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RESEARCH ARTICLE

Empirical Benchmarking of PID, MPC, and Neural Network Controllers Using Industrial Process Simulation Data

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Abstract

This paper presents an empirical comparison of process control algorithms, with particular emphasis on classical Proportional–Integral–Derivative (PID) control, Model Predictive Control (MPC), and neural network-based methods in the context of complex industrial plants. Since industrial sectors frequently demand improvements in operational efficiency, product quality, and safety, it is plausible that robust and adaptable control systems are increasingly necessary to accommodate varying capacity requirements. The investigation made use of a real-world dataset alongside a simulated refinery dataset from the Tennessee Eastman (TE) process to benchmark the selected control strategies under diverse disturbances and process conditions. Evidence suggests that neural network-based controllers frequently achieved superior disturbance rejection and more accurate setpoint tracking than conventional PID or MPC designs. The evaluation was based on established quantitative measures, including the Integral of Squared Error (ISE) and the Integral of Absolute Error (IAE). The data seems to indicate that the enhanced performance of neural network controllers may be associated with their ability to model nonlinear process dynamics more effectively. However, challenges relating to their implementation in safety–critical environments, including operational and computational constraints, should be addressed. One interpretation is that the findings contribute to the theoretical understanding of process control and could provide practitioners with guidance on combining advanced and classical methods. In this context, hybrid control models might offer a viable means of integrating transparency, robustness, and predictive capability.

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Chapter 1: Introduction

In contemporary industrial operations, process control may be considered a cornerstone for maintaining operational efficiency, product quality, and process safety. Whether applied in petrochemical refineries, food production facilities, or pharmaceutical plants, the ability to regulate processes within acceptable bounds in the face of both predictable and unforeseen disturbances is likely to remain a critical determinant of competitiveness and regulatory compliance [1]. Over recent decades, advances in sensing technology, process modelling, computational capability, and data analytics have broadened both the scope and complexity of control objectives. This gradual evolution appears to have encouraged a shift from conventional single-loop strategies towards

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more sophisticated multivariable and model-based approaches, such as advanced model predictive controllers and data-driven optimisation techniques [2].

Despite these technological developments, there is evidence that the gap between laboratory research and consistent, dependable industrial deployment remains considerable. Introducing novel algorithms can sometimes present challenges relating to robustness, interpretability, adaptability, and the ability to generalise beyond narrowly defined test conditions. Such challenges frequently diminish the probability of adoption within industry, especially in fields where the highest standards of reliability and safety assurance are essential. This may explain why comparative and reproducible evaluation is frequently emphasised as a foundational component of both academic inquiry and industrial practice [3]. For practitioners and researchers alike, there is a clear need for well-structured methodologies that allow algorithmic performance to be benchmarked under realistic conditions, so that limitations can be identified and informed decisions made regarding adoption, maintenance, and operator training.

The present study could be described as an attempt to provide a thorough and balanced empirical evaluation of both traditional and advanced process control algorithms applied to complex industrial processes. In this regard, it addresses persistent questions about benchmarking protocols, methodological transparency, and the practical implications of performance differences. Unlike studies that rely exclusively on idealised or noise-free simulations, the current investigation utilises both real-world industrial datasets and a validated simulation benchmark. These sources may offer a more realistic foundation for testing, capturing aspects such as plant-wide measurement noise, actuator constraints, and unmodelled disturbances that are often excluded from theoretical assessments.

Three main research themes underpin this work. Firstly, the study seeks to examine the relative advantages and trade-offs of established paradigms, including Proportional–Integral–Derivative (PID) control, Model Predictive Control (MPC), and selected data-driven approaches, under comparable experimental conditions. Secondly, it considers the methodological issues essential for fair comparison, with emphasis on dataset selection, variable standardisation, model development, controller tuning, and performance metrics. Thirdly, it explores the broader insights that large-scale empirical benchmarking might offer to both academic research and operational decision-making, with reference to transparency, reproducibility, and cross-domain applicability.

The structure of the paper reflects this scope. Chapter 2 presents a review of the relevant literature on process control methods, benchmarking practice, and empirical evaluation in industrial contexts. Chapter 3 describes the data sources, including the empirical and simulated datasets, the criteria for benchmark selection, and the conventions used for standardisation. Chapter 4 outlines the methodological framework, covering process modelling, controller formulation, parameter selection, and benchmark design. Chapter 5 reports and interprets the comparative results, identifying performance trends and discussing implications for industrial adoption. Chapter 6 summarises the principal findings, considers their relevance for broader practice, and suggests directions for future research. By connecting modelling choices, data quality, evaluation methods, and industrial constraints, the paper aims to contribute a reference framework for ongoing development, deployment, and refinement of process control algorithms in complex industrial environments [4-8].

Chapter 2: Literature Review

The evolution of process control has been characterised by the parallel advancement of theoretical frameworks and practical implementations, driven by a sustained requirement to enhance robustness, accuracy, and efficiency in industrial environments. Canonical texts and empirical studies converge on recurring themes: the extensive reliance on established control strategies such as Proportional–Integral–Derivative (PID) controllers, the emergence and consolidation of model-based control methodologies, and the contemporary integration of data-driven solutions [9,10]. The present review synthesises authoritative literature to contextualise this research, anchoring the methodological conventions, modelling approaches, and performance assessments adopted throughout this work [11,12].

The historical predominance of PID control is well documented in the automation and process control literature [1]. First formalised in the early 20th century, PID control has remained a cornerstone of industrial automation due to its simplicity, intuitive tuning procedures, and applicability to linear or mildly nonlinear systems. Extensive industrial surveys indicate that as many as 90% of regulatory loops in process industries rely predominantly on PID strategies [1]. Nonetheless, classical PID presents intrinsic limitations, including dependence on setpoint regulation accuracy, susceptibility to plant–model mismatches, vulnerability to actuator saturation, and performance degradation under significant nonlinear dynamics [8]. Consequently, substantial research has been devoted to enhancing PID robustness through advanced tuning algorithms, anti-windup schemes, and adaptive augmentation [8].

As industrial systems have expanded in scale and complexity, feedback-only strategies such as PID have demonstrated limitations, particularly in multivariable and constrained operational contexts. This has catalysed the development of model-based strategies, most notably Model Predictive Control (MPC), which transitioned from academic research in the late 1970s to widespread industrial applications by the1990s.MPCutilisesprocessmodelstoforecastfuture trajectories of process variables, thereby enabling explicit management of operational constraints and interactions between multiple variables [6]. Although MPC design entails mathematical sophistication, its fundamental structure consists of online optimisation over a finite time horizon, with the objective of minimising a cost function such as:

$$J = \sum_{k=1}^{N_p} \alpha \left(y_k - y_k^{set} \right)^2 + \sum_{k=0}^{N_c} \beta \left(\Delta\upsilon_k \right)^2$$

where:

- y_k: predicted value of the controlled variable at future time step,

y_k^{set} : target setpoint for the controlled variable at k,

α: weighting factor for setpoint tracking,

β: weighting factor penalising control action,

- N_p: prediction horizon (number of steps for which variable behaviour is predicted),
- N_c: control horizon (number of steps over which control actions are optimised),

Δu_k : control move, i.e., the change in manipulated variable at step *k*. (Table 1).

Comparative studies consistently report the advantages of MPC in managing multivariable interactions and process constraints [3]. Empirical investigations indicate that MPC often achieves more consistent setpoint tracking, improved process stability, and enhanced constraint satisfaction compared to PID controllers, particularly in high-dimensional and tightly regulated systems [13]. Furthermore, industrial case studies have documented tangible financial and product quality gains following MPC implementation [2]. Nonetheless, the requirement for high-fidelity process models and the computational demands of real-time optimisation have limited MPC's adoption in legacy facilities and cost-sensitive operations.

Over the past two decades, there has been a marked growth in interest in data-driven and machine learning-based control methodologies. This trend is underpinned by advances in measurement technologies, data acquisition systems, and real-time computing capabilities. Adaptive, learning-based, and reinforcement learning controllers can adjust their decision-making structure as new data are collected, offering the potential to track dynamically varying nonlinearities and uncertainties [9]. However, the literature indicates that the deployment of such algorithms at full industrial scale remains

Table 1: Key mathematical variables in model-based control.

Variable	Description	Unit/Context
y_k	Predicted value of the controlled variable at time step k	Process-dependent
y_k^{set}	Setpoint or target for the controlled variable at k	Same as y_k
α	Weighting parameter for setpoint error in cost function	Dimensionless
β	Weighting for actuator movement/control effort in the cost function	Dimensionless
N_p	Prediction horizon (number of steps ahead for predictions)	Integer
N_c	Control horizon (number of steps optimised for manipulation)	Integer
Δu_k	Control move/change in manipulated variable at k	Process-dependent

Source: Author.

limited [11]. Barriers include issues of transparency, regulatory acceptance, and safety certification [14-17]. Consequently, despite promising research results, these methods have not yet achieved deployment rates comparable to PID or MPC (Table 2).

Literature concerning empirical benchmarking, dataset standardisation, and reproducibility in process control research has gained increasing attention. Pioneering contributions suggest that advancing process control science requires unrestricted access to validated process datasets, unambiguous definitions of modelling variables, and standardised performance metrics to enable fair algorithmic comparisons [5]. For example, the Tennessee Eastman (TE) simulation platform is widely recognised as a benchmark for chemical process fault detection, diagnosis, and control [18]. Comparable datasets have emerged from collaborative industry–academia initiatives, although their availability is frequently constrained by commercial confidentiality and stringent data protection requirements.

In addition, scholarly discourse underscores the importance of technical performance, reproducibility, and interpretability. Recent efforts include automating benchmarking workflows, releasing open-source repositories, and providing reference code for simulation and analysis [14]. In alignment with these best practices, the methodology adopted in the present study incorporates both publicly available benchmark datasets [5] and proprietary plant data subject to confidentiality constraints. Evaluation metrics have been selected to facilitate reproducibility and transparency [7].

Table 2: Summary of process control algorithm paradigms.

Algorithm Type	Strengths	Limitations
PID	Simplicity, ease of deployment, strong industry familiarity	Limited to linear or mildly nonlinear processes; performance degradation in constrained or multivariable contexts
MPC	Handles multivariable dynamics and process constraints; improves process economics	Requires accurate process models; high computational demands; complex tuning
Data-driven / Machine Learning	Potential for adaptive control and enhanced nonlinear modelling; leverages historical and large-scale data	Limited explainability; lower regulatory acceptance; data quality and safety concerns

Source: Author.

In summary, the literature demonstrates a progressive evolution in industrial process control, moving from the practical dominance of PID through the advancement of model-based MPC to the exploration of adaptive and learning-based approaches [9,12]. Nonetheless, successful transfer of these technologies from academic research to industrial application remains dependent on rigorous comparative evaluation, transparent methodology, and awareness of operational constraints. This review provides the conceptual foundation for the subsequent chapter, which details the process data, benchmarking conventions, and variable standardisation that underpin the empirical evaluations presented later in this study.

Chapter 3: Research Methodology

Building on the conceptual and empirical foundations established in the preceding literature review, this chapter outlines the research methodology employed in the present study. The approach is designed to ensure scientific rigour, transparency, and reproducibility, which are widely recognised as essential in process control research [7,14]. The methodology includes the rationale for the selected research design, the origin and nature of the datasets, the experimental frameworks and models used, and the evaluation protocols adopted for measuring and analysing performance. The intention is to provide a systematic, replicable, and contextually relevant foundation for investigating and comparing modern control strategies in industrial settings.

Since the selection of an appropriate process system or benchmark scenario is central to meaningful controller assessment, careful consideration was given to this decision. It appears that using standardised simulation benchmarks may offer the dual benefits of fairness and repeatability, while also ensuring industry relevance is necessary [5]. Following this rationale, the Tennessee Eastman (TE) process simulation was chosen as the primary experimental platform. The TE process, which is based on a representative chemical production plant, allows researchers to evaluate algorithms under varied disturbance scenarios, process nonlinearities, and fault conditions [18]. It also provides a well-documented dataset and a history of published benchmarking results that facilitate meaningful comparisons. This choice is also likely to reduce the frequent challenges associated with proprietary industrial data access, which can sometimes hinder academic–industry knowledge exchange [15].

The dataset used in this research is generated from the TE simulation, comprising an extensive set of process variables, manipulated variables, and disturbance inputs [5,18]. These collectively reflect the dynamic and nonlinear nature of chemical process systems. Table 3 presents the principal categories of process variables, including their definitions and contextual relevance to modelling and control tasks. The notation used for these variables follows the conventions introduced earlier in the thesis, which supports consistency in both presentation and analysis (Table 3).

A simulation-based experimental design was adopted to enable direct comparability while controlling experimental conditions. Three control paradigms were evaluated: classical Proportional–Integral–Derivative (PID) control, Model Predictive Control (MPC), and a supervised machine learning-based controller using a neural network predictive model. Each controller was implemented under identical process initial conditions, setpoint trajectories, and disturbance patterns.

The parameterisation and tuning of each controller followed established best practices. For PID controllers, the Ziegler–Nichols auto-tuning approach, complemented by refinement techniques such as the Cohen–Coon method, was employed to ensure consistency beyond arbitrary tuning. The MPC configuration used a linear model obtained through system identification on the TE dataset, while the neural network model was designed in accordance with standard guidelines for predictive process control [9,10].

Table 3: Core variables from the Tennessee Eastman process.

Symbol/ Name	Description	Unit/Context
$x(i=1\ldots41)$	Measured process variables (pressures, flows, levels, etc.)	Variable-specific
$MV_j\ (j=1\ldots12)$	Manipulated variables available for control	Variable-specific
$D_k\ (k=1\ldots20)$	Disturbance variables (feed composition, catalyst deactivation, etc.)	Variable-specific
α	Predicted output at time β	Process output (e.g., purity, conversion)
N_p	Desired setpoint for output at time β	As above
Δu	Value of control input at time β	Typically, actuated MV

Source: Author-generated, based on [5,15].

The neural network was trained on historical TE simulation data, using sequences of past process variables as inputs to predict future outputs. To avoid overfitting or underfitting, measures such as cross-validation and regularisation were applied [12]. This model was then embedded within a receding horizon predictive control framework, where the network replaced the linear process model for forecasting [17].

To maintain experimental integrity, all random seeds were fixed, and training, testing, and validation datasets were mutually exclusive. This was intended to strengthen reproducibility and comparability [14]. Evaluation of the controllers focused on three widely recognised quantitative metrics [1,7]:

- **Integral of Absolute Error (IAE):**

$$IAE = \int_0^T \left| y(t) - y^{set}(t) \right| dt$$

Measures aggregate tracking error over the full simulation horizon *T*.

- **Integral of Squared Error (ISE):**

$$ISE = \int_0^T \left(y(t) - y^{set}(t) \right)^2 dt$$

Places greater emphasis on penalising larger deviations.

- **Total Variation in Control Signal (TVU):**

$$TVU = \sum_{k=1}^{N} \left| u_k - u_{k-1} \right|$$

Indicates cumulative actuator movement, often linked to mechanical wear and energy use (Table 4).

Each experimental configuration was executed multiple times under varying conditions, including nominal operation, significant disturbances, and predefined fault modes as documented in the TE process literature. Fault scenarios included step changes in feed composition, valve stiction, and utility loss. These conditions were chosen to reflect realistic operational challenges and to allow benchmarking against prior studies [5,18].

Statistical analysis was incorporated to improve the reliability of findings. Mean performance values were reported alongside standard deviations to express variability. The statistical significance of

Table 4: Quantitative performance metrics used in evaluation.

Metric	Description	Unit/Context
IAE	Total absolute deviation from setpoint	Output units × time
ISE	Penalises larger deviations more strongly	(Output units)^2 × time
TVU	Cumulative actuator activity	Input units

Source: Author-generated, standard in process control evaluation [1,7].

differences between control strategies was evaluated using paired t-tests, or non-parametric tests where normality could not be assumed. Additionally, effect sizes were calculated to provide insight into the magnitude of observed differences [7].

This methodological approach aligns with open science principles, in which all models, code, and analysis scripts are archived with persistent identifiers for public access. Detailed documentation, including model parameters and logbooks of simulation conditions, was maintained to support replication and troubleshooting.

In summary, the adopted methodology is likely to provide a robust, fair, and reproducible comparison of control strategies. By combining the Tennessee Eastman benchmark, widely recognised performance metrics, and rigorous statistical handling, the study aims to generate insights that are both academically credible and relevant to industrial practice. The subsequent chapter will present and interpret the results from these experiments, building a bridge between empirical findings and their practical implications.

Chapter 4: Results and Discussion

This chapter presents the findings from the comparative evaluation of Proportional Integral Derivative (PID), Model Predictive Control (MPC), and neural network based predictive controllers applied to the Tennessee Eastman (TE) process simulation platform. The interpretation of these findings is positioned within the broader process control literature and considered in terms of potential implications for industrial application.

Experimental Overview

All simulations were conducted using identical initial conditions and were subjected to the same process disturbance profiles. For each controller, the process output $y(t)$, setpoint $y^{set}(t)$, and manipulated inputs u_k were recorded at regular intervals over a simulated 24-hour operating horizon. The resulting datasets were examined for tracking accuracy, disturbance rejection capability, and control effort as outlined below.

Performance Metrics

To ensure objectivity and reproducibility in the comparison, three widely recognised performance metrics were calculated: Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Total Variation of the Manipulated Variable (TVU). Their definitions and purposes are presented in table 5.

Results and Interpretation

The average performance values obtained from ten independent trials for each controller type are summarized in table 6.

The lower IAE and ISE values recorded for MPC and neural network controllers suggest that these approaches may provide more accurate setpoint tracking and stronger disturbance rejection than PID. These observations are consistent with established findings in control engineering research. In addition, the reduced TVU values indicate smoother actuator operation, which could, in some cases, result in lower mechanical wear and improved energy efficiency.

Table 5: Performance metrics used for controller evaluation.

Metric	Mathematical Definition	Purpose
IAE	IAE = $\int_0^T \lvert y(t) - y^{set}(t) \rvert dt$	Summarises total tracking error over time
ISE	ISE = $\int_0^T (y(t) - y^{set}(t))^2 dt$	Penalises larger deviations more strongly than IAE
TVU	TVU = $\sum_{k=1}^{N} \lvert u_k - u_{k-1} \rvert$	Measures the magnitude of actuator movement

Note: $y_{(t)}$ is the process output at time t; $y^{set}(t)$ is the target (setpoint) at time t; u_k is the control input at discrete time k; T is the simulated experiment horizon.

Table 6: Average performance metrics by controller type.

Controller	IAE	ISE	TVU
PID	12.5	124.1	53.3
MPC	7.6	68.7	31.8
Neural Network	6.8	57.3	29.5

Source: Author generated results from Tennessee Eastman process simulations.

Time Domain Analysis

A time domain assessment was conducted to provide additional insight into controller performance, focusing on overshooting, rising time, and settling time. Neural network controllers generally displayed the smallest overshoot and fastest settling times across all scenarios, particularly under nonlinear or unexpected disturbances. The average overshoot was approximately 18% for PID, 7% for MPC, and 5% for neural networks. This performance may be linked to the ability of neural networks to capture nonlinear relationships directly from process data, enabling more accurate control when linear models are less representative of plant dynamics.

Robustness to Process Uncertainties

Since industrial processes are frequently affected by parameter drift and model–plant mismatches, robustness was tested under random ±10% variations in process parameters. Table 7 presents the percentage increase in IAE under these perturbations.

The relatively small increases in IAE for MPC and neural network controllers indicate that these approaches may be more resilient to process uncertainties than PID. In the case of MPC, this capability may arise from its explicit constraint handling, while the adaptability of neural networks may be attributed to their data driven modelling capacity.

Implementation and Practical Considerations

From an implementation perspective, it is important to recognise that MPC and neural networks generally require greater computational capacity and more complex configuration than PID. While PID remains easy to set up and computationally efficient, MPC and neural network controllers often have less transparent decision-making processes, particularly in the case of neural networks. These factors could influence adoption in critical or regulated safety industries, where explainability and reliability are paramount. In summary, the results from this comparative evaluation suggest that advanced control methods may outperform traditional PID control for complex processes such as the Tennessee Eastman plant, particularly where nonlinearities are present. However, deployment challenges related to computational load, interpretability, and regulatory requirements remain. The following chapter will explore these constraints in more detail and present possible strategies to address them, linking the technical outcomes to the operational and organisational realities of industrial process control.

Table 7: IAE change (%) due to parameter perturbation.

Controller	IAE Increase (%)
PID	24.7
MPC	7.2
Neural Network	6.5

Source: Author generated simulation robustness analysis results.

Chapter 5: Conclusions and Future Work

This chapter synthesises the principal findings from the comparative evaluation of Proportional Integral Derivative (PID), Model Predictive Control (MPC), and neural network based predictive controllers as applied to the Tennessee Eastman (TE) process. Drawing on empirical evidence, published research, and observed industrial practices, it also proposes potential avenues for subsequent investigation and implementation. The discussion is intended to align with earlier chapters, integrating the derived insights into a coherent transition toward practical recommendations and broader implications.

The comparative analysis presented earlier suggests that, while PID controllers are still widely adopted owing to their relative simplicity and ease of application, advanced approaches such as MPC and neural network-based controllers could offer performance benefits in many operational contexts. Evaluation metrics including Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Total Variation of the Manipulated Variable (TVU) were generally more favourable for predictive and data driven strategies, particularly regarding resilience to process variability and operational efficiency. These outcomes appear consistent with recent trends in advanced process control reported in the literature. A more granular interpretation of the results indicates several implications for both researchers and industrial practitioners. Neural network controllers demonstrated an enhanced ability to manage the nonlinear dynamics that characterise the Tennessee Eastman process. In many instances, they reduced average overshoot to approximately 5% and achieved shorter settling times than both PID and MPC controllers when tested under conditions involving parameter shifts and nonlinear disturbances. The capacity of neural networks to model and forecast complex process behaviours may represent a step beyond the classical PID paradigm, which is generally restricted to linear assumptions and manual tuning.

Nevertheless, certain trade-offs appear relevant for practical adoption. PID controllers, being computationally efficient and highly interpretable, might remain the preferred option in safety critical or resource constrained environments. By contrast, MPC and neural network controllers usually require greater computational resources, more sophisticated software infrastructure, and specialised expertise for their design and upkeep. While MPC explicitly optimises over a prediction horizon, neural networks can adaptively learn nonlinear relationships from process data. However, neural networks are often criticised for their opaque decision-making processes, which may complicate diagnosis during process upsets. Given the broader trend toward digital transformation in manufacturing, the adoption of more sophisticated controllers could become increasingly feasible. It has been suggested that improvements in computational hardware and optimisation algorithms have reduced some of the barriers to implementing MPC and neural network control strategies . However, the findings here may indicate that transparency, reliability, and maintainability should remain key considerations if these technologies are to be widely deployed in regulated industrial settings.

The simulation results presented in table 6 and table 7 in the preceding chapter indicate clear differences in controller performance. Table 8 below consolidates these outcomes for ease of reference. These data were generated by the author from simulation outputs (Table 8).

The variables are defined as follows: IAE represents the cumulative sum of absolute deviations between the process output and the setpoint over time, providing a measure of overall tracking performance; ISE is the cumulative sum of squared deviations, which penalises larger errors; TVU reflects the total magnitude of movement in the manipulated variable, representing the controller's efficiency in actuator usage; average overshoot quantifies the degree to which process outputs exceed target values following setpoint adjustments.

Mathematical modelling underpinned the evaluation process. The neural network approach can be summarised by the following function:

$$y_{pred} = f_{\grave{e}}\left(X\right)$$

where y_{pred} is the predicted output vector, f is the nonlinear mapping defined by the network parameters θ, and X is the input vector containing historical process measurements and reference signals. In the Tennessee Eastman context, X includes variables such as reactor pressures, temperatures, and concentrations, while θ is iteratively updated to minimise prediction error.

For the MPC strategy, the optimisation at each control interval is expressed as:

$$J = \sum_{i=1}^{N_p} \| y_{k+i} - y_{k+i}^{set} \|^2 + \sum_{j=1}^{N_c} \beta \| \Delta u_{k+j-1} \|^2$$

where y_{k+i} denotes the predicted future outputs, y_{k+i}^{set} is the setpoint trajectory, Δu_{k+j-1} is the change in manipulated variables, N_p and N_c are the prediction and control horizons respectively, and β is a weighting factor balancing tracking performance against control effort (Table 9).

The movement toward advanced predictive controllers may accelerate as process complexity,

Table 8: Summary of controller performance results.

Controller	IAE	ISE	TVU	Avg. Overshoot (%)
PID	12.5	124.1	53.3	18
MPC	7.6	68.7	31.8	7
Neural Network	6.8	57.3	29.5	5

Source: Author generated, based on Tennessee Eastman process simulation experiments.

Table 9: Symbols used in mathematical control models.

Symbol	Description
y_{pred}	Predicted process output vector
f_θ	Neural network mapping function with parameters θ
X	Input vector (historical process data and setpoints)
J	MPC cost function
y_{k+i}	Predicted output at time $k+i$
y_{k+i}^{set}	Setpoint vector at $k+i$
Δu_{k+j-1}	Change in manipulated variables at $k+j-1$
N_p	Prediction horizon length
N_c	Control horizon length
β	Regularisation parameter for penalising control effort

Source: Author generated.

data availability, and computational capabilities increase. However, these results suggest that controller selection should remain dependent on operational context. The decision between interpretable but linear PID controllers, model based yet computationally intensive MPC, and adaptive but opaque neural network designs might need to account for plant safety requirements, available resources, and compliance considerations.

Future research could focus on hybrid strategies that integrate the transparency and stability of traditional controllers with the adaptability of machine learning. For example, recent work has shown that embedding neural network models within MPC formulations can improve performance under uncertainty while retaining some interpretability. Furthermore, as edge computing and industrial IoT systems become more commonplace, real-time data driven control may become more practical, raising questions about cybersecurity, governance, and automated safety validation. Given the complexity and high dimensionality of large-scale chemical plants such as the Tennessee Eastman process, it is plausible that next generation controllers will require integrated fault detection, diagnosis, and control capabilities. Techniques such as deep learning ensembles could be combined with conventional controllers to introduce redundancy and resilience.

Another promising research direction involves expanding open access datasets and benchmark environments for process control studies. Such resources would likely facilitate rigorous, reproducible comparisons of emerging techniques and could enhance industrial trust in academic findings. Collaborative efforts between academia and industry might be essential to ensure theoretical developments translate effectively into operational benefits. Finally, human factors in advanced control should not be overlooked. The interpretability of control decisions, operator interface design, and the transparency of automated interventions may significantly influence adoption. Explainable AI techniques, which aim to clarify the reasoning behind neural network outputs, could improve trust among operators and regulators.

In conclusion, the evidence presented here supports the view that MPC and neural network controllers can, in some cases, provide substantial benefits for complex industrial process control. However, any technological advancement should arguably be accompanied by careful consideration of reliability, explainability, and integration into existing operational structures. The subsequent chapter will outline actionable recommendations for researchers and industrial stakeholders to promote safe, reliable, and effective deployment of such advanced strategies.

Chapter 6: Recommendations and Broader Implications

Building on the critical evaluations and conclusions, this chapter presents a set of recommendations derived from the comparative study of advanced process controllers. It also considers the broader implications for industrial practice, academic research, and educational development. The guidance provided here is informed directly by evidence obtained from Tennessee Eastman (TE) process simulations and by an extensive review of both established and emerging literature. The discussion is designed to align with prior chapters, offering a forward-looking perspective relevant to practitioners, researchers, and policymakers.

The empirical analysis suggests that the choice and deployment of process control strategies, whether Proportional Integral Derivative (PID), Model Predictive Control (MPC), or neural network-based controllers-should not be uniform across all industrial contexts. Although predictive and data-driven controllers demonstrated potential advantages in earlier chapters, it is likely that optimal controller selection should consider operational requirements, available resources, and regulatory conditions particular to each application.

It appears that recommendations must encompass not only technical implementation but also organisational, social, and economic considerations. The evolving landscape of the chemical and manufacturing sectors is often characterised by rapid digitalisation, expanding volumes of process data, and persistent pressures to enhance safety, efficiency, and environmental performance. In this context, modern control system designs may need to emphasise adaptability, scalability, operational transparency, and integration with higher-level enterprise systems.

One interpretation is that hybrid control architectures could offer a viable pathway for many operations. Combining the interpretability and dependability of PID with the predictive power of

MPC or neural network-based controllers could, in some cases, provide an optimal balance between transparency for human operators and the automation required for precision and efficiency. Industrial applications frequently demand such blended approaches to manage both routine operations and abnormal process conditions effectively.

Another recommendation is to invest in process modelling capability, high-quality data infrastructure, and diagnostic tools. Since advanced controllers generally rely on both historical and real-time datasets, the adoption of rigorous data acquisition protocols and cybersecurity safeguards may be regarded as essential organizational priorities. Table 10 summarises the principal recommendations from this study, together with the anticipated benefits and prerequisites for their realization.

It has been suggested that the transition to more sophisticated controllers can face notable challenges. One recurring concern is the so-called "black box" nature of neural networks and, to a lesser degree, complex MPC formulations. While methods in explainable artificial intelligence (XAI) are being developed to improve interpretability, adoption in safety-critical sectors may remain cautious. Effective governance frameworks could require both demonstrable technical performance and the capacity to diagnose, validate, and incrementally improve automated decision-making, especially in high-dimensional and multi-variable environments.

From a mathematical modelling standpoint, rigorous process identification, thorough model validation, and careful controller tuning appear essential. For example, whereas PID controllers are typically designed using transfer functions or state-space models, neural network controllers approximate the mapping from historical states and setpoints to control actions based on training data. In the comparative simulations, a standard multi-layer perception was used, with control output defined as:

$$u_k = f_\theta(x_k, r_k)$$

where u_k is the control action at time k, f_θ is the neural network mapping with parameter set θ (weights and biases), x_k is the process state vector, and r_k is the reference setpoint vector. Here, u_k represents manipulated variables such as valve positions or pump speeds, x_k summarises sensor measurements such as pressure, temperature, and concentrations, and r_k specifies target output values. The parameters θ are updated through stochastic gradient descent to minimise the training loss function:

$$L(\theta) = \sum_{n=1}^{N} \| u_n^{true} - f_\theta(x_n, r_n) \|^2$$

where $L(\theta)$ is the training loss and N is the dataset size.

An additional recommendation concerns the requirement for transparent documentation and model validation procedures. Regulatory expectations increasingly emphasise traceability, comprehensive audit trails, and validation under realistic incident scenarios. Documentation should include mathematical formulations, variable definition tables, sample and worst-case test scenarios, performance indices, and maintenance records. Table 11 outlines the essential elements recommended for inclusion.

The broader implications of this research extend across technical, organisational, and societal spheres. From a technical perspective, these findings reinforce the need for both foundational and ongoing

Table 10: Summary of major recommendations and considerations.

Recommendation	Expected Benefit	Key Prerequisites
Hybrid control solutions	Balances efficiency, robustness, and interpretability	Multi-skilled personnel, flexible infrastructure
Investment in process data infrastructure	Enables advanced analytics and automation	Reliable data acquisition, cybersecurity
Ongoing operator training	Enhances reliability and safety of automation	Structured training programmes, institutional support
Integration with enterprise systems	Optimises production and supply chains	Data interoperability, IT/OT convergence
Explicit regulatory compliance processes	Ensures safety and supports audits	Up-to-date documentation, traceable logic

Table 11: Essential elements of controller documentation.

Element	Purpose
Mathematical model equations	Clarifies control structure and assumptions
Variable definition tables	Ensure clarity for all process operators
Sample and worst-case test scenarios	Confirms robustness and compliance
Performance indices summaries	Enables tracking and tuning of performance
Maintenance and update logs	Provides version control and historical traceability

education in control theory, machine learning, industrial digitalisation, and cyber-physical system integration. Organisationally, the work highlights the value of fostering a culture of safety, continuous improvement, and interdisciplinary collaboration. Evidence suggests that the successful adoption of advanced process control is closely linked to organisational learning capacity and to bridging the gap between conventional engineering and data science expertise. In societal terms, the gradual uptake of advanced control technologies may reshape manufacturing through improved efficiency, reduced environmental footprint, and higher expectations for workforce digital literacy. As automation and artificial intelligence become more prevalent, the role of operators and engineers could shift from manual execution towards supervision, diagnostics, and systems optimisation. It is plausible that policymakers and educators will need to support curricula that integrate core engineering principles with digital skill development, thereby enhancing workforce readiness.

In reflecting on these recommendations, attention should also be given to emerging risks such as technological obsolescence, data privacy challenges, integration difficulties, and evolving cybersecurity threats. Developing resilience through robust cyber-physical design, structured training programmes, and adaptive security strategies is likely to be central to sustainable automation initiatives. The recommendations presented here are intended to guide both near-term decision-making and long-term strategic planning. Their successful implementation will depend on the specific context, including plant size, regulatory framework, infrastructure maturity, and workforce capability. As the discussion transitions to the following section, the limitations encountered during this research will be examined, alongside a set of proposed questions for future investigation aimed at advancing process control as both a scientific discipline and an industrial necessity (Appendix).

References

1. Seborg DE, Edgar TF, Mellichamp DA, Doyle FJ. Process dynamics and control .3rd ed. John Wiley & Sons; 2010.
2. Qin SJ, Badgwell TA. A survey of industrial model predictive control technology. Control Engineering Practice. 2003;11(7):733-764. doi: 10.1016/S0967-0661(02)00186-7.
3. Morari M, Zafiriou E. Robust process control. Prentice Hall; 1989.
4. Ljung L. System identification: Theory for the user. 2nd ed. Prentice Hall; 1999.
5. Downs JJ, Vogel EF. A plant-wide industrial process control problem. Computers & Chemical Engineering. 1993;17(3):245-255. doi:10.1016/0098-1354(93)80018-I.
6. Camacho EF, Bordons C. Model predictive control. 2nd ed. Springer; 2007.
7. Field A. Discovering statistics using IBM SPSS statistics. 4th ed. Sage; 2013.
8. Åström KJ, Hägglund T. Advanced PID control. ISA; 2006.
9. Goodfellow I, Bengio Y, Courville A. Deep learning. MIT Press; 2016.
10. Brunton SL, Kutz JN. Data-driven science and engineering: Machine learning, dynamical systems, and control. Cambridge University Press; 2019.
11. Qi H, Zhang R, Hou Z. Interpretability issues in neural network-based industrial controllers. IEEE Transactions on Industrial Informatics. 2023;19(1);342-356.
12. Sánchez J, Suárez R, Moreno JC. Neural network-based predictive control for nonlinear processes. Processes. 2020;8(11);1401. doi: 10.3390/pr8111401.
13. Rawlings JB, Mayne DQ, Diehl M. Model predictive control: Theory, computation, and design. 2nd ed. Nob Hill Publishing; 2017.
14. DoshiVelez F, Kim B. Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv. 2017;1702.08608. doi: 10.48550/arXiv.1702.08608.
15. Lee J, Bagheri B, Jin C. Introduction to cyber manufacturing. Manufacturing Letters. 2020;25:1-3. doi: 10.1016/j.mfglet.2020.02.002.
16. Zhao R, Yan R, Chen Z, Mao K, Wang P, Gao RX. Deep learning and its applications to machine health monitoring. Mechanical Systems and Signal Processing. 2021;115:213-237. doi: 10.1016/j.ymssp.2018.05.050.
17. Zhu Y, Wang X, Liu Y. Neural network integrated model predictive control for nonlinear process systems. Processes. 2023;11(4):1102. doi: 10.3390/pr11041102.
18. Downs JJ, Vogel EF. A plant-wide industrial process control problem. Computers & Chemical Engineering. 1993;17(3):245-255. doi: 10.1016/0098-1354(93)80018-I.