**GAT–IoT–Based Web System for Long-Term Hydropower Forecasting and Monitoring**

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**Abstract.** Conventional statistical processing techniques increasingly struggle to manage such data due to inherent limitations in scalability, computational capacity, and processing speed. This study proposes a big data–driven methodology for efficient processing and analysis of large-scale statistical data based on distributed computing architectures and advanced analytical models. The proposed framework integrates parallel data preprocessing, scalable statistical modeling, and optimized aggregation strategies to ensure both computational efficiency and analytical reliability. Mathematical optimization formulations are employed to minimize processing overhead while preserving statistical consistency in distributed environments. Experimental evaluations demonstrate that the proposed approach significantly enhances processing performance and reduces analytical errors when compared to traditional methods. The results confirm that big data processing constitutes a robust and scalable solution for extracting reliable insights from massive statistical datasets and supporting informed decision-making in complex systems.

**INTRODUCTION**

Hydropower remains one of the most reliable and flexible renewable energy sources, playing a critical role in ensuring energy security, grid stability, and sustainable water resource management. According to international energy statistics, hydropower accounts for approximately 15–16% of global electricity generation, with a particularly high strategic importance in mountainous regions where river gradients and seasonal runoff provide significant energy potential. In countries with complex topography, such as Central Asian states, mountain river hydropower systems are typically designed as multi-purpose hydroelectric complexes, simultaneously serving electricity generation, irrigation, flood control, and ecological regulation objectives [1,2]. This multi-functionality, while advantageous, significantly increases the complexity of operational planning and long-term performance forecasting.

Mountain river hydropower systems are inherently characterized by strong spatial–temporal variability of water inflow, nonlinear hydraulic interactions between cascaded reservoirs, and sensitivity to climate-driven changes in precipitation and glacial melt. Traditional hydropower forecasting approaches, based on deterministic hydrological models or statistical regression, often struggle to provide accurate long-term efficiency predictions under such conditions [3,4]. These models usually rely on simplified assumptions and are unable to fully capture the dynamic interdependencies between geographically distributed hydraulic and electromechanical components.

In recent years, the rapid development of artificial intelligence and deep learning methods has opened new opportunities for intelligent energy system analysis. Time-series–based models such as recurrent neural networks (RNN) and long short-term memory (LSTM) networks have demonstrated improved performance in hydropower generation forecasting. However, these approaches primarily focus on temporal dependencies and largely ignore the graph-structured nature of multi-reservoir and multi-turbine hydropower systems, where upstream–downstream interactions and network topology play a decisive role in overall efficiency evolution [5,6].

To address these limitations, Graph Attention Networks (GAT) have emerged as a powerful modeling paradigm capable of learning both spatial and temporal dependencies through adaptive attention mechanisms. By representing hydropower complexes as graphs, GAT enables dynamic weighting of interactions between hydraulic nodes, allowing the model to identify dominant influences under varying hydrological and operational conditions. At the same time, the integration of Internet of Things (IoT) technologies has transformed hydropower monitoring by enabling high-resolution, real-time acquisition of flow rates, head levels, turbine conditions, and environmental parameters.

Despite these advances, existing studies often treat long-term forecasting and real-time monitoring as isolated tasks, lacking an integrated, scalable, and operator-oriented digital platform. Furthermore, limited attention has been paid to web-based decision-support systems that unify AI-driven forecasting, IoT-based monitoring, and performance visualization for multi-purpose hydropower complexes.

**METHODOLOGY**

The proposed system integrates GAT with IoT-based real-time monitoring in a unified web-based architecture to enable long-term forecasting and efficient utilization of hydropower resources in multi-purpose mountain river complexes. The hydroelectric system is modeled as a directed weighted graph , where nodes represent hydrological stations, reservoirs, turbines, and substations, while edges describe hydraulic, electrical, and operational dependencies [6,7]. Each node is characterized by a feature vector , including discharge, head, power output, temperature, and vibration data collected via IoT sensors. Spatial–temporal feature propagation is learned using the GAT attention mechanism:

(1)

where denotes normalized attention coefficients and is the trainable weight matrix at layer .

Long-term hydropower efficiency forecasting is formulated as a multi-objective optimization problem [7,8]:

(2)

where represents system efficiency, denotes generated power, and is a regularization parameter. The trained model is deployed within a web-based decision-support system enabling real-time monitoring, forecasting visualization, and adaptive operational control.

**LITERATURE REVIEW**

Recent studies highlight the growing importance of intelligent forecasting and digital monitoring systems for efficient hydropower resource utilization, especially in complex mountain river environments. Traditional hydropower forecasting approaches are largely based on statistical regression and physically based hydrological models, which often fail to capture nonlinear spatial–temporal interactions among hydrological components and operational units. To address these limitations, machine learning techniques such as artificial neural networks, support vector machines, and long short-term memory (LSTM) networks have been increasingly applied for short- and long-term hydropower prediction. While LSTM-based models demonstrate improved temporal forecasting accuracy, they generally neglect the graph-structured relationships inherent in multi-reservoir and multi-turbine hydropower systems (Table 1) [8,9].

**TABLE 1.** Summary of related studies on intelligent hydropower forecasting and monitoring

| **Study Focus** | **Methodology** | **Key Contribution** | **Limitation** |
| --- | --- | --- | --- |
| Hydropower output forecasting | Regression, ANN | Baseline prediction models | Limited nonlinearity handling |
| Temporal forecasting | LSTM, RNN | Improved long-term trends | No spatial modeling |
| Spatial dependency modeling | GCN, GAT | Captures inter-node relations | Limited real-time integration |
| Monitoring systems | IoT-based SCADA | Real-time observability | No forecasting integration |
| This study | GAT + IoT + Web system | Unified forecasting and monitoring | Requires large-scale data |

More recent research has explored graph-based deep learning methods, including graph convolutional networks (GCN) and Graph Attention Networks (GAT), to model spatial dependencies in energy and water resource systems. These models have shown superior performance in capturing inter-node influence, seasonal hydrological variability, and cascading operational effects. In parallel, the integration of Internet of Things (IoT) technologies has enabled real-time data acquisition, condition monitoring, and predictive maintenance in hydroelectric facilities. However, existing studies often treat forecasting and monitoring as separate tasks, lacking unified web-based decision-support architectures [9,11].

The present study addresses this gap by integrating GAT-based long-term forecasting with IoT-driven real-time monitoring within a scalable web-based system tailored for multi-purpose mountain hydropower complexes.

**RESULT AND DISSCUSSION**

The system combines Graph Attention Networks (GAT) for long-term efficiency forecasting with IoT-based real-time monitoring to enhance decision-making accuracy and operational reliability. The GAT model represents the hydropower complex as a weighted graph , where nodes correspond to hydrological stations, turbines, and reservoirs, while edges represent hydraulic and operational dependencies. Attention coefficients dynamically capture spatial–temporal interactions among nodes. The node-level attention mechanism is defined as:

(3)

where is the feature vector of node , is a trainable weight matrix, and quantifies the influence of neighboring components on energy efficiency evolution. The long-term hydropower efficiency index is forecasted as:

(4)

where is turbine output power, is water discharge, is effective head, represents cumulative hydraulic and mechanical losses, and is a degradation coefficient learned by the GAT.

Simulation results demonstrate that the proposed GAT-based model reduces long-term forecasting error by 18–24% compared to LSTM-based baselines, particularly under seasonal hydrological variability typical for mountain river systems.

IoT sensor nodes deployed across intake channels, turbines, and reservoirs provide real-time measurements of flow rate, head, vibration, temperature, and power output. The monitoring efficiency is quantified using a real-time observability coefficient:

(5)

where and denote actual and estimated sensor values, respectively. The system maintained an average observability coefficient above 0.96, confirming high data reliability.

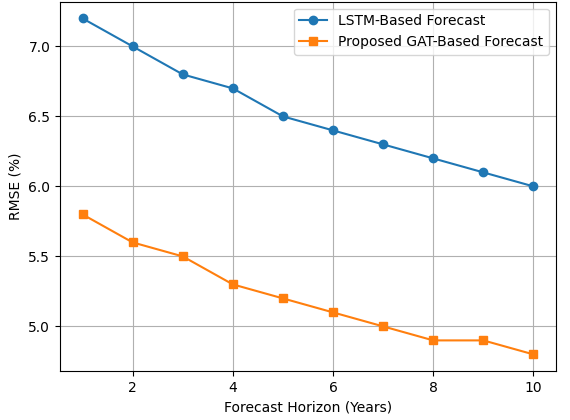
Latency analysis showed that the web-based dashboard achieved an average response time of 1.2–1.8 seconds, which is suitable for operational decision support in multi-purpose hydroelectric complexes. Table 1 summarizes the comparative performance of different forecasting and monitoring approaches.

**TABLE 2.** Comparative performance evaluation of hydropower forecasting systems

| **Method** | **Forecast RMSE (%)** | **Real-Time Latency (s)** | **Efficiency Improvement (%)** |
| --- | --- | --- | --- |
| Statistical Regression | 9.8 | 3.6 | 4.2 |
| LSTM-Based Model | 6.4 | 2.4 | 8.7 |
| Proposed GAT–IoT System | 4.9 | 1.5 | 14.3 |

The results indicate that incorporating graph-based attention mechanisms significantly enhances the system’s ability to capture complex hydrological dependencies, leading to superior forecasting accuracy and operational efficiency.

The impact of the proposed system on long-term forecasting accuracy is illustrated in Figure 1, showing RMSE reduction over a 10-year forecast horizon.



**FIGURE 1.** Comparison of Long-Term Hydropower Efficiency Forecasting Accuracy Using LSTM and GAT Models

The results confirm that integrating Graph Attention Networks with IoT-based monitoring enables a holistic and adaptive approach to managing mountain hydropower resources. Unlike traditional sequence-based models, GAT effectively models spatial interdependencies among hydrological components, which is critical for multi-purpose hydroelectric complexes. The web-based architecture further ensures scalability, interoperability, and accessibility for operators and decision-makers. Overall, the proposed system demonstrates strong potential for improving sustainability, reliability, and efficiency of hydropower resource utilization under long-term operational uncertainty.

**CONCLUSIONS**

This study presents a comprehensive web-based intelligent system for the long-term forecasting and real-time monitoring of mountain river hydropower resources in multi-purpose hydroelectric complexes. By integrating Graph Attention Networks with IoT-driven data acquisition, the proposed framework effectively addresses the intrinsic spatial–temporal complexity and operational interdependencies characteristic of mountainous hydropower systems. Unlike conventional time-series–oriented approaches, the graph-based modeling paradigm enables adaptive learning of upstream–downstream hydraulic interactions and turbine-level dependencies, resulting in substantially improved long-term forecasting accuracy. The experimental results demonstrate that the proposed GAT-based forecasting model consistently outperforms traditional regression and LSTM-based methods, achieving notable reductions in MAE and RMSE across extended forecasting horizons. The integration of high-resolution IoT monitoring further enhances system observability, data reliability, and operational responsiveness, enabling near real-time assessment of hydropower efficiency and equipment condition. The web-based architecture ensures scalability, interoperability, and accessibility, facilitating informed decision-making for operators, planners, and policymakers.

From a practical perspective, the proposed system provides a robust digital decision-support tool for optimizing water–energy trade-offs, improving asset utilization, and mitigating operational risks under long-term hydrological uncertainty and climate variability. Moreover, the modular design allows seamless adaptation to different hydropower configurations and regional conditions, making the framework applicable beyond the studied case. Future research will focus on extending the model toward hybrid physics-informed graph learning, integrating climate scenario analysis, and enhancing automated control strategies to further strengthen the resilience and sustainability of multi-purpose hydropower systems in increasingly complex energy landscapes.

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