Application of Artificial Intelligence for the Optimization of Hydropower Energy Generation

Krishna Kumar1,*, and R. P. Saini1

1Department of Hydro and Renewable Energy, Indian Institute of Technology, Roorkee, India

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.

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.

* Corresponding author. Email: kkumar@ah.iitr.ac.in
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](image)

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 subsections as given in Fig.3.

![Figure 3. AI application areas in hydropower](image)

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 back-propagation 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.

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

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 ANNNSC22, RMSE was found to be 0.54, while the REPTReeM2 model performed worst (0.82). For the M5M1 and ANNNSC22 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.
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. Egogwe 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.

\[ M(t) = K_p E(t) + K_i \int_0^t E(t) dt + K_d \frac{dE(t)}{dt} \]  

(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:

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

(2)

Where \( T \) is the sampling interval, \( E_i \) is Error at ith sampling interval, and \( E_{i-1} \) is an error at a previous sampling interval.

\[ M_i = K_p \left( 1 + \frac{K_d}{T} \right) E_i - \left( \frac{K_p K_d}{T} \right) E_{i-1} + \left( TK_p K_i \right) S_i \]  

(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.

\[ \text{RMSE} = \frac{1}{M} \sum_{i=1}^{M} (\hat{X}_i - X_i)^2 \]  

(4)

\[ \text{MAE} = \frac{1}{M} \sum_{i=1}^{M} |\hat{X}_i - X_i| \]  

(5)

\[ \text{MAPE} = \frac{1}{M} \sum_{i=1}^{M} \left| \frac{\hat{X}_i - X_i}{X_i} \right| \]  

(6)

Where \( \hat{X}_i \) and \( X_i \) 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.

Kaçkarli 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.

Ghose 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.

Hammad 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.
| 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 hydropower 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.

| Reference        | Method(s)         | Objective(s)          | Findings                                                                 |
|------------------|-------------------|-----------------------|---------------------------------------------------------------------------|
| Adhikary et al.  | Fuzzy logic       | Reservoir control     | Tabu Search Algorithm (TSA) predictive accuracy of the fuzzy model is reasonable |
| Theophilus et al.| ANFIS             | Reservoir control     | Design of Neuro-fuzzy controller to regulate water levels and control the flow |
| Molina et al.    | 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.
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-Diaz 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.
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.

| 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**: 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
- **SVR**: Support Vector Machine
- **SVRGA**: Support vector regression with genetic algorithm
- **TRAPMF**: Trapezoidal membership function
- **WWTP**: Wastewater treatment plant

## References

[1] Eid C, Codani P, Perez Y, Reneses J, Hakvoort R. Managing electric flexibility from Distributed Energy Resources: a review of incentives for market design. Renew Sustain Energy Rev 2016;64:237–47. https://doi.org/10.1016/J.RSER.2016.06.008.

[2] Andoni M, Robu V, Flynn D, Abrahams J, Geach D, Jenkins D,
McCallum P, Peacock A. Blockchain technology in the energy sector: a systematic review of challenges and opportunities. Renew Sustain Energy Rev 2019;100:143–74. https://doi.org/10.1016/j.rser.2018.10.014.

[3] Bedi G, Venayagamoorthy GK, Singh R, Brooks RR, Wang K-C. Review of Internet of Things (IoT) in electric power and energy systems. IEEE Internet of Things Journal 2018;5:847–70. https://doi.org/10.1109/JIOT.2018.2802704.

[4] Russell S, Norvig P. Artificial intelligence: a modern approach. third ed. 2010. https://doi.org/10.1017/S0269888900007724. arXiv:9809069v1.

[5] Conte F, Tobaru S, Lotfy ME, Yona A, Senjyu T. An effective Load shedding technique for micro-grids using artificial neural network and adaptive neuro-fuzzy inference system. AIMS Energy 2017;5:814–37. https://doi.org/10.3934/energy.2017.5.814.

[6] Zhang W, Zhang R, Wu C, Goh ATC, Lacasse S, Liu Z, et al. State-of-the-art review of soft computing applications in underground excavations. Geosci Front 2020;11:1095–106. https://doi.org/10.1016/j.gsf.2019.12.003.

[7] Kurt H, Aslan Y. Optimization of Power Output of a Micro-Hydro Power Station Using Fuzzy Logic Algorithm. Int J Tech Phys ProblEng2013;5:138–43.

[8] Herath P, Venayagamoorthy GK. A service provider model for demand response management. In: 2016 IEEE symposium series on computational intelligence (SSCI). IEEE; 2016. p. 1–8. https://doi.org/10.1109/SSCI.2016.7849846.

[9] Senthil Kumar AR, Goyal MK, Ojha CSP, Singh RD, Swamee PK. Application of artificial neural network, fuzzy logic and decision tree algorithms for modelling of streamflow at Kasol in India. Water Sci Technology 2013;68:2521–6. https://doi.org/10.2166/wst.2013.491.

[10] Kumar K., Singh R.P., Ranjan P., Kumar N. (2021) Daily Load Forecasting of Micro-Hydro Power Plant using Artificial Neural Network. In: Proceedings of the International Conference on Energy, Electronics and Telecommunications E2T 2021: 301–4.

[11] Fayaz M, Kim D. A prediction methodology of energy consumption based on deep extreme learning machine and comparative analysis in residential buildings. Electron 2018;7. https://doi.org/10.3390/electronics7100222.

[12] Shamshirband S, Mosavi A, Chau K. Sensitivity study of ANFIS model parameters to predict the pressure gradient with combined input and outputs hydrodynamics parameters in the bubble column reactor 2019. https://doi.org/10.20944/preprints201905.0044.v1.

[13] Louins H, Boukadoum M, Siveton V. Assessing Hydro Power System Relevant Variables: a Comparison Between a Neural Network and Different Machine Learning approaches 2002:45–51.

[14] Egoiogwe SV, Chukwudozie C, Nwobi C, Araoye TO, Arize CI, Anolife EC. Application of a Fuzzy Logic Controller for Hydropower Generator Speed Regulation. Eur J Eng Res Sci 2019;4:132−5. https://doi.org/10.24018/ejers.2019.4.3.1203.

[15] Luna I, Hidalgo IG, Pedro PSM, Barbosa PSF, Francato AL, Correia PB. Fuzzy inference systems for multi-step ahead daily inflow forecasting. PesquiOperacional2017;37:129−44. https://doi.org/10.1590/0101-7438.2017.037.01.0129.

[16] Journal E., Studies E., Vol M. Modelling of Hydropower Reservoir Variables for Energy Generation: Neural Network ApproachADULKA DIR, T. S., I SALAMI, A. W., I Anwar, A. R. 1 and Kareem, A. G. 2. Ethiop J Environ Stud Manag Vol 2013;6:310−6.

[17] Li G, Sun Y, He Y, Li X, Tu Q. Short-term power generation energy forecasting model for small hydropower stations using GA-SVM. Math ProblEng 2014;2014. https://doi.org/10.1155/2014/381387.

[18] Stokelj T., R Golob, Application of Neural Networks For Hydro Power Plant Water Inflow Forecasting, Infl W. Zs, 1000 2000:189−93.

[19] Shaktawat A, Vadhera S. Fuzzy logic based determination of cost overrun of hydro power plant. Int Conf Electr Power Energy Syst ICEPES 2016 2017:301−4. https://doi.org/10.1109/ICEPES.2016.7975947.

[20] Li L, Yao F, Huang Y, Zhou F. Hydropower generation forecasting via deep neural network. Proc - 2019 6th Int Conf Inf Sci Control Eng ICISCE 2019 2019:324−8. https://doi.org/10.1109/ICISCE48695.2019.00071.

[21] Mamlook R, Akash BA, Mohsen MS. A neuro-fuzzy program approach for evaluating electric power generation systems. Energy 2001:26:619−32. https://doi.org/10.1016/S0360-5442(01)00015-9.

[22] Valizadeh N, El-Shafie A, Mukhilsin M, El-Shafie AH. Daily water level forecasting using adaptive neuro-fuzzy interface system with different scenarios: Klang Gate, Malaysia. Int J Phys Sci 2011;6:7379−89. https://doi.org/10.5897/IJPS11.1314.

[23] Oltean G, Gordan M, Ş EŞIPO, Ncel ESTĂ, Dancea O. Electronics and Telecommunications Fuzzy Logic Based Decision Making for Hydroelectric Energy Generation in A Cascaded Hydropowerplants Electronics and Telecommunications 2009;50:42−8.

[24] Cheng CT, Lin JY, Sun YG, Chau K. Long-term prediction of discharges in Manwan Hydropower using adaptive-network-based fuzzy inference systems models. Lect Notes Comput Sci 2005;3612:1152−61. https://doi.org/10.1007/11539902_145.

[25] Dehghani M, Riahi-Madvar H, Hooshyaripor F, Mosavi A, Shamshirband S, Zavadskas EK, et al. prediction of hydropower generation using Grey wolf optimization adaptive neuro-fuzzy inference system. Energies 2019;12:1−20. https://doi.org/10.3390/en12020289.

[26] Kucukali S. Risk assessment of river-type hydropower plants using fuzzy logic approach. Energy Policy 2011;39:6683−8. https://doi.org/10.1016/j.enpol.2011.06.067.

[27] Ghosh S, Majumder M, Pal M. Development of performance index for evaluation of small scale hydro power plants by neural network and multi-criteria decision making. Int J Energy Stat 2016;04:1650019. https://doi.org/10.1142/s2335680416500198.

[28] Alrayess H, Gharbia S, Beden N, Keskin AU. Using Machine Learning Techniques and Deep Learning in Forecasting The
Hydroelectric Power Generation in Almus Dam, Turkey. 5th Int Symp Dam Saf 2018:635–47. 

[29] Hamid AT, Sulaiman MH Bin, Abdalla AN. Prediction of small hydropower plant power production in Himreen Lake dam (HLD) using artificial neural network. Alexandria Eng J 2018;57:211–21. https://doi.org/10.1016/j.aej.2016.12.011.

[30] Stokelj T, Paravan D, Golob R. Enhanced artificial neural network inflow forecasting algorithm for run-of-river hydropower plants. J Water Resour Plan Manag2002;128:415–23. https://doi.org/10.1061/(ASCE)0733-9496(2002)128:6(415).

[31] Feng G, Xia G, Chen B, Xiao Y, Zhou R. A method for rockburst prediction in the deep tunnels of hydropower stations based on the monitored microseismicity and an optimized probabilistic neural network model. Sustain 2019;11. https://doi.org/10.3390/su1113212.

[32] Jalalkamali A, Sedghi H, Manshouri M. Monthly groundwater level prediction using ANN and neuro-fuzzy models: A case study on Kerman plain, Iran. J Hydroinformatics2011;13:867–76. https://doi.org/10.2116/ hydro.2010.034.

[33] Kumar K, Saini RP. Materials Today : Proceedings Application of machine learning for hydropower plant silt data analysis. Mater Today Proc 2020. https://doi.org/10.1016/j.matpr.2020.09.375.

[34] Bina MT, Ahmadi D. Aggregate domestic demand modelling for the next day direct load control applications, IET Generation. TransmDistrib2014;8:1306–17. https://doi.org/10.1049/iet-gtd.2013.0567.

[35] Simmhan Y, Aman S, Kumbhare A, Liu R, Stevens S, Zhou Q, Prasanna V. Cloud-based software platform for big data analytics in smart grids, Comput Sci Eng2013;15:38–47. https://doi.org/10.1017/ICSE.2013.39.

[36] Pal S, Kumar R. Price prediction techniques for residential demand response using support vector regression. In: 2016 IEEE 7th power India international conference (PIICON). IEEE; 2016. p. 1–6. https://doi.org/10.1109/POWERI.2016.8077427.

[37] Park S, Ryu S, Choi Y, Kim J, Kim H, Park S, Ryu S, Choi Y, Kim J, Kim H. Datadriven baseline estimation of residential buildings for demand response. Energies 2015;8:10239–59. https://doi.org/10.3390/en80910239.

[38] Jazaeri J, Alpcan T, Gordon R, Brandao M, Hoban T, Seeling C. Baseline methodologies for small scale residential demand response. In: 2016 IEEE innovative smart grid technologies - asia (ISGT-Asia). IEEE; 2016. p. 747–52. https://doi.org/10.1109/ISGT-Asia.2016.7796478.

[39] Aninga A, Pora W. Baseline calculation of industrial factories for demand response application. In: 2018 IEEE international conference on consumer electronics - asia (ICCE-Asia). IEEE; 2018. p. 206–12. https://doi.org/10.1109/ICCE-ASIA.2018.8552114.

[40] Escriva-Escriga G, Alvarez-Bel C, Roldan-Blay C, Alcazar-Ortega M. New artificial neural network prediction method for electrical consumption forecasting based on building end-uses. Energy Build 2011;43:3112–9. https://doi.org/10.1016/J. EMBUILD.2011.08.008.

[41] Jiang H, Tan Z. Load forecasting in demand response. In: 2012 asia-pacific power and energy engineering conference. IEEE; 2012. p. 1–4. https://doi.org/10.1109/APPEEC.2012.6307716.

[42] Chen Qifang, Liu Nian, Wang Cheng, Zhang Jianhua. Optimal power utilizing strategy for PV-based EV charging stations considering Real-time price. In: 2014 IEEE conference and expo transportation electrification asia-pacific (ITEC asiapacific). IEEE; 2014. p. 1–6. https://doi.org/10.1109/ITEC-AP.2014.6941123.

[43] Pal S, Kumar R. Effective load scheduling of residential consumers based on dynamic pricing with price prediction capabilities. In: 2016 IEEE 1st international conference on power electronics, intelligent control and energy systems (ICPEICES). IEEE; 2016. p. 1–6. https://doi.org/10.1109/ICPEICES.2016.7853245.

[44] Takiyar S. Grid reliability enhancement by peak load forecasting with a PSO hybridized ANN model. In: 2015 4th international conference on reliability, infocom technologies and optimization (ICRITO) (trends and future directions), IEEE; 2015. p. 1–6. https://doi.org/10.1109/ICRITO.2015.7359274.

[45] Basnet SM, Aburub H, Jewell W. An artificial neural network-based peak demand and system loss forecasting system and its effect on demand response programs. In: 2016 clemson university power systems conference (PSC). IEEE; 2016. p. 1–5. https://doi.org/10.1109/PSC.2016.7462875.

[46] Paterakis NG, Catalao JPS, Tascikaraoglu A, Bakirtzis AG, Erdinc O. Demand response driven load pattern elasticity analysis for smart households. In: 2015 IEEE 5th international conference on power engineering, energy and electrical drives (POWERENG). IEEE; 2015. p. 399–404. https://doi.org/10.1109/POWERENG.2015.7266350.

[47] Chapuis J, Kraus F. Application of Fuzzy Logic for Selection of Turbines and Weirs in Hydro Power Plants. IFAC Proc Vol 1999;32:7190–5. https://doi.org/10.1016/s1474-6701(17)57227-4.

[48] Adhikary P, Roy PK, Mazumdar A. Safe and Efficient Control of Hydro Power Plant By Fuzzy Logic. Ijesat Inf Technol Adv Technol 2012:1270–7.

[49] Xu H, Wang D, Liu J. Processor control optimization for hydroelectric power based on neural network algorithm. Adv Model Anal C 2017;72:156–67. https://doi.org/10.18280/ama_c.720204.

[50] Theophilus EC, Enke P. Design and Development of Neuro-Fuzzy controller for Hydropower Generator Stability 2016;7.

[51] Öğüz Y, Güney I. Adaptive neuro-fuzzy inference system to improve the power quality of variable-speed wind power generation system. Turkish J ElectrEngComput Sci 2010;18:625–45. https://doi.org/10.3906/elk-0907-115.

[52] Falchetta G, Kasamba C, Parkinson SC. Monitoring hydropower reliability in Malawi with satellite data and machine learning. Environ Res Lett 2020;15. https://doi.org/10.1088/1748-9326/ab6562.

[53] Molina JM, Isasi P, Berlanga A, Sanchis A. Hydroelectric power plant management relying on neural networks and expert system integration. EngApplArtifIntell2000;13:357–69. https://doi.org/10.1016/S0952-1976(00)00009-9.
[54] Wotawa F, Friedrich G, Koitz-ristov IPR, Eds MA, Goebel R. Advances and Trends in Artificial Intelligence From Theory to Practice Series Editors. vol. 1. Springer International Publishing; 2019. https://doi.org/10.1007/978-3-030-22999-3.

[55] Li M, Deng CH, Tan J, Yang W, Zheng L. Research on Small Hydropower Generation Forecasting Method Based on Improved BP Neural Network 2016:1085–90. https://doi.org/10.2991/icmemtc-16.2016.214.

[56] Ak M, Kentel E, Kucukali S. A fuzzy logic tool to evaluate low-head hydropower technologies at the outlet of wastewater treatment plants. Renew Sustain Energy Rev 2017;68:727–37. https://doi.org/10.1016/j.rser.2016.10.010.

[57] Bai VR, Tamjis MR. Fuzzy Logic Model on Operation and Control of Hydropower Dams in Malaysia. Int Conf Comput Exp Eng Sci 2007:4:31–40. https://doi.org/10.3970/jcces.2007.004.031.

[58] Gunduz M, Sahin HB. An early cost estimation model for hydroelectric power plant projects using neural networks and multiple regression analysis. J CivEngManag2015;21:470–7. https://doi.org/10.3846/13923730.2014.890657.

[59] Tripathi P, Shrestha SK. Risk Assessment of Boot Hydropower Projects in Nepal Using Fuzzy Logic Approach. J Adv Coll EngManag2018;3:115. https://doi.org/10.3126/jacem.v3i0.18965.

[60] Shimray BA, Singh KM, Khelchandra T, Mehta RK. Ranking of Sites for Installation of Hydropower Plant Using MLP Neural Network Trained with GA: A MADM Approach. ComputIntellNeurosci 2017;2017. https://doi.org/10.1155/2017/4152140.

[61] Qu X, Yang J, Chang M. A Deep Learning Model for Concrete Dam Deformation Prediction Based on RS-LSTM. J Sensors 2019;2019. https://doi.org/10.1155/2019/4581672.

[62] Mosavi A, Salimi M, Ardabili SF, Rabczuk T, Shamshirband S, Varkonyi-Koczy AR. State of the art of machine learning models in energy systems, a systematic review. Energies 2019;12. https://doi.org/10.3390/en12071301.

[63] Pérez-Díaz JI, Fraile-Ardanuy J. Neural networks for optimal operation of a run-of-river adjustable speed hydropower plant with axial-flow propeller turbine. 2008 Mediterr Conf Control Autom - Conf Proceedings, MED’08 2008:309–14. https://doi.org/10.1109/MED.2008.4602228.

[64] Zaidi, Chandola, Allen, Sanyal, Stewart, Bhaduri, et al. Machine learning for energy-water nexus: challenges and opportunities. Big Earth Data 2019;2:228–67. https://doi.org/10.1080/20964471.2018.1526057.

[65] Babar M, Nguyen P, Cuk V, Kamphuis I. The development of demand elasticity model for demand response in the retail market environment. In: 2015 IEEE eindhovenPowerTech. IEEE; 2015. p. 1–6. https://doi.org/10.1109/PTC.2015.7232789.

[66] Alves MJ, Antunes CH, Carrasqueira P. A hybrid genetic algorithm for the interaction of electricity retailers with demand response. In: Lecture notes in computer science (LNCS), vol. 9597. European Conference on the Applications of Evolutionary Computation; 2016. p. 459–74. https://doi.org/10.1007/978-3-319-31204-0_30.