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NEURAL-NETWORK-ASSISTED MODEL PREDICTIVE CONTROL FOR ACTUATORS IN NUCLEAR POWER PLANT DRIVE SYSTEMS

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Abstract: This study develops a unified dynamic modeling framework for nuclear-grade actuators, such as fans, pumps, and valves, critical for reactor cooling, feedwater regulation, and ventilation. These actuators exhibit nonlinearities, cross-coupling, and operational constraints, challenging conventional controllers to maintain performance and safety under fluctuating conditions. To address this, a neural-network-assisted model predictive control (NN-MPC) architecture is proposed. The framework incorporates a mask-based input encoding strategy to represent all actuators within a single model, and a fully differentiable neural network is trained to approximate actuator dynamics. A bias-compensation mechanism is introduced to address multi-step prediction drift caused by process variations and aging. The resulting nonlinear MPC integrates actuator constraints, output limitations, rate restrictions, and real-time optimization, ensuring millisecond-level performance required in nuclear applications. The implementation workflow includes real-time execution analysis, anomaly detection, safety fallback logic, and hardware-in-the-loop validation. Experimental results demonstrate that the NN-MPC framework provides accurate modeling, high-performance control, and compliance with nuclear safety requirements. This research offers a robust pathway for advancing intelligent, data-driven control systems in next-generation nuclear power plants.
Keywords: Nuclear power plant actuators; Neural network prediction model; Model predictive control; Bias compensation; Real-time optimization

1 INTRODUCTION

Nuclear power plants are highly coupled, safety-critical energy systems whose operational performance depends strongly on the reliable and stable behavior of drive actuators such as fans, pumps, and valves. These electrically driven devices support essential functions including reactor coolant circulation, feedwater control for steam generators, plant ventilation and heat removal, chemical volume regulation, and emergency mitigation under accident scenarios. They constitute a vital part of the nuclear unit's capability to maintain steady-state operation and preserve safety margins [1]. The actuators are not only numerous but also distributed across various physical subsystems, forming complex dynamic chains that span multiple regions and loops. Their control performance directly influences thermohydraulic stability, operational boundaries of key equipment, and the coordination efficiency among reactor-side and turbine-side systems. Consequently, enhancing the dynamic performance, robustness, and predictability of these actuators has long been a core research focus in nuclear engineering control [2].

Compared with conventional industrial facilities, actuator control in nuclear power plants exhibits several distinctive characteristics. First, control strategies must conform to strict nuclear safety regulations governing allowable input ranges, actuation speeds, overshoot limits, steady-state accuracy, and behavior under abnormal or accident conditions [3]. Second, due to the structural complexity of nuclear systems, actuators are strongly coupled through hydraulic flow, differential pressure, thermal effects, and environmental interactions, resulting in nonlinear, time-varying, and tightly coupled dynamics [4]. Third, although the plant typically operates under relatively stable conditions, it is extremely sensitive to disturbances—such as load fluctuations, cooling water temperature variations, and system resistance changes—which may significantly affect actuator behavior; stability and robustness therefore remain primary design objectives. Furthermore, nuclear facilities cannot perform frequent online experiments or deliberate perturbations on actuators as in ordinary industrial systems, implying that control methods must achieve high reliability under limited data availability and restricted testing conditions [5]. Overall, the modeling, control design, and safety assurance of nuclear actuators involve challenges far exceeding those of typical industrial scenarios.

To date, proportional–integral–derivative (PID) control remains the dominant approach for nuclear actuator control due to its simplicity, ease of implementation, and long-standing operational experience in safety-critical environments. However, PID is inherently linear and therefore insufficient for compensating complex nonlinear dynamics. Moreover, PID cannot explicitly handle physical constraints such as stroke limits, maximum rotational speed, pressure-drop boundaries, or ramp-rate limits. Under strong disturbances, dynamic variations, or intensified coupling, PID controllers often exhibit overshoot, sluggish responses, or oscillatory behavior [6]. Additionally, the large number of actuators in nuclear power plants—with diverse operating characteristics—makes empirical PID tuning labor-intensive and inconsistent, compromising verifiability and maintainability. As modern nuclear power plants evolve toward digitalized and intelligent control systems, PID increasingly struggles to meet new demands related to fine regulation, energy efficiency, dynamic performance enhancement, and auditability.

Model predictive control (MPC), an optimization-based control framework that employs explicit handling of system constraints and multivariable coupling, is widely regarded as a promising pathway for upgrading actuator control in nuclear power plants [7]. MPC offers excellent predictability and auditability: control actions are derived from real-time optimization with a transparent mathematical structure suitable for rigorous verification, aligning well with nuclear safety requirements. However, MPC heavily relies on accurate prediction models. The nonlinear dynamics of fans, pumps, valves, and their hydraulic networks are difficult to represent using traditional mechanistic models; conversely, high-fidelity physical models impose excessive computational burdens incompatible with the sub-100-ms sampling periods commonly required in nuclear applications [8]. Therefore, obtaining models that are both accurate and computationally efficient remains a key barrier to large-scale MPC deployment for nuclear actuators.

Recent advances in neural networks (NNs) have demonstrated strong potential in nonlinear system modeling, fluid-system prediction, and actuator-level data-driven modeling [9]. Unlike mechanistic modeling, neural networks do not require complex thermohydraulic equations and can learn input–output relationships directly from operational data. This makes them particularly suitable for characterizing fan pressure–flow behavior, pump head–flow curves, and valve flow characteristics as a function of opening and differential pressure [10]. In nuclear power plants, much of the available data originates from normal operations, cold-state testing, and mode transitions—typically stable operating regimes—allowing neural networks to achieve high-accuracy approximations of actuator dynamics. Additionally, their flexible architecture enables unified input encoding, facilitating shared modeling across different actuator types and thereby supporting a unified control framework [11].

Nonetheless, neural networks alone are not sufficient for nuclear-grade control. Their lack of interpretability, uncertain generalization outside the training distribution, sensitivity to bias accumulation, and dependence on data make them unsuitable for direct use in closed-loop safety-critical control [12]. In particular, multi-step NN prediction errors may accumulate rapidly, causing predicted trajectories to deviate significantly from physical behavior—an unacceptable risk in nuclear applications without additional safeguards. Therefore, using NNs as stand-alone controllers does not satisfy nuclear safety, auditability, or performance predictability requirements.

Against this backdrop, combining neural network–based nonlinear modeling with the constraint optimization capabilities of MPC has emerged as an ideal solution—namely neural-network-assisted MPC (NN-MPC). In this framework, NNs provide accurate nonlinear prediction models, while MPC computes control actions under explicit constraints, thereby achieving high prediction fidelity and robust enforcement of nuclear safety requirements [13]. Importantly, NNs serve solely as predictive components, while MPC governs the final control decisions, preserving interpretability and compliance with nuclear standards. Through structured input encoding and a mask-based mechanism, the unified NN model accommodates fans, pumps, and valves within a single predictive architecture, significantly enhancing engineering maintainability [14].

Based on these considerations, this study proposes a unified NN-MPC control framework tailored for nuclear power plant actuators. The framework integrates unified dynamic modeling, NN-based prediction design, multi-step error compensation, MPC constraint formulation, and nuclear-grade safety mechanisms. The objective is to achieve high-accuracy, predictable, and robust control for diverse actuators while satisfying the stringent verifiability, auditability, and reliability requirements of the nuclear industry. Ultimately, the proposed methodology provides a practical and standardized technical route for the digitalization and intelligent modernization of nuclear power plant control systems.

2 UNIFIED MODELING FRAMEWORK FOR ACTUATORS IN NUCLEAR POWER PLANT DRIVE SYSTEMS

Actuators in nuclear power plants—including fans, pumps, and valves—exhibit differences in their operational objectives and working conditions. Nevertheless, from the perspective of control architecture and dynamic characteristics, they can all be abstracted into a generalized “motor–actuator–fluid loop” dynamic system. Fans regulate air flow and heat exchange by driving impellers; pumps deliver hydraulic power and boost pressure through impeller rotation; valves modulate flow distribution and hydraulic resistance by adjusting their opening via mechanical transmission. The dynamic behavior of these devices is jointly influenced by input commands, internal mechanical characteristics, and coupling with external fluid systems. As a result, they typically exhibit nonlinear, time-varying, strongly coupled dynamics with multiple operational constraints [3-4].

When designing advanced control strategies for nuclear power plants, establishing a unified dynamic modeling framework for these three types of actuators brings significant advantages. Such a unified representation not only reduces modeling complexity but also greatly enhances engineering consistency in deployment, auditing, verification, and maintenance of control algorithms [5].

From a control-system perspective, although fans, pumps, and valves produce different physical outputs, their actuation mechanisms share common features: each is driven by a controllable motor input (e.g., motor frequency, motor current, valve opening command) and generates measurable dynamic responses such as pressure, flow rate, temperature, or environmental state variables. This commonality makes it feasible to describe all three types of actuators using a unified input–state–output structure, thereby providing a consistent interface for neural network (NN) prediction models and model predictive control (MPC). In safety-critical nuclear applications, unified modeling is not merely a methodological convenience, but an engineering necessity. Nuclear-grade control systems demand strict auditability, verifiability, consistency, and traceability. By adopting a unified modeling framework, the number of models in the control system lifecycle can be greatly reduced, simplifying parameter review and version management and improving the overall engineering reliability of the control architecture [6].

2.1 Design Principles of the Unified Modeling Framework

The first step in establishing a unified model is to identify the common structural and control characteristics of fans, pumps, and valves. Although their physical mechanisms differ—for instance, rotational inertia dominates in fans and pumps, whereas valve dynamics are governed by mechanical transmission and the nonlinear relationship between opening and hydraulic resistance—all these systems can be abstracted as discrete-time nonlinear dynamics:

$$x(k+1)=f\big(x(k),u(k),d(k)\big),\ \ y(k)=h(x(k)) \tag{1}$$

where x(k) denotes internal system states such as motor speed, valve stem position, or other actuator-specific internal variables; u(k) represents control inputs (frequency command, motor current, valve opening); d(k) captures external disturbances and fluid-loop coupling, including hydraulic resistance, system load, or fluid temperature; and y(k) denotes system outputs such as flow rate, pressure difference, temperature, or environment-related variables.
The actuator must operate within strict physical and safety constraints:

$$umin\quad \le u(k)\le umax,\ \ ymin\quad \le y(k)\le ymax,\ \ |\Delta u(k)|\le \Delta umax \tag{2}$$

In nuclear-grade systems, each constraint has explicit safety implications. Violations may trigger protective actions or cause equipment degradation. Thus, the unified modeling framework must embed these safety constraints in the model structure to enable their explicit treatment within MPC.
To achieve unified modeling, this study introduces a standardized input encoding combined with a mask mechanism. The mask ensures that each actuator uses only the input channels relevant to its physical characteristics, while irrelevant channels are suppressed. This enables the unified model to maintain a consistent structure while preserving the flexibility needed to represent different devices. As a result, fans, pumps, and valves share model parameters and the same learning architecture, significantly reducing deployment complexity in nuclear applications.

2.2 Construction of the Unified Input－State－Output Structure

To ensure that the unified model captures both internal and external factors affecting actuator dynamics, the input vector is designed to include actuator states, command inputs, fluid variables, thermal parameters, and context information. Specifically, the input vector is defined as

$$s(k)=[x(k),u(k),\Delta p(k),q(k),T(k),z(k)] \tag{3}$$

where:
x(k) denotes internal actuator states (motor speed, impeller inertia, valve stem displacement, etc.);
u(k)is the control input;
Δp(k) and q(k) represent pressure difference and flow rate, the two fundamental fluid variables in nuclear hydraulic systems;
T(k) denotes temperature or thermohydraulic indicators;
z(k) includes contextual variables such as operation mode, actuator type code, or pipeline resistance parameters.
All actuators share the same structure of $s(k)$, but irrelevant channels are masked via:

$$\tilde{s}(k)=m\odot s(k) \tag{4}$$

where m is a device-specific 0–1 mask vector.
The mask mechanism achieves both generalization and structural consistency, ensuring that the unified neural model remains easy to train while being capable of representing significantly different actuator behaviors. Moreover, the unified structure enables effective cross-device feature sharing. Many dynamic properties—such as fluid inertia, mechanical inertia, or delayed response—share similar mathematical patterns across actuators. A unified input encoding thus improves model generalization and reduces the required amount of training data [8].

2.3 Normalization and Data Availability in Nuclear Applications

Because variables exhibit different scales—and because flow, pressure, and temperature distributions vary widely across operating conditions—normalization is essential to ensure numerical stability. In nuclear applications, fixed-range linear normalization or rated-condition-based normalization is preferred over adaptive normalization schemes that change with training data. Fixed normalization ensures auditability, traceability, and reproducibility, all of which are required in nuclear safety reviews [9].
Data availability is another practical constraint. Nuclear power plants typically provide only limited datasets, mainly including normal operation data, load-varying conditions, cold-state commissioning data, and historical fault logs. The unified modeling framework mitigates this issue by enabling multi-device training, thereby expanding the effective dataset and improving model coverage and generalization capability.

2.4 Nonlinear Dynamics of Nuclear-Grade Actuators

Due to their fluid-mechanical interactions, fans, pumps, and valves all exhibit strongly nonlinear dynamic properties. Examples include:
Pressure–flow characteristics of fans vary significantly with pipeline resistance.
Pump head curves show steep variations in low-flow regions.
Valve flow coefficient curves follow typical S-shaped profiles, and stem friction introduces hysteresis.
Such nonlinearities are difficult to capture using linear models, while high-fidelity mechanistic models are computationally intensive and unsuitable for real-time MPC applications.
To address this challenge, this study adopts neural networks as the core predictive component of the unified dynamic model. Neural networks provide excellent nonlinear approximation capability and can effectively represent actuator dynamics using limited industrial data [10]. Moreover, the unified input structure allows the neural network to handle heterogeneous devices within a single model.
Given the interpretability and verifiability requirements of nuclear applications, the study employs shallow architectures—such as small multilayer perceptrons (MLPs) or lightweight recurrent networks—to avoid the opacity and unpredictability of deep or highly complex neural structures [11].

2.5 Schematic Diagram of the Unified Modeling Framework

The logical structure of the unified modeling framework is illustrated in Figure 1:

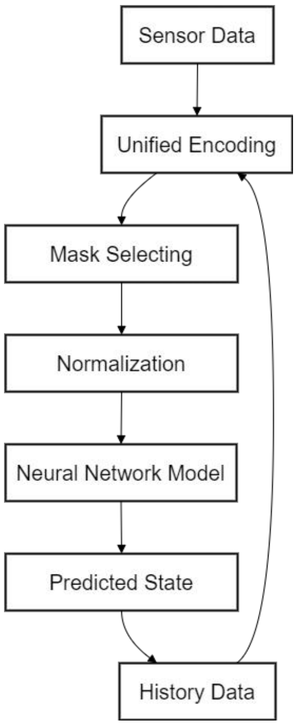

Figure 1 Unified Modeling Data Flow

Shows the information flow from actuators → unified input encoding → neural network predictor → MPC controller → actuator commands.
This diagram visualizes the complete data flow underlying the NN-MPC framework introduced in later chapters.

2.6 Requirements for Differentiable Predictive Models in MPC

Because the neural network serves as the predictive model within MPC, it must satisfy two critical requirements: differentiability and numerical stability. Differentiability is necessary for constructing Jacobians and gradients used in linearization and real-time optimization. Numerical stability ensures that predicted trajectories remain physically meaningful and do not generate nonphysical values such as negative flow or pressure [12].
To satisfy these requirements, the model employs smooth activation functions and avoids non-differentiable or excessively aggressive nonlinearities. A single-step prediction structure is adopted to reduce multi-step error accumulation, and multi-step robustness is further reinforced through the bias compensation mechanism introduced in subsequent chapters.

2.7 Engineering Value of the Unified Modeling Framework

The unified modeling framework provides substantial engineering benefits in nuclear applications. First, it enables a single predictive model to represent fans, pumps, and valves, thereby increasing consistency during system upgrades and reducing the burden of model auditing and nuclear-safety certification. Second, the unified model interfaces seamlessly with the NN-MPC controller, enabling consistent predictive control across heterogeneous actuators and improving plant-wide operational efficiency. Finally, the unified modeling approach enhances the manageability, controllability, and auditability of neural-network components in nuclear control systems, providing a clear technical pathway for digitalized and intelligent next-generation nuclear power plants (Figure 2).

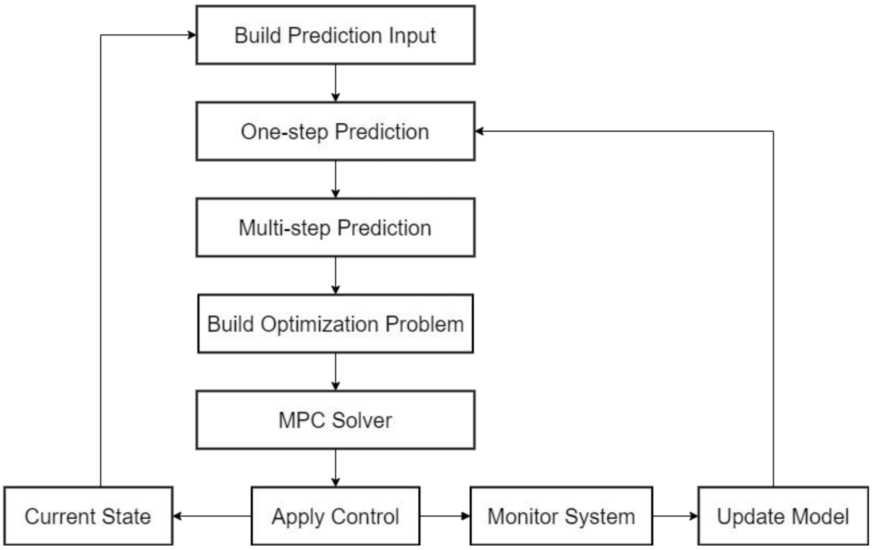

Figure 2 Closed-Loop NN-MPC Architecture

3 DESIGN OF THE NEURAL-NETWORK-ASSISTED MODEL PREDICTIVE CONTROL METHOD

The unified dynamic modeling framework developed for nuclear power plant actuation systems establishes a foundation for the construction of a Neural-Network-Assisted Model Predictive Control (NN-MPC) scheme. By exploiting the strong nonlinear function approximation capability of neural networks and the constraint-aware optimization structure of Model Predictive Control (MPC), the NN-MPC approach enables high-accuracy predictions and robust control of actuator systems characterized by nonlinear dynamics and multi-source disturbances. The combination of these two techniques effectively compensates for the limitations of conventional control strategies in fluid-coupled, highly constrained systems, making NN-MPC a promising direction for next-generation actuation control in nuclear power plants.

This chapter presents the complete NN-MPC methodology, including the design of the neural network prediction model, multi-step prediction construction, deviation compensation mechanisms, MPC optimization formulation, and the associated safety assurance strategies.

3.1 Structure of the Neural Network Prediction Model

Under the unified modeling framework, fans, pumps, and valves share the same neural-network architecture for dynamic prediction, enabling consistency and maintainability across heterogeneous devices. The neural network acts as a surrogate dynamic model that predicts the next-step state $\hat{x}(k+1)$ or output $\hat{y}(k+1)$ from the current state x(k), control input u(k), and operating condition variables. Considering the stringent real-time requirements of nuclear-class control loops, the prediction model must maintain a lightweight structure; hence 2–4-layer multilayer perceptrons (MLPs) or compact recurrent structures are typically adopted to ensure millisecond-level inference latency [10].

Using the unified input vector s(k), combined with the masking mechanism that filters out irrelevant channels, the model preserves device-specific characteristics while maintaining a common structure. The general neural network prediction model is formulated as

$$\hat{x}(k+1)=f_\theta\big(s(k)\big),\ \hat{y}(k+1)=\mathrm{h}\big(\hat{x}(k+1)\big) \tag{5}$$

where f_θ is a neural network parameterized by θ.

To satisfy the differentiability requirements of MPC solvers, smooth and fully differentiable activation functions such as ReLU or *tan*h are employed, enabling automatic differentiation to generate Jacobians and gradients for real-time optimization [11].

Given the safety-critical nature of nuclear applications, the prediction model must satisfy stability, interpretability, and traceability requirements. Therefore, fixed-length sliding windows are used instead of arbitrarily deep sequence structures to ensure verifiability. Furthermore, physical constraints must be embedded into the prediction outputs—for example, prohibiting negative flow rates or non-physical pressure predictions. To this end, post-processing layers, such as positivity enforcement or sigmoid-based bounding, are incorporated to ensure physical plausibility at every prediction step.

3.2 Multi-Step Prediction and Receding-Horizon Optimization

MPC requires a future prediction horizon of multiple steps, while neural networks typically provide only single-step predictions. Multi-step prediction is therefore constructed through iterative rollout of the single-step model:

$$\hat{x}(k+i+1)=f_\theta(\hat{x}(k+i),u(k+i),\ldots) \tag{6}$$

In this recursive process, the prediction of the previous step becomes the input to the next. Although straightforward, recursive rollout is susceptible to error accumulation, especially under strong nonlinearities, potentially causing trajectory divergence. For nuclear-class applications, prediction stability is vital; thus, a deviation correction mechanism must be integrated to ensure consistency and robustness.

The receding-horizon framework forms the core of MPC: although a sequence of control inputs is optimized over the future horizon, only the first control action is applied:

$$u(k)=u^*(k|k) \tag{7}$$

and the optimization is reconstructed in the next sampling period. This mechanism enables the controller to continually adapt to system dynamics and disturbances.

3.3 Deviation Compensation and Robust Prediction

Neural network prediction accuracy may degrade due to limited training data, equipment aging, or gradual shifts in operating conditions. To ensure conformance with nuclear-class safety and reliability requirements, a two-level deviation compensation mechanism is adopted: (1) short-term deviation compensation and (2) long-term drift monitoring.

(1) Short-term deviation compensation

At each sampling instant, the most recent measured state $x(k)$ replaces the predicted state $\hat{x}(k|k\text{-}1)$, and a deviation term is computed:

$$\delta(k)=x(k)-\hat{x}(k|k-1) \tag{8}$$

This deviation is injected into future predictions:

$$\tilde{x}(k+i)=\hat{x}(k+i)+\delta(k) \tag{9}$$

effectively suppressing error propagation over the prediction horizon and enhancing stability.

(2) Long-term drift detection and model recalibration

If the deviation remains consistently large, indicating that the trained model no longer matches the real equipment dynamics, the system enters a semi-online recalibration mode. Selected neural network parameters or partial layers are updated using recent data to restore model fidelity [12].

Deviation compensation is essential for maintaining long-term stability of NN-MPC under component aging, gradual environmental changes, and operating-condition shifts. The deviation compensation process is illustrated in Figure 3.

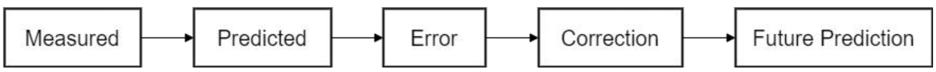

Figure 3 Flowchart of the Deviation Compensation Process

3.4 Formulation of the MPC Optimization Problem

The objective of MPC is to achieve accurate reference tracking while satisfying physical and safety constraints. The standard cost function is expressed as:

$$min\sum_{i=1}^{N_p} \| y(k+i)-y_{\mathrm{ref}}(k+i)\|_Q^2+\sum_{i=0}^{N_c-1} \|\Delta u(k+i)\|_R^2 \tag{10}$$

where N_p and N_c denote prediction and control horizons, respectively.

The control inputs and outputs of nuclear power actuators are subject to strict limits, which must be explicitly encoded as hard constraints:

$$\begin{gathered} u_{\min}\le u(k+i)\le u_{\max}, \\ \Delta u_{\min}\le \Delta u(k+i)\le \Delta u_{\max}, \\ y_{\min}\le y(k+i)\le y_{\max}. \end{gathered} \tag{11}$$

Because the neural network introduces nonlinearities, the resulting MPC problem becomes nonconvex and computationally demanding. To meet real-time requirements, fast optimization approaches such as real-time iteration Sequential Quadratic Programming (RTI-SQP) or ADMM-type accelerators are adopted. Automatic differentiation is employed to compute gradients and Jacobians efficiently, enabling millisecond-level solver execution [13].

3.5 Closed-Loop Architecture of the NN-MPC System

The complete closed-loop architecture of the NN-MPC system integrates sensing, neural-network prediction, deviation compensation, constrained optimization, and actuator execution. Its information flow is summarized in Figure 4.

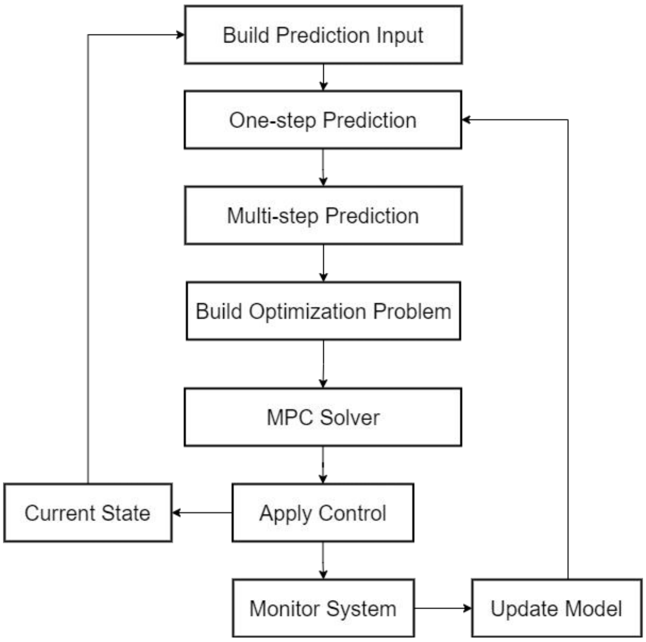

Figure 4 Closed-Loop Control Architecture of the NN-MPC System

This architecture highlights the tight interplay between data-driven prediction and optimization-based decision-making, forming a robust closed-loop suitable for safety-critical nuclear applications.

4 ENGINEERING DEPLOYMENT AND IMPLEMENTATION PATH OF NN-MPC IN NUCLEAR POWER PLANT ACTUATION SYSTEMS

The neural-network-assisted model predictive control (NN-MPC) framework offers high-accuracy nonlinear prediction and high-performance decision-making capabilities. However, deploying such an intelligent control framework in the actuation systems of nuclear power plants requires a rigorous engineering process. Challenges arise in control-system architecture adaptation, real-time computational assurance, hardware–software redundancy, model lifecycle management, version auditability, verification workflows, and coordination with safety-critical subsystems. Nuclear power plants represent mission-critical environments in which Digital Control Systems (DCS) must maintain exceptional reliability, traceability, maintainability, and fault isolation. Therefore, NN-MPC must be integrated in a manner that does not compromise established safety boundaries. Such integration extends far beyond algorithmic efficiency; it encompasses system-level capabilities for anomaly detection, graceful degradation, and safety isolation—hallmarks of nuclear engineering's uncompromising safety standards.

4.1 Layered Control Architecture and the Integration Strategy of NN-MPC

Industrial nuclear control systems typically follow a multilayer hierarchical structure comprising field devices, actuation and drive units, process control layers, and supervisory and coordination layers. This structure, formalized in industry standards, ensures that sensing, actuation, control, and supervisory functions are separated according to their timing and safety requirements. Accordingly, NN-MPC must adhere to this layered architecture and is positioned between the process-control layer and the plant's actuation units. It shall not coexist parallel to the reactor protection system (RPS) nor interfere with any safety-grade interlocks.

Within this architecture, the NN-MPC module receives real-time sensor measurements—valve positions, pump rotational speed, fan differential pressure, flow rate, and other process variables. The prediction module uses these inputs to estimate future states, and the MPC optimizer subsequently computes the admissible control action under explicit constraints. Unlike PID controllers, NN-MPC relies on richer information and more sophisticated preprocessing to forecast system behavior and capture fluid-dynamic coupling.

The functional position of NN-MPC in this hierarchical structure is illustrated in Figure 5. It operates as the core algorithmic module in the process-control layer, bridging sensors and actuators while remaining isolated from all nuclear safety logics.

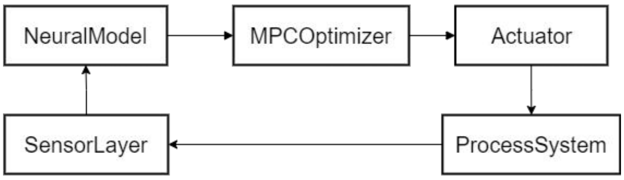

Figure 5 Integration of the NN-MPC Module within the Hierarchical Control Architecture of a Nuclear Power Plant

4.2 Engineering Assurance of Real-Time Operation and Computational Resources

Actuation systems in nuclear power plants—such as regulating valves, feedwater pumps, and cooling fans—typically operate with sampling periods on the order of tens to hundreds of milliseconds. Consequently, NN-MPC must complete data acquisition, model inference, gradient generation, constrained optimization, and command dispatch within this limited time window. Achieving this requirement demands optimizations across several engineering dimensions.

First, neural-network models deployed in the field are compressed through parameter pruning, reduced-precision floating-point formats, and activation-efficient architectures (e.g., ReLU) so that inference can run on industrial-grade controllers within milliseconds. Second, the MPC layer employs real-time iteration sequential quadratic programming (RTI-SQP), which performs only one linearization and one optimization step per sampling period. Automatic differentiation (AD) is used to derive Jacobians and gradients to maintain accuracy without manual linearization—an essential requirement for safety-critical nuclear applications.

NN-MPC must also conform to the DCS communication infrastructure, including redundant field buses, synchronized timing networks, and dual-channel communication pathways. If the NN-MPC module fails to produce an output within the scheduled control window, the system must automatically switch to a conservative fallback strategy, such as PID control or a predefined safe setpoint. This guarantees fail-safe behavior and ensures that NN-MPC is never a single point of failure [6].

The computational timing constraint can be formalized as:

$$\mathrm{TNN+TAD+TMPC+TIO} \leq \mathrm{Ts} \tag{12}$$

where:

- Ts: sampling period
- TNNT: neural-network forward-inference time
- TAD: automatic-differentiation time
- TMPCT: optimization solver time
- TIOT: input/output latency (sensor readout + actuator command)

This inequality is a core criterion in real-time verification reviews for nuclear-grade control software.

Deployment of Real-Time Iteration Solvers

Because the underlying system is nonlinear and constrained, NN-MPC must solve a nonlinear MPC problem at each step. In the RTI-SQP framework, each control cycle solves a single linearized subproblem:

$$H(k)\Delta U = -\nabla J(k) \tag{13}$$

where:

- $H(k)$: Gauss–Newton approximation of the Hessian
- $\nabla J(k)$: gradient of the cost function
- ΔU: control update

The fully differentiable neural network provides the required Jacobians directly via AD, enabling predictable computation and compliance with DCS certification procedures.

4.3 Model Version Management and Auditability

As data-driven components, neural networks require rigorous lifecycle management to ensure that every deployed model is transparent, traceable, and auditable. Each NN model version must undergo independent verification, including data-source auditing, training-process documentation, parameter integrity inspection, and behavioral boundary testing. Nuclear software standards mandate complete traceability; NN-MPC must therefore provide verifiable evidence for any prediction deviation or anomalous system response.

To achieve this, an engineering "model repository" is established to maintain version metadata, training datasets, training hyperparameters, and verification reports. Before field deployment, every model version must pass multistage validation—simulation testing, hardware-in-the-loop (HIL) experiments, and formal compliance reviews. Any model update triggers DCS consistency checks to prevent behavioral discontinuities in the actuation systems.

Model consistency across versions is validated using:

$$\mathrm{M}_{v_i}(s) \approx \mathrm{M}_{v_j}(s), \forall s \in D_{\mathrm{valid}} \tag{14}$$

ensuring that a new version does not introduce unexpected behavioral deviations over the validated operational domain.

Digital signatures, version locks, and strict repository policies ensure that the prediction model, optimizer, and gradient interfaces remain synchronized, thus meeting the requirements of nuclear software configuration management (SCM).

4.4 Anomaly Detection and Safety-Fallback Mechanisms

Given the potential failure modes of data-driven models, NN-MPC must incorporate robust anomaly detection and multi-layer safety fallback mechanisms. Anomalies are identified through prediction deviation, drift detection, and out-of-distribution (OOD) analysis. During extreme or unforeseen operating conditions—fan blockage, pump cavitation, or valve friction escalation—prediction errors increase sharply, triggering safety logic.
Fallback strategies typically include:
1. Switching to validated PID or linear MPC
2. Safely clamping actuators to predefined safe operating points
a) e.g., valves to a predefined safe opening
b) pumps to low-speed mode
c) fans to fixed airflow mode
These mechanisms ensure that even if NN-MPC becomes unavailable, the actuation system maintains thermal-hydraulic stability.
Prediction-error-based health monitoring is defined as:

$$e(k)=\| x(k)-\hat{x}(k) \| \tag{15}$$

If:

$$e(k)>\epsilon_{\text{safe}} \tag{16}$$

the system triggers fault-handling logic to switch to fallback control or reload a stable model version.
All anomaly events are logged for subsequent engineering review and provide critical evidence during nuclear-safety audits (defense-in-depth compliance).

4.5 HIL Verification and Multi-Stage Testing Framework

Before deployment on real equipment, NN-MPC must pass simulation-based verification and hardware-in-the-loop (HIL) testing. This process is essential not only in the nuclear industry but also for certifying data-driven predictive models in safety-critical control environments.
First, unified simulation models of fans, pumps, and valves are used to evaluate NN-MPC performance across a wide operating envelope. Subsequently, the NN-MPC controller is deployed on a real-time industrial controller connected to a HIL plant emulator. Extreme operating scenarios—motor faults, sensor noise spikes, sudden hydraulic-resistance changes—are simulated to verify stability, constraint satisfaction, and correct triggering of fallback logic.
Only after all verifications pass can the system proceed to field deployment.

4.6 Engineering Commissioning and On-Site Deployment Workflow

Deploying NN-MPC in a nuclear power plant requires coordination across plant operators, control engineers, commissioning teams, software-verification units, and third-party reviewers. The deployment process comprises three major phases:
a) Offline preparation:
b) model training, parameter tuning, simulation testing, HIL validation, DCS model instantiation
c) Semi-online commissioning:
d) NN-MPC receives real sensor inputs but operates in a “shadow mode,” not directly controlling actuators.
e) Its outputs are compared with operator decisions or baseline controllers to verify consistency.
f) Full deployment:
g) NN-MPC assumes full control after all safety audits and verification processes are completed.
After deployment, all predictions, control outputs, and anomalies are logged for long-term monitoring. If any abnormal behavior is detected, immediate fallback and isolation procedures guarantee safe operation.

4.7 Engineering Value and Future Prospects of NN-MPC

The successful deployment of NN-MPC brings significant benefits to nuclear-plant operation. By establishing a unified modeling and control framework, fans, pumps, and valves can achieve enhanced stability, improved tracking performance, and more efficient power regulation. The model-based predictive structure combined with neural-network nonlinear estimation offers an upgrade path toward more intelligent and adaptive control systems.
NN-MPC’s explainability, explicit constraint handling, and built-in safety mechanisms satisfy nuclear industry requirements for transparency and reliability, demonstrating that data-driven components can be safely integrated into nuclear-grade control systems.
Future nuclear power plants—including advanced reactors and next-generation digital control systems—will benefit from NN-MPC in more critical components such as reactor coolant pumps, main feedwater pumps, and steam-generator

secondary-side flow-regulation valves. The integration of NN-MPC with digital-twin platforms will further enable online model adaptation, structural optimization, and autonomous performance enhancement, marking a significant step toward intelligent, self-optimizing nuclear control systems.

5 CONCLUSION AND FUTURE PERSPECTIVES

This study addresses the nonlinear, strongly coupled, multi-constrained, and high-safety requirements inherent in the control of actuation systems within nuclear power plants. To meet these challenges, we propose a novel control framework that integrates unified dynamic modeling with neural-network-assisted model predictive control (NN-MPC). The work provides a comprehensive discussion spanning theoretical modeling, algorithmic design, engineering deployment, and safety verification. Actuation systems—such as fans, pumps, and valves—play essential roles in reactor cooling, steam-generator feedwater supply, ventilation and heat exchange, and the stable operation of auxiliary subsystems. Their performance directly affects thermal-hydraulic balance, energy-conversion efficiency, and safety margins of nuclear generating units. Consequently, developing an advanced control methodology that is verifiable, robust, and predictive is of substantial significance for the nuclear control community.

The first contribution of this work is the formulation of a unified modeling framework for nuclear actuation systems. Fans, pumps, and valves are abstracted into a consistent input–state–output structure, with a Mask-based mechanism that filters device-irrelevant features. This allows cross-device model sharing and consistent input encoding. Compared with conventional physics-based modeling—which often becomes prohibitive in complex flow-coupling scenarios due to high dimensionality, difficulty of generalization, and expensive calibration—this unified approach reduces model quantity, lowers maintenance cost, and resolves traceability challenges that hinder engineering validation. The framework provides both a data foundation and a structural foundation for NN-MPC, while ensuring model auditability and facilitating systematic lifecycle management and certification in nuclear-grade environments [4].

In terms of control-method design, this study develops an NN-MPC architecture based on single-step prediction, bias compensation, and rolling optimization. Neural networks leverage the unified input representation to approximate nonlinear actuation dynamics with high fidelity, while MPC provides explicit handling of input and output constraints together with interpretable optimization-based decision making. The proposed bias-correction mechanism effectively mitigates error accumulation during multi-step prediction, enabling the controller to remain stable under equipment aging, operating-condition variations, and dynamic changes in pipeline resistance. Moreover, the integration of a real-time iteration solver (RTI-SQP) substantially reduces computational overhead, ensuring that NN-MPC satisfies the strict real-time requirements of nuclear actuation loops.

A complete engineering deployment scheme tailored for nuclear power plants is also proposed. It includes real-time optimization strategies, model version management, anomaly detection, safety fallback mechanisms, and multi-stage testing workflows. A model repository with strict version control enables traceable auditing of neural-network models and MPC configurations. Out-of-distribution (OOD) detection and drift monitoring allow the system to promptly recognize model degradation. Robust fallback strategies—switching to PID or conservative MPC—guarantee that actuation behavior always remains within safety boundaries. Additionally, extensive simulation and hardware-in-the-loop (HIL) validation ensure that NN-MPC performs safely even under extreme operating conditions, providing engineering evidence compatible with nuclear-grade safety requirements.

From an industry perspective, the proposed NN-MPC framework provides essential methodological support for the digitalization and intelligent upgrade of nuclear power plants. As nuclear systems become more complex and as expectations for extended operational lifetimes and enhanced load-following capabilities increase, traditional control solutions are no longer sufficient to meet advanced performance and lifecycle management requirements. By combining data-driven modeling with constraint-aware optimization, NN-MPC offers superior generalization, adaptability, and situational responsiveness, thereby offering an efficient and robust control solution for next-generation nuclear energy systems.

Future research directions may be explored along three lines.

First, with ongoing advances in machine-learning architectures, new lightweight, interpretable, or safety-oriented neural networks may be integrated to further enhance the suitability of NN-MPC for nuclear actuation systems.

Second, digital-twin technology can be incorporated into the control loop to enable online simulation and model calibration, providing NN-MPC with more accurate and timely dynamic information to improve responsiveness to abnormal or fast-evolving events.

Third, distributed MPC or partitioned control architectures may be considered for NN-MPC deployment in scenarios with stronger subsystem coupling—such as coordinated control of main and auxiliary feedwater systems or reactor coolant pumps and regulating valves—to support more advanced strategies for economic operation and load-following.

Overall, the proposed NN-MPC framework establishes a complete theoretical and practical foundation encompassing unified modeling, predictive modeling, optimization-based control, bias compensation, safety mechanisms, and engineering deployment. The framework not only advances the unification and intelligence of actuation-system control in nuclear power plants but also ensures verifiability, safety, and deployability at the engineering level. As intelligent control technologies continue to penetrate the nuclear industry, NN-MPC holds strong potential to become a core control strategy for future nuclear power plants, providing key technical support for safe, efficient, and intelligent operation of nuclear energy systems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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