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Dynamic Spatial–Temporal Graph Neural Network for Cooling Capacity Prediction in HVDC Systems

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Abstract: Predicting the cooling capacity of converter valves is crucial for maintaining the stability and efficiency of high-voltage direct current (HVDC) systems. This task involves handling complex, multi-dimensional time-series data with strong inter-variable dependencies and temporal dynamics. Traditional machine learning methods, while effective in static scenarios, struggle to capture these dependencies, and existing deep learning models often lack the ability to jointly model spatial and temporal relationships. To address these challenges, we propose a novel framework that integrates Graph Neural Networks (GNNs) with temporal dynamics. The GNN component captures spatial dependencies by representing the data as a graph, where nodes correspond to system variables, and edges encode their relationships. Temporal dependencies are modeled using temporal convolutional layers and recurrent neural networks (RNNs), enabling the framework to learn both short-term variations and long-term trends. Additionally, a graph attention mechanism dynamically adjusts the importance of variable relationships, improving prediction accuracy and interoperability. The proposed method demonstrates superior performance over traditional machine learning and deep learning baselines on real-world cooling system data. These results validate the effectiveness of the framework for industrial applications such as cooling system monitoring and predictive maintenance.

Keywords: cooling capacity prediction; graph neural networks; temporal dynamics; industrial applications; predictive maintenance

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1. Introduction

Predicting the cooling capacity of converter valves is a critical aspect of maintaining the stability and efficiency of high-voltage direct current (HVDC) transmission systems. As the cornerstone of modern energy grids, HVDC systems play a vital role in long-distance power transmission due to their high efficiency and low energy loss. Within these systems, the cooling system ensures the thermal stability of key power components, such as thyristors and IGBTs, by regulating their operating temperatures. This process is essential to prevent overheating, which can lead to equipment failure, reduced lifespan, and unplanned maintenance costs. Furthermore, the increasing adoption of renewable energy sources and the integration of HVDC grids with intermittent energy inputs place additional stress on cooling systems, making predictive maintenance and performance optimization more important than ever. However, the accurate prediction of cooling capacity remains a challenging task due to the inherent complexity of these systems, which involve non-

linear interactions among multiple variables, such as voltage, current, coolant flow rate, and ambient temperature.

In recent years, data-driven approaches have gained increasing attention for predictive maintenance and performance optimization in industrial systems [1,2]. Traditional machine learning models, such as support vector machines (SVMs) [3] and gradient boosting machines (GBMs) [4], have been widely used due to their ability to model static relationships in data. However, these methods often struggle to capture temporal dependencies and inter-variable relationships, which are crucial for dynamic environments like cooling systems. For instance, the cooling capacity at any given time is influenced not only by current system states but also by historical trends, requiring models that can effectively learn from time-series data. Moreover, traditional models rely on handcrafted features and domain expertise, which may limit their ability to generalize to diverse operational conditions.

Deep learning techniques, particularly recurrent neural networks (RNNs) [5] and convolutional neural networks (CNNs) [6], have emerged as powerful tools for handling time-series data. RNNs are well suited for capturing temporal dependencies, while CNNs excel in extracting local patterns. However, both approaches primarily treat the input variables independently, limiting their ability to model complex interactions between variables. These limitations underscore the need for a unified framework that can jointly model spatial and temporal dependencies to accurately predict cooling capacity in HVDC systems. Furthermore, scaling such methods to industrial-scale systems introduces challenges related to computational efficiency and interpretability, both of which are essential for real-world deployment.

Graph Neural Networks (GNNs) have recently shown great potential in capturing the spatial relationships in structured data [7]. By representing data as graphs, GNNs encode relationships between variables as edges and attributes as node features, enabling the modeling of complex interdependencies. For instance, in a cooling system, variables such as voltage, current, and temperature can be treated as nodes, while their correlations form the edges. Temporal Graph Neural Networks (TGNNs), such as the Temporal Graph Convolutional Network (TGCN) [8], extend this framework by incorporating temporal dynamics, allowing the model to jointly learn spatial and temporal features. Additionally, these methods offer a natural way to handle non-Euclidean data structures, making them particularly suitable for systems with inherently graph-like properties. Furthermore, attention mechanisms [9] have been introduced in GNNs to dynamically adjust the importance of relationships, improving model interpretability and adaptability under varying conditions.

Despite their success in other domains, such as traffic flow prediction [10] and social network analyses [11], the application of GNN-based methods to industrial cooling systems remains underexplored. Existing methods either fail to capture the dynamic nature of inter-variable relationships or require extensive domain knowledge to construct the graph structure. This gap highlights the need for a method that dynamically learns these dependencies while maintaining scalability and robustness in industrial scenarios.

To address these challenges, we propose a novel framework that integrates **Graph Neural Networks (GNNs)** with **temporal dynamics** for cooling capacity prediction in HVDC systems. Our proposed framework introduces a novel integration of Graph Neural Networks (GNNs) with temporal dynamics specifically tailored for predicting the cooling capacity of converter valves in HVDC systems. While GNNs have been applied to various domains, their utilization in modeling the complex, time-dependent interactions within industrial cooling systems remains underexplored. By combining GNNs with temporal modeling, our approach captures both the spatial and temporal dependencies inherent in these systems, offering a more comprehensive and accurate predictive tool. This integration not only enhances prediction accuracy but also provides a scalable and robust solution

adaptable to the dynamic nature of industrial environments. The contributions of this work are threefold:

- We propose a hybrid framework that combines a GNN with temporal modeling to simultaneously capture spatial and temporal dependencies in multi-dimensional time-series data.
- We introduce a graph attention mechanism that dynamically prioritizes feature relationships, enhancing the interpretability and adaptability of the model.
- We validate the proposed method on real-world cooling system data, demonstrating its superior performance compared to traditional machine learning and deep learning models.

2. Related Work

2.1. Cooling Capacity Prediction

Cooling capacity prediction plays a crucial role in ensuring the stability and efficiency of high-voltage direct current (HVDC) systems. Traditional approaches to predicting cooling performance often rely on physical models, which simulate the thermal behavior of components based on governing equations. While these models provide a theoretical basis for understanding cooling mechanisms, their accuracy heavily depends on precise parameter calibration, which is often challenging in real-world applications due to the complexity of operational environments.

To overcome these limitations, data-driven methods have been increasingly adopted. Machine learning algorithms, such as support vector machines (SVMs), random forests, and gradient boosting methods, have shown promise in modeling cooling performance based on historical data. However, these methods primarily capture static relationships within the data and fail to account for temporal dependencies critical to dynamic systems. Recent advancements in deep learning, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have demonstrated superior performance in time-series prediction tasks. Nevertheless, these models often overlook inter-variable relationships, which are crucial in multi-dimensional systems like cooling networks.

2.2. Graph Neural Networks for Structured Data

Graph Neural Networks (GNNs) [7,9,12] have emerged as a powerful tool for analyzing structured data by leveraging the inherent graph structure of relationships among entities. GNNs generalize traditional neural networks to graph domains by incorporating node and edge information, enabling effective modeling of spatial dependencies. Recent advancements have expanded GNNs' applicability to various domains, including time-series analyses, industrial process monitoring, and fault diagnosis. In time-series analyses, GNNs have been employed to model complex temporal and spatial dependencies. For instance, the Fourier Graph Neural Network (FourierGNN) [13] rethinks multivariate time-series forecasting from a pure graph perspective, capturing both spatial and temporal dynamics within a unified framework. Additionally, GNNs have been applied to tasks such as forecasting, classification, anomaly detection, and imputation, demonstrating their versatility in handling various time-series challenges.

In industrial process monitoring and fault diagnosis [14], GNNs have been utilized to capture intricate topologies and dependencies among components. For example, Interaction-Aware Graph Neural Networks (IAGNNs) have been proposed for fault diagnosis in complex industrial processes, effectively modeling sensor–signal interactions to enhance diagnostic performance. Similarly, Hierarchical Spatio-Temporal Graph Networks (HiSTGCNs) have been developed for fault diagnosis, leveraging hierarchical structures to capture both local and global correlations in industrial systems. These advancements

highlight the potential of GNNs in modeling complex dependencies in structured data. However, challenges remain in effectively capturing dynamic temporal relationships and scaling to large, heterogeneous graphs. Future research directions include developing more efficient algorithms for dynamic graph learning, improving interpretability, and exploring applications in diverse industrial contexts.

2.3. Temporal Graph Modeling

TGNNs [13] extend traditional GNNs by integrating temporal dynamics into the graph structure, enabling the modeling of time-evolving relationships. For instance, Temporal Graph Convolutional Networks (TGCNs) combine graph convolution operations with recurrent layers, such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs), to simultaneously capture spatial and temporal dependencies. Similarly, the attention-based mechanisms employed in Graph Attention Networks (GATs) enhance TGNNs by dynamically weighting the importance of edges and nodes, thereby improving interpretability.

Despite their success in domains like traffic flow forecasting and social network analyses, the application of TGNNs to cooling capacity prediction remains underexplored. Existing studies often assume a fixed graph structure, which may not effectively capture the dynamic changes in relationships among variables inherent in industrial cooling systems. For example, the Multi-Scale Dynamic Graph Neural Network (MSDG) [15] has been proposed for industrial time-series anomaly detection, aiming to reveal dynamic spatial–temporal correlations embedded in multivariate sensor data. However, methodologies like MSDG are primarily designed for anomaly detection and may not directly address the specific challenges of predicting cooling capacity in HVDC systems.

Furthermore, while frameworks such as LasTGL have been introduced to integrate unified and extensible implementations of common temporal graph learning algorithms for various advanced tasks, their application in industrial settings, particularly for cooling capacity prediction, has not been extensively studied. Therefore, there is a need for tailored TGNN approaches that can adapt to the dynamic nature of industrial cooling systems, capturing both spatial and temporal variations to improve predictive performance [16].

A comprehensive survey in [17] systematically reviewed STGNN models, highlighting their effectiveness in capturing complex dependencies across time points. Additionally, Ref. [18] provided an extensive overview of GNN methods tailored for spatio-temporal data, discussing various approaches to address intricate spatial and temporal dependencies in diverse application domains. Furthermore, Ref. [19] introduced a formalization of learning settings and tasks within temporal GNNs, presenting a novel taxonomy that categorizes existing approaches based on temporal representation and processing. In the context of industrial applications, the research in [20] focused on graph construction for complex spatio-temporal data, enhancing GNN-based approaches in modeling sensor data presented as time series with spatial information. These studies collectively underscore the rapid developments in STGNNs and their expanding applicability across various fields.

2.4. Summary and Research Gap

Existing studies in cooling capacity prediction and temporal graph modeling highlight the following gaps:

- **Limited Temporal–Spatial Integration:** Traditional methods fail to simultaneously capture temporal dependencies and spatial relationships among variables.
- **Lack of Dynamic Relationship Modeling:** Most graph-based approaches assume a fixed graph structure, overlooking the dynamic nature of variable interactions in real-world cooling systems.

- **Insufficient Interpretability:** Many existing methods lack mechanisms to explain the importance of relationships or variables in the prediction process.

To address these limitations, this paper proposes a hybrid framework that combines a GNN with temporal modeling and incorporates a graph attention mechanism. This approach enables the simultaneous modeling of temporal and spatial dependencies while dynamically adjusting relationship weights, improving both prediction accuracy and model interpretability. Our proposed framework introduces a novel integration of Graph Neural Networks (GNNs) with temporal modeling and a graph attention mechanism, specifically designed for predicting the cooling capacity of converter valves in high-voltage direct current (HVDC) systems. This approach addresses several limitations present in existing methods:

- Traditional GNNs often rely on static graph structures, which may not accurately represent the evolving relationships between variables in dynamic systems. In contrast, our framework constructs dynamic graphs that adaptively capture the temporal evolution of inter-variable relationships, enabling the model to reflect the current state of the system more accurately.
- While Temporal Graph Convolutional Networks (TGCNs) combine GNNs with temporal modeling, they may not fully capture the complex temporal dependencies present in industrial systems. Our framework employs advanced temporal modeling techniques that effectively capture both short-term fluctuations and long-term trends, enhancing predictive performance in time-series forecasting tasks.
- Standard GNNs and TGCNs may treat all node connections uniformly, potentially overlooking the varying significance of different relationships. We incorporate a graph attention mechanism that assigns learnable weights to edges, allowing the model to prioritize more influential relationships. This enhances interpretability by highlighting critical interactions that drive system behavior.
- The application of GNNs and TGCNs to industrial domains like HVDC systems is relatively unexplored, with existing models often tailored to other fields such as social networks or traffic prediction. Our framework is specifically designed for the unique characteristics of HVDC systems, addressing challenges such as non-linear interactions among variables like voltage, current, and temperature, thereby providing a tailored solution for cooling capacity prediction.

3. Proposed Framework

To predict the cooling capacity of converter valves, we propose a framework that integrates **Graph Neural Networks (GNNs)** with **temporal dynamics**. This hybrid approach captures both spatial dependencies among variables (e.g., voltage, current, and temperature) and their temporal evolutions over time. By leveraging the graph structure to encode relationships and temporal modeling for sequential patterns, our method provides accurate and robust predictions. The proposed framework is designed to handle the complex, dynamic, and multi-dimensional nature of cooling systems, offering both high precision and scalability. See Figure 1.

The framework is composed of four key components, each designed to address specific challenges:

1. **Graph Construction:** Encodes relationships among features into a graph structure, allowing spatial dependencies to be explicitly modeled.
2. **Temporal Graph Convolutional Network (TGCN):** Integrates graph convolution and temporal convolution to jointly capture spatial and temporal dependencies.
3. **Graph Attention Mechanism (GAT):** Dynamically adjusts the importance of relationships between variables, enhancing model interpretability and predictive performance.

4. **Temporal Dependency Modeling:** Utilizes recurrent layers (e.g., LSTM or GRU) to capture long-term dependencies across time steps.

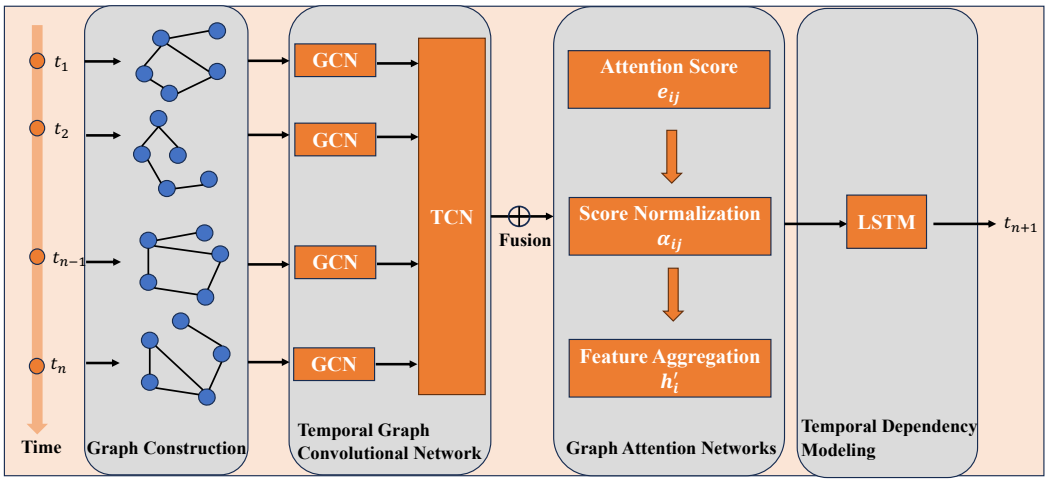


Figure 1. The proposed framework for cooling capacity prediction. The framework consists of four main components: graph construction, Temporal Graph Convolutional Network (TGCN), graph attention mechanism (GAT), and temporal dependency modeling. Input data (e.g., voltage, current, temperature) are first transformed into a graph structure, where nodes represent variables, and edges encode relationships. The TGCN combines graph convolution and temporal convolution to extract spatial–temporal features, which are refined by the GAT for dynamic edge weighting. Finally, the temporal dependencies are captured using LSTM to predict the cooling capacity.

3.1. Graph Construction

Cooling systems involve multiple interdependent variables such as voltage, current, coolant flow rate, and ambient temperature. To explicitly model the relationships between these variables, we construct a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with the following:

- **Nodes ($\mathcal{V}$):** Each node represents a variable in the dataset.
- **Edges ($\mathcal{E}$):** Each edge represents a relationship between two variables. For example, the correlation between voltage and current might be strong, while the correlation between ambient temperature and coolant flow rate might be weaker.

To quantify these relationships, an adjacency matrix $\mathbf{A}$ is computed using Pearson correlation:

$$\mathbf{A}_{ij} = \frac{\mathrm{Cov}(\mathbf{x}_i, \mathbf{x}_j)}{\sigma_i \cdot \sigma_j},$$

where $\mathrm{Cov}(\mathbf{x}_i, \mathbf{x}_j)$ is the covariance between variables $\mathbf{x}_i$ and $\mathbf{x}_j$, and σ_i and σ_j are their standard deviations. This ensures that $\mathbf{A}_{ij}$ captures the strength and direction of the linear relationship between variables.

We choose Pearson correlation for its simplicity, interpretability, and computational efficiency, making it particularly suitable for industrial applications like HVDC cooling systems. Pearson correlation provides a straightforward measure of linear dependency between variables, which aligns well with the cooling system's physical characteristics, where many key relationships exhibit strong linear components. For example, variables such as ambient temperature and coolant flow rate often have direct linear effects on cooling capacity, making Pearson correlation an effective metric for capturing these dependencies. Additionally, its symmetric and bounded nature ($-1 \leq \mathbf{A}_{ij} \leq 1$) ensures that the graph structure remains interpretable and numerically stable during computation.

To enhance numerical stability and improve the effectiveness of graph convolution, the adjacency matrix is normalized [7]:

$$\hat{\mathbf{A}} = \mathbf{D}^{-1/2}\mathbf{A}\mathbf{D}^{-1/2},$$

where $\mathbf{D}$ is the degree matrix of $\mathbf{A}$. This normalization ensures that the impact of highly connected nodes is balanced during graph convolution, reducing potential biases introduced by a variable scale or connectivity.

While we acknowledge that Pearson correlation may not fully capture non-linear or dynamic relationships, it offers a practical and efficient solution for the initial graph construction. Furthermore, the Graph Neural Network (GNN) layers in our framework are designed to learn higher-order and non-linear relationships during training, complementing the simplicity of the Pearson-based graph structure.

3.2. Temporal Graph Convolutional Network (TGCN)

The Temporal Graph Convolutional Network (TGCN) is the core component of our framework, combining spatial and temporal modeling into a unified structure:

- **Graph Convolution:** Captures spatial dependencies by propagating information across the graph. Each graph convolutional layer updates the representation of each node by aggregating features from its neighbors:

$$\mathbf{H}^{(l+1)} = \sigma\left(\hat{\mathbf{A}} \cdot \mathbf{H}^{(l)} \cdot \mathbf{W}^{(l)}\right),$$

  where $\mathbf{H}^{(l)}$ is the node embedding matrix at layer l, $\mathbf{W}^{(l)}$ is a learnable weight matrix, and σ is an activation function such as ReLU [21]. This operation ensures that each node's representation reflects information from its neighbors, enabling the model to capture local spatial patterns.
- **Temporal Convolution:** Extracts short-term temporal features by applying 1D convolution along the time dimension:

$$\mathbf{H}_t^{(l+1)} = \text{Conv1D}\left(\mathbf{H}_t^{(l)}\right),$$

  where $\mathbf{H}_t^{(l)}$ represents the temporal features at time step t for layer l. The convolution kernel size is chosen to balance between capturing immediate temporal dependencies and maintaining computational efficiency.

By alternating graph and temporal convolutions, the TGCN effectively integrates spatial and temporal features, enabling robust predictions, even in highly dynamic environments.

3.3. Graph Attention Mechanism (GAT)

The graph attention mechanism (GAT) [9] is introduced to dynamically prioritize important relationships, allowing the model to focus on the most relevant connections:

- **Attention Score Calculation:** For each pair of connected nodes, the attention score is computed as

$$e_{ij} = \text{LeakyReLU}\left(\mathbf{a}^T \cdot \left[\mathbf{W}_h\mathbf{h}_i \| \mathbf{W}_h\mathbf{h}_j\right]\right),$$

  where $\mathbf{h}_i$ and $\mathbf{h}_j$ are node embeddings, $\mathbf{W}_h$ is a learnable weight matrix, and $\mathbf{a}$ is the attention vector.
- **Score Normalization:** The attention scores are normalized using softmax:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k\in\mathcal{N}(i)}\exp(e_{ik})}.$$

This ensures that the sum of attention weights for each node is 1, improving stability.

- **Feature Aggregation:** The updated embedding for each node is computed as a weighted sum of its neighbors' features:

$$\mathbf{h}_i' = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} \cdot \mathbf{W}_h \cdot \mathbf{h}_j\right).$$

The GAT improves the interpretability of the model by highlighting the most influential relationships.

3.4. Temporal Dependency Modeling

To capture long-term temporal dependencies, we use recurrent layers such as LSTM [22]. LSTM processes the temporal embeddings generated by the TGCN, producing a final temporal representation:

$$\mathbf{h}_t = \text{LSTM}(\mathbf{H}_t),$$

where $\mathbf{H}_t$ represents the temporal embeddings at time step t. The LSTM's ability to maintain a memory of previous time steps ensures that the model can capture sequential patterns over long durations.

3.5. Optimization

The model is trained using the Mean Squared Error (MSE) loss function, defined as

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2,$$

where $\hat{y}_i$ and y_i are the predicted and true cooling capacities, respectively. The Adam optimizer [23] is employed to minimize the loss, with dropout and weight decay applied to prevent overfitting. The detailed steps of the training process are summarized in Algorithm 1.

Algorithm 1 Graph Neural Networks with Temporal Dynamics

Input: Time-series data $\mathbf{X} \in \mathbb{R}^{T \times N}$, adjacency matrix $\mathbf{A}$, window size T.

1: Normalize adjacency matrix $\hat{\mathbf{A}}$.
2: Extract spatial features using $\mathbf{A}$ and $\mathbf{H}$.
3: Extract temporal features from $\mathbf{H}_t$.
4: Compute attention scores e_{ij} and normalized weights α_{ij}.
5: Aggregate features into $\mathbf{h}_i'$.
6: Model temporal dependencies with LSTM to obtain $\mathbf{h}_t$.
7: Predict $\hat{y}_{t+1}$ using fully connected layers.
8: Minimize the loss $\mathcal{L}$ to optimize model parameters.

Output: Predicted cooling capacity $\hat{y}_{t+1}$.

4. Experiments

This section evaluates the performance of the proposed method in predicting the cooling capacity of converter valves. The experiments were conducted on a real-world dataset collected from HVDC systems, focusing on the effectiveness, accuracy, and interpretability of the proposed model. Additionally, we compared the performance of the proposed framework with several baseline methods and analyzed its scalability.

4.1. Dataset and Experimental Setup

4.1.1. Dataset Description

To evaluate the performance of the proposed framework, we used a dataset collected from an industrial high-voltage direct current (HVDC) cooling system over six months. The data consist of multi-dimensional time-series variables sampled every 10 min. See Figure 2. The key variables include the following:

- **Voltage (V):** Describes the input voltage of the system, ranging from 450 V to 550 V.
- **Current (A):** Represents the system load current, with values between 250 A and 350 A.
- **Coolant Flow Rate (L/s):** Measures the flow rate of the coolant, ranging from 2.0 L/s to 3.0 L/s.
- **Ambient Temperature (°C):** Reflects the external environmental influence on cooling efficiency, with values between 20 °C and 35 °C.
- **Cooling Capacity (kW):** The target variable, indicating the cooling power per unit time, ranging from 100 kW to 150 kW.

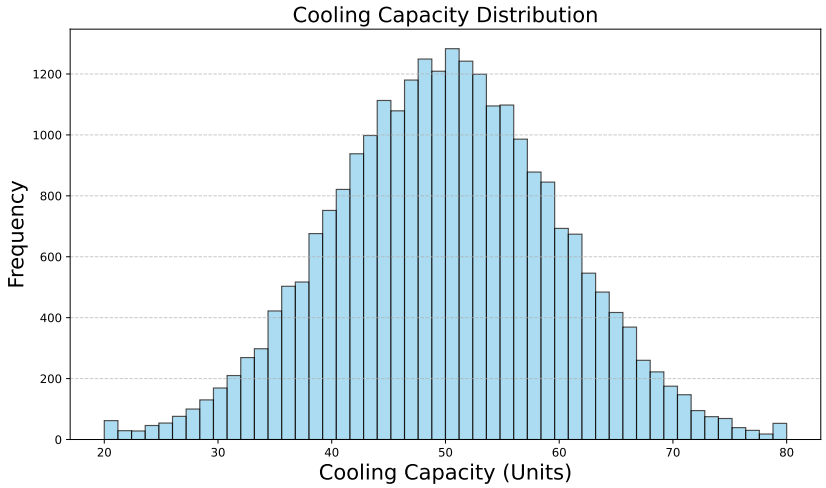


Figure 2. Histogram of cooling capacity distribution in the HVDC cooling system dataset.

To enhance model performance, the following preprocessing steps were applied to the raw dataset:

- **Timestamp Alignment:** Missing data were imputed using interpolation to ensure a complete time series.
- **Noise Removal:** High-frequency noise was filtered using wavelet transformation.
- **Normalization:** All input variables were normalized to the range $[0, 1]$ to eliminate dimensional effects.
- **Sliding Window Construction:** A sliding window of size 24 (corresponding to 4 h) was used to transform the time series into input samples. Each sample contained 24 historical time steps as input and the next time step as the output cooling capacity.

To further validate the robustness of the proposed framework, synthetic data were generated to simulate system behavior under diverse conditions:

- **High-Load Scenario:** Increased current values to 400 A to simulate extreme operating conditions.
- **Low-Temperature Environment:** Reduced ambient temperature to 10 °C to examine the cooling system under cold environments.
- **Non-Periodic Disturbances:** Introduced random disturbances at specific time intervals to test model stability.

To ensure a fair evaluation, the dataset was divided into training (70%), validation (15%), and testing (15%) subsets. A sliding window approach was adopted for sample generation, with the previous 24 time steps used to predict the next cooling capacity value [22].

4.1.2. Experimental Setup

The following baseline models were selected for comparison:

- **Support Vector Machine (SVM):** A traditional machine learning model for static prediction tasks [24].
- **Gradient Boosting Machine (GBM):** A boosting-based ensemble learning model [4].
- **Long Short-Term Memory (LSTM):** A deep learning model designed for sequential data [22].
- **Graph Convolutional Network (GCN):** A graph-based model for spatial dependency modeling [25].
- **Temporal Graph Convolutional Network (TGCN):** A hybrid model combining a GCN and an RNN for spatial–temporal modeling [15].

All models were implemented in Python using PyTorch. The experiments were conducted on an NVIDIA Tesla V100 GPU with 32 GB of memory. The Adam optimizer was used with a learning rate of 0.001, and all models were trained for 100 epochs, with a batch size of 64.

4.2. Evaluation Metrics

The performance of the models was evaluated using the following metrics:

- **Mean Squared Error (MSE):** Measures the average squared difference between predicted and actual values.
- **Root Mean Squared Error (RMSE):** The square root of the MSE, representing the standard deviation of prediction errors.
- **Coefficient of Determination (R^2):** Indicates the proportion of variance explained by the model [26].

4.3. Results and Analysis

4.3.1. Overall Performance

Table 1 presents a performance comparison of the proposed method and baseline models on the test dataset.

Table 1. Performance comparison of proposed method and baselines.

Model	MSE	RMSE	R^2
SVM	0.0085	0.0922	0.81
GBM	0.0062	0.0787	0.85
LSTM	0.0057	0.0755	0.87
GCN	0.0071	0.0843	0.83
TGCN	0.0049	0.0700	0.89
Proposed Method	**0.0035**	**0.0592**	**0.92**

The proposed method achieves the lowest MSE and RMSE and the highest R^2, outperforming all baseline models. This demonstrates its ability to capture both spatial and temporal dependencies effectively.

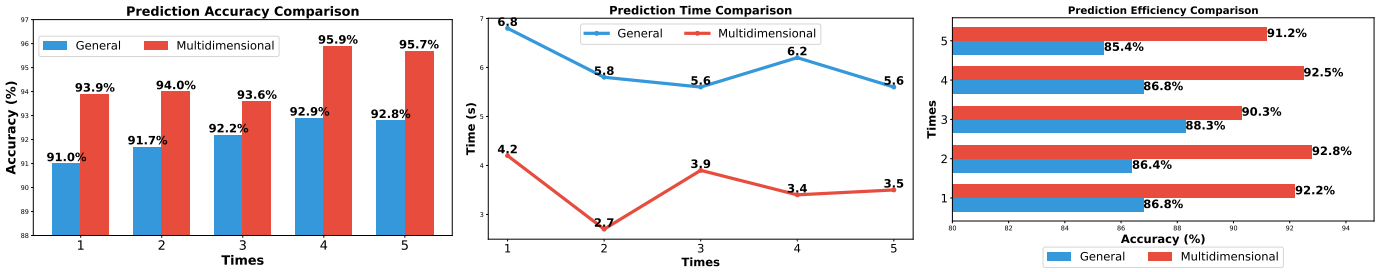
4.3.2. In-Depth Analysis of Prediction Performance

To comprehensively evaluate the proposed method, we conducted experiments on prediction accuracy, prediction time, and prediction efficiency. These metrics provide

a holistic understanding of the model's performance in terms of precision, computational cost, and practical applicability. The general prediction method in this study is represented by the best-performing baseline, the Graph Convolutional Network (GCN).

Prediction Accuracy. The prediction accuracy results are shown in Figure 3a. The proposed method, based on multidimensional time-series data, achieves a significantly higher accuracy than the general GCN-based method:

- The accuracy of the general method ranges from 91.0% to 92.9%, with an average accuracy of 92.12%.
- The accuracy of the proposed method ranges from 93.6% to 95.9%, with an average accuracy of 94.62%.



(**a**) Prediction Accuracy Comparison (**b**) Prediction Time Comparison (**c**) Prediction Efficiency Comparison

Figure 3. Comparison of the proposed method and the baseline (GCN) in terms of prediction accuracy, prediction time, and prediction efficiency. (**a**) Prediction accuracy comparison: The proposed method achieves a significantly higher accuracy, with an average accuracy of 94.62%, compared to 92.12% for the baseline. (**b**) Prediction time comparison: The proposed method demonstrates a reduced prediction time, with an average of 3.54 s, compared to 6 s for the baseline. (**c**) Prediction efficiency comparison: The proposed method achieves a higher prediction efficiency, averaging 91.80%, compared to 86.74% for the baseline. These results highlight the superior accuracy, efficiency, and computational performance of the proposed method in predicting the cooling capacity of converter valves.

These results indicate that the proposed method outperforms the general method in accuracy, demonstrating its ability to better capture the spatial–temporal dependencies in cooling capacity prediction.

Prediction Time. The prediction time results are presented in Figure 3b. The proposed method demonstrates superior computational efficiency compared to the general GCN-based method. The key observations include the following:

- The general method takes 5.6 to 6.8 s for prediction, with an average time of 6 s.
- The proposed method reduces the prediction time to a range of 2.7 to 4.2 s, with an average time of 3.54 s.

This reduction in prediction time highlights the computational efficiency of the proposed method, making it more suitable for real-time industrial applications.

Prediction Efficiency. The prediction efficiency, defined as the ratio of successful accurate predictions within a fixed time frame, is depicted in Figure 3c. The proposed method significantly improves prediction efficiency compared to the general GCN-based method. The results show the following:

- The prediction efficiency of the general method ranges from 85.4% to 88.3%, with an average efficiency of 86.74%.
- The prediction efficiency of the proposed method ranges from 90.3% to 92.8%, with an average efficiency of 91.80%.

The higher prediction efficiency achieved by the proposed method further validates its practical value in industrial settings, where timely and accurate predictions are crucial.

4.3.3. Heatmap Analysis of Attention Weights

The goal of this experiment is to analyze the attention weights learned by the graph attention mechanism (GAT) through heatmap visualization. By examining the relationships among key variables in the cooling system, we aim to uncover how these relationships influence the model's predictions of cooling capacity. This experiment focuses on understanding the contribution of critical variables, verifying the model's ability to capture the physical characteristics and dependencies within the system, and providing insights that can assist in optimizing system performance and diagnosing faults.

The attention weights α_{ij}, which represent the relative importance of one variable (source node) to another (target node), were extracted from the trained GAT. These weights were visualized as a heatmap, where rows correspond to source variables, and columns correspond to target variables, as illustrated in Figure 4. The key variables considered in this experiment include voltage, current, coolant flow rate, ambient temperature, and cooling capacity. The heatmap provides a clear depiction of how the model prioritizes different variable relationships, with higher weights indicating stronger influence. The visualization helps to assess whether the model aligns with the known physical dynamics of the cooling system and highlights the dominant relationships that drive the prediction task.

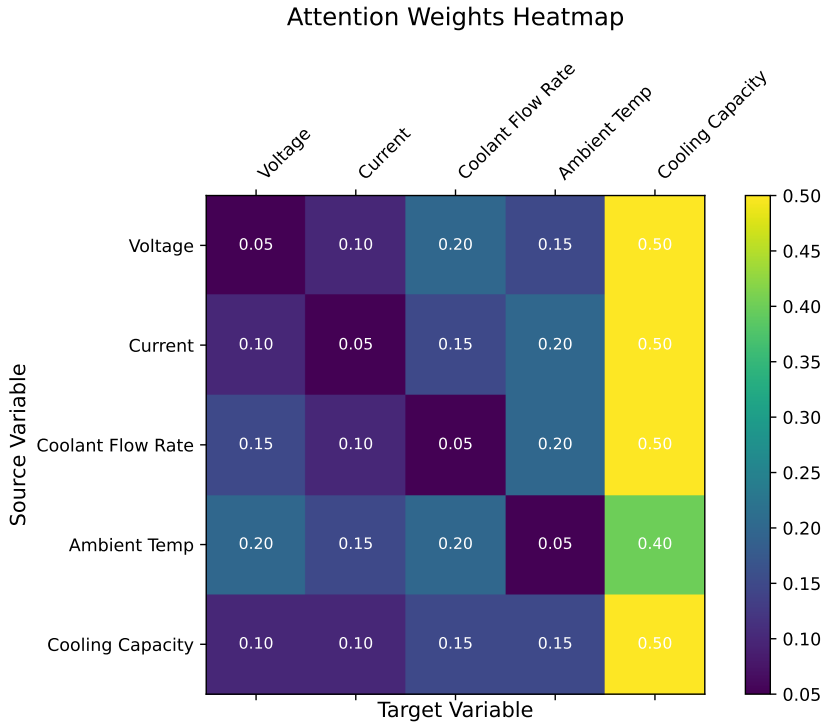


Figure 4. Heatmap visualization of attention weights learned by the graph attention mechanism (GAT). Rows represent the source variables, and columns represent the target variables. Higher attention weights (darker colors) indicate stronger influence of the source variable on the target variable. The heatmap highlights the dominant roles of ambient temperature and coolant flow rate in cooling capacity prediction, consistent with the physical principles of heat exchange.

The heatmap reveals that ambient temperature and coolant flow rate exhibit the highest attention weights, confirming their dominant roles in cooling capacity prediction. This finding is consistent with the physical principles of heat exchange, where these variables directly impact the system's performance. Variables such as voltage and current, while showing relatively lower attention weights, still contribute to the overall prediction by influencing intermediate system states. The analysis demonstrates that the model effectively captures critical relationships among variables and provides a transparent

mechanism for understanding its decision-making process. These insights enhance the interpretability of the proposed framework and offer actionable guidance for system monitoring and optimization.

5. Discussion

The experimental results demonstrate the effectiveness of the proposed method in accurately predicting the cooling capacity of converter valves. Compared to traditional machine learning models (e.g., SVMs and GBMs) and deep learning models (e.g., LSTM and GCNs), our approach achieves superior performance by leveraging both spatial and temporal dependencies in the data. Specifically, the integration of a graph attention mechanism allows the model to dynamically prioritize relationships between variables, thereby improving prediction accuracy and interpretability.

5.1. Advantages of the Proposed Method

The success of the proposed method can be attributed to its unique combination of spatial and temporal modeling. Unlike conventional methods that treat variables independently, the proposed model uses a graph structure to capture their interdependencies, which are critical in complex cooling systems. For instance, relationships such as the influence of ambient temperature on coolant flow rate are explicitly represented in the graph structure. Additionally, the temporal modeling component enables the model to learn both short-term variations and long-term trends, further enhancing its predictive capabilities. The ablation study confirms the contributions of individual components, highlighting the importance of the graph attention mechanism and temporal modeling. This design ensures that the framework is not only accurate but also interpretable, offering insights into the key drivers of cooling system behavior.

Moreover, the proposed framework is designed to generalize well to other industrial systems with similar characteristics. The graph structure and temporal modeling components are inherently flexible, allowing the method to adapt to systems with different configurations or variable dependencies. While this study focuses on a specific HVDC cooling system, the results suggest that the proposed approach has the potential to be applied to other domains, such as energy system monitoring, predictive maintenance, and process optimization.

5.2. Limitations and Future Work

Despite its advantages, the proposed method has certain limitations:

- **Dependence on Graph Structure:** The performance of the model relies on the accuracy of the initial graph structure, which is currently constructed based on predefined rules (e.g., Pearson correlation coefficients). While this approach captures dominant linear relationships, it may fail to account for non-linear or dynamic dependencies that exist in real-world systems. Future work will focus on dynamically learning the graph structure from data using advanced techniques such as attention-based graph construction or neural architecture search. These methods have the potential to capture more complex relationships, further improving prediction accuracy.
- **Scalability:** Although the model demonstrates excellent performance on medium-sized datasets, its computational complexity increases with the number of variables and the length of time-series data. This may pose challenges when scaling to very large datasets or deploying the model in real-time applications. To address this, we plan to explore more efficient architectures and optimization techniques, such as graph sampling or hierarchical graph learning, to reduce computational costs without sacrificing accuracy.

- **Data Availability:** The proposed method requires a sufficient amount of high-quality labeled data for training. In industrial settings, obtaining such data can be challenging due to sensor limitations, missing values, or data privacy concerns. Future research could focus on semi-supervised or self-supervised learning techniques to mitigate this issue, enabling the model to leverage unlabeled data effectively. Additionally, data augmentation strategies could be employed to simulate realistic scenarios and improve model robustness.
- **Generalizability to Other Systems:** While the results demonstrate the method's effectiveness for the target HVDC cooling system, its applicability to other systems has not yet been fully validated. For example, systems with significantly different variable types, scales, or dynamics might require modifications to the graph construction process or hyperparameter tuning. Future work will involve testing the model on datasets from other industrial systems with diverse configurations to further assess its generalizability. Transfer learning techniques could also be explored to adapt the model to new systems with limited labeled data, reducing the cost of retraining.

In conclusion, the proposed framework provides a robust solution for cooling capacity prediction by effectively integrating spatial and temporal modeling. While challenges remain in terms of graph construction, scalability, and data availability, the identified directions for future research aim to address these limitations and further enhance the method's performance and applicability across a wide range of industrial domains.

6. Conclusions

In this paper, we propose a novel method that integrates Graph Neural Networks (GNN) with temporal dynamics for predicting the cooling capacity of converter valves. The method effectively captures both spatial dependencies among variables and temporal dependencies over time, addressing the challenges posed by multi-dimensional time-series data. By incorporating a graph attention mechanism, the proposed method dynamically adjusts the importance of relationships, enhancing both interpretability and performance.

The experimental results demonstrate that the proposed method outperforms traditional machine learning and deep learning baselines, achieving the lowest MSE and RMSE scores while maintaining high interpretability. An ablation study further validates the significance of the graph attention mechanism and temporal modeling components.

This work contributes to the growing body of research on graph-based temporal modeling and provides a practical solution for industrial applications, such as cooling system monitoring and fault prediction. In future work, we aim to explore dynamic graph learning techniques and optimize the model for real-time deployment.

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