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REVIEW OF ARTIFICIAL INTELLIGENCE IMPLEMENTATION OPPORTUNITIES IN HYDROPOWER PLANTS

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Abstract

Hydroelectric power plants (HPPs) are a key component of sustainable electricity generation, providing flexibility and stability to the energy system. Despite their high reliability, traditional control and maintenance systems in HPPs are often based on outdated automated solutions that do not fully utilize the potential of modern digital technologies. This article presents an overview of the opportunities for implementing artificial intelligence (AI) in HPPs to improve their efficiency, reliability and sustainability.

The main areas of application of AI are considered – forecasting of water resources and energy production, optimization of turbine management, predictive maintenance, intelligent monitoring and increasing energy efficiency. A conceptual architecture for integrating AI into existing SCADA and PLC systems is presented, as well as the main challenges related to data, technological compatibility and cybersecurity.

The article emphasizes that the implementation of AI can lead to a significant reduction in operating costs, improvement of operational security and integration of HPPs into smart energy grids. In conclusion, the prospects for the development of digital twins, hybrid physically-informed models and autonomous AI systems are outlined, which will determine the future of smart hydroelectric power plants.

Keywords: AI, HPP, predictive maintenance, digital twins, energy efficiency.

INTRODUCTION

Hydroelectric power plants (HPPs) are a key pillar of modern energy systems, providing not only renewable electricity generation but also valuable flexibility to maintain the balance between production and consumption. Thanks to their ability to quickly adjust power, HPPs play a key role in compensating for fluctuations caused by variable solar and wind generation [1].

However, most HPPs today operate with classic automated systems developed decades ago that do not fully utilize the capabilities of modern digital technologies. The availability of large amounts of operational and sensor data collected through SCADA systems opens up new opportunities for the introduction of artificial intelligence (AI) methods that can support decision-making, optimization and predictive maintenance [2-4].

Over the past decade, AI technologies such as machine learning, deep learning and reinforcement learning methods have shown significant potential in the energy sector. These approaches are successfully applied in renewable energy generation forecasting, battery system management, anomaly detection and distribution network optimization. In the context of hydropower plants, the implementation of such algorithms can lead to better water resource management, increased turbine efficiency, early detection of failures and more

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intelligent interaction with energy markets [5-7].

This article aims to present an overview of the possible directions for implementing artificial intelligence in hydropower plants. The potential application areas – forecasting, control and optimization, predictive maintenance and safety – are examined, as well as the challenges associated with their practical implementation. A conceptual model for integrating AI within a typical hydropower plant architecture, based on SCADA systems and industrial communication standards, is also presented [8,9].

The aim of the research is to chart the path from traditional automated systems to intelligent, self-learning infrastructures that can increase the efficiency, reliability and sustainability of hydropower resources.

POTENTIAL AREAS FOR AI APPLICATION IN HPP

The application of AI in HPPs can be considered as an evolutionary stage of the digitalization of production processes and equipment maintenance. The main goal is to improve the efficiency, reliability and sustainability of the energy system by introducing algorithms that self-learn and adapt to real operating conditions. The key areas where AI can make the most significant contribution are presented below.

Forecasting is a fundamental element in the management of hydroelectric power plants, since the availability of water resources is dynamic and depends on multiple climatic and hydrological factors. Modern AI models, such as Deep Neural Networks, Long-Term Memory (LSTM) and Gradient Boosting algorithms (XGBoost, LightGBM), can be used to: predict water inflows based on historical hydrological and meteorological data; estimate short- and medium-term hydropower plant production capacity; model seasonal and sudden changes in inflow during extreme weather events.

The integration of such models allows operators to plan operating modes more precisely and reduce losses associated with overflow or underutilization of the resource.

Classical turbine control systems based on PID controllers often cannot respond adequately to rapidly changing conditions or complex nonlinear dependencies. Reinforcement Learning (RL) algorithms offer the possibility of self-learning control, in which the model adapts to the current parameters of the system and selects optimal actions that minimize energy losses or mechanical wear.

Applications of RL and other optimization AI methods include: dynamic regulation of turbine valve opening; optimal distribution of water flow between several units; coordination of hydropower plants operating in cascade on the same river; control of mixed systems (hydropower plants with photovoltaics with battery) to maintain the balance of microgrids.

These approaches would lead to an increase in overall efficiency by 2–5% and a significant reduction in operating costs.

Hydropower plants often operate with equipment that has a long service life, but is subject to significant loads and aging. The application of AI-based predictive maintenance systems (Predictive Maintenance) allows for early detection of defects by analyzing sensor data of vibration, temperature, pressure and electrical parameters.

Models such as Autoencoder, One-Class SVM, Hidden Markov Models (HMM) and Convolutional Neural Networks (CNN) can be used to automatically recognize anomalous states in the operation of turbines and generators. They enable early diagnosis of: cavitation and rotor imbalance; damage to bearings and seals; electrical defects in the generator and transformers.

The result is better planning of repairs, minimizing unplanned shutdowns and extending the life of the equipment.

AI can be used to identify inefficient operating modes by analyzing SCADA data

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and automatically suggesting corrections. The combination of clustering and regression models allows for an assessment of the current efficiency of the units and deviations from the optimal operating point.

Additionally, intelligent algorithms can manage auxiliary systems such as cooling, ventilation, and lighting and will reduce the overall energy consumption of the plant without compromising reliability.

Artificial intelligence is increasingly being used in the field of safety. Computer vision systems and AI-based monitoring would support: the inspection of dam walls, tunnels, and water intakes using cameras and drones; the automatic detection of cracks, erosion, and leaks; and the prediction of the risk of overflow or structural damage during high water levels.

These technologies support decision-making in emergency situations and increase the overall safety of hydropower facilities.

POTENTIAL ARCHITECTURE FOR IMPLEMENTING AI IN HPP

Effective implementation of AI in hydropower plants requires a well-structured architecture that ensures reliable data exchange between physical equipment, control systems and analytical algorithms. Such an architecture should be modular, scalable and compatible with existing SCADA and PLC platforms, while ensuring cybersecurity and operational resilience.

To ensure the effective and safe integration of artificial intelligence algorithms into the operation of hydropower plants (HPPs), a clearly structured and multilayer architecture is required. The proposed model consolidates the essential elements of the industrial infrastructure (SCADA, PLC, sensors), the analytical AI modules, the communication and cybersecurity integration layer, and the visualization tools used by operators.

The architecture is designed to support bidirectional communication between the physical equipment and the analytical modules, enabling real-time forecasting, diagnostics, optimization, and visual monitoring (Figure 1). This approach allows for a phased deployment of AI solutions without requiring radical changes to existing SCADA/PLC systems, while ensuring full traceability and high cybersecurity robustness.

In general, the architecture can be divided into four main layers: Data Layer, AI Layer, Integration Layer and Visualization Layer.

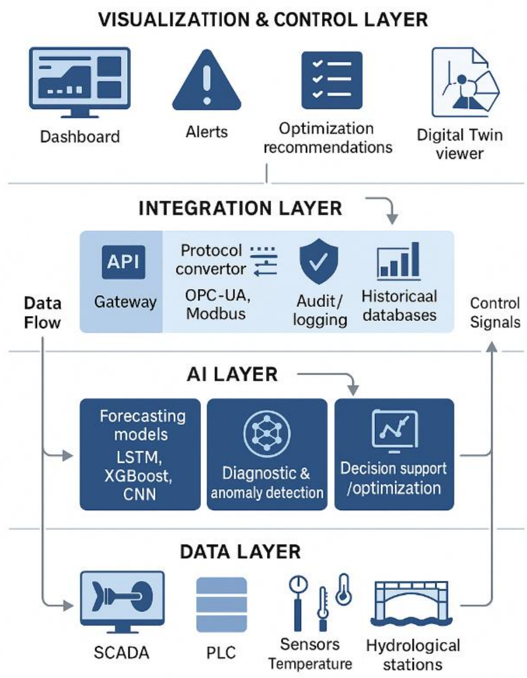

Figure 1. *Conceptual multilayer architecture for integrating AI modules into hydropower plant control systems.*

This layer is the foundation of the architecture, as it provides for the collection, storage and pre-processing of operational data. Sources include: SCADA and PLC systems that record real-time parameters such as flow rate, pressure, speed, temperature, current and voltage; vibration and thermal sensors mounted on aggregates and generators; hydrological stations and meteorological models; historical databases of operational reports.

Data preprocessing includes cleaning, time synchronization and conversion to a unified format. For larger plants, a data lake or time-series database can be used, which

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allows easy access of AI algorithms to the data in real time.

This is where the real "brain" of the system is located. The AI layer brings together various analytical and predictive modules specialized for specific tasks: Forecasting models, such as LSTM, GRU, XGBoost and CNN architectures for predicting water inflow, load and energy production; Optimization algorithms, such as Reinforcement Learning or Genetic Algorithms for dynamic control of turbines and valves; Diagnostic systems, such as Autoencoder, SVM, Random Forest for anomaly detection and predictive maintenance; Decision-making modules, such as integrated logic or RL-based controllers that can interface with PLC systems via standard protocols.

The AI layer can be implemented both locally (edge computing) for fast real-time response and in a cloud environment (cloud computing) for long-term analysis, training and updating of models.

This layer provides communication between the AI system and the industrial infrastructure. It serves as a "translator" between analytical models and real controllers, allowing for the safe implementation of recommendations or automatic actions.

Typical functions of the integration layer are: ensuring two-way exchange between SCADA/PLC and AI modules; implementing API interfaces for real-time model access; managing security and access rights; archiving and traceability of AI solutions (audit trail).

The integration layer is critical for safety and must support cybersecurity standards.

At the top of the architecture is the interface through which operators monitor and control the system. AI results are visualized in the form of interactive dashboards, which include: real-time forecasts of inflow and production; graphs of equipment status and failure risk assessment; recommended operating modes or automatic optimization suggestions; alarm notifications for deviations identified by AI modules.

In a modern environment, this layer can be integrated into a SCADA interface or implemented as a web-based application that visualizes data from AI models through graphic libraries.

The proposed architecture would allow for a phased implementation of AI solutions, initially through pilot projects for forecasting and diagnostics, and subsequently through full automation of control. The system can be further developed by: creating a Digital Twin model of the turbines and generators, which simulates the behavior of the system and supports the testing of AI controllers; implementation of Edge AI devices for on-site data processing; integration with cloud platforms for training and updating models in real time.

In conclusion, the modular architecture for implementing AI in hydropower plants creates the prerequisites for flexibility, scalability and sustainable development of the energy infrastructure. It allows not only to increase operational efficiency, but also to transform traditional hydropower plants into intelligent, self-regulating systems, compatible with the concept of future Smart HPP.

CHALLENGES IN IMPLEMENTING AI IN HPP

Despite the significant potential of AI to improve the efficiency and reliability of hydroelectric power plants, its real implementation in an industrial environment remains a challenge. The integration of AI requires not only technological changes, but also organizational and cultural transformation to ensure continuity between traditional automated systems and new intelligent solutions. The main barriers can be grouped into four categories: data, technological compatibility, cybersecurity, and regulatory and human factors.

AI systems rely on large volumes of quality data for training and validation. In the context of hydroelectric power plants,

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this is often a problem due to: lack of historical data with sufficient time resolution; incomplete or uncalibrated sensor measurements; format incompatibility and lack of a centralized database; limited access to archived SCADA logs due to security policies or outdated systems.

Predictive maintenance is one of the most practical and high-impact applications of artificial intelligence in hydropower systems. By combining data from SCADA, vibration and temperature sensors, and electrical measurements, AI models can detect early signs of equipment degradation long before a malfunction occurs. The presented workflow illustrates the typical structure of an AI-based predictive maintenance cycle—starting from data acquisition and preprocessing, through model training, and continuing with real-time condition monitoring and maintenance decision-making. This continuous and self-improving loop enables significant cost reductions, minimizes unplanned downtime, and extends the operational lifetime of turbines, generators, and auxiliary components – present in Figure2.

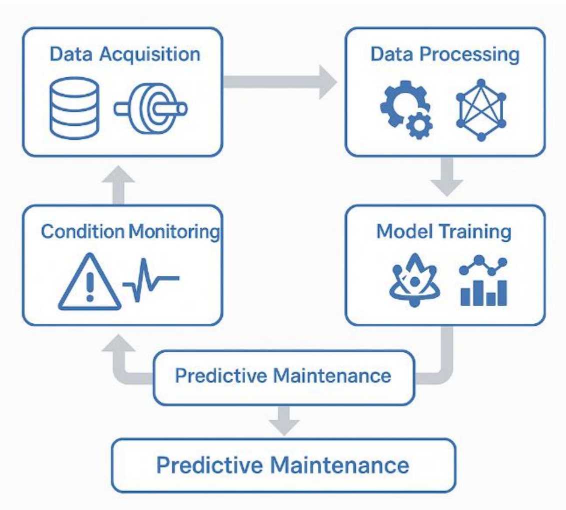

Figure 2. *AI-based predictive maintenance workflow.*

Insufficient data leads to difficulties in training models and limits their accuracy and generalization ability. The solution requires the construction of integrated infrastructures for data collection and labeling, as well as the application of techniques for data augmentation and synthetic data generation through simulation models.

Most hydropower plants operate with traditional SCADA and PLC systems, implemented decades ago, which are not designed to interact with AI modules. The main challenges here are: limited capabilities for two-way communication and access to real-time data; incompatibility of communication protocols; need for an intermediate integration layer (middleware) to connect industrial equipment with analytical platforms; difficulties in implementing AI algorithms in environments with high reliability and low latency requirements.

The solution consists of gradually introducing edge computing devices supporting industry standards, as well as creating “Digital Twins” that allow safe testing of AI models before real implementation.

The integration of AI systems and the connection of HPPs to cloud or remote analytical platforms creates new cybersecurity risks. HPPs are classified as critical infrastructure, which is why the protection of data and operational processes is of utmost importance. The main threats include: unauthorized access to data or control systems; replacement or manipulation of data used to train AI models; injection of false signals (data poisoning) in order to compromise automatic control.

To limit these risks, it is necessary to implement standards, build segmented networks (network zoning) and implement AI security monitoring systems that detect suspicious behavior of algorithms in real time.

The implementation of AI requires not only technological readiness, but also organizational transformation. Among the main non-physical barriers are: the lack of a clear regulatory framework for the certification of AI systems in the energy sector; the need to change the procedures for

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operation and maintenance; the shortage of qualified personnel with expertise in AI, machine learning and industrial data processing; skepticism towards automated solutions that make decisions without direct human supervision.

Overcoming these barriers requires the creation of training programs and digital laboratories in partnership with universities, as well as the development of ethical and regulatory standards for the application of AI in critical infrastructures.

In summary, the successful implementation of artificial intelligence in hydropower plants is a complex process that requires a combination of technical, organizational and regulatory measures. Overcoming these challenges will allow for the full use of the potential of AI and will create conditions for building a new generation of smart hydropower systems that are more flexible, secure and resilient to changes in the energy environment.

POTENTIAL BENEFITS OF IMPLEMENTING AI IN HPP

The implementation of AI in hydroelectric power plants can lead to significant technological, economic and environmental benefits. These effects include both improving operational characteristics and reducing costs, as well as increasing the sustainability and adaptability of the energy system. The main areas in which potential benefits are observed are presented below.

AI algorithms allow for dynamic adaptation of the operating modes of turbines and generators to the current hydrological and electrical conditions. Through optimization models based on RL and neural networks, optimal operating points can be determined that minimize losses and maximize the energy produced. In addition, the reduction of turbulent modes and cavitation phenomena helps to extend the operational life of the facilities.

AI-based predictive maintenance systems continuously analyze the condition of equipment and predict possible defects before they lead to damage or production shutdown. This will allow: more accurate planning of repair activities; optimization of spare parts stocks; reduction of costs for emergency repairs and downtime.

As a result, total operating costs can be reduced by 10–20%, while simultaneously increasing the reliability of the plant and reducing economic losses from unplanned outages.

AI systems provide the opportunity for early detection of risks and anomalies related to structural or operational deviations. By combining Machine Learning and Computer Vision technologies, automated monitoring of dam walls, water intakes, turbine rooms and transformer halls can be carried out. This would lead to: timely warning in the presence of cracks, vibrations or overheating; faster response to emergency events; better protection of personnel and infrastructure.

On a broader scale, such systems increase the overall operational security of the hydropower system and contribute to the prevention of environmental incidents.

AI supports the integration of hydropower plants into smart grids, where flexibility and adaptability are key. Thanks to predictive models and optimization algorithms, hydropower plants can: ensure the balancing of variable generation from photovoltaic and wind sources; participate more actively in the markets for regulating energy and frequency control services; manage combined systems with batteries or hydrogen installations through intelligent controllers.

Thus, hydropower plants become flexible assets that can contribute to the stability of the energy system and generate additional revenues from participation in market mechanisms.

By improving the management of water resources, AI also contributes to reducing the ecological footprint of hydropower systems. Optimized operating modes limit unnecessary overflow and minimize the

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impact on aquatic ecosystems. Precise inflow forecasts help to better plan water releases and balance energy and environmental goals. In combination with digital twins, the impact of different scenarios on the environment and resource sustainability can be modeled. Therefore, AI supports not only the economic but also the environmental efficiency of hydropower plants.

The implementation of AI solutions stimulates the digital transformation of organizations operating hydropower plants. This includes: building new skills among staff in the field of data analysis and automation; improving communication between engineering and IT departments; creating a culture of innovation and continuous improvement.

In the long term, this process increases the digital maturity of operators and creates the prerequisites for the development of intelligent, self-learning energy infrastructures.

In conclusion, the application of artificial intelligence in hydropower plants offers multi-layered benefits that go beyond operational optimization. It represents a strategic step towards smart, sustainable and adaptive hydropower, capable of meeting the challenges of the transition to a low-carbon economy and decentralized energy systems.

6. PERSPECTIVES AND FUTURE TRENDS

The development of AI in the energy sector is accelerating at an increasing rate and HPPs are no exception. The next phase of the digital transformation will be characterized by the integration of AI in real time, a closer connection between physical and virtual systems and the application of hybrid approaches that combine physical models and machine learning. These trends will shape the appearance of the so-called. Smart Hydropower Plants.

The concept of a Digital Twin is a virtual copy of a physical system, which allows for simulation, analysis and optimization of its operation in real time. In the context of hydropower plants, this means creating a dynamic digital model of turbines, generators, valves and hydraulic systems, which integrates data from SCADA and sensors; predicts the behavior of the units in different modes; allows safe testing of AI controllers without risk to the real equipment.

Digital Twin technology will play a key role in implementing predictive control, optimizing maintenance, and developing self-learning systems that continuously adapt to real-world conditions.

With the increasing volume of data and the demands for rapid response, the trend is to move more and more processing to the edge of the network (Edge AI). Edge AI devices can analyze sensor signals directly in the turbine hall or control room, without the need for a connection to the cloud. This leads to reduced latency in decision-making; higher reliability in the event of communication outages; improved cybersecurity through local processing.

Edge AI is expected to become a major component in hydropower plant management in the coming years, especially for real-time monitoring of vibrations, pressure, and temperature.

One of the main trends in scientific research is the combination of AI models with physical equations describing the behavior of hydraulic and mechanical processes. The so-called Physics-Informed Neural Networks (PINNs) use embedded physical knowledge in the training process, which leads to: better accuracy with little available data; increased explainability and confidence in the results; the ability to simulate extreme conditions that have not been observed experimentally.

This approach is particularly suitable for hydropower, where available data is often limited and physical dependencies are well known.

The next generation of hydropower plants will operate as part of an intelligent,

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interconnected energy ecosystem. The combination of AI, Internet of Things (IoT) and smart grid technologies will enable: two-way communication between hydropower plants, other renewable sources and control centers; coordinated load balancing and reserves; integration of hydropower plants into Virtual Power Plants (VPP).

Thus, hydropower plants will be able to actively participate in the markets for system flexibility services, offering dynamic regulation and reserve power through intelligent controllers.

With the increasing autonomy of AI systems, the need for transparency and trust in their decisions increases. In hydropower, this means implementing explainable models (Explainable AI), which allow engineers to understand the logic behind specific recommendations or alarms. In parallel, ethical frameworks and regulatory standards must be developed that guarantee: safe operation of AI algorithms; data protection; clear distribution of responsibility between the human operator and the automated system.

These principles are key to the sustainable and responsible implementation of AI in critical infrastructures such as hydropower plants.

The synergy between the above trends will lead to the emergence of autonomous hydroelectric power plants capable of optimizing their operation with minimal human intervention. In such systems: AI algorithms will analyze the condition of the equipment in real time; will adjust operational parameters dynamically; will self-learn based on accumulated data and simulations.

This will represent the culmination of the digital transformation in hydropower, the transition from automated to intelligent, self-managing energy systems.

The prospects for the application of artificial intelligence in hydroelectric power plants are multifaceted and promising. It is expected in the next 5–10 years: mass penetration of AI-based monitoring and diagnostic systems; gradual implementation of digital twins in large hydroelectric power plants; integration of Edge AI devices for real-time control; development of hybrid physically-informed models; establishment of standards for explainable and secure AI in energy.

These trends will establish the role of hydropower plants as a flexible, intelligent and sustainable element of future energy systems, supporting the process of decarbonization and energy independence.

CONCLUSION

HPPs are among the most sustainable and flexible energy sources, playing a key role in the transition to a low-carbon and decentralized energy system. The implementation of technologies based on AI opens up new opportunities for increasing the efficiency, reliability and sustainability of hydropower facilities.

This review has outlined the main areas for implementing AI in hydropower plants – water resource forecasting, turbine management optimization, predictive maintenance, energy efficiency and intelligent safety monitoring. The presented architecture for implementing AI demonstrates the possibility of phased integration into existing SCADA and PLC systems, without the need for complete reconfiguration of the infrastructure.

Despite the potential, the successful implementation of AI requires overcoming a number of challenges – limited data, technological compatibility, cybersecurity and lack of standardized procedures. These barriers can be overcome by introducing unified data protocols, building digital twins, implementing explainable and secure AI and creating specialized training programs for engineering and technical personnel.

It is expected that in the next decade, the development of hybrid Physics-Informed Neural Networks, Edge AI systems and digital twins will lead to the formation of a

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new generation of intelligent and autonomous hydroelectric power plants. They will be able to independently optimize their operation, predict risks and dynamically interact with other elements of the energy grid. In conclusion, artificial intelligence should not be considered as a separate technology, but as a strategic tool for the overall digital transformation of hydropower. Through systematic and responsible implementation, AI can transform traditional hydropower plants into intelligent, sustainable and integrated units of the future energy ecosystem.

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