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Application of Artificial Intelligence for the Optimization of Hydropower Energy Generation

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Abstract

Hydropower is one of the most promising sources of renewable energy. However, a substantial initial investment requires for the construction of large civil structures. Feasibility study, detailed project report preparation, construction planning, and timely execution of work are the important activities of a hydropower plant. Energy generation in hydropower plants are mainly depends on discharge and head. Therefore, an accurate estimation of discharge and head is important to decide the plant capacity. Erosion, cavitation, and operation & maintenance are the key challenges in hydropower energy generation. Artificial Intelligence (AI) has become popular, which can be utilized for site selection, parameters assessment, and operation & maintenance optimization. In this paper, a literature review on applications of AI in hydropower has been presented, and an attempt has also been made to identify the future potential areas of hydropower plants.

Keywords: AI, ANN, Fuzzy logic, Machine Learning, Deep Learning, Hydropower, Energy.

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1. Introduction

An increase in renewable energy generation poses critical challenges for grid stability. There are various popular renewable energy sources available in nature like solar, wind, and hydropower. Hydropower is generated by rotating the turbine through the water. Variability and intermittency characterize the majority of RES, making it challenging to predict power generation. These features make it more challenging to operate and maintain power systems, as more flexibility is needed to protect their regular operation and stability [1]. Now the power system operation has entered into the digital era, new technologies such as Internet-of-Things (IoT), real-time monitoring and control [2], as well as cybersecurity can contribute to more effective, safe, reliable, resilient, and sustainable power systems [3]. Hydropower is a renewable energy source, and almost 17% of the power is generated through hydropower. The construction and installation of a hydropower plant is a challenging task. Most of the hydropower plants suffer from erosion and cavitation problems due to silt in the flowing water. A typical layout of a hydropower plant is shown in Fig.1. The main components of hydropower plants are turbine, generator, and power evacuation systems. Running a hydro machine in its defined efficiency zone may help to maintain the system's plant efficiency and life.

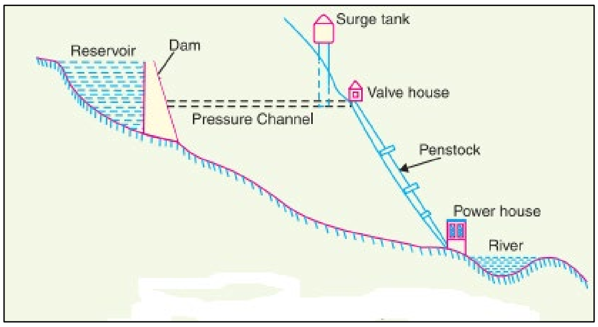

Figure 1. A typical layout of a hydropower plant (Source: Electrical Engineering Info., India)

Artificial Intelligence (AI) can be utilized in planning, feasibility study, discharge prediction, energy generation prediction, and maintenance planning. AI can be categorized into the following sub-sections.

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a) Machine Learning

Machine Learning is an application of computers to perceive, process, and analyze data to solve real world problems. It uses computational methods to 'learn' information from the data. An increase in the number of samples for learning improves performance. There are two types of learning, supervised and unsupervised learning. Supervised learning trains a model to predict future effects on known input and output data, whereas hidden patterns are discovered in unsupervised learning on known input.

b) Deep Learning

It is a process of implementing high-dimensional data to gain insights to solve more complex problems. Deep learning is a kind of machine learning in which a model learns directly from images, text, or sound to perform the classification task. Deep learning is typically conducted using the architecture of a neural network. The term 'deep' refers to the number of layers in the network.

c) Artificial Neural Network (ANN)

A typical artificial neuron network configuration is depicted in Fig.2. where the inputs X_n are connected to neurons that multiply their weight (W_n) to generate the product W_nX_n and then all the weighted inputs are added. The result is the argument of the transfer function (*f*). Most common ANN architectures consist of one input layer, one output layer, whereas more than one hidden layer.

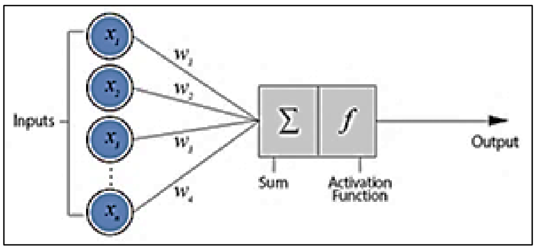


Figure 2. A typical architecture of ANN

A neural network can learn from data to recognize patterns and splits the data into abstraction layers. It can be conditioned on several examples to identify patterns of elements, power, and weights during connections. These weights are automatically updated for a defined learning rule until the neural network successfully completes the task.

d) Fuzzy Logic

A mathematical tool focused on 'degree of fact' concepts instead of the standard conventional Boolean computational logic. Fuzzy logic is a simple way of converting an input space to an output. It usually starts with mapping input to output. Mapping inputs to the appropriate outputs requires determining the appropriate number of tips between input and output.

e) Adaptive Neuro-Fuzzy Interface System (ANFIS)

It is a kind of ANN, which is based on the inference system. Since it incorporates neural networks and fuzzy logic concepts, it can use the advantages of both within a single system.

The remaining part of this paper is organized in the following sections. Section 2 is the main part of this paper that describes the literature review on applications of AI in hydropower. The review is focused on the application areas of AI for performance optimization, forecasting of parameters, monitoring and control optimization, policy and feature selection, feasibility study, evaluation and capability assessment, and Section 3 discusses the conclusions and future scope.

2. Literature review

AI is a multidisciplinary field that uses various disciplines, such as computer science, neuroscience, economics, information theory, mathematics, psychology, control theory, and optimization with techniques and perspectives. The word artificial intelligence refers to the design and research of intelligent entities [4]. To review the application areas of AI in hydropower, it has been categorized in the following sub-sections as given in Fig.3.

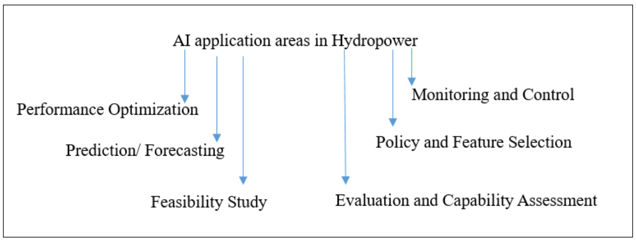
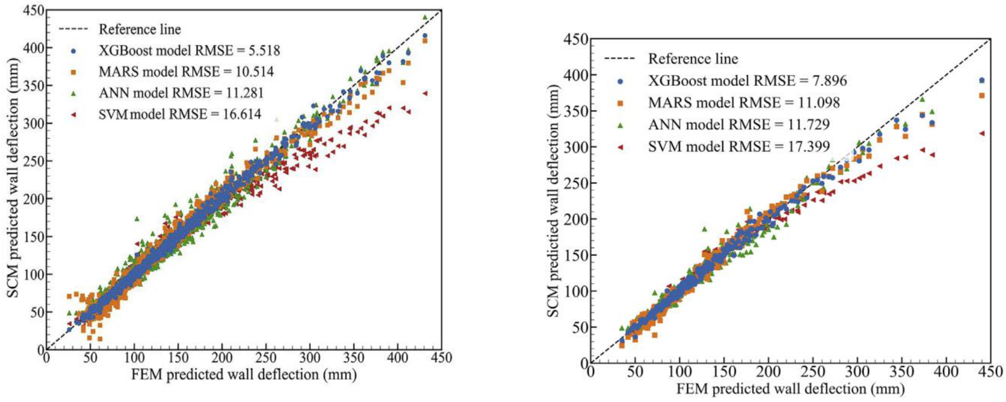


Figure 3. AI application areas in hydropower

i) Applications of AI for performance optimization:

Various methods are presently being utilized for the performance optimization of the hydropower plant. Conteh et al. [5] developed an optimal load-shedding technique capable of shedding the required load. It utilizes the backpropagation artificial neural network. To further optimize the capability of load shedding for any range of input data, both neural network and fuzzy logic are combined to form an adaptive neuro-fuzzy inference system. The first scenario was obtained by closing the breaker as the generation sources start operating at their maximum limit. Further, the second scenario was acquired by a sudden decrease in power, resulting in plant failure. Load shedding errors from the two methods show that the ANFIS method is more robust than the backpropagation artificial neural network method. Zhang et al. [6] compared the computing performance of various techniques. Figs. 4 and 5 show the training and test results of the XGBoost, MARS, ANN, and SVM models.

For the test data, the RMSE, R2, bias factor, and MAPE between the FEM versus SCM estimates provided by the XGBoost model and found as 7.90, 0.99, 1.00, and 0.04, respectively. The MARS model has given the RMSE, R2, bias factor and MAPE for the test trends as 11.10, 0.97, 1.02, and 0.07, respectively. For the expected values from the ANN model, the RMSE, R2, bias factor, and MAPE were obtained as 11.73, 0.97, 1.00, and 0.07, respectively. The SVM model's RMSE, R2, factor bias, and MAPE were 17.40, 0.94, 1.01, and 0.06, respectively.



(a) **(b)**

Figure 4. (a) Training and (b) Testing results of FEM wall deflection [6]

Kurt et al. [7] investigated power generation on Kayabogazi Dam. Three smaller units were suggested for installation. An FL algorithm has been used to optimize the output of the turbines for the power capacity and power demand constraints, whereas Herath et al. [8] forecasted the price of energy. A summary of the application of AI for performance optimization of hydropower plants is given in Table-1.

Table 1. Summary of applications of AI for performance optimization

Author(s)	Method (s)	Objective (s)	Findings
Conteh et al. [5]	ANFIS	Optimal load shedding that can shed the required amount of load for grid stability	The intended quantity of load can be shed at a faster rate and enhances the stability of the system
Kurt et al. [7]	Fuzzy logic controller	The operation of the turbines for the power potential and power demand constraints optimization using FL algorithm	Selection of the number of units to optimize the energy generation

ii) Applications of AI for the forecasting of plant parameters:

Senthil et al. [9] predicted the sediment loading using ANN generated in a watershed. They concluded that the high variability of hydro-climatic factors with sediments makes the sediment modeling process cumbersome and tedious. Compared to other soft computing techniques, the M5 model performed well. For M5M1 and ANNSC22, RMSE was found to be 0.54, while the REPTree model performed worst (0.82). For the M5M1 and ANNSC22 models, the best value of the correlation coefficient is 0.96, while the correlation coefficient of the REPTReeM2 model is 0.90. Kumar et al. [10] applied the machine learning technique for the forecasting of day plant load, which will help to stabilize the grid. Fayaz et al. [11] used a deep learning algorithm to predict energy consumption in buildings. For that, average statistical measurement values of both periods were calculated as given in Table 2. The statistical values show that DELM has better efficiency than the other counterpart algorithms.

Table 2. Average values of statistical measures [11]

Statistical Measures	MAE	MAPE	RMSE
ANN	2.4317	7.0830	4.8561
ANFIS	2.4556	6.8841	2.8174
DELM	2.1677	6.1271	2.4657

Shamshirband et al. [12] used an ANFIS and CFD approach to predict the pressure gradient. The investigation results indicated that the input parameters and the number of rules significantly influence the algorithm's accuracy. Lounis et al. [13] investigated the performance of five pattern classification algorithms to predict the discharge flow in hydropower plants. The results indicated the strong superiority of the neural network method over other approaches. Egoigwe et al. [14] analyzed the flow rate of hydroelectric plants, which varies with time due to the rotation of the turbine. The results showed that the speed regulation for hydropower generation had been 319.8 m/s and 65 m/s, respectively with and without a fuzzy logic controller. It means the Fuzzy Logic Controller yields better results and increases turbine rotational speed. A general equation to model the hydropower generator speed controller is given in Eq.1.

$$M(t) = K_p E(t) + K_i \int_0^t E(t)dt + K_d \frac{dE}{dt} \tag{1}$$

Where K_p, K_i, and K_d are the proportional, integral, and derivative constants, respectively. *E(t)* is the error as a function of time, and M(t) is the controller output. The derivative mode accounts for the error, as the measurement method was corrupted at a faster response time. The digital equivalent of Eq.1 is given below:

$$M_i = K_p \left[E_i + T K_i \sum_{j=1}^{i} E_i + \frac{K_d}{T}(E_i - E_{i-1}) \right] \tag{2}$$

Where T is the sampling interval, E_i is Error at i^{th} sampling interval, and E_{i-1} is an error at a previous sampling interval

$$M_i = K_p \left(1 + \frac{K_d}{T}\right) E_i - \left(\frac{K_p K_d}{T}\right) E_{i-1} + (T K_p K_i) S_i \tag{3}$$

Where S_i is the sum of error.

Luna et al. [15] presented a TS-FIS model for inflow forecasting. The validation of the model has been performed using MAPE, RMSE, and MAE. The model has shown a good performance value of the mass curve coefficient varies from 79% to 98%. Abdulkadir et al. [16] modeled reservoir variables of dams for energy generation using a multilayer neural perceptron network. The neural network description received a strong forecast of 0.89 and 0.77 correlation coefficients for the Kainji and Jebba hydropower reservoirs, respectively. Li et al. [17] predicted the short-term power generation using a support vector machine (SVM) and the genetic algorithm (GA). Stokelj et al. [18] predicted the inflow of water using the neural network architecture. Shaktawat et al. [19] presented a Fuzzy tool to determine the cost overrun of a hydropower plant. Cost overrun in a hydropower plant results in a rise in the price of electricity production. The method for evaluating overruns would help the investors to determine uncertainty.

Li et al. [20] applied a deep neural network for the prediction of power generation. As a result, the HGDNN model decreases the RMSE value to 202.92. In addition, HGDNN records an improvement of at least 6%, 9%, and 49% respectively on RMSE, MAE, and MAPE compared to the ST-ResNet. The measuring parameters are listed below.

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(\hat{X}_t - X_t)^2} \tag{4}$$

$$MAE = \frac{1}{M}\sum_{i=1}^{M}|\hat{X}_t - X_t| \tag{5}$$

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{\hat{X}_t - X_t}{X_t}\right| \tag{6}$$

Where$\hat{X}_t$ and X_t are the predicted and actual hydropower generation value at time t, and M is the number of samples collected.

Mamlook et al. [21] compared neuro-fuzzy programming using different choices for producing electricity. Based on the cost-to-benefit ratio, solar, wind, and hydropower were considered the best systems for generating electric power, and nuclear power is the worst choice. Valizadeh et al. [22] predicted the daily water level of the dam using ANFIS. Rising the reservoir level alongside precipitation as inputs in both sets of models significantly improved the fitness of the predicted and observed results. As the distance of the gauge station was unknown, the distance between gauge can be identified using various models in different time delays of the inputs; however, it demonstrates the appropriate length in inputs and outputs to provide a precise prediction. Oltean et al. [23] presented a method for constructing fuzzy models through subtractive clustering to allocate energy generation on cascaded hydropower plants. This model shows a 6.47% value for the mean absolute percent error in the test data set. For the model, 90% of the data in test data sets produced a fundamental percent error of less than 13.59%. The model was performed very well for much of the test data point. Cheng et al. [24] simulated the ANFIS model to forecast long-term discharge. For validation and training, the correlation coefficients between the predictive and observational values are found as 0.889 and 0.918, respectively. It has also been found that the ANFIS model can provide more accurate predictions by comparing results with a suitable ANN model.

Dehghani et al. [25] applied the Grey Wolf Optimization (GWO) method coupled with the ANFIS to predict hydropower development. Twenty combinations of inputs were used, including the dam inflow, rainfall, and hydropower in various months, while the production was for one month of hydropower generation in all scenarios. Then, the hydropower generation has been projected using the coupled model. Results showed that the GWO-ANFIS model could satisfactorily predict the hydropower generation while ANFIS was not better in nine input-output combinations.

Kucukali et al. [26] concluded that the results of the ANN model showed a positive relationship between the real and predicted inflow of reservoirs with a relatively high correlation coefficient value for all selected locations. This shows the model is ideal for modeling the inflow of reservoirs.

Ghosh et al. [27] proposed a new way of indicating HPP output. The MCDM and ANN methods were applied to give each of the required parameters. According to the data, the most important parameter (MIP) is water availability, while accessibility is the least important. The ANN model was created as a stand-alone HPP status prediction system. To allow ongoing evaluation of the possible site, a dynamic, adaptable time-variant version of the index could be developed.

Alrayess et al. [28] utilized machine learning techniques in short-term energy generation forecasting. Three models ANN, Support Vector Machine (SVM), and Deep Learning (DL), were used to predict Almus HEPP's energy generation. The correlation values for ANN, SVM, and DL were found as 0.766, 0.682, and 0.998, respectively. Also, the squared correlation values for ANN, SVM, and DL were obtained as 0.587, 0.466, and 0.995, respectively. The results showed that the DL algorithm performs better than other techniques.

Hammid et al. [29] applied ANN to predict the output of hydropower plants in terms of net turbine head, water flow rate, and power generation on data collected over ten years during the study. ANN provides an efficient instrument of analysis and diagnosis to model the nonlinear plant output. It has been concluded that the ANN may predict the plant performance with a coefficient of correlation between the predicted and observed output variables has a value higher than 0.96. Stokelj et al. [30] presented an improved ANN model for the short-term water inflow forecasting and on successful bidding techniques. Feng et al. [31] developed a rockburst system based on Micro Seismic (MS) monitoring data and an enhanced Probabilistic Neural Network (PNN) model. To maximise the smoothing factor in the PNN parameter, the modified firefly method was utilised. The results reveal that the anticipated and learning samples had 100% and 86.75% accuracy for accurate rockburst rates, respectively.

Jalalkamali et al. [32] examined the potential of Neuro-Fuzzy (NF) and ANN techniques to predict groundwater levels. The NF computation techniques were also found to have higher efficiency than the ANN models. Kumar et al. [33] classified the daily volume of silt density, which can be used for the predictive analysis of operation and maintenance of hydropower plants.

Bina et al. [34] estimated the aggregate day-ahead power demand of individual household appliances. Tree-based strategies for load forecasting have also been commonly used in DR [35]. For price scheme optimization of retailers or aggregators, GA typically considers individuals [36]. A lot of work is available on the baseline load estimation for residential areas [37, 38], industries [39], buildings, and office premises [40].

Most of the information at the market level concerned predicting competitive residential pricing schemes [41, 42, and 43]. However, forecasting aggregate loads may also concentrate on evaluating day-to-day peak demand, either at the building level or at the feeder or neighborhood level [44, 45]. Also, residential load forecasting was conducted at different aggregation speeds [46].

Table 3 gives the summary of applications of AI for forecasting hydropower plant parameters.

Table 3. Summary of the applications of AI for the forecasting of hydropower parameters

Author(s)	Method (s)	Objective (s)	Findings
Senthil et al. [9]	ANN	Prediction of sediment loading	REPTree model provides better insight with less computational time
Fayaz et al. [11]	ANN and ANFIS	Energy consumption forecasting	DELM is much better than ANN and ANFIS for short-term and long-term energy consumption projections
Lounis et al. [13]	Machine learning	Flow prediction	The neural network approach is superior to the other techniques
Egoigwe et al. [14]	Fuzzy logic controller	Flow rate prediction	When the speed reaches 254.8m/s, the fuzzy logic controller gives a better result
Luna et al. [15]	TS-FIS model	Inflow forecasting	The value of the mass curve coefficient (performance indices) varies from 79% to 98%
Abdulkadir et al. [16]	ANN	Energy generation prediction	One day ahead energy generation has been predicted to stabilize the grid
Li et al. [17]	GA-SVM	Energy generation prediction	The GA-SVM model is an effective method for improving short-term forecasting accuracy
Shaktawat et al. [19]	Fuzzy logic controller	Cost prediction	The cost overrun of hydropower projects was calculated with ease and less computing time
Li et al. [20]	Deep neural network	Generation prediction	HGDNN method gives a better prediction of hydropower generation
Cheng et al. [24]	ANFIS	Discharge prediction	A comparison of the various membership functions for ANFIS shows that TRAPMF performs best in long-term discharge prediction
Dehghani et al. [25]	ANFIS	Energy generation forecasting	GWO-ANFIS can forecast the hydropower generation satisfactorily
Ghosh et al. [27]	MCDM and ANN	Performance of hydropower plant prediction	In terms of predictive power, the ANN model outperformed the regression model
Alrayess et al. [28]	ANN, SVM, and DL	Short term energy generation forecasting	The correlation values verified that the Deep Learning model gives results more accurately with high performance than ANN and SVM
Hammid et al. [29]	ANN	Head prediction	The ANN modeling can be used to predict the behavior of small hydropower plants
Feng et al. [31]	ANN	Rockburst prediction	The MIVA-MFA-PNN model is performing well for Rockburst prediction
Jalalkamali et al. [32]	ANN and Fuzzy logic controller	Water level prediction	The NF computing technique is suitable for modeling of the groundwater level
Kumar et al. [33]	SOM	Predictive maintenance	SOM can be used for daily silt data analysis and to plan the maintenance of the machines
Bina et al. [34]	Gaussian Copulas	Aggregate demand forecasting	The utilization of the distribution transformers and feeders can be improved
Park et al. [37]	SOM, K-means	Baseline estimation	In DR management, the data-driven approach is a possible method for CBL estimation where a large amount of smart metering data is collected
Jazaeri et al. [38]	Nonlinear regression, ANN	Baseline estimation	Among the techniques, machine learning produces the smallest bias
Arunaun et al. [39]	ANN	Baseline estimation	Baseline calculation by neural networks using the LM algorithm is the most accurate method
Escriva et al. [40]	ANN	Baseline load forecast	The versatile and adaptive algorithm based on artificial neural networks (ANNs) is suitable to predict building energy consumption accurately

iii) Applications of AI in monitoring and control of Hydropower plants:

Monitoring and control are the essential aspects of a hydropower plant. Chapuis et al. [47] introduced a hydropower plant outflow controller structure. The outflow control has been distinguished by the fact that many actuators (turbines and weirs) were required to control the total outflow of the reservoir. Adhikary et al. [48] used Fuzzy Logic for safe reservoir control through spillway gates. They concluded that the predictive accuracy of the fuzzy model based on the Tabu Search Algorithm (TSA) is reasonable. Xu et al. [49] discussed the usage of the Smart Control Theory in terms of the description and optimization of control parameters based on the Fuzzy Control Theory and the Neural Network Theory.

Theophilus et al. [50] presented a variable hybrid Fuzzy-based logic controller and a graded neural network called the Neuro-Fuzzy technique. Fuzzy logic for reservoir control based on rule and membership function has been demonstrated in the design. This has improved the turbine speed's stability to ensure optimum hydropower generation within the expected range in real-time.

Oğuz et al. [51] proposed a risk management framework for the run of the river hydroelectric power plants. Expert judgments were also established for the relative value of the risk factors. The results of the survey showed that site geology and environmental issues were the most related risks.

Falchetta et al. [52] analyzed the hydro-climatic extremes that affect the reliability of the electricity supply. The framework uses algorithms of random forest regression to reduce data scarcity and estimate volatility in river discharges while ungauged. The validated forecasts were used to determine the effect of hydro-climatic events on the efficiency of hydropower. Molina et al. [53] introduced a new design for hydropower plant operations based on monitoring various signals. To prevent malfunctions, the NNPM used an ART-MAP to identify different situations from the plant state variables. Also, a unique process has been developed for the ART-MAP module to generate a complete training set. Table 4 shows the summary of the applications of AI in the monitoring and control of hydropower plants.

Table 4. Summary of the applications of AI in monitoring and control of hydropower plant

Reference	Method (s)	Objective (s)	Findings
Adhikary et al. [48]	Fuzzy logic controller	Reservoir control	Tabu Search Algorithm (TSA) predictive accuracy of the fuzzy model is reasonable
Theophilus et al. [50]	ANFIS	Reservoir control	Design of Neuro-fuzzy controller to regulate water levels and control the flow
Molina et al. [53]	ANN	Parameter for monitoring	The ART model predicts variable values correlated with potential abnormal circumstances

iv) Application of AI in policy and feature selection:

Wotawa et al. [54] demonstrated the uses of deep learning to find optimum reservoir operating policies in hydropower river systems. Deng et al. [55] analyzed the characteristics of load generation combining with the wavelet transform. PSO has been used to refine the initial neural network weights and thresholds. After being checked in some provinces by the actual case, the precision of the load prediction reaches 93.7% higher than the accuracy of the assessment criteria for the high-voltage network. Kentel et al. [56] evaluated the most sustainable option of low-head (LH) hydropower technology for hydropower generation at wastewater treatment plant outlets by analyzing the economic, technical, and environmental criteria. Due to its superior performance on financial and environmental requirements, the Archimedean screw is a better alternative than the Kaplan turbine for hydropower production at the outlet of a WWTP. Bai et al. [57] developed a Fuzzy logic model to derive optimum macro-level operational rules for better performance and power generation control. A fuzzy inference method using "if-then" rules can model the qualitative dimensions of human understanding and reasoning processes without using detailed quantitative analyses. A summary of the applications of AI in policy and feature selection for hydropower plants is given in Table 5.

Table 5. Summary of the application of AI in policy and feature selection

Author(s)	Method (s)	Objective (s)	Findings
Ak et al. [56]	Fuzzy logic controller	Best criteria selection	The Archimedean screw is a better alternative than the Kaplan turbine for a specific case of WWTP
Bai et al. [57]	Fuzzy logic controller	Optimal operation rule selection	It helps to operate a machine in its efficiency zone.

v) Applications of AI for feasibility study:

Gunduz et al. [58] analyzed the feasibility of investment in a hydroelectric power plant using ANN based on the project costs and the amount of investments. Tripathi et al. [59] applied the Fuzzy Rating Tool to measure the risk associated with Boot hydropower projects in Nepal. Shimray et al. [60] concluded that site selection for plant construction is complex and requires careful consideration. Construction of hydropower plants requires heavy financial expenditure, manpower, and time constraints. Therefore, a systematic approach is necessary to prevent adverse effects on the environment and consequently on humanity. ANN-based formalism shows that MLP-GA can give precise priority to potential sites for the installation of hydropower plants. Table 6 presents a summary of AI applications for the feasibility study of hydropower plants.

Table 6. Summary of applications of AI for feasibility study

Author(s)	Method (s)	Objective (s)	Findings
Gunduz et al. [58]	ANN	Investment feasibility	The economic viability of a project can be analyzed
Tripathi et al. [59]	Fuzzy logic controller	Risk assessment	Risk index can be used as an early indicator of project problems
Shimray et al. [60]	ANN	Site selection	MLP-GA can accurately prioritize potential sites

vi) Application of AI for accuracy evaluation and capability assessment:

Qu et al. [61] concentrated on the prediction of concrete dam deformation based on RS-LSTM on the theory of Rough Set (RS) and a Long-Term Memory (LSTM) network. Mosavi et al. [62] applied an ANFIS model to control the output voltage and the variable-speed turbine frequency. Pérez-Díazet et al. [63] analyzed the axial-flow propeller turbine control capabilities of both the speed of the turbine and the position of the guide vanes. An experimental setup of a hydropower plant was built to study the dynamics of the run-of-river plant, as shown in Fig. 6. Head is created through pump; asynchronous generator has been connected through a turbine to the grid with some control mechanism. A Venturi flow meter and torque meter has been installed to measure discharge and torque. The experiment showed that it is possible to increase the turbine's performance by changing the position of the guide vanes accordingly.

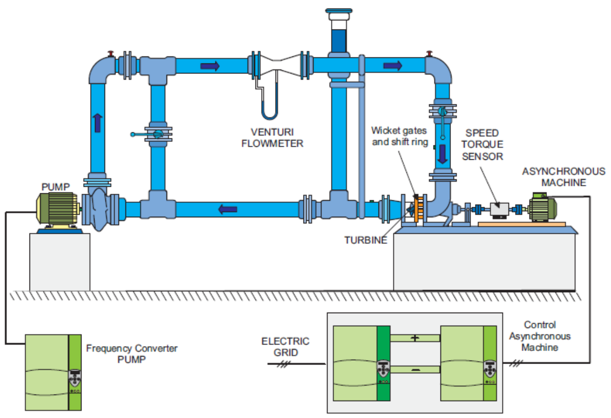


Figure 6. Turbine test bench [63]

Zaidi et al. [64] explained the methodology for data and machine learning on the energy-water nexus. It has been revealed that possible study topics and collaboration opportunities between the energy-water nexus and machine learning communities can lead to mutual synergistic benefit.

Further, it may also be helpful to develop a demand elasticity model for the aggregation of consumers [65], and PSO can be used for scheduling the customers' consumption [66]. Table 7 gives a summary of the applications of AI for accuracy evaluation and capability assessment.

Table 7. Summary of the application of AI for accuracy evaluation and capability assessment

Author(s)	Method (s)	Objectives	Findings
Pérez-Díaz et al. [63]	ANN	Regulating capability assessment	The performance of the turbine can be improved by adequately changing the position of the guide vanes
Zaidi et al. [64]	Machine learning	Energy water-nexus	Machine Learning can be utilized to understand the views of the water and its applications
Babar et al. [65]	Markov decision	Analysis of the price elasticity of demand	The price elastic behaviour of the consumer's aggregated demand has been formulated.

3. Conclusions and Recommendations

Literature review on the applications of AI in the hydropower sector have been conducted, and the following conclusions have been drawn:

i) AI is presently being utilized to forecast load, silt, head, discharge, energy demand & supply, and site selection.
ii) The construction of a hydropower plant requires huge initial investments. Therefore, proper planning is necessary to optimize the resources. In addition to that, it has been observed that the monitoring of machines at part-load operation is essential to minimize losses.
iii) ANN has been mainly used for energy generation forecasting, inflow prediction, energy demand prediction, and economic feasibility analysis. On the other hand, fuzzy logic has been mainly used for plant operation optimization, energy cost prediction, and reservoir operation. It has also been found that DELM performs better than ANN and ANFIS for short-term and long-term energy consumption prediction.
iv) In future AI can be utilized in effective monitoring and operation & maintenance optimization of hydropower plants.

Abbreviations:

ANFIS	Adaptive neuro-fuzzy inference system
CBL	customer baseline load
CFD	Computational Fluid Dynamics
DELM	Deep Extreme Learning Machine
DL	Deep learning
DR	Demand response
GWO	Grey wolf optimization
HGDNN	Hydropower Generation Forecasting with Deep Neural Network
LM Algorithm	Levenberg-Marquardt Algorithm
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARS	Multivariate adaptive regression splines
MFA	Modified firefly algorithm
MIVA	Mean impact value algorithm
MLP-GA	Multilayer perceptron-genetic algorithm
NF	Neuro-Fuzzy
NNPM	Neural Network Predictive Maintenance
PNN	Probabilistic neural network
PSO	Particle Swarm Optimization
RES	Renewable Energy Sources
RMSE	Root Mean Square
SCM	Supply Chain Management
SOM	Self-organizing map
SVM	Support Vector Machine
SVRGA	Support vector regression with genetic algorithm
TRAPMF	Trapezoidal membership function
WWTP	Wastewater treatment plant

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