Action-based prediction for Nuclear Power Plants at Severe Accident

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1. Introduction

Nuclear Power Plants (NPPs) serve as a crucial source of stable and efficient energy worldwide. However, severe accidents, which can arise from unforeseen system failures or external factors, pose a significant threat and necessitate effective management and mitigation. Such accidents typically exceed the assumptions of Design Basis Accidents (DBAs) and are triggered by multiple system failures, as evidenced by historical events like Three Mile Island, Chernobyl, and Fukushima Daiichi. The Fukushima Daiichi accident in 2011, for instance, clearly demonstrated the limitations of standard Emergency Operating Procedures (EOPs) in effectively responding to severe accidents, as a station blackout and subsequent loss of cooling led to core melt and hydrogen explosions [1].

In severe accidents, operators face immense pressure to make critical decisions under stress, with incomplete data, and within limited timeframes. Severe Accident Management Guidelines (SAMGs) are therefore essential, providing a symptom-based guidance framework to assist operators amidst extreme uncertainty. Unlike procedures, SAMGs offer a range of flexible mitigation options tailored to the plant's current status, with strategies continuously reviewed and updated as new data becomes available. However, predicting accident progression or the precise effects of mitigation actions on plant behavior is one of the most cognitively demanding and error-prone tasks for operators, particularly under degraded conditions. This complexity stems from intertwined challenges such as information loss due to instrument failure, unpredictable system interdependencies, severe time pressure, multiple viable action paths with uncertain outcomes, and cognitive overload from processing vast, conflicting data. Given these inherent difficulties, human prediction alone may be insufficient in severe accident scenarios, underscoring the vital role of AI-driven prediction models in supporting SAMG decision-making [2].

To effectively support SAMG operations, prediction models must satisfy several key requirements. Firstly, Prediction Accuracy is paramount, demanding reliable forecasts of critical plant parameters under severe accident conditions. Secondly, Uncertainty Estimation for Prediction Results is crucial to quantify the confidence level or variance in predicted outcomes, thereby reflecting the degraded and uncertain nature of severe accidents. Thirdly, Action-based Prediction is essential, as the model must accurately reflect the specific mitigation actions taken by operators, given that different interventions can lead to vastly different outcomes. Lastly, Real-time Prediction capability is indispensable to support timely decision-making during rapidly evolving accident scenarios [3].

Addressing these critical requirements, this study proposes a novel action-based prediction algorithm. This algorithm integrates Autoformer, Temporal Convolutional Network (TCN), Variational Autoencoder (VAE), and conditional generative models to provide real-time predictions of NPP system trends, incorporating the impact of mitigation actions and quantifying associated uncertainties. Specifically, by leveraging Autoformer instead of the traditional Transformer, our approach aims to enhance long-term time-series prediction performance, while TCN and VAE further strengthen prediction accuracy and uncertainty estimation capabilities. This comprehensive algorithm is designed to predict both the positive and negative effects of various mitigation actions, offering a holistic view to facilitate informed decision-making in complex severe accident scenarios.

2. Methodologies

This section details the core methodologies employed in the proposed action-based prediction algorithm. The proposed model integrates Autoformer for robust long-term time-series forecasting, TCN for efficient feature extraction, VAE for uncertainty quantification, and a conditional generative model to incorporate mitigation actions.

2.1 Autoformer

Autoformer introduces two key innovations: a decomposition block and an auto-correlation mechanism, which collectively enhance forecasting accuracy and efficiency by leveraging the intrinsic periodicity of time series data [4].

2.1.1 Decomposition Block

Given an input time series $X \in \mathbb{R}^{L \times D}$, where L is the sequence length and D is the number of features, the decomposition block operates as follows. First, the trend component, X_{trend}, is extracted using a moving average operation as shown in Eq. (1).

$$X_{trend} = \text{AvgPool}(\text{Pad}(X)) \quad (1)$$

Here, AvgPool denotes the moving average pooling operation, and Pad refers to padding the sequence to handle edge effects. Subsequently, the seasonal component, $X_{seasonal}$, is obtained by subtracting the extracted trend from the original series, as depicted in Eq.(2).

$$X_{seasonal} = X - X_{trend} \quad (2)$$

2.1.2 Auto-Correlation Mechanism

The auto-correlation mechanism computes the auto-correlation of the input series to find the optimal time lag (periods). For a given query Q and key K, instead of direct dot-product attention, Autoformer computes the auto-correlation, as described in Eq, (3).

$$AutoCorrelation(Q, K) = softmax\left(\frac{1}{\tau}\sum_{l \in \mathcal{L}} Corr(Q, K_l)\right) \quad (3)$$

In this equation, $Corr(Q, K_l)$ represents the correlation between query Q and key K shifted by lag l, $\mathcal{L}$ is the set of candidate lag, and τ is a scaling factor. The output of this correlation is then used to weight the values V to produce the final output. This allows the model to focus on relevant periodic patterns, significantly improving the efficiency and accuracy of long-term forecasting.

2.2 Temporal Convolutional Network (TCN)

A TCN is a deep learning architecture specifically designed for sequence modeling, offering advantages such as parallel processing and flexible receptive fields. TCN utilize causal convolutions to ensure that predictions at a given timestep only depend on past inputs, and dilated convolutions to efficiently capture long-range dependencies without increasing the number of parameters. This makes TCNs well-suited for extracting relevant features from the complex, multivariate time-series data characteristic of NPP operations [5].

2.3 Variational Autoencoder (VAE)

A VAE is a powerful generative model capable of learning a latent representation of the input data. In our algorithm, VAE Is crucial for quantifying the uncertainty associated with the predictions. By modeling the prediction as a probabilistic distribution rather than a single point estimate, the VAE provides confidence intervals for the forecasted parameters. This probabilistic output is vital for high-stakes applications like NPP severe accident management, where understanding the range of possible outcome is as important as the prediction itself [6].

2.4 Conditional Generative Model

To enable action-based prediction, our algorithm incorporates a conditional generative model. This model allows the prediction process to be guided by specific mitigation actions chosen by the operator. By providing conditional inputs (e.g., pump activation status, valve positions), the model can generate distinct future scenarios corresponding to different operational interventions. This capability is essential for evaluating the potential positive and negative impacts of various mitigation strategies in real-time [7].

3. Development of Action-based Prediction Model

The proposed action-based prediction model constitutes a hybrid neural architecture that synergistically integrates advanced capabilities of Autoformer, VAE, and TCN. This architecture systematically decomposes input time-series data, encodes temporal features into a structured latent manifold, and generates predictions through parallel decoding pathways with intelligent fusion mechanisms. Figure 1 illustrates the comprehensive architectural framework. The architecture encompasses five fundamental components: (1) series decomposition module, (2) Autoformer encoder, (3) VAE bottleneck layer, (4) parallel decoder pathways, and (5) gated fusion mechanism. Detailed specifications and functional contributions of each component are delineated below.

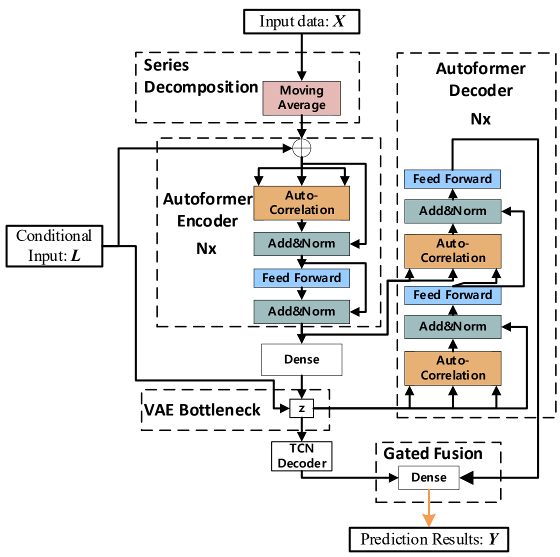

Fig. 1. Architecture of action-based prediction model.

3.1 Series Decomposition Module

The series decomposition module performs initial preprocessing of multivariate time-series inputs. Raw temporal signals inherently contain superimposed long-term trends and complex periodic patterns. This module implements moving average filtering to isolate trend components representing long-term state evolution. Subsequently, trend subtraction extracts seasonal components containing high-frequency cyclical dynamics. This decomposition enables subsequent encoding layers to focus computational resources on learning intricate temporal dependencies within seasonal variations, thereby enhancing feature extraction efficacy.

3.2 Autoformer Encoder

The Autoformer encoder extracts salient temporal features from decomposed seasonal components. A fundamental innovation involves replacing conventional self-attention mechanisms with auto-correlation operations. Rather than computing point-wise correlations, auto-correlation leverages Fast Fourier Transform (FFT) to efficiently identify period-based dependencies from series-level perspectives. This approach demonstrates particular efficacy for time-series exhibiting strong periodicities. The encoder simultaneously processes seasonal data and operator-specified conditional actions, generating high-dimensional representations capturing fundamental sequence patterns.

3.3 VAE Bottleneck Layer

The VAE bottleneck performs dimensionality reduction of high-dimensional feature representations into structured probabilistic latent spaces. This process transcends simple compression; the VAE architecture imposes prior distributions on latent representations. Through Kullback-Leibler divergence regularization, learned distributions are constrained to match specified priors, ensuring proper latent space topology. Latent vectors are sampled from learned distributions using reparameterization techniques, yielding robust continuous representations that capture essential data characteristics while filtering non-essential noise, thereby enhancing model generalization.

3.4 Parallel Decoders

The prediction of future trends is generated through two parallel, specialized decoding paths that are both seeded by the latent vector z from the VAE bottleneck.

3.4.1. TCN decoder pathway

This pathway employs stacked dilated causal convolutions for temporal modeling. The TCN architecture provides extensive receptive fields while maintaining computational efficiency. Primary advantages include capturing local causal relationships and fine-grained temporal patterns with high fidelity.

3.4.2. Autoformer decoder pathway

This pathway implements transformer decoder architecture utilizing auto-correlation mechanisms for self-attention operations. Cross-attention mechanisms reference original encoded representations. This structure excels at modeling global long-range dependencies and preserving periodic properties across prediction horizons.

3.5 Gated Fusion

The gated fusion layer implements intelligent combination of parallel decoder outputs. Rather than simple averaging, this layer employs dynamic arbitration mechanisms. Processing predictions from both pathways, the layer computes time-step-specific gate signals using dense layers with sigmoid activation. These gates function as learned weights, dynamically determining relative contributions of each decoder to final predictions at each temporal point. This approach enables adaptive leveraging of local pattern recognition from TCN and global dependency modeling from Autoformer, yielding unified predictions exceeding individual pathway performance.

4. Implementation

4.1 Data Collection

The dataset collection utilized the Modular Accident Analysis Program (MAAP) version 5.06, a validated severe accident analysis code for APR1400 reactor configurations. Development of an action-based prediction network necessitates a comprehensive dataset encompassing diverse accident scenarios. A large-break loss-of-coolant accident (LBLOCA) concurrent with complete safety injection pump failure was designated as the initiating event. Given the unavailability of safety injection systems, the mitigation strategy prioritized primary system water injection (Mitigation-03), incorporating shutdown cooling pumps (SCP), charging pumps (CHP), and external injection pumps (EIP) as primary mitigation mechanisms.

4.1.1. Sampling strategy optimization

To ensure comprehensive dataset coverage while maintaining computational efficiency, a preliminary investigation was conducted to optimize sampling intervals for critical input parameters. The optimization objective targeted identification of maximum feasible intervals capable of training networks to achieve a conservative performance criterion, specifically a mean absolute percentage error (MAPE) below 3%. This optimization process examined two primary parameters: LBLOCA break size and mitigation equipment activation timing.

Initially, the LBLOCA break size sampling interval underwent optimization. A high-fidelity reference dataset was generated encompassing break sizes from 6 to 30 inches at 0.1-inch resolution. Neural networks were subsequently trained utilizing progressively coarser data subsets (specifically 0.5-inch, 1-inch, and 2-inch intervals) and evaluated against the reference dataset. Analysis demonstrated that 1-inch interval sampling achieved a test MAPE of 2.904% while minimizing training scenario requirements. This interval configuration was adopted as it optimally balanced predictive accuracy with computational resource utilization.

Subsequently, mitigation equipment activation timing intervals underwent optimization. For this analysis, the LBLOCA break size was maintained constant at 10 inches, while a reference dataset was generated through simulation of activation times spanning 30 minutes to 12 hours at 1-minute resolution. Analogous to the break size optimization methodology, networks were trained utilizing datasets with expanded temporal intervals (specifically 10-minute, 20-minute, 30-minute, and 40-minute increments). Results indicated that 30-minute interval sampling yielded optimal performance, achieving a test MAPE of 1.616%.

4.1.2. Latin hypercube sampling

A comprehensive dataset comprising 10,000 scenarios was generated to systematically explore the parameter space defined by 25 discrete LBLOCA break sizes (ranging from 6 to 30 inches at 1-inch intervals) and 25 distinct activation timings for each mitigation strategy. Latin hypercube sampling (LHS) methodology was implemented to ensure systematic parameter variation, yielding a statistically well-distributed dataset for action-based prediction network training [8]. Table I presents the comprehensive parameter matrix and corresponding discretization levels utilized in the LHS implementation.

Table I: Summary of the factors and ranges considered for LHS.

Factor	Level	Range
LOCA break size	25	6 to 30 inches (1-inch interval)
SCP activation time	25	No action, 30-min to 12 hr. (30-min intervals)
CHP activation time	25	No action, 30-min to 12 hr. (30-min intervals)
EIP activation time	25	No action, 30-min to 12 hr. (30-min intervals)

4.2 Optimization and Training

To ensure optimal performance, hyperparameter optimization was conducted prior to network training. The network architecture incorporates 35 input parameters, comprising sensor measurements from severe accident diagnostic monitoring instrumentation. A total of 18 output parameters were identified through systematic analysis of Severe Accident Management Guidelines (SAMG) requirements. The temporal prediction horizon was configured at 120 discrete time steps, corresponding to a 120-minute (2-hour) forward prediction window. Furthermore, three binary conditional variables representing operational states of shutdown cooling pumps (SCP), charging pumps (CHP), and external injection pumps (EIP) were integrated to facilitate action-conditional predictions.

The proposed architecture underwent systematic optimization across nine critical hyperparameters, with performance metrics evaluated using mean absolute percentage error (MAPE) and coefficient of determination (R^2). Bayesian optimization was executed through 100 iterations to identify the optimal hyperparameter configuration, as delineated in Table II.

Table II: Summary of hyperparameter tuning via Bayesian optimization

Hyperparameter	**Value set or range**	**Optimized**
Input time steps	{10, 20, 30, 40, 50}	30
Encoder layers	[2, 10]	4
Autoformer dimensions	[100, 1,000]	256
VAE dimensions	[100, 1,000]	128
TCN dimensions	[100, 1,000]	64
Decoder layers	[4, 20]	4
Batch size	{32, 64, 128, 256}	64
Optimizer	{Adam, AdamW}	AdamW
Learning rate	[1E-06, 1E-04]	5.2E-05

Model training utilized the comprehensive dataset of 11,673 simulated scenarios, yielding 9,598,265 discrete time-step datasets. The dataset underwent stratified partitioning into 9,338 training scenarios (7,678,612 datasets) and 2,335 test scenarios. To mitigate overfitting, 20% of training data (1,535,722 datasets) was randomly allocated for validation purposes. An early stopping mechanism was implemented, terminating training upon detection of validation loss stagnation over 30 consecutive epochs. The optimization process achieved final validation loss convergence at 5.654×10^{-6}, yielding a validation MAPE of 1.284% and R^2 of 0.999, demonstrating exceptional predictive fidelity.

4.3 Result

Network performance evaluation utilized 2,335 test scenarios corresponding to 1,919,653 individual datasets. Evaluation assessed accuracy and reliability for 120-minute forward predictions across 18 output parameters. The proposed framework achieved test MAPE of 2.534% and R^2 of 0.987, demonstrating exceptional predictive fidelity. Literature indicates MAPE below 10% signifies reliable predictive capability [9], while R^2 exceeding 0.99 indicates strong prediction-observation agreement [10].

Fig. 2. illustrates reactor vessel level predictions under various mitigation strategies. Analysis examined 20-inch LBLOCA scenarios with complete safety injection failure, comparing shutdown cooling pump, charging pump, and external injection pump. Results demonstrate framework capability for accurate state evolution prediction under diverse operational interventions.

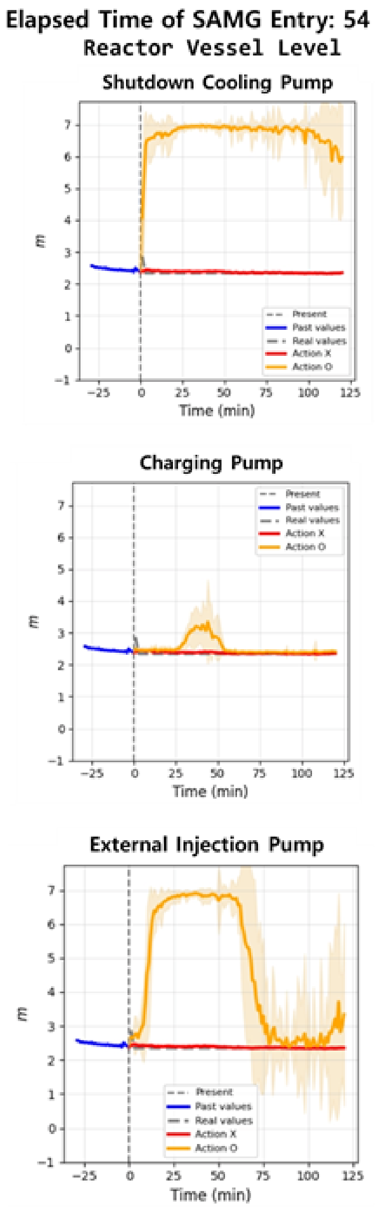

Fig. 2. Mitigation-action based prediction result for reactor vessel at 20-inch LLOCA

5. Conclusion

This investigation presents a novel action-conditional prediction framework addressing fundamental limitations in severe accident management systems. Through synergistic integration of Autoformer, VAE, and TCN architectures with conditional input mechanisms, the framework achieves high-fidelity multi-horizon predictions while explicitly modeling operator interventions. The framework enables systematic evaluation of mitigation strategy efficacy, facilitating quantitative assessment of intervention timing and equipment selection impacts on accident progression. This capability provides critical decision support for emergency response organizations through real-time strategy optimization and consequence assessment. Results substantiate significant advancement in severe accident management technology, enhancing uncertainty-aware decision-making under degraded information conditions characteristic of severe accident environments.

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