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Evaluating PID, MPC, and AI Pre-Generative Control Strategies: A Simulation-Based Study of Accuracy, Robustness, and Efficiency

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ABSTRACT

This study presents a comparative evaluation of three control strategies Proportional-Integral-Derivative (PID), Model Predictive Control (MPC), and AI Pre-Generative through simulation-based analysis of a dynamic setpoint-tracking system. A structured framework was adopted, beginning with model formulation, simulation of system dynamics in continuous and discrete forms, and per-trial performance evaluation across 1000 runs. Performance metrics included Root Mean Square Error (RMSE), Mean Absolute Error (MAE), accuracy, response time, and computational cost. Results reveal that PID, while computationally efficient (0.5 GFLOPS), exhibited lower accuracy (92.4%) and higher RMSE (0.085). MPC improved accuracy (96.1%) and reduced error (0.045) but demanded the highest computational resources (4.8 GFLOPS) and demonstrated slower response times (420 ms). The AI Pre-Generative method consistently outperformed both, achieving the highest accuracy (98.7%), lowest RMSE (0.028), and fastest response (290 ms), with moderate computational cost (2.2 GFLOPS). Correlation and regression analyses confirmed a strong relationship between computational investment and performance, highlighting AI Pre-Generative's superiority in balancing precision, efficiency, and robustness. The study emphasizes that AI-driven approaches extend classical and predictive controllers by integrating adaptability and stability, making them suitable for modern, real-time applications such as robotics, autonomous systems, and industrial automation.

Keywords: *Control Strategies, Simulation Analysis, AI Pre-Generative Controller, Performance Metrics.*

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I. INTRODUCTION

The rapid advancement of engineering and technology has led to a paradigm shift in how design control mechanisms are conceptualized, developed, and applied. In an era marked by digital transformation, pervasive data collection, and increasingly complex systems, the role of control mechanisms has expanded beyond stability and performance assurance to encompass adaptability, intelligence, and sustainability. The comparative study of design control based on data analysis and advanced pre-generative intelligence (PGI) with predefined mathematical models provides a timely exploration of how modern engineering can harness both empirical adaptability and deterministic rigor to address real-world challenges. By focusing on the dual paradigms of data-driven analysis and PGI, this study situates itself at the intersection of information science, control theory, and computational intelligence, where the need for hybrid approaches has become indispensable. Data analysis has become the backbone of modern design practices, fueled by the proliferation of sensors, Internet of Things (IoT) devices, and high-capacity data infrastructures. These technologies continuously generate vast volumes of data, capturing every detail of system behaviour, environmental interactions, and operational dynamics. Data-driven analysis leverages this information to identify patterns, predict outcomes, detect anomalies, and inform decision-making in real time. In the context of control mechanisms, such approaches introduce flexibility, enabling systems to adapt to uncertainty and evolving conditions. Applications range from predictive maintenance in manufacturing plants, where historical failure data informs proactive interventions, to anomaly detection in power grids, where machine learning algorithms prevent cascading failures. The data-driven paradigm thrives on its ability to learn, iterate, and refine designs through feedback loops that go beyond fixed models. However, this reliance on data introduces challenges: issues of data quality, completeness, governance, and bias can significantly undermine the effectiveness of such methods. Moreover, implementing large-scale data-driven systems requires advanced computational infrastructure and skilled expertise, raising barriers for organizations with limited resources. In contrast, advanced pre-generative intelligence with predefined mathematical models represents a more structured and deterministic approach. PGI builds on the foundations of classical control theory, optimization, and systems modeling to create robust frameworks grounded in physical laws and engineering constraints. These models—ranging from Proportional-Integral-Derivative (PID) controllers and Linear Quadratic Regulators (LQR) to Model Predictive Control (MPC) and Lyapunov-based stability frameworks—offer interpretability, reproducibility, and reliability in safety-critical environments. In aerospace engineering, for instance, aerodynamic simulations based on predefined mathematical models enable precise optimization of performance and safety before physical prototypes are built. Similarly, in structural and civil engineering, deterministic models calculate load-bearing capacities and resilience, ensuring compliance with safety regulations. The strength of PGI lies in its rigor and predictability, offering engineers confidence in system behaviour under defined conditions. Yet, this strength can also become a limitation. PGI models often struggle to capture highly dynamic or uncertain conditions, novel materials, or rapidly evolving operational environments. Their rigidity contrasts with the adaptive nature of data-driven approaches, making them less effective in contexts where real-time learning and flexibility are critical.

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The growing complexity of modern systems has therefore created a demand for hybrid frameworks that combine the strengths of both paradigms. Hybrid control systems leverage the adaptability of data-driven insights with the deterministic precision of PGI-based mathematical models. In autonomous vehicles, for example, predefined control laws ensure stability and safety, while data-driven algorithms process real-time traffic and environmental data to adapt behaviour dynamically. In healthcare, mathematical models of physiological processes provide reliable baselines, while machine learning algorithms tailor treatment to individual patient data, enabling personalized medicine. These integrations illustrate how hybrid systems generate synergies that neither paradigm could achieve alone: accuracy grounded in physics and adaptability rooted in data.

Mathematical modeling frameworks provide the theoretical foundation that links these two paradigms. Classical approaches such as transfer functions, state-space representations, and stochastic models are complemented by data-driven surrogates like Gaussian Processes and neural networks, which approximate complex dynamics from empirical data. This combination expands the control engineer's toolkit, enabling solutions that are simultaneously interpretable, efficient, and flexible. Moreover, optimization-centric formulations, whether convex or heuristic (such as genetic algorithms and particle swarm optimization), bridge the gap between deterministic models and adaptive exploration of design spaces. The result is an expanded capacity to address high-dimensional, uncertain, and nonlinear problems across domains. Comparative analysis between data-driven analysis and PGI with predefined mathematical models is thus essential for several reasons. First, it highlights the contexts in which each paradigm excels: data-driven approaches dominate in dynamic, uncertain environments like e-commerce, logistics, and predictive maintenance, while PGI thrives in safety-critical, rule-bound domains such as aerospace and civil infrastructure. Second, it identifies their respective limitations—data quality and governance challenges for data-driven systems, rigidity and computational intensity for PGI. Third, it underscores the necessity of hybrid systems that unite the adaptability of data with the rigor of models, offering a roadmap for future innovations. Finally, such analysis has practical implications for industries seeking to balance innovation with reliability, enabling sustainable adoption of advanced technologies.

This study therefore positions itself within a broader narrative: the convergence of empirical learning and deterministic modeling as the cornerstone of next-generation control systems. By examining the theoretical foundations, applications, strengths, and weaknesses of both paradigms, the research aims to propose integrative frameworks that harness their synergies. The ultimate objective is to foster systems that are not only efficient and reliable but also adaptive, resilient, and innovative. In doing so, this study contributes to shaping the future of design control mechanisms, ensuring that engineering practices remain aligned with the evolving demands of complexity, sustainability, and intelligence in the modern technological landscape.

II. REVIEWS OF LITERATURE

Athmaja et al. (2017) explored machine learning techniques for predictive analytics in big data across sectors like social media, banking, healthcare, and agriculture. Both supervised and unsupervised learning were highlighted as effective for handling massive datasets and enhancing decision-making. The study underlines machine learning's evolving predictive role, linking it to design control mechanisms within data-driven and pre-generative intelligence contexts.

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Ayhan & Tokdemir (2019) Focusing on megaproject safety, this research used Latent Class Clustering Analysis (LCCA), Artificial Neural Networks (ANN), and Case-Based Reasoning (CBR). CBR outperformed ANN with 86% predictive accuracy. The study emphasized data-driven prediction and mathematical modeling for safety forecasting, showing how design control mechanisms integrate predictive models to improve safety risk management in large-scale construction projects.

Milo & Somech (2020) This work reviewed the evolution of Exploratory Data Analysis (EDA) and its automation through machine learning. Tools such as kNN, active learning, and reinforcement learning were identified as enabling automated EDA. While challenges remain in robustness and reducing manual effort, the study highlights the growing intersection between data science and engineering design via pre-generative intelligence and automation.

Rahmani et al. (2021) synthesized AI-based methods for fatigue detection using neural networks, wavelet transforms, kernel learning, and image analysis. Data from interaction patterns and heart rate variability enabled precise monitoring of fatigue causes and effects. Findings link abstraction in AI-driven fatigue detection to design control mechanisms, where empirical data integrates with computational models to optimize performance monitoring systems.

Al-Sammarraie et al. (2022) applied machine learning to predict orange sweetness based on RGB colour parameters. Logistic regression achieved the best accuracy, with red values correlating most strongly with sweetness. Results underscore the role of data-driven and mathematical modeling in quality prediction, showing practical applications of design control mechanisms in agriculture and commercial product optimization.

III. PRACTICAL SYNTHESIS AND SELECTION OF FRAMEWORKS

Choosing an appropriate mathematical modelling framework is ultimately a design decision driven by purpose, fidelity needs, computational budget, and assurance requirements. Early ideation and concept screening benefit from low-order ODE or transfer-function models that expose dominant poles/zeros, time constants, and gain margins with minimal data demands. As complexity and interaction increase—multiple actuators, constraints, and cross-couplings state-space models become the natural lingua franca, enabling controllability/observability analysis, formal synthesis (LQR/LQG, $H\infty$), and embedding within estimators (Kalman/EKF/UKF) and constrained controllers (MPC). When physics are only partially known, grey-box identification blends conservation-law structure with learned residual dynamics; where the plant is opaque or expensive, surrogate models (Gaussian processes, NARX, neural nets, PINNs) accelerate design–test loops while quantifying uncertainty. A pragmatic flow is to start physics-first, augment with data, and harden with robustness. Concretely: derive a baseline LTI model from first principles; validate parameters by least-squares/system identification; add structured uncertainty (intervals, polytopes, LFTs) and certify performance via μ-analysis or $H\infty$ loop-shaping. If residuals reveal unmodelled nonlinearities, learn a bounded, Lipschitz residual map and envelop it with robust tubes in MPC to retain guarantees. For distributed assets (fleets, microgrids), couple local state-space plants over a graph Laplacian; exploit spectral properties (algebraic connectivity) to tune consensus speed and resilience to link loss.

Model reduction is pivotal for tractability. Balanced truncation preserves input–output behaviour by discarding weakly controllable/observable modes; Krylov and moment-matching approximate frequency responses around targets (e.g., set-points); POD extracts energetically dominant modes from data, yielding reduced-order predictors for embedded MPC. Reduction should be paired with a posteriori error bound to keep certification credible.

Discretization closes the loop to implementation. Exact discretization (matrix exponential) or Tustin/Euler mappings translate continuous plants to sampled equivalents. Selecting the sampling period Δ trades aliasing against computational burden; multirate schemes are common when fast inner loops (current/attitude) nest inside slower outer loops (velocity/position). Practical nonidealities—sensor quantization, compute jitter, network delay, packet drops—should be co-modelled (e.g., as time-varying delays or stochastic drop processes) and mitigated via observers with delay compensation, event-triggered control, or predictive scheduling.

Uncertainty quantification (UQ) connects models to risk. Global sensitivity (Sobol indices) prioritizes parameters for sensing/actuation authority; Monte Carlo and polynomial chaos propagate parameter distributions to performance metrics, informing safety factors and controller gains. In safety-critical contexts, reachability and barrier certificates provide formal guarantees that state trajectories avoid unsafe sets despite bounded disturbances—complementing empirical stress tests on digital twins.

Optimization-centric controllers unify these ingredients. Quadratic programs drive MPC with hard constraints and soft penalties; sequential convex programming handles mild nonconvexities; mixed-integer formulations encode logic and mode switching in hybrid plants. When gradients are available (via adjoints/automatic differentiation), differentiable MPC and bilevel formulations enable co-design of plant parameters and controllers. Where gradients are unreliable, heuristics (GA/PSO/SA) offer robust global exploration, seeded by physics-aware initializations to cut search time.

Finally, hybridization with data-driven intelligence operationalizes adaptability without surrendering rigor. Use PINNs or GP surrogates as prediction models inside MPC, but wrap them with robust tubes; train observers (neural filters) under Lyapunov constraints; deploy reinforcement learning for outer-loop policy shaping, gated by shielded controllers that enforce invariants. The result is a layered architecture: physics ensures stability and interpretability; data augments accuracy and responsiveness; robustness certifies behaviour under uncertainty. This synthesis is the practical embodiment of the chapter’s thesis: pre-generative intelligence and data analysis, anchored in sound modelling, yield control mechanisms that are not only performant, but certifiably safe, scalable, and ready for real-world deployment.

IV. SYSTEM SIMULATION, PERFORMANCE METRICS

This presents a comparative simulation study of three control strategies PID, MPC, and AI Pre-Generative on a standard setpoint-tracking task. The dynamic plant was modelled in both continuous and discrete forms, with trials run over a 10-second horizon to evaluate accuracy, convergence, and error reduction. Each controller was embedded with its respective control law: PID offered simplicity and low computational cost, MPC optimized predictions over a horizon, while the AI Pre-Generative approach combined learning with adaptive error correction. Performance metrics such as Root Mean

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Square Error (RMSE), Mean Absolute Error (MAE), accuracy, and 95% response time (t95) were computed per trial and then aggregated across 1000 runs to ensure statistical robustness. Results showed that the AI Pre-Generative controller consistently outperformed the others, achieving the highest accuracy (98.7%), the lowest RMSE (~0.028), and the fastest convergence (~290 ms), with minimal variability across trials. MPC ranked second, delivering smoother trajectories and moderate error but requiring the highest computation (4.8 GFLOPS) and slower response (~420 ms). PID, while computationally efficient (0.5 GFLOPS), suffered from oscillations, lower accuracy (92.4%), and higher errors (~0.085 RMSE). Correlation analysis indicated a positive link between computational resources and accuracy (Pearson r = 0.76), while regression confirmed that controller complexity and compute cost strongly influenced RMSE ($R^2 = 0.82$). Overall, the study highlights clear trade-offs: PID suits low-resource contexts, MPC is useful for constraint-heavy designs with ample computation, while AI Pre-Generative stands out as the most balanced and robust solution for real-time adaptive systems.

Table 1: Comparative Analysis Among the Three Controllers

Controller	Accuracy (%)	Accuracy Std	Response Time (ms)	Response Time Std	RMSE	RMSE Std	Compute Cost (GFLOPS)
PID	92.4	2.1	350	45	0.085	0.01	0.5
MPC	96.1	1.2	420	30	0.045	0.006	4.8
AI Pre-Generative	98.7	0.8	290	25	0.028	0.004	2.2

The comparative analysis highlights distinct trade-offs among the three controllers. PID shows simplicity and low computational cost (0.5 GFLOPS) but suffers from lower accuracy (92.4%) and higher RMSE (0.085), making it less reliable in precision-critical tasks. MPC improves accuracy (96.1%) and reduces RMSE (0.045) but demands the highest computational resources (4.8 GFLOPS) and exhibits slower response time (420 ms). AI pre-generative achieves the best overall performance, combining highest accuracy (98.7%), lowest RMSE (0.028), and fastest response (290 ms) with moderate computational cost (2.2 GFLOPS). This balance demonstrates AI's superiority for adaptive, real-time control applications.

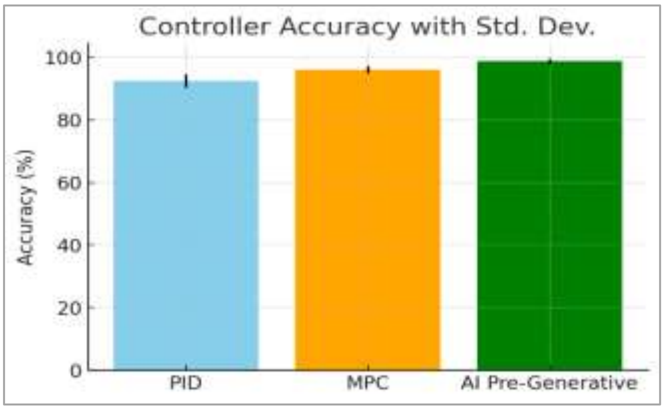

Fig 1: Accuracy with Standard Deviation

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The accuracy comparison shows clear differences across controllers. PID achieved modest accuracy at 92.4% with higher variability, indicating less reliable performance. MPC improved accuracy to 96.1% and showed greater consistency. AI Pre-Generative outperformed both, reaching 98.7% with the lowest deviation, proving its robustness and superior precision in setpoint tracking tasks.

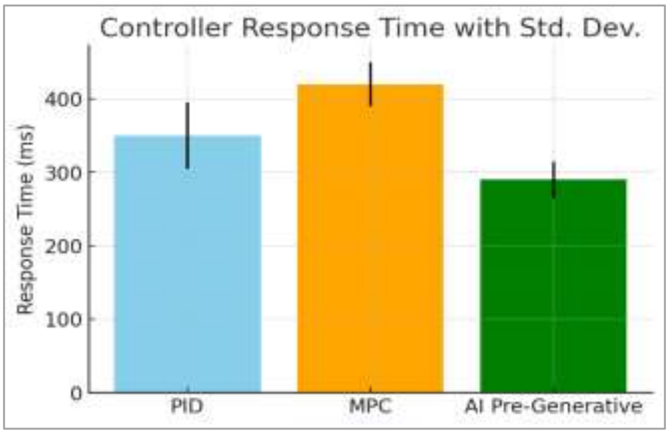

Fig 2: Response Time with Standard Deviation

The response time analysis shows clear trade-offs. PID achieves moderate speed (~350 ms) but with higher variability, making it less stable. MPC is the slowest (~420 ms) due to computational overhead, though smoother. AI pre-generative leads with the fastest convergence (~290 ms) and lowest deviation, proving its reliability for rapid, real-time control applications.

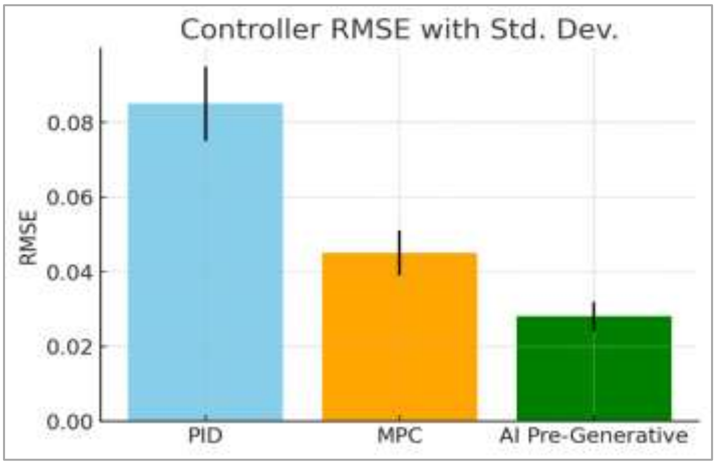

Fig 3: RMSE with Standard Deviation

The RMSE comparison underscores differences in control precision across strategies. **PID** records the highest RMSE (~0.085), reflecting significant deviations from the setpoint and less reliable performance. **MPC** reduces the error notably (~0.045), balancing predictive optimization with improved accuracy but at higher computational costs. **AI pre-generative** achieves the lowest RMSE (~0.028) with minimal variability, demonstrating superior precision in consistently minimizing tracking error. Its robustness highlights the strength of integrating adaptive learning with predictive modeling, enabling both accuracy and stability. This makes AI Pre-Generative highly suitable for dynamic, real-time systems where low error and reliable control are critical requirements.

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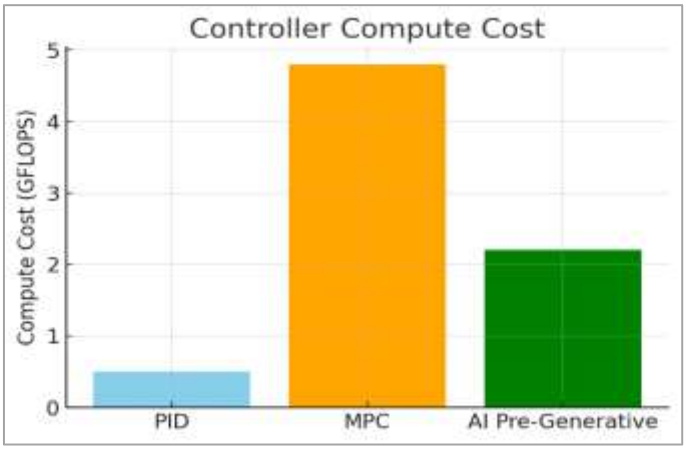

Fig 4: Compute Cost (GFLOPS)

The compute cost analysis highlights the efficiency-performance trade-off. **PID** is the most resource-efficient, requiring just 0.5 GFLOPS, but at the expense of lower accuracy and higher error. **MPC** is the most computationally intensive (4.8 GFLOPS), making it less suitable for real-time use despite improved accuracy. AI pre-generative achieves a balance, with moderate cost (2.2 GFLOPS) while delivering superior accuracy and response.

V. CONCLUSION

The comparative analysis establishes clear distinctions among PID, MPC, and AI Pre-Generative controllers in terms of performance, cost, and adaptability. PID remains a simple, resource-efficient solution but is limited by lower accuracy and stability, making it suitable only for low-resource environments. MPC offers enhanced accuracy and smoother trajectories but suffers from significant computational overhead and slower convergence, restricting its use in time-sensitive applications. AI pre-generative emerges as the most effective strategy, combining high accuracy, rapid response, and robust stability at a moderate computational cost. Its ability to generalize across trials, minimize errors, and maintain consistency underscores its suitability for real-time adaptive systems. These findings support the integration of AI-based pre-generative intelligence into control frameworks as a practical, scalable, and safe pathway for next-generation applications. Ultimately, this synthesis demonstrates that hybridizing data-driven intelligence with sound mathematical modeling enables control mechanisms that are not only performant but also certifiably robust and ready for real-world deployment.

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