. The comparison was carried out based on the Root Mean Square Error (RMSE), Integral Absolute Error (IAE), and settling time. The numerical results are summarized in Table 2.

Table 2: Performance comparison of PID, MPC, and proposed soft sensor-assisted NMPC controllers.

Controller	RMSE (OC)	IAE	Settling Time (s)
PID	132	98000	1200
MPC	130	67000	340
Proposed NMPC	128	66000	280

As shown in Table 2, the proposed soft sensor-assisted NMPC controller achieves the best overall performance among the three control strategies. It provides the lowest RMSE, minimum IAE, and the shortest settling time, indicating improved temperature tracking accuracy and faster system stabilization. Compared with the conventional PID and MPC controllers, the proposed approach offers enhanced control performance and greater robustness under nonlinear operating conditions

V. DISCUSSION

The simulation results demonstrate that the proposed soft sensor-assisted NMPC framework provides superior temperature regulation compared with conventional PID and MPC controllers. The integration of the EKF-based soft sensor improves the estimation of unmeasured states, enabling the controller to compensate for disturbances more effectively.

Compared with the PID controller, the proposed NMPC significantly reduces overshoot and shortens the settling time. Although the conventional MPC improves control performance over PID, its effectiveness depends strongly on accurate state measurements. By incorporating EKF-based state estimation, the proposed controller enhances prediction accuracy and maintains stable operation under nonlinear conditions.

The numerical comparison presented in Table 2 further confirms the advantages of the proposed approach. The proposed NMPC achieved the lowest RMSE and IAE values together with the shortest settling time, indicating improved tracking accuracy and disturbance rejection capability.
These results suggest that the proposed framework is suitable for temperature regulation of nonlinear pyrolysis reactors where process uncertainties and measurement noise are unavoidable.

VI. CONCLUSION

This study addressed the challenge of precise temperature regulation in a nonlinear pyrolysis reactor, where conventional control strategies are limited by complex reaction kinetics, process disturbances, and system uncertainties. A soft-sensor-assisted Nonlinear Model Predictive Control (NMPC) framework was developed by integrating an Extended Kalman Filter (EKF) with predictive control. The reactor was modelled using energy balance equations, heat transfer, and reaction kinetics to represent the nonlinear process dynamics. Simulation results confirmed that the developed framework outperformed conventional PID and MPC controllers under identical operating conditions. The closed-loop system maintained the reactor temperature close to the desired setpoint (499.75 °C), with negligible overshoot (0.014 °C), low tracking error, and favourable performance indices (RMSE = 129.53 °C and IAE = 68060). The EKF successfully estimated the reactor states with an RMSE of 0.40 °C, enabling effective compensation of process disturbances. As a result, the integrated control strategy provided faster response, stable operation, and reliable temperature regulation while maintaining energy-efficient operation.

Future work will focus on experimental validation using a laboratory- or industrial-scale pyrolysis reactor. In addition, advanced soft-sensing techniques, adaptive parameter estimation, reinforcement learning, and multivariable predictive control may be incorporated to further enhance controller performance under varying operating conditions.

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Conflict of Interest

There are no conflicts of interest regarding the publication of this paper

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