Advanced Prediction of Nuclear Power Plant Transients via Operator Action-Timing Feature Engineering

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1. Introduction

Accurate forecasting of plant states during nuclear power plant accidents is essential for operator decision support and plant safety. Prediction accuracy strongly depends on how models represent operator actions on Engineered Safety Features (ESF). Conventional data-driven approaches encode actions as binary variables (0/1), which is ambiguous. This encoding does not distinguish an unscheduled action from a scheduled-but-not-yet-executed action, forcing the model to extrapolate past trends without awareness of imminent events.

This study introduces a feature engineering method that exposes information about future operator actions at the current time. We define an Action-Timing Feature that takes positive values for the remaining time to an action and negative values for the elapsed time since the action. As the value approaches zero, the model learns that an action is imminent; after crossing zero, it learns the resulting dynamics. We compare a model augmented with this feature against a baseline using the same Transformer Encoder, demonstrating that gains stem solely from the proposed data processing.

2. Methodology

2.1 Data Configuration

We used 3,000 severe-accident simulation cases based on a Large Break Loss-of-Coolant Accident (LBLOCA). Scenarios varied by break location/size and by operator actuation times for Safety Injection (SI), Containment Spray (CS), and Main Feedwater (CF). The dataset was split into training/validation/test sets of 2,000/500/500 cases. Inputs comprise 21 major process variables over the first 20 minutes after the accident; targets are three key variables over the following 120 minutes.

2.2 Feature Set Configuration for Comparative Experiment

To isolate the effect of the proposed method, we trained two models with identical Transformer Encoder architecture and hyperparameters, differing only in input features.

Baseline Model
- Process features (13): key measured variables (e.g., reactor pressure, coolant temperature).
- Action-status features (3): SI_Status, CF_Status, CS_Status (0 before the action, 1 after).

Proposed Model
- Process Features (13): identical to the baseline.
- Action Status Features (3): set to 1 if an action is scheduled at any future time, independent of timing.
- Action Timing Features (3): SI_Timing, CF_Timing, CS_Timing

The timing feature is a relative time computed as (action time - current time t). It is positive before the action, approaches 0 as the action nears, and becomes negative after execution. We apply Min–Max scaling to the relative-time values across the entire dataset for stable learning.

This pairing of status and timing yields a clear and comprehensive representation from which the model can learn all action-related situations.

Table I: Feature Input Configuration

	SI_on	SI_time	CF_on	CF_time	CS_on	CS_time
0	1.0	0.01840	1.0	0.01360	1.0	0.33257
1	1.0	0.01817	1.0	0.01336	1.0	0.33234
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2.3 Prediction Model: Transformer Encoder

Both models use the same Transformer Encoder to capture complex temporal dependencies in time-series data. The model is trained to predict three target variables for the next 120 minutes given the first 20 minutes of inputs after the initiating event.

3. Results and Analysis

The advantage of the proposed features is most evident in difficult cases. Figures 1 and 2 compare predictions from the two models with ground truth for a representative test case (ID: 2501). In this case, major actions occur after the input window ($t > 19$ min), inducing abrupt state changes.

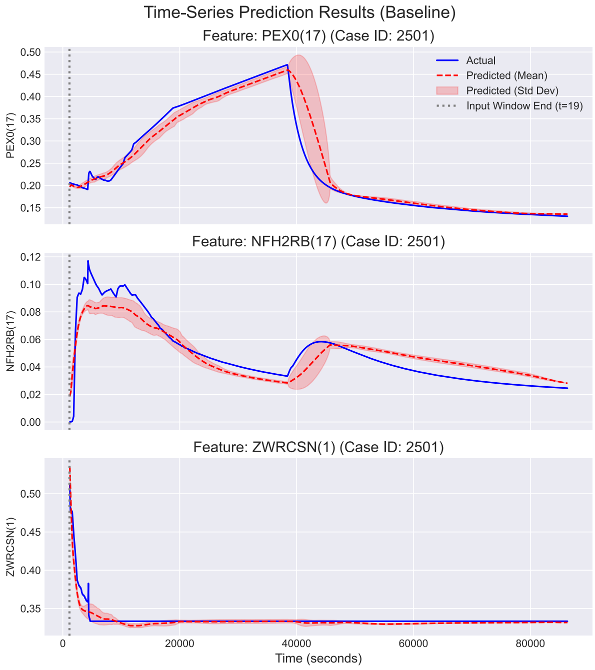

Fig. 1. Baseline model prediction (Case 2501).

Trained with process variables plus binary status only, the baseline extrapolates early upward trends and misses sharp peaks and subsequent drops around 40,000 and 45,000 s. This failure stems from the absence of future action information. Large deviations from truth and wide predictive uncertainty indicate low confidence. The baseline struggles to reproduce realistic accident behavior when operator interventions drive dynamics.

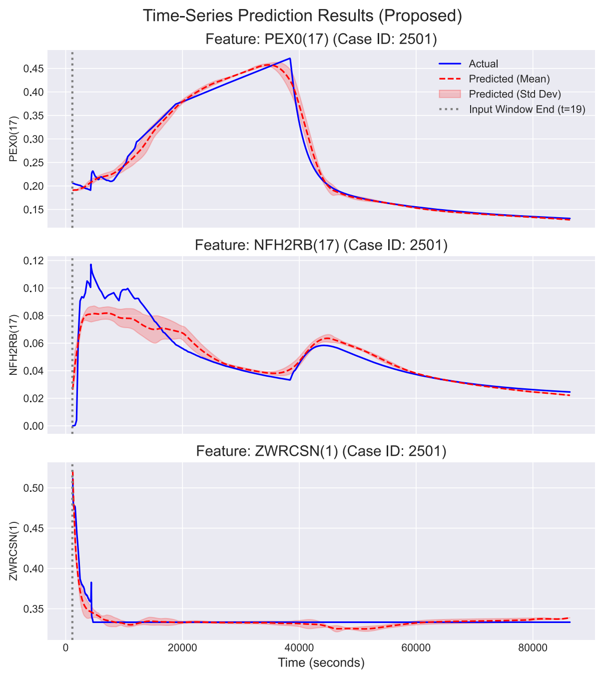

Fig. 2. Proposed model prediction (Case 2501).

With action-timing features, the model correctly anticipates peaks and rapid descents that the baseline misses. The model leverages when the action will occur and learns its dynamic impact. Uncertainty bands stay narrow around the truth across variables, indicating stable confidence.

Together, these results show that the proposed features enable anticipatory prediction of dynamics induced by future operator interventions using only information available up to the present.

Quantitative evaluation on the 500-case test set supports the qualitative findings. As shown in Table II, both models achieve low mean absolute error (MAE), but the proposed model consistently performs better. The baseline's inability to account for post-action behavior produces error rates roughly 10% higher across all targets.

Table II: MAE comparison between baseline and proposed models

Model	Baseline	Suggested
CTMT Press.	0.0101	0.0091
H2 Conc.	0.0099	0.0090
RV Water Lv.	0.0098	0.0089

4. Conclusion

We proposed an action-timing feature engineering method that exposes future operator actions to the predictor at the current time. By converting relative time to a continuous dynamic feature and providing it alongside status, we substantially improved prediction over a baseline lacking timing information.

Quantitatively, MAE decreased for all target variables (Table II). Qualitatively, the model captured inflection points at action times where the baseline failed. The method helps the model learn causal links between present measurements and scheduled future events, surpassing simple pattern extrapolation.

This practical approach can enhance the reliability of operator decision support and training simulators that require faithful reflection of decisive operator actions while relying solely on currently available measurements.

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REFERENCES

[1] A. Vaswani et al., "Attention is all you need," Advances in neural information processing systems, vol. 30, 2017.

[2] Electric Power Research Institute, Inc., MAAP 5 User's manual, 2008.