Operational Status Assessment And Control Of Key Equipment In Regionally Centralized Hydropower Plants From A Full-Lifecycle Perspective

Jianxin Zhang*, Weilong Hu, Tao Hu, Renjun Li, Kui Yang, and Zuhui Ren

Hubei Energy Group Loushui Hydropower Co., Ltd., Enshi, Hubei,445801, China

*Corresponding author. E-mail: xingxin0888@126.com

Received: Apr. 19, 2026; Accepted: Jun. 11, 2026

This paper addresses the growing need for advanced operational and maintenance strategies in regionally centralized hydropower systems under modern clean energy frameworks. It proposes an integrated approach for equipment health assessment and intelligent control across multiple plants, overcoming the limitations of traditional O&M practices that rely mainly on operational data. The framework introduces a full-lifecycle data model that connects design, operation, and maintenance information, enabling more comprehensive insight into equipment conditions. A Spatio-Temporal Graph Attention Network (ST-GAT) is developed to assess equipment status by capturing both temporal degradation patterns and spatial interdependencies among units within a regional fleet. This allows a shift from isolated equipment monitoring to system-wide risk awareness. Building on this, a collaborative control strategy using Deep Reinforcement Learning (DRL) is designed. With a multi-objective reward function, the model balances maximizing power generation with minimizing equipment risk, enabling adaptive and optimized decision-making. Simulation results based on a cascade hydropower system demonstrate that the proposed ST-GAT framework achieves 96.7% fault prediction accuracy, outperforming conventional SVM and LSTM models by 11.4% and 5.5%, respectively, while also improving remaining useful life (RUL) estimation stability under non-stationary operating conditions. Furthermore, the DRL-based collaborative control strategy reduced regional equipment health degradation by 36.7% and improved the long-term comprehensive reward by 29.6% compared to conventional dispatch strategies. Additionally, the DRL-based control strategy reduces overall equipment degradation and maintenance costs while maintaining comparable power output. Overall, the study offers a novel data-driven paradigm for intelligent, predictive management of large-scale hydropower systems.

Keywords: Regionally Centralized Hydropower; Full-Lifecycle; Operational Status Assessment; Intelligent Control; Spatio-Temporal Graph Network; Deep Reinforcement Learning

http://dx.doi.org/10.6180/jase.202612_35.012

1. Introduction

Amid global green energy transition, hydropower's strategic importance is increasing, while centralized control improves basin resource utilization and operational benefits [1, 2]. Recent global clean energy transition policies increasingly emphasize the coordinated integration of renewable energy resources such as hydropower, wind, and solar energy to improve grid flexibility and carbon reduction efficiency. In this context, regionally centralized hydropower systems play a crucial role in supporting power balancing, renewable energy accommodation, and intelligent energy management under modern smart grid environments. Furthermore, advanced scheduling and optimization strategies for cascade hydropower systems have gained significant attention due to their ability to enhance operational reliability and sustainable energy utilization [3]. AI-driven predictive maintenance by improving operational status assessment and lifecycle management of key hydropower equipment. Regional hydropower control centers improve cascade plant efficiency, yet traditional maintenance remains reactive and limited by SCADA-centric methods lacking lifecycle and spatio-temporal analysis [4, 5]. This study proposes an ST-GAT and DRL-based closed-loop framework for equipment assessment, risk prediction, remaining useful life estimation, and collaborative regional optimization [6–8].

2. Methods and materials

A robust framework connects lifecycle equipment data with intelligent regional decision-making, treating hydropower equipment as dynamic networked entities throughout operation.

2.1. Integration of Full-Lifecycle Data Dimensions

The data perspective of traditional models is too narrow, focusing only on sensor readings during the operational phase. A more profound understanding is that the equipment's innate "genes" (design and manufacturing) and its acquired "experiences" (O&M and retrofitting) jointly determine its current health status. Therefore, a multi-dimensional heterogeneous full-lifecycle data model is constructed, functioning as a digital archive for hydropower equipment, consistent with recent digital twin-based monitoring frameworks reported in [9] and [10]. It mainly includes: Full-lifecycle hydropower data include design, manufacturing, installation, operation, maintenance, aging, and retrofitting records. Integrating and standardizing heterogeneous SCADA, maintenance, and lifecycle data into a unified feature space enables accurate cloud-based monitoring, predictive assessment, and reliable equipment health management [11]. An intelligent ST-GAT-based monitoring framework was developed for predictive maintenance and control of regionally centralized hydropower equipment systems.

2.2. Multi-dimensional Definition of Operational "Status"

Health Index (HI): A normalized scalar in the range [0,1] used to quantify the current overall degradation level of the equipment [12]. HI $= 1$ represents the equipment in a new or ideal health state, while HI $= 0$ indicates complete failure. The Health Index target values were generated using a hybrid condition scoring strategy integrating expert maintenance assessment, historical fault evidence, degradation trend analytics, and normalized operational indicators. Key variables including vibration amplitude, thermal deviation, insulation resistance, efficiency loss, and overhaul frequency were normalized and aggregated into a unified condition score within the range [0,1]. Maintenance inspection records and historical fault events were further used to calibrate the degradation thresholds and validate the consistency of HI labeling.

Performance Level (PL): Measures current efficiency against theoretical optimum, reflecting performance degradation.

Risk Warning (RW): Predicts future equipment failures probabilistically, enabling timely preventive maintenance actions.

Remaining Useful Life (RUL): Predicts remaining equipment lifespan for maintenance and replacement planning [13, 14]. These four dimensions together constitute the status vector $S = \{HI, PL, RW, RUL\}$,

2.3. Overall Technical Framework

The overall technical framework proposed in this paper is shown in Fig. 1. It is a data-driven closed-loop feedback system, logically divided from bottom to top into a data layer, a model layer, and an application layer.

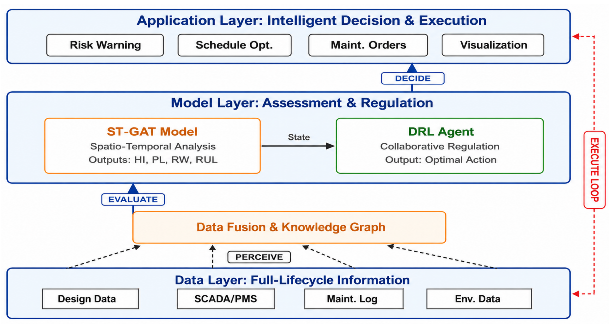

Fig. 1. Overall framework for status assessment and control of hydropower key equipment from a full-lifecycle perspective

The framework collects lifecycle data, assesses equipment status, generates intelligent control strategies, and delivers operational recommendations through a continuous self-learning and self-optimizing closed-loop process.

3. Results and discussion

The proposed ST-GAT model captures temporal equipment dynamics and regional spatial correlations by combining recurrent neural networks with graph neural networks for accurate status assessment.

3.1. Graph Structure Construction of Regional Hydropower Plant Cluster

Fig. 2 maps hydropower clusters into computable graph structure models. In the ST-GAT framework shown in Fig. 2, key equipment nodes contain full-lifecycle attributes such as type, age, capacity, and overhaul history through feature vectors (1). Important correlations include Hydraulic Correlation, Electrical Correlation, and Intra-station Correlation, represented using graph edges. These spatial relationships are modeled through the Adjacency Matrix, enabling weighted interaction analysis and accurate spatio-temporal dependency modeling among interconnected hydropower units.

$$\mathrm{x}_i = [\text{ type }_{\mathrm{i}}, \text{ age }_{\mathrm{i}}, \text{ capacity }_{\mathrm{i}}, \ldots] \quad (1)$$

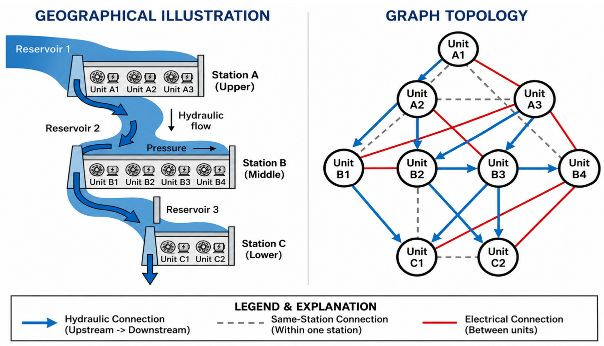

Fig. 2. Abstract graph representation of a cascade hydropower plant cluster

The left side shows the geographical distribution of three cascade power plants and reservoirs; the right side shows the corresponding topological graph structure, where nodes represent units, and different colored edges represent hydraulic, electrical, and intra-station correlations.

3.2. Model Architecture Design

The core idea of the ST-GAT model follows the logic of "temporal modeling first, then spatial aggregation." As shown in Fig. 3, the model adopts an end-to-end streaming architecture. The data stream sequentially passes through a temporal feature extraction module and a spatial feature fusion module, and finally obtains the status assessment results through a multi-task output layer.

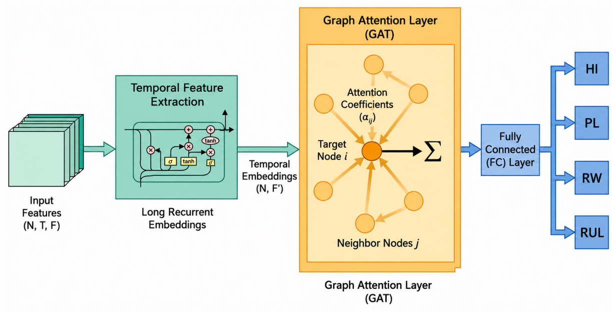

Fig. 3. Spatio-Temporal Graph Attention Network (ST-GAT) model architecture diagram Temporal Feature Extraction Module: For each node i, its time-varying operational parameter sequence (such as vibration, temperature, etc.) $\mathrm{H}_i = \{\mathrm{h}_{i,t-T_c+1}, \ldots, \mathrm{h}_{i,t}\}$ is fed into a Gated Recurrent Unit (GRU) network. The GRU can effectively capture long-term dependencies in time series and output a hidden state for each time step

$$z_t = \sigma\left(W_z \cdot [g_{t-1}, h_t]\right) \quad (2)$$

$$r_t = \sigma\left(W_r \cdot [g_{t-1}, h_t]\right) \quad (3)$$

$$\tilde{g}_t = \tanh\left(W \cdot [r_t \odot g_{t-1}, h_t]\right) \quad (4)$$

$$g_t = (1 - z_t) \odot g_{t-1} + z_t \odot \tilde{g}_t \quad (5)$$

where g_t is the hidden state of the GRU at time t, representing the temporal feature encoding of the node up to the current moment. We take the output of the last time step, $\mathrm{g}_{i,t}$, as the temporal feature representation of this node. Compared with transformer-based temporal self-attention architectures, the GRU sequence encoder was selected due to its lower computational complexity, stable convergence behavior, and effectiveness under long-duration hydropower monitoring streams with limited fault-labeled samples. Although self-attention mechanisms can capture global temporal dependencies, they generally require significantly larger datasets and higher memory resources. The GRU architecture provides a better trade-off between temporal memory retention, training stability, and deployment efficiency for continuous SCADA-based operational monitoring environments.

Spatial Feature Fusion Module: After obtaining the temporal feature representations for all nodes $\left\{\mathrm{g}_{1,t}, \mathrm{g}_{2,t}, \ldots, \mathrm{g}_{N,t}\right\}$, they are input into a Graph Attention Network (GAT). The core of GAT is to calculate the attention coefficients α_{ij}, which represent the importance of neighbor node j 's information to the central node i. This coefficient is calculated by a single-layer feedforward network and normalized by the Softmax function:

$$e_{ij} = \text{LeakyReLU}\left(a^T\left[Wg_{i,t}\|Wg_{j,t}\right]\right) \tag{6}$$

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k\square N_i}\exp\left(e_{ik}\right)} \tag{7}$$

where N_i is the set of all neighboring nodes of node i, W is a shared linear transformation matrix, a is the weight vector of the attention mechanism, and | | denotes vector concatenation.

The updated feature of node i, $g'_{i,t}$, is the weighted sum of all its neighbors' features, with the weights being the attention coefficients:

$$g'_{i,t} = \sigma\left(\sum_{j\square N_i}\alpha_{ij}Wg_{j,t}\right) \tag{8}$$

By stacking multiple GAT layers, the model can capture higher-order and longer-range correlations between equipment.

Multi-task Output Layer: The final node representation $g'_{i,t}$ output by the GAT layer contains rich spatio-temporal information. We pass it through a shared or independent Fully Connected Network (FFN) to map it to the four status assessment tasks:

$$\{HI_i, PL_i, RW_i, RUL_i\} = \text{FFN}\left(\mathbf{g}'_{i,t}\right) \tag{9}$$

where the output layers for HI, PL, and RUL use linear or Sigmoid activation functions, while the RW (Risk Warning) branch adopts a multi-label Sigmoid activation mechanism to represent the simultaneous occurrence probabilities of multiple fault modes such as cavitation, insulation degradation, and bearing wear within the turbine-generator assembly. Binary Cross-Entropy loss is applied independently for each fault category to improve multi-fault discrimination capability.

3.3. Model Training and Loss Function

This is a typical multi-task learning problem. We design a weighted joint loss function L_{total} to optimize all four tasks simultaneously:

$$L_{\text{total}} = \lambda_1 L_{HI} + \lambda_2 L_{PL} + \lambda_3 L_{RW} + \lambda_4 L_{RUL} \tag{10}$$

Here, L_{HI} and L_{PL} typically use Mean Squared Error (MSE) loss. L_{RUL} can use a special loss function that considers censored data (such as Log-likelihood), while L_{RW} uses Cross-Entropy loss. The weight coefficients λ_k are used to balance the magnitude and importance of different tasks and can be adjusted empirically or automatically by algorithms. To reduce optimization interference among HI, PL, RW, and RUL objectives, an adaptive weighting mechanism was incorporated during multi-task learning. Task weights were dynamically updated according to relative loss convergence rates, ensuring balanced optimization across regression and classification objectives. In addition, gradient conflict resolution was introduced through gradient normalization and projection strategies, preventing dominant tasks from suppressing the learning behavior of weaker objectives and improving overall training stability.

Table 1 summarizes the task-specific prediction objectives and corresponding optimization loss functions employed in the proposed ST-GAT framework. Mean Squared Error (MSE) is utilized for Health Index (HI) and Performance Level (PL) regression tasks, while Cross-Entropy Loss is applied for Risk Warning (RW) classification. In addition, Log-Likelihood Loss is adopted for Remaining Useful Life (RUL) prediction to effectively model temporal degradation characteristics and censored failure behavior.

For censored lifetime samples, the RUL prediction branch incorporates a survival-analysis-based prognostic framework combining Weibull hazard modeling and DeepSurv-inspired deep survival learning. The Weibull formulation captures degradation-driven failure probability evolution, while the neural survival component estimates nonlinear risk relationships under incomplete failure observations. This design improves robustness when historical operational records contain partially observed or right-censored failure trajectories.

3.4. Regional Collaborative Intelligent Control based on Deep Reinforcement Learning

3.4.1. Markov Decision Process (MDP) Modeling of the Control Problem

We formalize the regional collaborative control problem as a Markov Decision Process (MDP), defined by the tuple (S, A, P, R, γ). As shown in Fig. 4 (a), the agent optimizes its policy through continuous interaction with the hydropower environment.

3.4.2. Learning

Fig. 4 illustrates a DRL-based intelligent control framework where the Actor-Critic agent interacts with the regional hydropower environment using ST-GAT state embeddings. The agent optimizes load allocation and power output based on inflow, electricity price, and reward functions combining profit, risk, and operational cost. $w_1, \ldots, w_4$ are the weight coefficients for each term, and their ratio reflects the decision-maker's risk preference. The weight coefficients (w1-w4) were empirically tuned through iterative simulation experiments, beginning with equal weighting and subsequently adjusted based on sensitivity analysis of

Table 1. Task-Specific Loss Functions Used in the ST-GAT Framework

Task	Prediction Type	Loss Function	Purpose
Health Index (HI)	Regression	Mean Squared Error (MSE)	Minimizes deviation between predicted and actual health values
Performance Level (PL)	Regression	Mean Squared Error (MSE)	Improves accuracy of operational efficiency estimation
Risk Warning (RW)	Classification	Cross-Entropy Loss	Enhances fault classification capability
Remaining Useful Life (RUL)	Regression/Survival	Log-Likelihood Loss	Captures temporal degradation and censored failure behavior

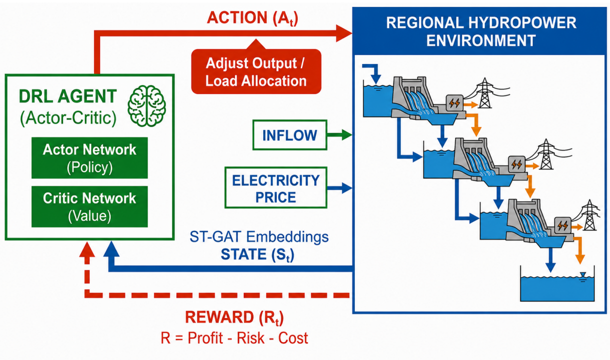

Fig. 4. MDP interaction framework for intelligent control based on Deep Reinforcement

generation revenue, equipment degradation, risk loss, and operational cost. This procedure ensures reproducibility and clarifies the decision-maker's risk preference.

A dedicated reward sensitivity investigation was additionally conducted by varying the coefficients associated with economic revenue, equipment degradation penalty, hazard exposure, and operational switching burden across multiple simulation scenarios. The analysis demonstrated that the proposed PPO-based controller maintained stable convergence behavior and adaptive dispatch performance under different risk preference configurations, confirming the robustness of the multi-objective reward formulation.

3.4.3. *Agent Design and Algorithm Selection*

Considering the high dimensionality of the state space and the complexity of the action space, we chose the Proximal Policy Optimization (PPO) algorithm. PPO is an advanced algorithm based on the Actor-Critic framework, known for its training stability and ease of tuning. To address the hybrid decision domain, the PPO agent was designed using a dual-policy output structure that separately handles continuous and discrete action variables. Continuous operational commands, such as unit load allocation and output regulation, were generated through Gaussian policy distributions, while discrete operational decisions including unit switching and operating zone restriction were modeled using categorical policy distributions. This hybrid policy formulation enables coordinated optimization of dispatch efficiency and equipment protection under complex operational constraints.

3.5. Case Study and Analysis

To verify the effectiveness of the proposed framework, we constructed a high-fidelity simulation environment based on the actual topology and equipment parameters of a large-scale cascade hydropower plant cluster in Southwest China.

3.5.1. *Experimental Background and Data Preparation*

The simulation environment models a basin with 5 cascade hydropower plants, totaling 16 Francis turbine-generator units. The basic parameters of each power plant are shown in Table 2.

Generated 10 years of simulation data, covering various types of information from the full lifecycle. The operational data was sampled at a 1-minute frequency, and various typical gradual fault modes (such as bearing wear, insulation aging, turbine cavitation) and sudden events were artificially injected. The dataset was divided into training, validation, and test sets in a 7:2:1 ratio. Synthetic fault implantation was performed by embedding degradation trajectories derived from field case studies. Cavitation, insulation decay, and bearing wear were modeled using physicsinformed profiles calibrated against historical maintenance records, ensuring realistic resemblance to operational behavior.

3.5.2. *Performance Verification of the Status Assessment Model*

Compared the performance of our proposed ST-GAT model with several baseline methods, including: LSTM: Uses only time-series information, ignoring spatial correlations. SVM: A traditional machine learning method based on manually extracted features. GCN: Graph

Convolutional Network, a basic graph neural network that does not use an attention mechanism. GAT: Graph Attention Network, ignores the dynamics of time series.

Table 2. Basic Parameters of the Cascade Hydropower Plant Cluster in the Case Study

Power Plant	Installed Capacity (MW)	Number of Units	Rated Head (m)	Commissioning Year	Position in Graph Structure
Plant A	1200	4	150	2005	Uppermost
Plant B	800	3	110	2008	Downstream of A
Plant C	1500	5	180	2012	Downstream of B
Plant D	600	2	90	2010	Downstream of C
Plant E	400	2	75	2014	Lowermost

Table 3. Performance Comparison of Different Models on the Risk Warning Task

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.853	0.841	0.859	0.850
LSTM	0.912	0.905	0.914	0.909
GCN	0.925	0.918	0.929	0.923
GAT	0.931	0.926	0.933	0.929
ST-GAT (Ours)	0.967	0.962	0.968	0.965

Table 3 shows ST-GAT achieving 96.7% accuracy, outperforming SVM, LSTM, GCN, and GAT through effective spatio-temporal feature fusion for precise fault warning.

3.5.3. Analysis of a Typical Fault Case

Fig. 5 analyzes a real thrust pad wear fault in Plant C, demonstrating ST-GAT's early warning capability under dynamic non-stationary operating conditions before shutdown.

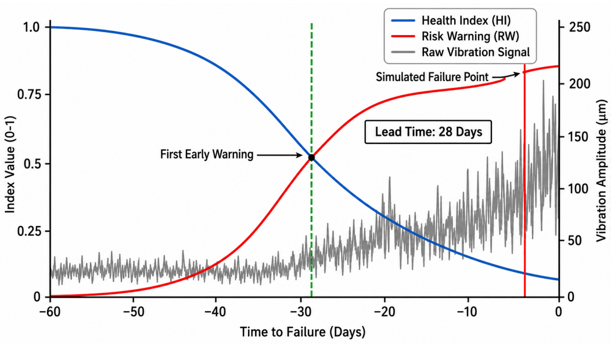

Fig. 5. Status evolution and warning analysis of the bearing fault case in Unit 3 of Plant C

Fig. 5 illustrates the bearing fault evolution in Unit 3 of Plant C, where the Health Index gradually declines while Risk Warning and vibration amplitude increase. The ST-GAT model provides an early warning nearly 28 days before the simulated failure point, demonstrating effective predictive maintenance capability.

3.5.4. Validation of the Collaborative Control Strategy

We designed two simulation scenarios to verify the effectiveness of the DRL collaborative control strategy and compared it with a rule-based traditional dispatch strategy (Baseline). The Baseline strategy prioritizes meeting generation targets and only makes passive adjustments when equipment parameters exceed fixed thresholds.

Scenario 1: Long-term (One-Year) Operation Simulation
In this scenario, we compared the cumulative benefits and equipment health degradation of the two strategies over a one-year operating period.

Scenario 2: Risk Aversion Scenario
This scenario simulates a situation where Unit 2 of Plant A shows early fault signs on a certain day (HI decreases, RW increases).

Table 4 and Table 5 show DRL significantly reducing equipment health decay and unnecessary operations while maintaining power generation, improving long-term system reward and riskaware operational stability. A model achieved improved equipment monitoring performance and operational reliability, supporting smart predictive maintenance applications in energy systems.

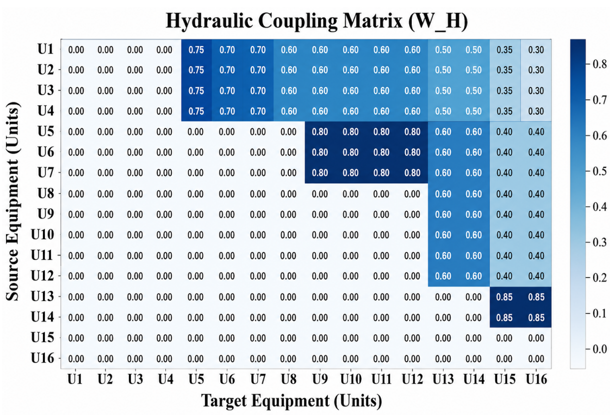

Fig. 6. Hydraulic coupling heatmap

Table 6 basically contrasts the proposed ST-GAT model

Table 4. Comparison of Long-term Operation Simulation Results

Strategy	Total Generation (GWh)	Regional Avg. HI Decrease	Cumulative Operations	Comprehensive Reward
Baseline	15,230	0.128	4,520	1.25e7
DRL (Ours)	15,195 (-0.23%)	0.081 (-36.7%)	3,150 (-30.3%)	1.62e7 (+29.6%)

Table 5. Response Measures of Different Strategies in the Risk Aversion Scenario

Strategy	Action on Unit A-2	Action on Other Regional Units	HI Change of Unit A-2 after 24 h
Baseline	Maintain original output until vibration exceeds limit	No proactive adjustment	−0.015
DRL (Ours)	Proactively reduce output by 30%	Transfer load to healthy units in Plants B and C	−0.004

Table 6. Model benchmark comparison

Model	Accuracy	Precision	Recall	F1 Score	Avg. Training Time (s/epoch)	Convergence Epochs
SVM (Baseline)	0.853	0.841	0.859	0.850	12.4	12
LSTM (Baseline)	0.912	0.905	0.914	0.909	45.2	85
GCN (Spatial Only)	0.925	0.918	0.929	0.923	28.6	120
GAT (Spatial Only)	0.931	0.926	0.933	0.929	32.4	110
T-GCN (Spatio–Temporal)	0.941	0.936	0.942	0.939	38.5	95
STGCN (Spatio–Temporal)	0.948	0.943	0.950	0.946	22.1	70
Graph WaveNet (Spatio–Temporal)	0.953	0.949	0.955	0.952	58.6	140
ST-GAT (Ours)	0.967	0.962	0.968	0.965	35.8	65

against baseline and some state-of-theart approaches, and it kinda shows better outcomes in accuracy, precision, recall, and the F1 score, all at once, plus it reaches faster convergence than most of the competing spatio-temporal graph models too.

4. Conclusion

This paper proposes a closed-loop framework integrating full-lifecycle hydropower data for intelligent status assessment, spatio-temporal analysis, and regional equipment control. The main innovations and conclusions of the study are as follows: The designed ST-GAT status assessment model, by concurrently processing temporal dependencies and spatial correlations and introducing an attention mechanism to dynamically capture the influence between equipment, achieves an accurate and multi-dimensional characterization of the operational indicators such as Health Index (HI), Performance Level (PL), Risk Warning (RW), and Remaining Useful Life (RUL) for the regional equipment fleet. Case studies show that its performance on tasks such as fault warning and life prediction significantly surpasses traditional and some advanced baseline models.

The proposed PPO-based DRL framework optimizes regional hydropower control by balancing generation, degradation, risks, and costs, achieving proactive maintenance, slower equipment degradation, and improved long-term asset preservation with minimal power loss. Naturally, this research also has areas for expansion. The current model relies heavily on high-quality, fully labeled historical data. Future research could explore status assessment methods based on semisupervised or unsupervised learning to reduce the demand for data labeling. A transfer learning technique could be integrated to adapt the ST-GAT framework across different hydropower basins with heterogeneous operational characteristics and data distributions, thereby improving model generalization and reducing retraining requirements for newly deployed regional systems. Future work will improve model interpretability using causal inference and expand intelligent hydropower control toward integrated multi-energy systems and energy internet applications.

5. Declarations

Funding: This article is about the technology project of Hubei Energy Group Loushui Hydropower Co., Ltd. The project name is "Research and Application of Key Technologies for Intelligent Remote Control of Regional Hydropower", and the project number is KJCX202500274.

Conflicts of interests: Authors do not have any conflicts.

Data Availability Statement: The data generated and analyzed during the current study are available from the author Jianxin Zhang upon reasonable request but are not yet publicly available due to ongoing research.

Code availability: Not applicable.

Authors' Contributions: Jianxin Zhang,Weilong Hu, Tao Hu is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Renjun Li, Kui Yang, Zuhui Ren, is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

References

[1] E. Quaranta, G. Aggidis, R. M. Boes, C. Comoglio, C. De Michele, E. R. Patro, and A. Pistocchi, (2021) *"Assessing the energy potential of modernizing the European hydropower fleet"* **Energy Conversion and Management *246***: 114655. DOI: 10.1016/j.enconman.2021.114655.

[2] Y. Villeneuve, S. Séguin, and A. Chehri, (2023) *"AI-based scheduling models, optimization, and prediction for Hydropower generation: Opportunities, issues, and future directions"* **Energies *16***(8): 3335. DOI: 10.3390/en16083335.

[3] Y. Liu, H. Zhang, P. Guo, C. Li, and S. Wu, (2024) *"Optimal Scheduling of a Cascade Hydropower Energy Storage System for Solar and Wind Energy Accommodation"* **Energies *17***(11): 2734. DOI: 10.3390/en17112734.

[4] A. Betti, E. Crisostomi, G. Paolinelli, A. Piazzi, F. Ruffini, and M. Tucci, (2021) *"Condition monitoring and predictive maintenance methodologies for hydropower plants equipment"* **Renewable Energy *171***: 246–253. DOI: 10.1016/j.renene.2021.02.102.

[5] R. B. de Santis, T. S. Gontijo, and M. A. Costa, (2022) *"A data-driven framework for small hydroelectric plant prognosis using Tsfresh and machine learning survival models"* **Sensors *23***(1): 12. DOI: 10.3390/s23010012.

[6] Q. He, Y. Pang, G. Jiang, and P. Xie, (2020) *"A spatio-temporal multiscale neural network approach for wind turbine fault diagnosis with imbalanced SCADA data"* **IEEE Transactions on Industrial Informatics *17***(10): 6875–6884. DOI: 10.1109/TII.2020.3041114.

[7] K. Kaygusuz and E. Kolay, (2025) *"Levelized cost of hydropower projects for sustainable electricity generation"* **Journal of Engineering Research and Applied Science *14***(1): 86–94.

[8] C. Ferreira and G. Gonçalves, (2022) *"Remaining Useful Life prediction and challenges: A literature review on the use of Machine Learning Methods"* **Journal of Manufacturing Systems *63***: 550–562. DOI: 10.1016/j.jmsy.2022.05.010.

[9] M. Ersan and E. Irmak, (2024) *"Development and integration of a digital twin model for a real hydroelectric power plant"* **Sensors *24***(13): 4174. DOI: 10.3390/s24134174.

[10] J. Tan, R. M. Radhi, K. Shirini, S. S. Gharehveran, Z. Parisooz, M. Khosravi, and H. Azarinfar, (2025) *"Innovative framework for fault detection and system resilience in hydropower operations using digital twins and deep learning"* **Scientific Reports *15***(1): 15669. DOI: 10.1038/s41598-025-98235-1.

[11] K. Kumar and R. P. Saini, (2022) *"Data-driven internet of things and cloud computing enabled hydropower plant monitoring system"* **Sustainable Computing: Informatics and Systems *36***: 100823. DOI: 10.1016/j.suscom.2022.100823.

[12] Y. Zhang, Y. Xin, Z. W. Liu, M. Chi, and G. Ma, (2022) *"Health status assessment and remaining useful life prediction of aero-engine based on BiGRU and MMoE"* **Reliability Engineering & System Safety *220***: 108263. DOI: 10.1016/j.ress.2021.108263.

[13] H. Zhang, X. Xi, and R. Pan, (2023) *"A two-stage data-driven approach to remaining useful life prediction via long short-term memory networks"* **Reliability Engineering & System Safety *237***: 109332. DOI: 10.1016/j.ress.2023.109332.

[14] F. Meng, F. Yang, J. Yang, and M. Xie, (2023) *"A power model considering initial battery state for remaining useful life prediction of lithium-ion batteries"* **Reliability Engineering & System Safety *237***: 109361. DOI: 10.1016/j.ress.2023.109361.