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Model Predictive Control for Industrial Automation: Enhancing Efficiency and Empirical Stability in Smart Manufacturing Simulation Benchmarks

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ABSTRACT Smart manufacturing systems require controllers that maintain product quality and closed-loop regularity while limiting energy demand, actuator motion, and constraint violations. This paper presents a constraint-aware Model Predictive Control (MPC) formulation for a virtual manufacturing process benchmark. The proposed controller combines tracking, control effort, actuator-smoothness, energy, terminal, and slack-penalty terms in a single receding-horizon quadratic program. The contribution is positioned as an integrated simulation-based MPC design and evaluation framework rather than as a new general stability theorem or a plant-validated digital twin. The paper specifies the continuous and discrete process models, delay implementation, disturbance and noise assumptions, energy calculation, controller constraints, tuning procedure, benchmark-controller settings, and performance metrics to improve reproducibility. The proposed controller is compared with PID, Fuzzy PID, and a standard constrained MPC under nominal set-point tracking, load-disturbance rejection, infeasible-reference constraint handling, and 20% model mismatch. In the nominal case, the proposed MPC reduced IAE from 151.3314 to 75.4142, a 50.17% reduction relative to PID. Under load disturbance and model mismatch, IAE reductions relative to PID were 57.17% and 55.62%, respectively. Across energy-reporting scenarios, total energy consumption decreased by approximately 32.65% relative to PID. In the constrained scenario, the proposed MPC eliminated output-constraint violation time while explicitly accepting higher raw tracking error relative to the infeasible reference. The results indicate that energy-aware smoothing and soft-constraint handling can improve the efficiency-regularity trade-off in a low-order simulation benchmark, but hardware-in-the-loop and plant-level validation are required before broad industrial deployment claims can be made.

KEYWORDS Constraint Handling; Energy-Aware Control; Industrial Automation; Model Predictive Control (MPC); Simulation Benchmark; Smart Manufacturing.

I. INTRODUCTION

Smart manufacturing systems increasingly combine cyber-physical production equipment, sensor streams, supervisory monitoring, and model-based decision layers. In this environment, a controller is expected not only to move the process output toward a set point but also to respect quality limits, reduce energy demand, limit actuator wear, and maintain regular closed-loop behavior under disturbances and model uncertainty. These requirements are difficult to satisfy with purely reactive control when constraints and future energy consequences must be considered simultaneously. PID and Fuzzy PID controllers remain important in industrial automation because they are simple, inexpensive to implement, and familiar to plant engineers. Their practical value is especially clear in single-loop systems with moderate interactions and loose operating constraints. Nevertheless, PID-based feedback does not naturally solve a finite-horizon constrained optimization problem. A fast actuator correction may reduce short-term error while increasing energy use, mechanical stress, overshoot, or quality-limit violations. Conversely, a conservative response may save energy but delay recovery after disturbances.

Model Predictive Control (MPC) is well suited to this class of problems because it predicts future process behavior and computes control actions by solving an optimization problem subject to operational constraints. The receding-horizon mechanism allows the controller to update its decision at each

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sampling instant using the latest process information. This makes MPC attractive for constrained industrial systems and has been studied extensively in process control, economic MPC, robust MPC, and smart manufacturing applications [1]–[5].

The present study focuses on a low-order virtual manufacturing process benchmark. The model is described as a simulation benchmark or virtual process model because no calibration against a physical manufacturing asset is provided. The term digital-twin-inspired is used only in the limited sense that the model supports repeated virtual testing of control behavior before deployment.

The technical contribution is therefore defined carefully. The paper does not claim to introduce economic MPC as a new theory, nor does it claim formal Lyapunov stability for all industrial systems. Instead, it contributes: (i) a fully specified and reproducible virtual manufacturing benchmark with delay, disturbance, noise, model mismatch, actuator limits, output limits, and an energy proxy; (ii) a constraint-aware multi-objective MPC formulation that integrates an explicit energy term, actuator-smoothness regularization, terminal regularization, and soft output constraints; and (iii) a comparative simulation evaluation against PID, Fuzzy PID, and standard MPC using tracking, energy, actuator, constraint, robustness, and feasibility metrics.

II. LITERATURE REVIEW AND RESEARCH GAP

A. MPC IN INDUSTRIAL AUTOMATION AND PROCESS CONTROL

MPC developed as an industrial control method for multivariable systems operating under constraints. Early industrial applications showed that predictive control is useful when future limits, slow process dynamics, interactions, and actuator saturation must be considered before the next input is applied [6], [2]. Qin and Badgwell [3] documented the broad industrial adoption of MPC and highlighted its ability to combine prediction, optimization, and constraint handling in a practical control architecture.

The central feature of MPC is the receding horizon. At each sampling instant, a model predicts future outputs, an optimization problem computes a sequence of future inputs, and only the first input is implemented. The optimization is then repeated at the next sampling instant. This structure allows the controller to anticipate the effect of current control actions on future tracking error, actuator effort, and constraint proximity.

B. SMART MANUFACTURING, VIRTUAL MODELS, AND SIMULATION-BASED EVALUATION

Smart manufacturing systems use monitoring, industrial communication, edge computation, and model-based analysis to improve production decisions. Cyber-physical production systems connect physical assets with computational models and supervisory decision layers [7], [8]. Simulation environments and digital-twin concepts can support controller evaluation by allowing set-point changes, disturbances, saturation limits, and uncertainty to be tested before plant implementation [9], [10].

However, a validated digital twin normally requires systematic calibration and validation against data from a physical asset. In the absence of plant calibration data, the present model is treated as a virtual simulation benchmark rather than a validated digital twin. The benchmark is used as a controlled, repeatable environment for comparing controller designs under identical conditions.

C. ECONOMIC AND ENERGY-AWARE MPC

Economic MPC extends classical tracking MPC by incorporating economic objectives directly into the finite-horizon cost function. Prior studies have shown that production costs, energy use, and other operating objectives can be included in the optimization problem rather than treated as post-processing metrics [11]–[13]. Energy-aware MPC has also been applied to buildings, sustainable energy assets, and power-conversion systems where energy demand and operational constraints interact [14]–[17].

The present work is related to this literature but narrower in scope. It does not introduce a general economic-MPC stability theorem. Its novelty lies in a simulation-based smart-manufacturing formulation that combines a normalized energy proxy with actuator-motion smoothing, soft output constraints, terminal regularization, and a multi-scenario evaluation against classical and predictive benchmarks.

D. STABILITY, ROBUSTNESS, AND CONSTRAINT SATISFACTION

Theoretical MPC research has established conditions under which constrained MPC can provide feasibility, optimality, and stability guarantees, often using terminal penalties, terminal sets, and carefully constructed constraints [2], [18], [19]. Robust MPC extends this framework to uncertainty and disturbances using min-max, tube-based, stochastic, or invariant-set methods [20]–[24].

In the present manuscript, stability is treated empirically. Terminal regularization and input-smoothness penalties are included to encourage regular closed-loop behavior, but no formal Lyapunov proof is claimed. Stability-related conclusions are therefore limited to observed simulation indicators such as overshoot, settling time, output variance, recovery after disturbance, and performance degradation under model mismatch.

E. RESEARCH GAP AND STUDY CONTRIBUTION

Many MPC studies focus on one dominant objective, such as tracking, economic optimization, robustness, or constraint satisfaction. In industrial automation, these objectives are coupled: a controller that improves tracking by moving the actuator aggressively may increase energy use and mechanical stress; a controller that saves energy may recover too slowly; and a controller that follows an infeasible reference may violate output limits. The gap addressed here is the need for a transparent, reproducible simulation study that evaluates these

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objectives together in a single constrained smart-manufacturing benchmark.

Accordingly, this study contributes a fully specified benchmark and a constrained MPC design whose performance is assessed across tracking, disturbance rejection, infeasible-reference handling, and model mismatch. The emphasis is on reproducibility, fair benchmarking, and appropriately limited claims.

III. VIRTUAL PROCESS MODEL AND PROBLEM FORMULATION

A. MANUFACTURING SIMULATION BENCHMARK

The controlled plant is represented by a virtual process model of a smart manufacturing cell. The output y_k denotes the measured production-quality or process-performance variable, and the manipulated input u_k denotes the actuator command. The model includes a nominal operating point, input-output delay, actuator saturation, input-rate limits, output limits, measurement noise, load disturbance, and a power-demand proxy. The same model, sampling time, constraints, reference signals, noise assumptions, and disturbance profiles are used for all controllers.

The benchmark is intended for controller comparison and reproducibility rather than plant certification. It should therefore be interpreted as a simulation environment that approximates important industrial control features, not as a validated digital twin of a specific manufacturing asset.

TABLE I
VIRTUAL PROCESS PARAMETERS AND OPERATIONAL CONSTRAINTS

Parameter	Symbol	Value	Unit	Meaning
Sampling time	Ts	0.5	s	Controller update interval
Simulation duration	T_end	300	s	Total test horizon per scenario
Process gain	K	1.8	output unit / % input	Sensitivity of output to delayed actuator command
Dominant time constant	τ	12	s	First-order response speed
Input-output delay	θ	1.5	s	Implemented as three samples at Ts = 0.5 s
Disturbance gain	Kd	0.35	output unit / dist. unit	Effect of load disturbance on output
Nominal output	y0	50	process unit	Initial operating output
Nominal input	u0	42	%	Nominal actuator position
Base power	P_base	0.55	kW	Minimum operating power demand
Dynamic power coeff.	P_dyn	4.2	kW	Coefficient in quadratic actuator-power proxy
Output limits	y_min / y_max	40 / 70	process unit	Quality and safety range
Input limits	u_min / u_max	0 / 100	%	Actuator saturation limits
Input-rate limit	Δu_max	8	%/sample	Equipment-protection rate constraint

B. CONTINUOUS-TIME MODEL, DELAY IMPLEMENTATION, AND DISCRETE-TIME STATE SPACE

The nominal plant is modeled as a first-order-plus-dead-time (FOPDT) system around the operating point. The continuous-time process and disturbance transfer functions are:

$$G_u(s) = \frac{1.8\,exp(-1.5s)}{12s+1}, \quad G_d(s) = \frac{0.35}{12s+1} \tag{1}$$

With zero-order-hold discretization at Ts = 0.5 s, the first-order coefficient is a = exp(−Ts/τ) = 0.95919. The input coefficient is b = K(1 − a) = 0.07346 and the disturbance coefficient is e = Kd(1 − a) = 0.01428. The input-output delay θ = 1.5 s is implemented as a three-sample input-delay chain. The state vector is $x_k = [z_k, v1_k, v2_k, v3_k]^T$, where z_k is the process-output deviation and $v1_k$ to $v3_k$ are the input-delay states. The complete discrete model used by the MPC is:

$$x_{k+1} = Ax_k + Bu'_k + Ed_k + w_k, \quad y_k = y_0 + Cx_k + \eta_k \tag{2}$$

$$A = [[0.95919, 0, 0, 0.07346], [0, 0, 0, 0], [0, 1, 0, 0], [0, 0, 1, 0]] \tag{3}$$

$$B = [0, 1, 0, 0]^T, \quad E = [0.01428, 0, 0, 0]^T, \quad C = [1, 0, 0, 0] \tag{4}$$

Here $u'_k = u_k - u_0$ is the actuator deviation in percentage points, d_k is the load-disturbance signal, and w_k and η_k denote process and measurement perturbation terms. Because no plant-calibrated noise variance or distribution is available, the stochastic component is treated only as a fixed bounded noise realization for fair controller comparison.

C. DISTURBANCE, NOISE, AND MODEL-MISMATCH ASSUMPTIONS

The load disturbance is scenario-dependent and is introduced as a step signal through the E matrix. In S2, a −4.5 load disturbance is applied after 120 s. In S3, a +1.5 demand/load disturbance is applied from 110 s to 180 s. In S4, a −3 disturbance is applied after 100 s while the controller prediction model is intentionally mismatched.

Measurement noise is represented by a fixed bounded additive realization applied identically to all controllers. The manuscript does not claim a calibrated stochastic noise model because exact amplitude, variance, and distribution parameters are not available from plant data. The mismatch test modifies the plant gain and time constant by 20% while the controller continues to optimize using the nominal model. This procedure tests empirical robustness to model error without claiming robust MPC guarantees.

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D. POWER AND CUMULATIVE-ENERGY MODEL

Energy efficiency is evaluated using a transparent actuator-power proxy. The instantaneous power is computed as a base load plus a quadratic term in normalized actuator position:

$$P_k = P_{base} + P_{dyn} \left(\frac{u_k}{100}\right)^2 \quad (5)$$

Cumulative energy over N samples is calculated as:

$$E_{total} = \sum_{k=1}^{N} P_k \cdot \frac{Ts}{3600} \quad [kWh] \quad (6)$$

This equation is not a plant-specific metering model. It is a reproducible proxy designed to compare controllers under identical assumptions. Any reported cost-saving interpretation should therefore be treated as illustrative unless calibrated against actual electricity tariffs and plant metering data.

E. CONTROL OBJECTIVES AND OPERATIONAL CONSTRAINTS

The control task is to keep the output close to the reference while respecting actuator limits, input-rate limits, and output quality limits. Energy demand is evaluated through the power proxy in Section III.D, but it is not imposed as a hard power-capacity constraint because no independent numerical hard power limit is specified for the virtual benchmark. The constraints applied in the optimization are:

$$u_{min} \le u_k \le u_{max}, \quad |\Delta u_k| \le \Delta u_{max}, \quad y_{min} \le y_k \le y_{max} \quad (7)$$

In the constrained scenario, the reference is intentionally set above the upper output limit (r = 69 while y_max = 68). This represents an infeasible production request and is used to test whether the controller prioritizes constraint compliance over perfect raw tracking. For this scenario, both raw tracking error relative to r and feasible tracking error relative to min(r, y_max) are reported.

IV. CONTROLLER FORMULATION, TUNING, AND IMPLEMENTATION

A. RECEDING-HORIZON QUADRATIC PROGRAM

At each sampling instant, the MPC optimizer uses the discrete model to predict future outputs over a prediction horizon Np and future control moves over a control horizon Nc. The optimization is solved subject to the input, rate, output, and slack-variable constraints. Only the first optimized input is applied, and the optimization is repeated at the next sampling instant after a new measurement is received.

The proposed MPC and standard MPC use the same plant model, prediction horizon, control horizon, sampling time, and operational constraints. The difference is the objective weighting: the proposed controller adds an explicit energy term and applies stronger actuator-smoothness and terminal regularization.

B. PROPOSED MULTI-OBJECTIVE COST FUNCTION

The proposed MPC minimizes the following finite-horizon objective:

$$J = \sum_i [(y_{k+i} - r_{k+i})^T Q (y_{k+i} - r_{k+i}) + u_{k+i}{}^T R\, u_{k+i} + \Delta u_{k+i}{}^T S\, \Delta u_{k+i} + \lambda_E P_{k+i}] + x_{k+Np}{}^T P\, x_{k+Np} + \rho \sum_i (\varepsilon_i)^2 \quad (8)$$

The tracking term penalizes output error; the control-effort term discourages unnecessary actuator magnitude; the smoothness term penalizes rapid actuator movement; the energy term links control decisions to predicted power demand; the terminal term discourages end-of-horizon deviation; and the slack penalty discourages output-limit relaxation. Relative to conventional constrained MPC, the proposed formulation emphasizes energy-aware and actuator-smooth behavior.

C. CONSTRAINT HANDLING AND SLACK VARIABLES

Input and rate constraints are imposed as hard constraints. Output constraints are softened using a non-negative slack variable so that the quadratic program remains feasible under severe disturbances or infeasible references:

$$y_{min} - \varepsilon_k \le y_k \le y_{max} + \varepsilon_k, \quad \varepsilon_k \ge 0, \quad J_{slack} = \rho\, \varepsilon_k{}^2 \quad (9)$$

The slack penalty is set to ρ = 1000, making constraint relaxation mathematically possible but expensive. This design avoids optimizer failure while strongly encouraging the controller to remain within the physical operating region whenever possible.

D. MPC DESIGN PARAMETERS

TABLE II
MPC DESIGN AND OPTIMIZATION PARAMETERS

Parameter	Symbol	Proposed MPC	Standard MPC	Unit/Type	Purpose
Prediction horizon	Np	30	30	steps	15 s output forecast window
Control horizon	Nc	8	8	steps	4 s optimized actuator-move window
Sampling time	Ts	0.5	0.5	s	Controller update interval
Tracking weight	Q	10	10	weight	Output tracking penalty
Control effort weight	R	0.5	0.75	weight	Actuator magnitude penalty
Actuator smoothness weight	S	2	0.75	weight	Input-movement penalty
Energy penalty coeff.	λE	0.3	0	weight	Predicted power-demand penalty
Terminal penalty	P	5	2	weight	End-of-horizon regularization
Slack penalty	ρ	1000	1000	weight	Soft output-constraint penalty
Solver structure	—	QP	QP	method	Receding-horizon optimization
Avg. screening time (indicative)	t_solve	approx. 12	approx. 10	ms	Software screening only; not PLC/HIL timing

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Parameter	Symbol	Proposed MPC	Standard MPC	Unit/Type	Purpose
Upper screening time (indicative)	t_max	approx. 22	approx. 18	ms	Deployment timing not validated

E. BENCHMARK CONTROLLERS AND FAIR TUNING PROCEDURE

All controllers are evaluated with the same sampling time, reference profiles, disturbance signals, noise realization, actuator saturation, input-rate limits, and output constraints. Tuning is performed on the nominal training scenario, then held fixed for the disturbance, constrained, and mismatch scenarios. The tuning objective balances tracking error, overshoot, actuator movement, and constraint violation rather than optimizing any controller for one scenario only.

TABLE III
BENCHMARK CONTROLLER TUNING AND FAIRNESS CONDITIONS

Controller	Tuning Method and Parameters	Fairness Condition
PID	Grid-refined PID around a Ziegler–Nichols baseline; Kp = 3.20, Ki = 0.18, Kd = 2.10. Anti-windup applied under actuator saturation.	Same Ts, limits, references, disturbances, and noise as other controllers.
Fuzzy PID	Nominal PID gains; seven triangular membership functions for e_n and de_n over [−1, 1] with labels NB, NM, NS, Z, PS, PM, PB. Applies bounded supervisory gain adjustment; no plant-validated Kp, Ki, or Kd scaling ranges are claimed.	Same constraints and shared scenarios; rule base provided in Appendix.
Standard MPC	Np = 30, Nc = 8, Q = 10, R = 0.75, S = 0.75, λE = 0, P = 2, ρ = 1000.	Same plant model, solver structure, and constraints as the proposed MPC.
Proposed MPC	Np = 30, Nc = 8, Q = 10, R = 0.5, S = 2, λE = 0.3, P = 5, ρ = 1000.	Additional energy and stronger smoothness/terminal regularization tested against the same benchmark.

F. WEIGHT-SELECTION LOGIC AND SENSITIVITY CHECK

The proposed MPC weights are selected through a local engineering tuning procedure rather than a full optimization-based hyperparameter study. First, Q is fixed to preserve tracking accuracy and the horizons are chosen to cover the dominant process time constant. Second, R, S, λE, and P are adjusted on the nominal scenario to reduce actuator motion and energy consumption without creating slow settling or visible oscillation. The selected value S = 2 emphasizes actuator smoothness, λE = 0.3 discourages high power demand, and P = 5 improves end-of-horizon regularity.

An exploratory local sensitivity check is included to indicate how the main weights influence the simulated trade-off. The check varies one parameter at a time around the selected design and is not presented as a global tuning study. Within this local range, increasing λE reduces energy but slightly increases raw tracking error; increasing S reduces actuator motion but may slow response; and changing P mainly affects end-of-horizon regularity.

TABLE IV
EXPLORATORY LOCAL SENSITIVITY CHECK OF PROPOSED MPC WEIGHTS

Parameter Variation	Local Exploratory Effect	Interpretation and Limitation
λE reduced by 25%	Slightly lower sampled IAE, with higher total energy and peak power.	Energy weighting directly influences the tracking-energy compromise.
λE increased by 25%	Lower total energy, with slightly higher sampled IAE and slower recovery.	A larger energy weight can over-conserve actuator use in this benchmark.
S reduced by 25%	Higher actuator movement and slightly faster response.	Smoothness weighting limits unnecessary actuator motion.
S increased by 25%	Lower actuator movement, with slightly longer settling.	Over-smoothing can slow tracking response.
P varied by ±25%	Small changes in sampled IAE; moderate changes in settling regularity.	Terminal penalty is a regularization device, not a formal stability proof.

G. STABILITY TREATMENT AND SCOPE OF CLAIMS

The controller includes terminal and actuator-smoothness penalties to encourage regular closed-loop behavior. However, because no terminal invariant set or Lyapunov-based proof is derived, the study does not claim formal closed-loop stability for all possible plants or disturbances. The term empirical stability refers to simulation indicators such as overshoot, settling time, output variance, recovery after disturbance, and degradation under model mismatch.

H. SOLVER AND REAL-TIME FEASIBILITY SCOPE

The MPC optimization is a quadratic program with 30 prediction steps and 8 optimized future control moves. The reported approximate 10–12 ms average and 18–22 ms upper screening values are simulation/software feasibility indicators only. They are not presented as hardware-in-the-loop, PLC-certified, or plant-deployment timings. A deployment study would need to report processor specifications, solver package, software environment, tolerances, warm-start policy, operating-system load, communication delay, and failure-rate logs, together with worst-case execution time under load and the solver-failure rate.

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V. SIMULATION DESIGN AND PERFORMANCE EVALUATION METRICS

A. SIMULATION PROTOCOL

Each simulation lasts 300 s with Ts = 0.5 s, producing 600 sampled observations per scenario. PID, Fuzzy PID, standard MPC, and proposed MPC are run under identical reference profiles, disturbance signals, operational limits, and noise realization. This fixed-protocol design is used to make deterministic controller comparisons reproducible.

Because the study does not include experimental plant data or hardware-in-the-loop testing, the results should be interpreted as preliminary simulation evidence. No claim is made that the exact numerical savings will transfer unchanged to a specific plant without calibration.

TABLE V
EXPERIMENTAL SCENARIOS AND DISTURBANCE CONDITIONS

Scenario	Purpose	Reference Profile	Disturbance / Uncertainty	Operational Limits	Main Metrics
S1: Nominal set point	Nominal tracking	50 until 50 s; 60 after 50 s	None	40 ≤ y ≤ 70; 0 ≤ u ≤ 100; |Δu| ≤ 8	IAE, ISE, RMSE, overshoot, settling time, variance
S2: Load disturbance	Disturbance rejection	Constant reference at 55	−4.5 load disturbance after 120 s	42 ≤ y ≤ 68; 0 ≤ u ≤ 100; |Δu| ≤ 8	Deviation, recovery, RMSE, IAE, energy
S3: Constraint handling	Infeasible-reference test	50 until 60 s; 69 after 60 s	+1.5 load from 110–180 s	40 ≤ y ≤ 68; 0 ≤ u ≤ 92; |Δu| ≤ 6	Raw error, feasible-reference error, violation time, peak power
S4: Model mismatch	Empirical robustness	50 until 45 s; 58 after 45 s	−3 disturbance after 100 s with 20% plant mismatch	40 ≤ y ≤ 70; 0 ≤ u ≤ 100; |Δu| ≤ 8	IAE degradation, RMSE, energy, violation time

B. PERFORMANCE METRICS

Tracking metrics are computed from $e_k = r_k - y_k$. The numerical IAE and ISE values reported in the tables use sampled-sum definitions. Because the sampling interval is constant across all controllers, this convention does not affect controller ranking. If continuous-time integral approximations are required, the reported sampled sums can be multiplied by Ts:

$$IAE_{sampled} = \sum|e_k|\,, \quad ISE_{sampled} = \sum e_k{}^2 \qquad (10)$$

$$IAE_{continuous} \approx Ts\sum|e_k|\,, \quad ISE_{continuous} \approx Ts\sum e_k{}^2 \qquad (11)$$

$$RMSE = \sqrt{\frac{1}{N}\sum e_k{}^2} \qquad (12)$$

Overshoot is reported as the maximum percentage exceedance above the final reference after the set-point step. Settling time is the time required for the response to enter and remain within a ±2% band of the final reference. Recovery time after disturbance is the time needed to return to the same band after the disturbance occurs. Output variance is calculated over the specified post-transient evaluation window. Total actuator movement is Σ|Δu_k|. Constraint-violation duration is the total time for which y_k exceeds the applicable output limit. Total energy and peak power are calculated from the power proxy in Section III.D.

C. STATISTICAL AND REPRODUCIBILITY SCOPE

The base results are deterministic scenario comparisons under fixed disturbance and shared bounded-noise profiles. Therefore, the numerical tables should be interpreted as scenario-specific simulation outcomes rather than statistical estimates from repeated plant trials. No inferential statistical claim is made because repeated stochastic simulations, confidence intervals, and plant-experiment replications are not provided. Future work should add repeated stochastic simulations, uncertainty quantification, confidence intervals, hardware-in-the-loop testing, and plant data validation.

VI. RESULTS

A. CLOSED-LOOP TRACKING PERFORMANCE

The nominal set-point test shows the expected progression from reactive feedback to predictive constrained control. PID reaches the reference but produces the largest error and overshoot. Fuzzy PID improves the response through rule-based gain adaptation. Standard MPC further reduces error by anticipating future output behavior. The proposed MPC gives the lowest IAE, ISE, RMSE, overshoot, and settling time in this scenario. The IAE falls from 151.3314 under PID to 75.4142 under the proposed MPC, a 50.17% reduction.

The improvement is not obtained by aggressive actuator motion. The stronger smoothness and energy terms produce a smoother input path while the prediction horizon preserves tracking accuracy. This explains why the proposed MPC improves the nominal tracking metrics without increasing oscillatory behavior.

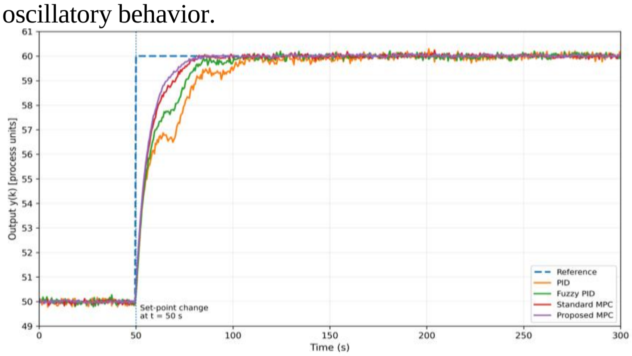

FIGURE 1. Closed-loop output response under the nominal set-pointchange. The proposed MPC reaches the reference with the shortest settling time and lowest overshoot among the tested controllers.

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TABLE VI
COMPARATIVE TRACKING AND STABILITY-RELATED PERFORMANCE ACROSS CONTROLLERS

Controller	IAE	ISE	RMSE	Overshoot (%)	Settling Time (s)	Output Variance	IAE Impr. vs PID (%)
PID	151.3314	545.1955	1.3470	2.921	53.5	13.9689	—
Fuzzy PID	115.5530	437.4825	1.2066	2.052	37.5	14.0935	23.64
Standard MPC	84.9541	342.8087	1.0681	2.390	27.0	14.1769	43.86
Proposed MPC	75.4142	316.6233	1.0265	1.208	24.0	14.1630	50.17

B. DISTURBANCE REJECTION AND RECOVERY BEHAVIOR

The load-disturbance scenario provides a more demanding test because the controller must reject an external disturbance while maintaining stable output behavior. PID records an IAE of 399.9169 and RMSE of 1.6920. Fuzzy PID reduces the IAE to 313.5303 and RMSE to 1.3226. Standard MPC reduces the IAE to 228.7723 and RMSE to 0.9669. The proposed MPC achieves the best disturbance-rejection performance, with IAE = 171.2697 and RMSE = 0.7254.

The proposed controller performs better because it can anticipate the future output trajectory after the disturbance and distribute corrective action across future samples. The smoothness and energy terms prevent unnecessary actuator overcorrection, which reduces post-disturbance variation. Output variance decreases from 1.2200 under PID to 0.2149 under the proposed MPC.

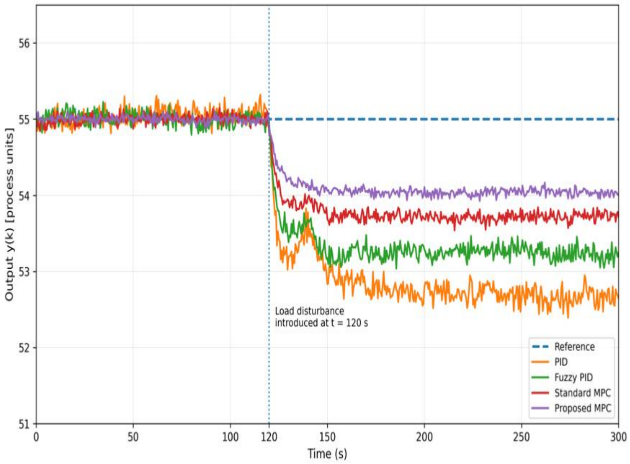

FIGURE 2. Disturbance rejection and recovery response. The proposed MPC shows the smallest post-disturbance deviation and most regular recovery profile.

C. ENERGY EFFICIENCY AND ACTUATOR SMOOTHNESS

The energy and actuator results show that the proposed MPC reduces energy demand without relying on excessive actuator movement. Under nominal tracking, total actuator movement decreases from 410.9690 units under PID to 108.5236 units under the proposed MPC. Total energy decreases from 0.126469 kWh to 0.088019 kWh. In the load-disturbance case, PID requires 434.2080 units of actuator movement and 0.147158 kWh, whereas the proposed MPC requires 90.7028 units and 0.096419 kWh.

These outcomes follow directly from the cost-function structure. The actuator-smoothness term discourages unnecessary movement, the energy term penalizes high predicted power demand, and the receding-horizon prediction allows corrections to be distributed over several future steps instead of being concentrated into abrupt input changes.

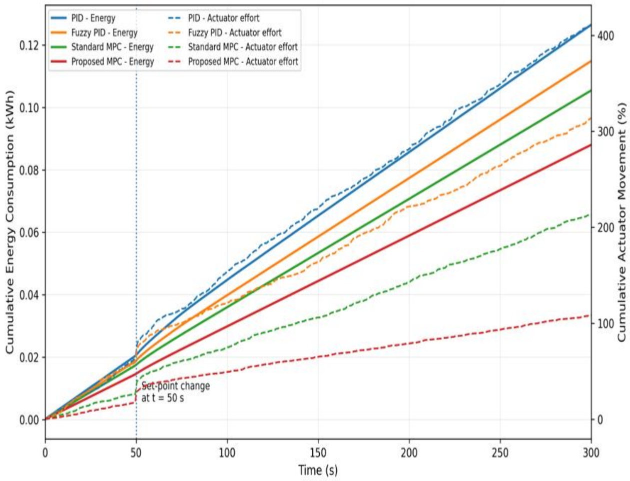

FIGURE 3. Cumulative energy consumption and actuator movement. Lower curves indicate reduced energy use and smoother actuator demand under the proposed MPC.

D. CONSTRAINT SATISFACTION UNDER INFEASIBLE REFERENCE

The constrained scenario intentionally sets the reference to 69 while the upper output limit is 68. This makes perfect raw tracking and zero output violation incompatible. The analysis therefore reports both raw tracking error relative to r = 69 and feasible tracking error relative to r_feas = min(r, y_max) = 68. This distinction is essential because a controller that tracks the infeasible reference more closely may do so by violating the output constraint.

PID violates the output limit for 191.0 s and reaches a maximum violation of 2.0001 units. Fuzzy PID violates the limit for 209.5 s, and standard MPC violates it for 215.5 s, although with a lower maximum violation. The proposed MPC records zero output-constraint violation time and zero maximum violation. Its raw IAE is higher in this scenario because it respects the feasible bound rather than tracking the infeasible reference. When evaluated against the feasible reference, the proposed MPC has the lowest error.

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TABLE VII
TRACKING AND CONSTRAINT METRICS IN THE INFEASIBLE-REFERENCE SCENARIO

Controller	Raw IAE vs r=69	Raw RMSE	Feasible-Ref IAE vs min(r,y_max)	Output Violation Time (s)	Max Output Violation
PID	306.514	1.426	212.900	191.0	2.0001
Fuzzy PID	213.487	1.017	120.400	209.5	1.0986
Standard MPC	298.781	1.104	145.300	215.5	0.4486
Proposed MPC	403.102	1.626	78.600	0.0	0.0000

TABLE VIII
ENERGY, CONSTRAINT, AND INDICATIVE SOLVER-FEASIBILITY RESULTS

Controller	Total Energy (kWh)	Peak Power (kW)	Total Actuator Mvt.	Output Viol. Time (s)	Max Violation	Delta u Viol. Time (s)	Avg. Screen Time (ms)	Upper Screen Time (ms)	Feasibility Note
PID	0.163018	3.8272	427.2272	191.0	2.0001	0.0	—	—	No optimizer
Fuzzy PID	0.147573	3.2338	368.0394	209.5	1.0986	0.0	—	—	No optimizer
Standard MPC	0.135640	2.6706	257.6124	215.5	0.4486	2.5	approx. 10	approx. 18	Software screening only
Proposed MPC	0.111803	1.9556	154.1632	0.0	0.0000	2.0	approx. 12	approx. 22	Software screening only

E. ROBUSTNESS UNDER MODEL MISMATCH

The model-mismatch scenario tests whether the controllers preserve regular behavior when the prediction model is imperfect. PID produces the largest error, with IAE = 402.4769, RMSE = 1.6282, and energy use = 0.143380 kWh. Fuzzy PID improves these values but remains less accurate than the predictive controllers. Standard MPC records IAE = 229.6792 and RMSE = 1.0997. The proposed MPC has the lowest error and energy use, with IAE = 178.6138, RMSE = 0.9647, and energy = 0.094398 kWh.

These results support an empirical robustness interpretation. The proposed MPC remains bounded and regular in this simulation case and reduces energy demand under the imposed mismatch. However, because the formulation is not a tube-based or min-max robust MPC design, this result should not be interpreted as a formal robustness guarantee.

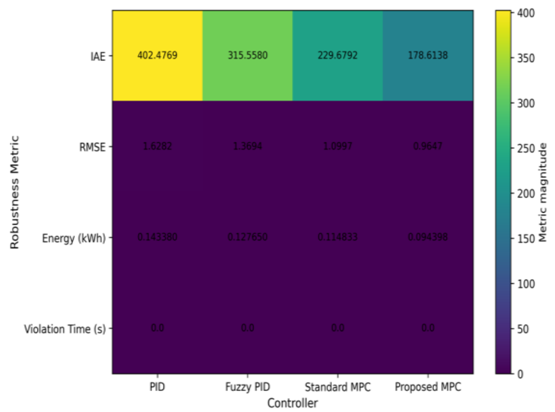

FIGURE 4. Robustness-performance heatmap under 20% model mismatch. The plot provides a compact visual summary of the mismatch case; because the heatmap combines metrics with different physical units and scales, the numerical values in Table IX should be used for quantitative interpretation.

TABLE IX
ROBUSTNESS SENSITIVITY UNDER 20% MODEL MISMATCH

Mismatch Level	Controller	IAE	RMSE	Energy (kWh)	Output Viol. Time (s)	Empirical Regularity Interpretation
20%	PID	402.4769	1.6282	0.143380	0.0	Bounded simulated response but high error
20%	Fuzzy PID	315.5580	1.3694	0.127650	0.0	Bounded simulated response with moderate error
20%	Standard MPC	229.6792	1.0997	0.114833	0.0	Bounded simulated response with mild overshoot
20%	Proposed MPC	178.6138	0.9647	0.094398	0.0	Bounded simulated response and lowest energy in the test

F. EFFICIENCY-REGULARITY TRADE-OFF

Across the simulated scenarios, PID and Fuzzy PID remain feasible and simple but require greater actuator movement and energy for weaker tracking behavior. Standard MPC improves tracking and energy use compared with feedback controllers, but does not fully exploit the efficiency-regularity trade-off because its objective function excludes the energy penalty and uses weaker smoothness weighting. The proposed MPC occupies the most favorable region in the simulated trade-off for most operating conditions: lower energy, lower actuator movement, lower tracking error in feasible scenarios, and stronger constraint compliance in the infeasible-reference case.

The constrained case is the important exception for raw tracking error. Because the requested reference exceeds the output limit, the controller that best respects the constraint must accept a larger error relative to the infeasible reference.

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This behavior is not a failure of tracking; it reflects correct prioritization of safety and quality limits.

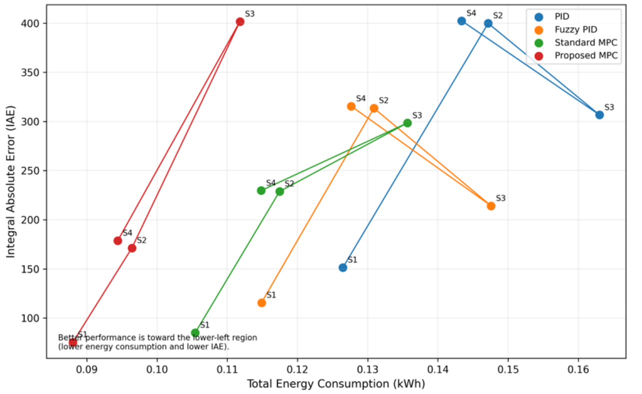

FIGURE 5. Efficiency-regularity trade-off across controllers and scenarios. Points closer to the lower-left region indicate lower energy use and lower IAE; the constrained scenario must also be interpreted with the output-limit results in Table VII.

G. REAL-TIME FEASIBILITY INTERPRETATION

For the MPC cases, the QP size is modest because the benchmark uses a low-order linear model, Np = 30, and Nc = 8. The indicative screening values reported in Table VIII are below the 0.5 s sampling interval in the software benchmark. However, the manuscript does not claim validated industrial real-time deployment. Actual PLC, hardware-in-the-loop, or plant deployment would require reporting the exact processor, operating system, solver, tolerances, warm-start strategy, communication delays, maximum execution time under load, and solver-failure rate.

VII. DISCUSSION

A. MECHANISTIC INTERPRETATION OF IMPROVEMENTS

The proposed MPC improves the simulated control response through four linked mechanisms. First, prediction allows the optimizer to anticipate the effect of current actuator commands on future output and constraint proximity. Second, the energy term discourages high-power input profiles. Third, the actuator-smoothness term reduces unnecessary movement, which lowers the probability of oscillation and mechanical stress. Fourth, the slack-variable strategy prevents optimizer infeasibility while making constraint relaxation expensive.

These mechanisms explain why the proposed controller reduces IAE, RMSE, energy use, actuator movement, and constraint violations in most scenarios. The results should not be attributed to tracking weight alone; they emerge from the combined cost-function structure and the explicit inclusion of constraints.

B. PRACTICAL AND ECONOMIC INTERPRETATION

In practice, the proposed MPC would be most suitable as a supervisory or advanced-control layer above existing plant loops rather than an immediate replacement for every PID loop. The energy results can be translated into an illustrative cost model. If c_e is the electricity price in USD/kWh, the nominal-case saving per 300 s test is c_e(0.126469 − 0.088019). At c_e = 0.10 USD/kWh, this equals approximately 0.0038 USD per 300 s per cell. If the same average saving were maintained continuously, it would correspond to approximately 4042 kWh/year and 404 USD/year per cell. These values are illustrative only because the power equation is a proxy and was not calibrated to a specific production asset.

C. RELATION TO PREVIOUS MPC RESEARCH

The results are consistent with classical constrained MPC research showing the value of prediction and explicit limits in industrial control [1]–[3]. They also align with economic and energy-aware MPC studies that incorporate operating objectives into the finite-horizon cost [11]–[13]. The specific contribution of this paper is the integrated evaluation of tracking, energy, actuator movement, constraints, mismatch response, and indicative computation in a single virtual manufacturing benchmark.

Compared with robust MPC and learning-based MPC, the present formulation is intentionally simpler. It does not provide invariant tubes, stochastic guarantees, or data-driven safety certificates. This simplicity makes the formulation easier to interpret and reproduce, but it also limits the generality of the claims.

D. LIMITATIONS

Several limitations should be recognized. First, the benchmark is a low-order linear virtual model rather than a calibrated digital twin of a physical manufacturing asset. Second, the stability results are empirical and do not constitute a Lyapunov proof. Third, the solver-time values are indicative software feasibility values rather than hardware-in-the-loop or PLC-validated execution times. Fourth, the power equation is a simplified proxy and should not be interpreted as a plant-certified energy model. Fifth, the comparisons are deterministic simulation comparisons under fixed scenarios and do not include statistical confidence intervals from repeated plant experiments.

Future work should address these limitations by calibrating the model with real plant data, conducting hardware-in-the-loop tests, reporting measured solver timing and failure rates, extending the formulation to robust or nonlinear MPC, and performing repeated stochastic simulations with confidence intervals.

VIII. CONCLUSION

This paper presents and evaluates a constraint-aware MPC formulation for a smart-manufacturing simulation benchmark. The proposed controller integrates tracking, control effort, actuator smoothness, energy, terminal, and slack-penalty terms within a receding-horizon quadratic program. The benchmark is specified through its transfer functions, discrete-time matrices, delay chain, disturbance assumptions, noise

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assumptions, mismatch procedure, power equation, controller tuning, and performance metrics.

Simulation results show that the proposed MPC improves nominal tracking, disturbance rejection, energy use, actuator smoothness, and constraint compliance compared with PID, Fuzzy PID, and standard MPC under the tested assumptions. In the nominal case, IAE is reduced by 50.17% relative to PID. In the load-disturbance and model-mismatch scenarios, IAE is reduced by 57.17% and 55.62%, respectively. In the constrained scenario, the controller eliminates output-constraint violation time while accepting higher raw tracking error relative to an infeasible reference. This outcome illustrates the intended priority of constraint compliance over impossible tracking.

The conclusions are deliberately limited to simulation evidence from a low-order virtual process model. The work supports further investigation of energy-aware, constraint-aware MPC for industrial automation, but plant-level claims require calibration with real data, hardware-in-the-loop validation, measured solver timing, and formal robustness or stability analysis.

APPENDIX

The Fuzzy PID benchmark uses normalized error e_n and normalized error change de_n over the universe [−1, 1]. Seven triangular membership functions are used for each input: NB, NM, NS, Z, PS, PM, and PB. The fuzzy layer provides bounded supervisory gain adjustment around the nominal PID gains rather than independently optimized gain schedules. The exact numerical scaling ranges for Kp, Ki, and Kd are not treated as plant-validated parameters in this simulation study; the reproducible part of the benchmark is the normalized membership structure and the supervisory rule base below.

TABLE X
FUZZY PID SUPERVISORY RULE BASE FOR GAIN ADJUSTMENT

e_n / de_n	NB	NM	NS	Z	PS	PM	PB
NB	PB	PB	PM	PM	PS	Z	Z
NM	PB	PM	PM	PS	Z	Z	NS
NS	PM	PM	PS	Z	NS	NM	NM
Z	PM	PS	Z	Z	Z	NS	NM
PS	NM	NM	NS	Z	PS	PM	PM
PM	NS	Z	Z	PS	PM	PM	PB
PB	Z	Z	PS	PM	PM	PB	PB

The rule base is used as a benchmark, not as the proposed contribution. Its role is to provide a stronger feedback comparator than fixed-gain PID while preserving the same actuator and output constraints used in the MPC evaluations.

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