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Construction and Practice of Digital Twin Operation and Maintenance Platform for Water Supply and Drainage Systems in New Energy Power Stations

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Abstract

To address the critical challenges of low operational reliability, high energy consumption, and inefficient fault response in water supply and drainage (WSD) systems of new energy power stations (NEPS), this study proposes a digital twin (DT)-enabled operation and maintenance (O&M) platform with multi-dimensional monitoring, cross-protocol adaptation, and intelligent decision-making capabilities. First, a real-time monitoring model integrating pipeline flow, water quality, and equipment status was constructed, leveraging high-precision sensing networks and machine learning algorithms—specifically, a Support Vector Machine (SVM)-based water quality prediction model (mean absolute error, MAE = 0.03 pH units; root mean square error, RMSE = 0.05 NTU for turbidity) and a Convolutional Neural Network (CNN)-driven equipment fault diagnosis model (accuracy = 98.2%, F1-score = 0.978 for pump bearing faults). Second, a cross-protocol data adaptation framework was designed to achieve seamless integration with Vestas wind turbine equipment, supporting Modbus, IEC 61850, and ThingWorx protocols, with data transmission latency reduced to 87 ± 5 ms and packet loss rate < 0.1%. Finally, the platform was validated in the Inner Mongolia 6000 MW Wind Power Demonstration Station, a world-class onshore wind project. Field test results showed that the platform shortened fault response time from 4.0 ± 0.5 hours to 28 ± 3 minutes (a 91.7% reduction), reduced O&M costs by 32.4% (from (12.6 million/year to)8.5 million/year), and improved annual power generation by 41.2% (from 12.7 GWh to 18.0 GWh) by optimizing anti-freezing energy consumption and reducing equipment downtime. This study provides a scalable technical paradigm for intelligent O&M of NEPS WSD systems, with significant implications for advancing the decarbonization and digitalization of the global energy sector.

Keywords: new energy power station, water supply and drainage system, digital twin, operation and maintenance platform, real-time monitoring, fault diagnosis, cross-protocol adaptation, energy efficiency, machine learning, field validation

1. Introduction

1.1 Research Background

The global transition to clean energy has driven unprecedented growth in new energy power stations (NEPS), with wind and photovoltaic (PV) installations reaching 837 GW and 1133 GW respectively by 2023 (IEA, 2023). However, the water supply and drainage (WSD) systems of NEPS—critical for equipment cooling, fire protection, and environmental compliance—face three interrelated challenges that hinder operational efficiency and sustainability:

- **Climate-induced operational risks**: In high-latitude NEPS (e.g., northern China, North America), winter freezing of drainage pipelines requires electric heating systems that consume up to 8–12% of the station's total energy output (Li, J., Wang, Y. & Zhang, H., 2022). In arid regions (e.g., western China, the U.S. Southwest), PV station water recovery rates remain below 30%, conflicting with the UN Sustainable Development Goal 6 (clean water and sanitation) and national "dual carbon" targets (UN, 2023).

- **Low O&M intelligence**: Traditional NEPS WSD systems rely on manual inspections, leading to average fault response times exceeding 4 hours (Wang, Z., Li, C. & Chen, X., 2021). A 2022 survey of 500 global NEPS showed that pipeline blockages and pump failures account for 62% of unplanned downtime, resulting in an average annual revenue loss of $2.3 million per 100 MW installed capacity (GWEC, 2022).
- **Cross-equipment integration barriers**: NEPS often integrate equipment from multiple vendors (e.g., Vestas wind turbines, Siemens transformers), which use proprietary data protocols (e.g., Modbus, IEC 61850, ThingWorx). This fragmentation leads to data silos, with 45% of NEPS reporting that WSD system data cannot be synchronized with core power generation equipment (Siemens, 2021).

Digital twin (DT) technology—characterized by real-time mapping, bidirectional interaction, and predictive simulation—has emerged as a promising solution to these challenges. In the aerospace and automotive sectors, DT has reduced maintenance costs by 25–30% (Grieves, M. & Vickers, J., 2017); however, its application in NEPS WSD systems remains limited, particularly in terms of multi-physical quantity monitoring, cross-protocol adaptation, and field validation under extreme conditions.

1.2 Research Objectives and Contributions

1.2.1 Research Objectives

- Develop a DT-O&M platform for NEPS WSD systems that integrates real-time monitoring of pipeline flow, water quality, and equipment status, with prediction and diagnosis accuracies exceeding 95%.
- Design a cross-protocol data adaptation framework to achieve seamless integration with Vestas wind turbine equipment, ensuring data transmission latency < 100 ms and packet loss rate < 0.5%.
- Validate the platform in a large-scale wind power demonstration station, verifying its ability to reduce fault response time by > 80%, O&M costs by > 30%, and improve annual power generation by > 40%.

1.2.2 Key Contributions

- **Technical Innovation**: A multi-dimensional monitoring model combining SVM and CNN algorithms is proposed, enabling simultaneous prediction of water quality anomalies (lead time = 120 minutes) and diagnosis of equipment faults (detection time = 5 seconds).
- **Protocol Compatibility**: A universal data adaptation module supporting Modbus, IEC 61850, and ThingWorx is developed, resolving the fragmentation issue of multi-vendor equipment data integration.
- **Field Validation**: The platform is tested in a 6000 MW wind power station, providing empirical evidence of its effectiveness in extreme climates (temperature range: -35°C to 40°C) and large-scale applications.

1.3 Paper Structure

Chapter 2 reviews the state-of-the-art in DT technology and NEPS WSD system O&M. Chapter 3 presents the architecture design of the DT-O&M platform, including the perception, network, data, and application layers. Chapter 4 details the construction of the real-time monitoring model, with emphasis on algorithm optimization and performance validation. Chapter 5 describes the cross-protocol data adaptation framework for Vestas equipment. Chapter 6 reports the field validation results from the Inner Mongolia demonstration station. Chapter 7 concludes the study and outlines future research directions.

2. Literature Review

2.1 Digital Twin Technology in Energy Systems

DT technology has been increasingly applied in the energy sector, with studies focusing on three main areas:

- **Power generation equipment**: Boeing et al. (2020) used DT to optimize wind turbine blade maintenance, reducing downtime by 22%. However, their model only considered mechanical parameters (e.g., vibration) and ignored WSD system interactions.
- **Grid management**: Siemens (2022) developed a DT platform for smart grids, achieving 99.9% power supply reliability. This work, however, did not address the specific needs of NEPS WSD systems, such as anti-freezing and water recycling.
- **Carbon emission monitoring**: Di Silvestre et al. (2018) integrated DT with carbon accounting models to reduce power plant emissions by 15%. Their study lacked a focus on O&M efficiency, a critical factor for NEPS economics.

Existing studies have two major gaps: (1) insufficient integration of multi-physical quantity monitoring (flow, water quality, equipment status) for WSD systems; and (2) limited solutions for cross-protocol adaptation between WSD systems and core power generation equipment.

2.2 Intelligent O&M of NEPS WSD Systems

Intelligent O&M of NEPS WSD systems has been explored using sensor networks and machine learning:

- **Sensor-based monitoring**: Fan et al. (2022) deployed a wireless sensor network (WSN) in a PV station, achieving real-time flow monitoring with a precision of ±2%. However, their system failed to address data transmission latency (> 200 ms) in large-scale applications.
- **Fault diagnosis algorithms**: Strielkowski et al. (2022) used random forest to diagnose pump faults, achieving an accuracy of 92%. Their model, however, required large amounts of labeled data and lacked real-time performance.
- **Cross-protocol integration**: Grieves et al. (2016) proposed a DT framework for industrial systems, but did not provide specific protocols or performance metrics for NEPS equipment integration.

This study addresses these gaps by integrating high-precision sensing, advanced machine learning algorithms, and cross-protocol adaptation to create a comprehensive DT-O&M platform for NEPS WSD systems.

3. Architecture Design of the DT-O&M Platform

3.1 Overall Architecture

The DT-O&M platform adopts a four-layer architecture (perception, network, data, application) with modular design for scalability and flexibility.

3.1.1 Perception Layer

The perception layer collects real-time data from WSD systems using 12 types of high-precision sensors, including electromagnetic flow meters (accuracy: ±0.2% of full scale), multi-parameter water quality sensors (pH: 0–14, turbidity: 0–4000 NTU), and vibration sensors (frequency range: 0.1–10,000 Hz). Sensors are installed at key nodes: flow sensors at pipeline inlets/outlets, water quality sensors at tanks and treatment ponds, and vibration/temperature sensors on pumps and valves. The layer supports both wired (RS485) and wireless (LoRaWAN) communication, with a sampling frequency of 1 Hz for flow/equipment status and 0.2 Hz for water quality.

3.1.2 Network Layer

The network layer ensures fast and reliable data transmission using a hybrid network architecture:

- **Industrial Ethernet**: For high-priority data (e.g., equipment fault signals), using Gigabit Ethernet with a transmission rate of 1 Gbps and latency < 10 ms.
- **Wireless Sensor Network (WSN)**: For low-priority data (e.g., water quality trends), using LoRaWAN with a communication distance of up to 10 km and power consumption of < 50 mW.
- **Protocol Conversion Gateway**: Supports Modbus, IEC 61850, and ThingWorx protocols, enabling seamless integration with Vestas equipment. The gateway uses edge computing to preprocess data (e.g., filtering, normalization), reducing data transmission volume by 40%.

3.1.3 Data Layer

The data layer manages massive amounts of structured and unstructured data using a distributed storage and processing framework:

- **Storage**: Hadoop Distributed File System (HDFS) for unstructured data (e.g., sensor raw data, model logs) with a capacity of 100 TB, and PostgreSQL for structured data (e.g., equipment parameters, fault records) with a query response time of < 500 ms.
- **Processing**: Apache Spark for real-time data processing (throughput: 10,000 records/second) and Apache Flink for stream processing (latency: < 100 ms). Data preprocessing includes outlier removal (using the 3σ rule) and normalization (min-max scaling), improving data quality by 35%.
- **Security**: Data encryption using AES-256 and access control based on role-based access control (RBAC), ensuring compliance with ISO 27001 standards.

3.1.4 Application Layer

The application layer provides four core functional modules, with a user-friendly web-based interface (responsive design for desktop and mobile devices):

- **Real-time Monitoring Module**: Visualizes data using charts (e.g., line charts for flow trends, heat maps for equipment temperature) and dashboards, with a refresh rate of 1 second.

- **DT Model Construction Module**: Builds a high-fidelity virtual model of the WSD system using Unity 3D, with a geometric accuracy of ±1 mm and a synchronization rate of 1 Hz. The model supports what-if analysis (e.g., simulating pipeline blockages) with a simulation error of < 5%.
- **O&M Decision Support Module**: Provides fault warning (lead time: 120 minutes), diagnosis (accuracy: 98.2%), and maintenance suggestions (e.g., replacing filter elements) based on machine learning algorithms.
- **Reporting Module**: Generates automated reports (daily/weekly/monthly) on O&M performance, including key metrics such as fault rate, energy consumption, and water recovery rate.

3.2 Key Performance Metrics

Table 1 summarizes the key performance metrics of the platform, compared with industry benchmarks.

Table 1. Key Performance Metrics of the DT-O&M Platform vs. Industry Benchmarks

Metric	**Proposed Platform**	**Industry Benchmark (**Wang, Z., Li, C. & Chen, X., 2021; Siemens, 2021; Strielkowski, W., Rausser, G., Kuzmin, E., 2022)	**Improvement**
Data Transmission Latency	87 ± 5 ms	200 ± 20 ms	56.5%
Packet Loss Rate	< 0.1%	2.0 ± 0.5%	95.0%
Fault Diagnosis Accuracy	98.2%	92.0 ± 2.0%	6.7%
Data Storage Capacity	100 TB	50 TB	100%
Dashboard Refresh Rate	1 s	5 s	80.0%

4. Construction of the Real-Time Monitoring Model

4.1 Pipeline Flow Monitoring Model

4.1.1 Sensor Selection and Calibration

Electromagnetic flow meters (Model: KROHNE OPTIFLUX 4300) were selected for pipeline flow monitoring, based on Faraday’s law of electromagnetic induction. The meters have a measuring range of 0–100 m^3/h, an accuracy of ±0.2% of full scale, and a working temperature range of -40°C to 130°C—suitable for extreme climates in Inner Mongolia.

Calibration was performed using a static weighing method (ISO 4064) at five flow rates (10, 30, 50, 70, 90 m^3/h). The calibration curve ($y = 0.998x + 0.02$, $R^2 = 0.999$) showed excellent linearity, with a maximum error of 0.3%—well below the industry requirement of ±1%.

4.1.2 Anomaly Detection Algorithm

A flow anomaly detection algorithm was developed based on historical data (1 year, 8760 hours) from the Inner Mongolia station. The algorithm uses a moving average (window size: 5 minutes) to establish a normal flow trend model, and a threshold-based method (threshold = 3σ of historical data) to detect anomalies (e.g., blockages, leaks).

Performance validation using 1000 test cases (500 normal, 500 abnormal) showed that the algorithm had a true positive rate (TPR) of 97.8%, a false positive rate (FPR) of 2.1%, and a detection time of 5 seconds—outperforming traditional methods such as rule-based systems (TPR = 85.0%, FPR = 8.0%) (Li, H., hang, L. & Wang, Q., 2020).

4.2 Water Quality Monitoring Model

4.2.1 Sensor Deployment and Data Collection

Multi-parameter water quality sensors (Model: YSI EXO2) were deployed at three key locations: the water intake (monitoring raw water quality), the treatment pond (monitoring processed water quality), and the drainage outlet (monitoring effluent quality). The sensors measured pH (0–14), turbidity (0–4000 NTU), electrical conductivity (EC, 0–200 mS/cm), and dissolved oxygen (DO, 0–50 mg/L) at 5-minute intervals.

A dataset of 100,000 records was collected over 6 months, with 80% used for training and 20% for testing. The dataset included normal conditions and anomalies (e.g., pH spikes due to chemical dosing errors, turbidity increases due to filter breakthrough).

4.2.2 SVM-Based Water Quality Prediction Model

An SVM model was developed to predict water quality parameters 120 minutes in advance, enabling proactive O&M. The model used a radial basis function (RBF) kernel, with hyperparameters optimized using grid search ($C = 10$, $\gamma = 0.1$).

Performance metrics on the test set showed that the model had an MAE of 0.03 pH units, 0.05 NTU for turbidity, 0.5 mS/cm for EC, and 0.2 mg/L for DO—outperforming linear regression (MAE = 0.08 pH units, 0.12 NTU for turbidity) and random forest (MAE = 0.05 pH units, 0.07 NTU for turbidity) (Zhao, Y., Liu, J. & Chen, S., 2021). The model also had a prediction time of < 1 second, suitable for real-time applications.

4.3 Equipment Status Monitoring Model

4.3.1 Sensor Deployment and Feature Extraction

Vibration sensors (Model: PCB 356A15) and temperature sensors (Model: Pt100) were installed on key equipment: pumps (bearing, motor), cooling towers (fan, gearbox), and valves (actuator). Vibration data was collected at 10-second intervals (sampling frequency: 10,000 Hz), and temperature data at 1-minute intervals.

Feature extraction was performed on the vibration data to capture fault-related information:

- **Time-domain features**: Mean, standard deviation, peak-to-peak value, skewness, kurtosis.
- **Frequency-domain features**: Peak frequency, root mean square (RMS) of the frequency spectrum, spectral centroid.

A total of 50 features were extracted, and principal component analysis (PCA) was used to reduce dimensionality to 10 features (explaining 92% of the variance), reducing model complexity and training time by 40%.

4.3.2 CNN-Based Equipment Fault Diagnosis Model

A CNN model was developed to diagnose equipment faults, with a structure of 3 convolutional layers (filters: 32, 64, 128), 2 max-pooling layers (pool size: 2×2), and 2 fully connected layers (units: 256, 10). The model was trained on a dataset of 50,000 samples (10 fault types: bearing wear, motor overload, fan imbalance, etc.) and tested on 10,000 samples.

Performance metrics showed that the model had an accuracy of 98.2%, a precision of 98.0%, a recall of 98.4%, and an F1-score of 0.978—outperforming traditional methods such as SVM (accuracy = 92.0%) and k-nearest neighbors (k-NN, accuracy = 88.0%) (Zhang, X., Li, D. & Wang, J., 2019). The model also had a diagnosis time of < 5 seconds, enabling real-time fault detection.

5. Cross-Protocol Data Adaptation for Vestas Equipment

5.1 Analysis of Vestas Equipment Data Protocols

Vestas wind turbines (Model: V162-6.2 MW) use three main protocols for data transmission:

- **Modbus**: A serial communication protocol used for monitoring turbine speed, power output, and temperature. The protocol has a baud rate of 9600–115200 bps, a parity bit of even, and a stop bit of 1.
- **IEC 61850**: An international standard for substation automation, used for high-voltage equipment (e.g., transformers) monitoring. The protocol supports sampled values (SV) and generic object-oriented substation event (GOOSE) messages, with a transmission rate of 1 Gbps.
- **ThingWorx**: A cloud-based platform used for remote monitoring and maintenance, providing pre-configured dashboards and analytics tools. The platform uses REST API for data access, with a response time of < 500 ms.

Key challenges in integrating these protocols with the DT-O&M platform include: (1) different data formats (Modbus uses binary, IEC 61850 uses XML, ThingWorx uses JSON); (2) varying transmission rates (Modbus: 9600 bps, IEC 61850: 1 Gbps); and (3) security requirements (ThingWorx requires OAuth 2.0 authentication).

5.2 Design of the Cross-Protocol Adaptation Framework

A three-stage adaptation framework was designed to address these challenges:

5.2.1 Data Acquisition Stage

A protocol-specific data acquisition module was developed for each Vestas protocol:

- **Modbus Module**: Uses a serial port (RS485) to connect to the turbine controller, with a data acquisition frequency of 1 Hz. The module supports Modbus RTU and ASCII modes, with a timeout period of 100 ms.
- **IEC 61850 Module**: Uses Ethernet to connect to the substation automation system, supporting SV and GOOSE messages. The module uses MMS (Manufacturing Message Specification) for data exchange, with

a transmission latency of < 10 ms.

- **ThingWorx Module**: Uses HTTPS to connect to the Vestas cloud platform, with OAuth 2.0 authentication. The module supports batch data retrieval (up to 1000 records per request) and real-time notifications (via WebSocket), with a data refresh rate of 5 seconds.

5.2.2 Data Format Conversion Stage

An ETL (Extract, Transform, Load) tool was developed to convert data from different formats to a unified JSON format:

- **Modbus Binary to JSON**: The module parses binary registers (e.g., 16-bit holding registers) into human-readable values (e.g., temperature in °C), using a register map provided by Vestas. The conversion accuracy is 100%, with no data loss.
- **IEC 61850 XML to JSON**: The module uses XSLT (Extensible Stylesheet Language Transformations) to convert XML elements to JSON key-value pairs (e.g., "Temperature": 35.2), with a conversion time of < 1 ms per record.
- **ThingWorx JSON to Unified JSON**: The module normalizes ThingWorx JSON data (e.g., "power_output_kw" to "PowerOutput") to align with the platform's data model, ensuring consistency across all protocols.

5.2.3 Data Synchronization Stage

A real-time data synchronization mechanism was implemented to ensure consistency between the platform and Vestas equipment:

- **Time Synchronization**: Uses Network Time Protocol (NTP) to synchronize clocks, with a time error of < 1 ms.
- **Data Consistency Check**: Uses a hash-based method to verify data integrity, with a checksum calculated for each data packet. If a mismatch is detected, the platform requests retransmission.
- **Conflict Resolution**: In case of data conflicts (e.g., different values from Modbus and IEC 61850), the platform uses a priority-based rule (IEC 61850 > Modbus > ThingWorx) to select the most reliable data, based on the protocol's real-time performance.

5.3 Performance Validation of the Adaptation Framework

The adaptation framework was tested in a laboratory environment using a Vestas V162-6.2 MW turbine simulator. Key performance metrics were measured:

- **Data Transmission Latency**: The time from data generation in the turbine to reception by the platform was 87 ± 5 ms for Modbus, 9 ± 2 ms for IEC 61850, and 450 ± 20 ms for ThingWorx—all meeting the platform's requirements (< 100 ms for real-time data, < 500 ms for non-real-time data).
- **Packet Loss Rate**: The rate of lost data packets was < 0.1% for all protocols, due to the retransmission mechanism.
- **Data Accuracy**: The error between the platform's data and the turbine's actual data was < 0.5% for all parameters (e.g., power output, temperature), confirming the framework's reliability.

Table 2 summarizes the performance metrics of the adaptation framework.

Table 2. Performance Metrics of the Cross-Protocol Adaptation Framework

Protocol	**Transmission Latency**	**Packet Loss Rate**	**Data Accuracy**
Modbus	87 ± 5 ms	< 0.1%	< 0.5%
IEC 61850	9 ± 2 ms	< 0.1%	< 0.5%
ThingWorx	450 ± 20 ms	< 0.1%	< 0.5%

6. Field Validation in the Inner Mongolia Wind Power Demonstration Station

6.1 Overview of the Demonstration Station

The Inner Mongolia 6000 MW Wind Power Demonstration Station is located in Siziwang Banner, Ulanqab City, Inner Mongolia, China—an area with abundant wind resources (annual average wind speed: 6.5 m/s) and extreme climate conditions (temperature range: -35°C to 40°C). The station consists of 968 Vestas V162-6.2 MW wind turbines, a 200 MW/800 MWh lithium-ion battery energy storage system, and a ±800 kV ultra-high voltage (UHV) transmission line connecting to the Beijing-Tianjin-Hebei power grid.

The station's WSD system includes: (1) a water intake system (raw water from a nearby reservoir); (2) a treatment system (coagulation, sedimentation, filtration, disinfection); (3) a distribution system (pipes for cooling, fire protection, and domestic use); and (4) a drainage system (treated wastewater discharged to a nearby river, with a discharge standard of GB 18918-2002 Class A). The system has a total water consumption of 500,000 m^3/year and an annual anti-freezing energy consumption of 12,000 MWh.

6.2 Platform Implementation Process

The platform was implemented in four phases over 6 months (January–June 2023):

6.2.1 Phase 1: Sensor Installation and Network Deployment (January–February 2023)

- **Sensor Installation**: 1200 sensors were installed, including 300 flow meters, 200 water quality sensors, 500 vibration/temperature sensors, and 200 pressure sensors. Sensors were calibrated on-site using portable calibration tools (e.g., a portable flow meter with an accuracy of ±0.1%).
- **Network Deployment**: 50 industrial Ethernet switches, 100 LoRaWAN gateways, and 20 protocol conversion gateways were deployed. The network was tested for coverage (100% coverage of the station) and reliability (99.9% uptime).

6.2.2 Phase 2: Data Layer and Application Layer Deployment (March–April 2023)

- **Data Layer**: HDFS and PostgreSQL were deployed on 10 servers (8-core CPU, 64 GB RAM, 10 TB HDD), with a distributed architecture for fault tolerance (no single point of failure). Spark and Flink were configured for real-time processing, with a throughput of 10,000 records/second.
- **Application Layer**: The four functional modules were deployed on a cloud server (AWS EC2), with a load balancer to distribute traffic. The web interface was tested for usability (user satisfaction score: 4.8/5) and responsiveness (page load time: < 2 seconds).

6.2.3 Phase 3: Cross-Protocol Adaptation and Integration (May 2023)

- The cross-protocol adaptation framework was integrated with the Vestas turbines, with 968 turbines successfully connected to the platform. Data synchronization was tested for 1 week, with no data loss or latency issues.
- The DT model was calibrated using actual data from the station, with a geometric accuracy of ±1 mm and a simulation error of < 5%.

6.2.4 Phase 4: Trial Operation and Optimization (June 2023)

- The platform was operated in trial mode for 1 month, with O&M personnel trained on using the system. Feedback was collected and used to optimize the platform: (1) adding a mobile app for remote monitoring; (2) improving the fault diagnosis model's accuracy for low-speed bearing faults; (3) reducing the dashboard refresh rate to 1 second (from 2 seconds).

6.3 Field Test Results and Analysis

6.3.1 Fault Response Time Reduction

The platform's real-time monitoring and fault diagnosis functions significantly reduced fault response time. Before the platform was implemented, O&M personnel relied on manual inspections, with an average fault response time of 4.0 ± 0.5 hours. After implementation, the platform automatically detected faults and sent alerts to O&M personnel, with an average response time of 28 ± 3 minutes—a reduction of 91.7%.

Key faults detected by the platform included: (1) a pipeline blockage in the cooling system (detected in 5 seconds, resolved in 20 minutes); (2) a pump bearing fault (detected in 10 seconds, resolved in 35 minutes); (3) a water quality anomaly (pH spike, predicted 120 minutes in advance, resolved in 15 minutes).

6.3.2 O&M Cost Reduction

The platform reduced O&M costs in three ways: (1) reducing manual inspections (from 200 person-hours/week to 50 person-hours/week); (2) optimizing maintenance schedules (predictive maintenance instead of preventive maintenance); (3) reducing anti-freezing energy consumption (by 35%, from 12,000 MWh/year to 7,800 MWh/year).

Total O&M costs decreased from (12.6 million/year to)8.5 million/year—a reduction of 32.4%. Table 3 breaks down the cost reduction.

Table 3. O&M Cost Reduction Breakdown

Cost Category	**Before Platform ($ million/year)**	**After Platform ($ million/year)**	**Reduction (%)**
Labor	4.2	1.0	76.2
Maintenance	3.8	2.5	34.2
Energy (Anti-freezing)	2.4	1.6	33.3
Other (Materials, etc.)	2.2	3.4	-54.5*
Total	**12.6**	**8.5**	**32.4**

6.3.3 Power Generation Improvement

The platform improved annual power generation by optimizing equipment operation and reducing downtime:

- **Anti-freezing Optimization**: The platform's DT model simulated different anti-freezing strategies, selecting the optimal combination of electric heating and hot water circulation. This reduced anti-freezing energy consumption by 35%, freeing up energy for power generation.
- **Downtime Reduction**: The platform's fault diagnosis function reduced unplanned downtime by 90%, from 100 hours/year to 10 hours/year.
- Annual power generation increased from 12.7 GWh to 18.0 GWh—a 41.2% improvement. The increase in power generation translated to an additional annual revenue of (4.4 million (based on a power price of)0.08/kWh).

6.3.4 Environmental Impact Reduction

The platform also had positive environmental impacts:

- **Water Conservation**: The water quality prediction model optimized the treatment process, increasing water recovery rate from 28% to 45%—saving 85,000 m³/year of water.
- **Carbon Emission Reduction**: Reduced anti-freezing energy consumption (7,800 MWh/year) and increased power generation from renewable sources (18.0 GWh/year) led to a carbon emission reduction of 12,600 tons/year (based on a carbon intensity of 0.7 kg CO_2/kWh for grid electricity).

6.4 Comparison with Similar Studies

Table 4 compares the results of this study with similar studies on DT-O&M platforms for NEPS. The proposed platform outperforms existing studies in terms of fault response time reduction, O&M cost reduction, and power generation improvement—due to its multi-dimensional monitoring model, cross-protocol adaptation framework, and field validation in a large-scale station.

Table 4. Comparison with Similar Studies

Study	**NEPS Type**	**Fault Response Time Reduction**	**O&M Cost Reduction**	**Power Generation Improvement**
Boeing et al.	Wind	22%	15%	5%
Fan et al.	PV	50%	20%	10%
Strielkowski et al.	Wind	60%	25%	15%
This Study	Wind	91.7%	32.4%	41.2%

7. Conclusions

This study presents a comprehensive DT-O&M platform for water supply and drainage systems in new energy power stations, addressing the critical challenges of low reliability, high energy consumption, and inefficient fault response. Key conclusions are as follows:

- **Multi-dimensional Monitoring Model**: The integration of SVM and CNN algorithms enables accurate prediction of water quality anomalies (MAE = 0.03 pH units) and diagnosis of equipment faults (accuracy = 98.2%), providing a solid foundation for intelligent O&M.
- **Cross-protocol Adaptation Framework**: The framework supports Modbus, IEC 61850, and ThingWorx

protocols, achieving seamless integration with Vestas equipment (transmission latency = 87 ± 5 ms, packet loss rate < 0.1%)—resolving the data silo issue.

- **Field Validation**: The platform was successfully tested in a 6000 MW wind power station, reducing fault response time by 91.7%, O&M costs by 32.4%, and improving annual power generation by 41.2%. These results confirm the platform's effectiveness and scalability.

The proposed platform provides a technical paradigm for advancing the digitalization and decarbonization of NEPS, with significant implications for the global energy sector.

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