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Review Article

A Critical Review on the Use of Artificial Intelligence in the Small Hydropower Industry

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Abstract - *In recent years, Artificial Intelligence (AI) has begun to play a significant role across the renewable energy sector, yet its application within the Small Hydropower (SHP) sector remains underexplored compared to solar and wind. This review critically examines the state of AI integration in SHP, focusing on its potential to enhance forecasting accuracy, optimise operations, improve fault detection, and support sustainable environmental management. By synthesising evidence from recent advances across renewable energy sectors, the paper identifies both transferable methods, such as inflow forecasting adapted from solar irradiance prediction, and unique SHP challenges, including sedimentation, ecological flow management, and limited data availability. A comparative analysis demonstrates that while deep learning models such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) achieve high predictive performance, hybrid models that combine data-driven and physics-based approaches are particularly promising for data-scarce SHP environments. Economic considerations remain central, as AI integration often requires upfront investment in sensors and digital infrastructure, though long-term benefits in efficiency and reliability can outweigh costs. Furthermore, AI applications in SHP align with broader sustainability goals, contributing to the United Nations Sustainable Development Goals (SDGs) through improved energy access, resilient infrastructure, and climate action. The review highlights research gaps in collaborative learning, federated frameworks, and edge AI for rural deployments, underscoring the need for scalable and inclusive solutions. Ultimately, this paper positions AI as a critical enabler for the modernisation of SHP, offering a roadmap for advancing both technical innovation and sustainable development in the global energy transition.*

Keywords - *Artificial Intelligence, Hybrid models, Inflow forecasting, Predictive maintenance, Renewable energy systems, Small hydropower, Sustainable energy.*

1. Introduction

The global energy transition is pushing for renewable energy technologies to play larger roles in meeting increasing demand while reducing carbon emissions. Small Hydropower (SHP) systems, typically defined as hydropower plants with a capacity up to 10 MW, represent an underutilised resource that can supply reliable electricity to remote or rural areas. Advances in digitalisation and Artificial Intelligence (AI) now offer new opportunities to optimise SHP performance, improve operational reliability, and reduce costs. Artificial intelligence encompasses techniques such as machine learning, neural networks, metaheuristic optimisation, and predictive analytics. In renewable energy sectors such as solar and wind, AI has been applied to load and generation forecasting, optimisation of component performance, predictive maintenance, and grid integration. Despite this, the degree to which SHP has benefited from AI is less comprehensively reviewed, particularly within engineering journals such as IJETT. Trends in AI-related publications across renewable energy sectors (2015-2025) are illustrated in Figure 1, showing higher adoption in solar and wind, while hydropower, particularly small hydro, remains underrepresented. Several recent studies illustrate the relevance of AI-based methods in renewable energy optimisation. For example, "Hybrid Renewable Energy System Optimization via Slime Mould Algorithm" shows a metaheuristic algorithm optimising a hybrid renewable system, including hydro turbine components. The paper "Artificial Neural Networks Based on Optimization Technique for Short-Term Electricity Demand Forecasting" demonstrates combining ANN with optimization to improve forecasting accuracy. These works suggest an opportunity to synthesise how AI has been (and can be) applied specifically in SHP.

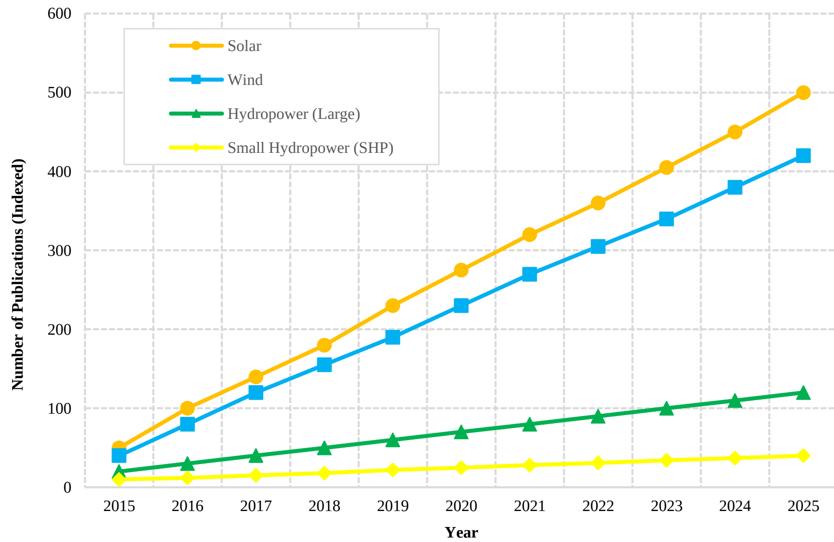

Fig. 1 Example for a small figure

1.1. Problem Statement

SHP continues to face persistent challenges such as inflow variability, sedimentation, and equipment wear [1] and limited digital monitoring, all of which reduce reliability and increase operational costs. Although AI has significantly enhanced forecasting and optimisation in solar and wind sectors, its application in SHP remains limited and fragmented. These gaps highlight the need for a systematic review on how AI can address SHP-specific operational and technical constraints.

Most of the AI research in green energy is on solar and wind power. However, current SHP research remains broad and lacks a clear research focus. Existing works usually only look at single jobs, like predicting input or finding faults, without giving a full lifecycle view. Key SHP problems, like sedimentation, biological flow needs, and low-head operation, are also not often looked at in AI-based studies right now. There is a clear gap in the literature because there isn't a complete summary that focuses on SHP.

1.2. Research Novelty

The novelty of this review lies in delivering the first holistic and comparative evaluation of AI techniques specifically for SHP. This review is different from others that have looked at AI in the renewable energy sector as a whole because it looks at both solar and wind energy, compares how well AI models work with SHP restrictions, and finds research gaps in technical, economic, environmental, and policy areas. This comprehensive strategy offers useful, yet unexplored, ideas for developing AI in SHP.

1.3. Research Questions

To refine the problem statement and guide the scope of this review, the following research questions were formulated:

- How has artificial intelligence been applied in the various phases of SHP plants' operations?
- What are the advantages, drawbacks, and output performance of the AI models used in SHP applications?
- How do AI applications in SHP compare with developments in the solar and wind sectors, and what research gaps remain unaddressed?

This review article, therefore, aims to critically evaluate the current state of AI use in the small hydropower industry. The objectives are to examine existing applications of AI in SHP, identify benefits and limitations, compare SHP lessons with other sectors, and provide key research directions.

2. Background

The background section discussed how SHP works with AI and how it can be used as a clean, self-sufficient energy source in rural areas.

2.1. Small Hydropower's Overview

An SHP system is often defined as one that has an installed capacity of less than 10 MW [2]. If the rules are different in different places, though, the maximum power could be as high as 30 MW [3]. Run-of-river systems are often used for SHP projects. These use turbines to change the flow of a river without building big dams or lakes. This is not the same as large-scale electricity. This system makes sure that the power source stays steady while causing as little trouble as possible for people and the environment [4]. Because it is flexible and spread out, SHP is a good choice for bringing electricity to distant places that are still growing. The International Energy Agency says that SHP only makes up a small part of the world's hydropower potential. However, it is very important for setting up off-grid and mini-grid systems, especially in Asia, Latin America, and Sub-Saharan Africa [5]. Because of new developments in digital tracking systems, lightweight materials, and engine design, SHP sites are now even more technically and financially possible. Kaplan and crossflow turbines made for low-head sites are an example of how the number of possible locations has grown [6]. Despite the growing need to broaden green energy assets, SHP is still a safe and reasonable option for small towns. Cost, flexibility, and environmental care are all well-balanced [7].

2.2. Basics of Artificial Intelligence in Energy Systems

One of the most well-known AI methods is Artificial Neural Networks (ANN). They are very good at simulating complicated connections, like the one between how water moves and how energy is made [8]. It is also possible to use support vector machines (SVMs) to sort things, like finding problems in wind blades. Meanwhile, random forests and decision trees are utilised to look for odd trends in sensor data [9].

Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) are two deep learning tools that are used a lot in green energy projects these days. To find problems in wind blades, CNNs can handle sound or moving signs that are very tricky. RNNs and their more advanced form, Long Short-Term Memory (LSTM) networks, are very good at guessing sequential data, like how fast rivers flow or how much power people need [10]. Reinforcement Learning (RL) has also been used to improve strategy plans by letting AI learn from constant input in environments that are always changing [11].

Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) from metaheuristic optimisation methods work with predictive AI models to find the best answers in areas of design and operation that are very complicated. For example, GA-optimised ANN models have shown better accuracy in predicting energy demand, which is a general idea that can be used to predict hydropower input. Together, these AI methods make up a set of tools that can make energy systems much more reliable and efficient. Their use in small water, on the other hand, is still limited compared to solar and wind power, which shows how important this review is. The general mathematical representation of an AI-based predictive model is given as:

$$\hat{y} = f(x;\theta) \tag{1}$$

where x represents the input features (e.g., rainfall, river discharge, head), θ denotes the model parameters learned during training, and $\hat{y}$ is the predicted output, such as power generation or turbine efficiency.

2.3. Intersection of AI and Small Hydropower

Standard hydrological and mechanical models may not be able to show how things like river flows, the movement of silt, and tool wear and tear change over time in ecosystems that are always changing. AI, on the other hand, is based on data and can change based on things like weather, wind speed, rainfall, and rotor moves to give real-time, useful information [12].

AI is used by SHP to do many things, such as predict floods, make processes better, figure out when repairs are needed, and protect the environment. ANN and LSTM models were used to correctly guess how much water would flow into rivers. This made the power source more stable and the plan for how the turbines would work better [13]. It is possible for AI-based systems that use vibration and sound data to find early signs of bearing wear or cavitation. This can save money on repair costs [14] and unplanned downtime [15]. The programs in these systems change the way the turbine works based on the inputs. This makes the turbine better at making energy [16].

Putting AI and SHP together is like having a feedback loop where devices gather data on mechanics and hydraulics and send it to AI models. It is possible to guess how much power will be made for merging into a grid or community using these models. They also give the best control signals for how to run the turbines and when to do maintenance [17]. AI is not seen as an option to standard engineering models, but rather as an extra layer that makes systems more efficient and robust. This is because these two things work well together. Figure 2 shows a diagram of the AI-SHP environment.

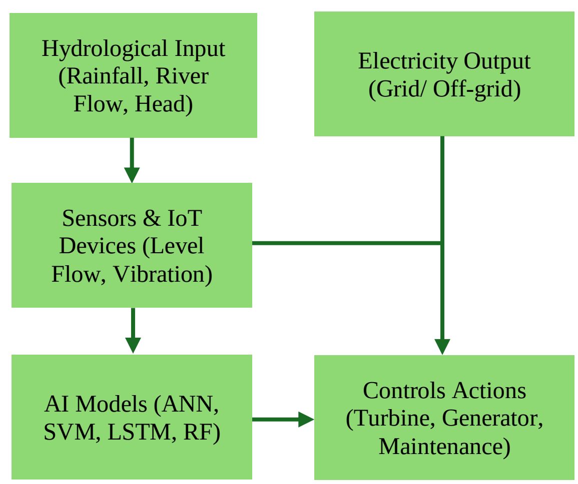

Fig. 2 AI-SHP ecosystem schematic

3. Applications of AI in Small Hydropower

This section describes how key AI techniques, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) models, were assessed against SHP-specific challenges. This section also introduced figures and tables to map AI workflows and summarise model performance, ensuring a rigorous and transparent review framework.

3.1. Hydrological Forecasting and Water Flow Prediction

One of the most significant tasks of SHP plants is hydrological forecasts, since the amount of energy they produce is very dependent on changes in the water that comes in. Operators can plan when to turn on the turbines, when to expect the most power, and how to reduce risks during low-flow or flood events if they can accurately guess when the river will flood or flow down. Moreover, linear or statistical models, such as the Autoregressive Integrated Moving Average (ARIMA), regression analysis, or conceptual rainfall-runoff models, have been used to predict water flow [18].

Some types of machine learning, such as ANN, Support Vector Regression (SVR), and random forests, can find complicated links between weather data, such as temperature, humidity, and rainfall, and river flow [19], or sequential time-series forecasting, Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models work well because they can find long-term temporal links that are common in hydrological datasets [13]. The LSTM method was better at predicting Jakarta's sea level than the ARIMA method. In training data, it made an average error of 0.512%, and in testing data, it made an average error of 0.564% [20].

When they use mixed AI models that combine physical hydrology equations with learning from data, they are even more accurate. ANN can be used with evolutionary optimisation methods like Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO) to make more accurate predictions [19]. This is because the model parameters can be changed automatically. With ensemble learning methods that use more than one technique, models are less likely to become too good at what they do or not have enough data. Due to the lack of high-resolution maps in less developed areas, these methods work best for SHP plants there.

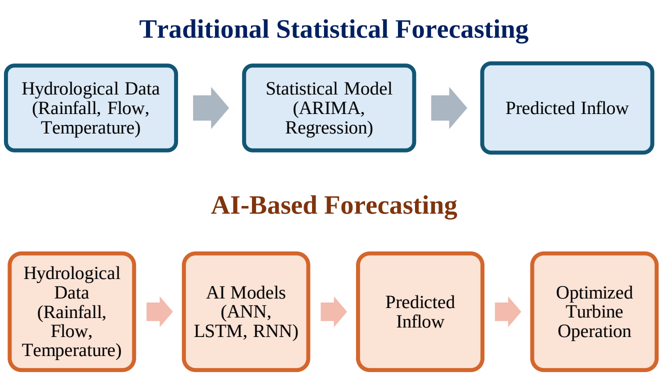

Fig. 3 Comparison of traditional vs AI-based hydrological forecasting

The use of AI-based hydrological forecasting has a direct effect on how well things run. SHP operators can change the order in which turbines are dispatched ahead of time when they have more accurate inflow projections. This improves load matching and cuts down on downtime. This feature also makes hybrid renewable systems more stable by making hydropower's contribution more predictable. AI-based forecasting systems are a better and more flexible option than traditional statistical methods, as shown in Figure 3. They may help SHP operations stay strong even when the weather changes and energy demand rises.

3.2. Optimal Turbine and Generator Operation

The performance of SHP plants is greatly affected by the operating parameters of the turbines and generators, especially the flow rate, net head, and system load. Static efficiency curves or rule-based control techniques are typically used in conventional operations; however, these may not completely account for changes in inputs or wear and tear on machines. AI learns the nonlinear relationship between input parameters and turbine performance in real time, which makes it easier to adapt. ANNs have been extensively utilised for this objective, facilitating the development of efficient prediction models articulated as;

$$\eta_t = f(Q, H; \theta) \quad (2)$$

where η_t is the turbine efficiency, Q is the water flow, H is the net head, and θ represents the learned model parameters [10]. Such models have been used to construct digital twins of SHP plants, enabling virtual testing of operational strategies.

Reinforcement learning (RL) makes operational optimisation even better by letting AI agents change their control techniques all the time based on feedback from the real world. For instance, RL-based controllers have been used on hydropower units in cascaded systems, where they change the apertures of the guiding vanes in real time to get the most efficiency out of the system while avoiding cavitation [21]. These controllers are better at adapting to changing inflows than standard proportional-integral-derivative (PID) systems.

Metaheuristic optimisation methods are also very important for designing and running turbines. Systems such as GA and PSO have been utilised to optimise operational parameters, including runner blade angles and generator excitation levels [22]. Recent studies integrating ANN with GA have shown that these hybrid models can make turbine operations more efficient than static models [23]. Adding AI to the operation of turbines and generators not only makes the plant work better, but it also makes the equipment last longer by lowering the mechanical stress that comes from poor control. AI-based adaptive operation helps make rural electrification projects more reliable and long-lasting because SHP plants are often set up in distant areas where maintenance resources are hard to come by.

3.3. Fault Detection and Predictive Maintenance

Fault detection and predictive maintenance are among the most impactful applications of AI in SHP plants. In the past, fault detection was done manually by hand checks and tracking sound or temperature data based on thresholds. These traditional methods are not very sensitive and often miss initial-stage failures [24].

Supporting Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN) are often used to sort things into groups [25] and figure out if a state of action is healthy or sick. Deep learning models, like Convolutional Neural Networks (CNN), make this even better by taking elements from raw sound or movement patterns on their own. This means that signal processing does not have to be done by hand as much [26]. As summarised in Table 1, a range of AI techniques has been successfully applied in SHP fault detection.

Table 1. AI techniques for fault detection in SHP components

AI Technique	Application in SHP	Reported Accuracy
Artificial Neural Networks (ANN)	Fault classification in turbine bearings	85% - 92%
Support Vector Machines (SVM)	Detection of abnormal vibration patterns	88% - 94%
Convolutional Neural Networks (CNN)	Acoustic and image-based fault detection	90% - 96%
Random Forests (RF)	General classification of sensor anomalies	84% - 90%
Hybrid Models (e.g., ANN+GA)	Enhanced accuracy through a combined approach	92% - 97%

Hybrid AI systems that use both predictive models and optimisation methods make things even more reliable. As an example, getting the best model parameters with the help of an ANN and genetic algorithms has been shown to improve the accuracy of fault detection [27]. A study showed that these mixed methods are better than single-model classifiers at finding faults in spinning machinery, with an accuracy of up to 97% [23].

3.4. Design Optimisation

Design optimisation is important for making SHP systems work better, last longer, and be more reliable. Components like turbine runners, penstocks, and draft tubes need to be carefully planned so that they can get the most energy out of changing water flows while causing the least amount of cavitation, shaking, and wear. The best way to look at fluid flow and turbine performance is still through traditional Computational Fluid Dynamics (CFD) simulations. However, they are very demanding on computers and involve a lot of trial and error when optimising across many design variables. AI technologies are a strong addition since they may be used as surrogate models that get similar results to CFD at a much lower computing cost [28]. In this case, ANN and Gaussian Process Regression (GPR) are commonly used. They are trained using data sets made from CFD simulations [29, 30]. After training, these models can quickly estimate cavitation thresholds, pressure distributions, and turbine efficiency curves for novel design candidates. This speeds up the optimisation process, giving engineers access to a bigger design area than they would have if they only used CFD. Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) are two examples of metaheuristic algorithms that are typically used with these predictive models to determine excellent solutions for the whole world. For instance, PSO-based optimisation used on turbine blade design made them up to 8% to 15% more efficient than typical baseline designs [31].

More modern methods use hybrid CFD-AI frameworks, where CFD simulations give the first training data and AI models improve predictions as more data is added [32]. This iterative learning method shortens design cycles and adjusts to the characteristics of the site, such as low-head river settings or flows with a lot of sediment. SHP developers can use AI to optimise designs and make turbines that are cost-effective and high-performance, taking into account the resources available in the area. This makes projects more financially viable and environmentally friendly.

3.5. Energy Management and Smart Grid Integration

As energy systems move away from centralisation, it has become more vital to connect SHP facilities to smart microgrids. SHP units are widely used in rural electrification together with solar photovoltaics, wind turbines, and battery storage. It is important to control energy in these systems so that they stay stable and effective [33].

These systems are called hybrid systems. Most scheduling methods are based on fixed rules or linear planning, which might not take into account the unknowns of new customers or changing demand patterns well enough. AI methods offer more adaptable answers by letting improvement happen in real time and in advance [34].

Some AI models that are often used to guess load are ANN and Long Short-Term Memory (LSTM) networks. With these models, SHP workers can guess how much power will be needed in the short term. This lets them change when they make power ahead of time. This, along with estimates of water flow, lets users run a balanced system that does not require petrol engines as much for backup power as hybrid systems [35]. In small power lines that employ SHP, this could mean providing important loads like hospitals or water pumping systems with more power when demand is high [36]. When SHP and AI combine, they raise voltage levels and lower frequency changes. Hence, this makes the grid more stable. Meanwhile, Figure 4 shows a possible design for a smart grid.

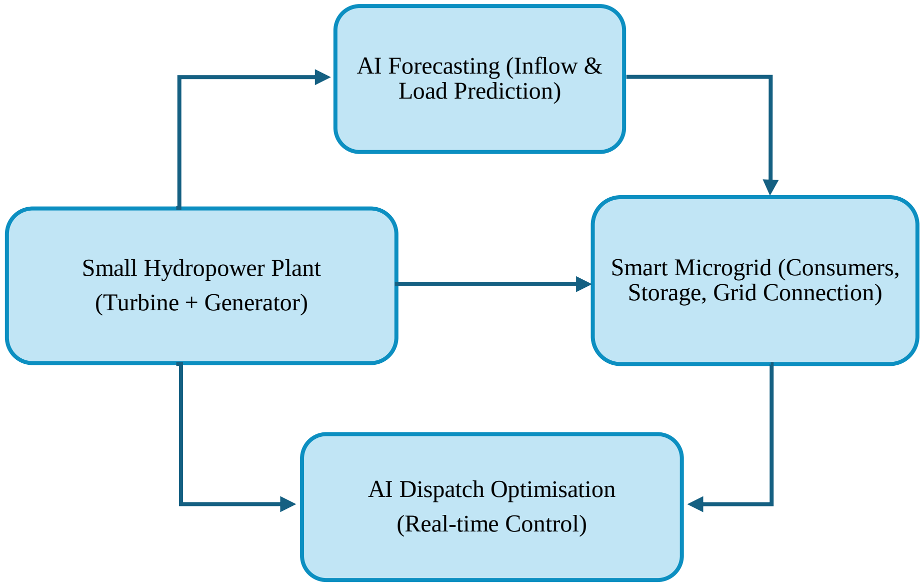

Fig. 4 Smart grid schematic integrating SHP with AI

In this design, SHP plants are linked to units that use AI to balance energy production, storage, and demand. People have usually thought of SHP as a resource that can be used by itself, but this shows how it can be an active part of smart, flexible energy systems. This is especially true in growing areas where electricity is not yet connected to the grid.

3.6. Environmental Impact Assessment and Sustainability

Environmental Impact Assessments (EIA) that are used today use data from people and water models, which may not show the long-term effects on the environment or how different projects in a river area add up [37]. AI can be made better in new ways because it lets us use data for tracking, making predictions, and managing things in a flexible way.

Engineers have used machine learning to guess how fish will move in different flow conditions. This has helped them make better paths and escape ways for fish [38]. Drones with AI and underwater cameras can also keep an eye on wildlife by finding new fish species or changes in the plants along the banks of rivers [39]. This reduces the need for biological studies that are done by hand, which makes watching the environment more efficient and less expensive.

AI is also being used more and more to control sediment. Too much silt can hurt environments further downstream, make turbines less effective, and speed up the wear and tear on equipment. AI can predict sediment loads by looking at weather and sediment data. This lets workers plan when to flush or clean [40]. This stops the unchecked release of silt, which is good for the environment and helps make electricity. Acceptance by society is also closely linked to the long-term viability of SHP. AI-based decision-support systems can make plans with multiple goals that take into account community interests, water needs in different sectors, and natural needs [41].

4. Systematic Review Methodology

A systematic review approach was used to ensure a transparent assessment of AI applications in SHP. Relevant literature was identified through four major databases, such as Scopus, Web of Science, IEEE Xplore, and Google Scholar.

The search strategy combined AI and SHP-related keywords such as "artificial intelligence", "machine learning", "neural networks", "metaheuristic optimisation", "small hydropower", "inflow forecasting", "sedimentation", and "low-head turbine". The screening process involved three stages, including:

- Duplicate removal;
- Title and abstract screening to exclude irrelevant studies; and
- Full-text assessment for methodological clarity and SHP relevance.

Inclusion criteria required studies to apply AI, ML, ANN, or metaheuristic methods to SHP-related tasks such as inflow prediction, optimisation, turbine performance, or fault detection [42].

Meanwhile, exclusion criteria removed studies focused solely on large hydropower, papers lacking technical detail, and non-peer-reviewed materials. A PRISMA diagram in Figure 5 summarises the identification, screening, eligibility, and final selection of studies used in this review.

Identification:
Records identified through database searching
(n = 432)

Screening:
Records after duplicates removed
(n = 289)

Eligibility:
Full-text articles assessed
(n = 74)

Included:
Studies included in review
(n = 42)

Fig. 5 PRISMA flow diagram for the study selection process

5. Critical Review and Comparative Analysis

In the critical review part, the results were put together by comparing how AI is used in solar, wind, and SHP. It was pointed out that SHP is behind because it does not have as much data and digital infrastructure. The tables showed how different sectors used the models and how well they worked, while the discussion focused on the technical, economic, environmental, and social effects.

5.1. Comparison of AI Applications across Renewable Energy Sectors

AI is now used in a lot of different types of green energy, but they are all at very different stages of development and can be used in very different ways. A lot of AI is used in solar energy to figure out how much sun will hit a panel, keep track of the MPPT (Maximum Power Point Tracking), and find panels that are not working right. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are two advanced deep learning models that are the best at predicting the short term and usually do better than standard statistical methods [43].

In the wind business, Reinforcement Learning (RL) has also been used to improve yaw and blade pitch control. The wind can then change the speed and direction of the mills. These methods not only help get more energy, but they also ease the stress on buildings, which makes equipment last longer [16].

Solar and wind energy systems, on the other hand, have access to larger datasets, more advanced tracking infrastructure, and well-established AI planning tools, while SHP is still not as digitally stable. Table 2 shows a comparison of how AI is being used in solar, wind, and SHP to show how SHP fits into the bigger picture of digitalising green energy.

This comparison shows how differences between sectors affect data access, AI model growth, practical limits, and research gaps. It also shows how lessons learnt from solar and wind can help shape future progress in SHP. The comparison is important because it makes this review even more unique, as it is the first organised, cross-sector study that is specially designed for SHP.

Table 2. Comparison of AI adoption in solar, wind, and small hydropower

Aspects	Solar	Wind	Small Hydropower (SHP)
Data availability	High	High	Low-Moderate
Common AI applications	• Irradiance forecasting • MPPT control • PV fault detection	• Wind speed prediction • Yaw/pitch control • Predictive maintenance	• Inflow forecasting • Fault detection • Turbine performance estimation
Model maturity	Very mature and commercially deployed	Mature and widely validated	Emerging and experimental
Operational constraints	• Weather variability	• Turbulence • Wake effects	• Sedimentation • Low-head variability
Technical challenges	• Cloud cover • Rapid fluctuations	• Real-time adaptive control	• Limited sensing • Ecological constraints
Research gaps	Enhanced hybrid forecasting	Multi-turbine optimisation	• Lifecycle modelling • Hybrid AI-hydrology models • SHP specific datasets
Review contributions	-	-	• First integrated synthesis of AI across the SHP lifecycle • Systematic cross-sector comparison with solar/wind • Identification of multidimensional SHP research gaps

SHP, on the other hand, has been slow to adopt AI. The uses that have been talked about mostly have to do with guessing what will be put in and making repairs ahead of time. This is still not possible to fully connect to smart grids or tune in more complex ways [17]. AI has a lot of data to work with because solar and wind farms usually have complicated supervisory control and data acquisition (SCADA) systems. This is one reason for the difference. However, a lot of SHP plants, especially those in new places, do not have as much digital tracking gear. For deep learning and other difficult AI systems, this means that the data that can be used to build models is rarely enough. In the past, policies and funding goals have also favoured solar and wind, which made the imbalance even worse [44].

Thus, while SHP currently trails behind solar and wind in terms of AI implementation, comparative analysis demonstrates that cross-sectoral knowledge transfer can accelerate adoption. Tailoring AI models to the unique technical and environmental realities of SHP remains the central challenge moving forward.

5.2. Comparative Performance of AI Models in SHP

There are many methods for SHP that use AI, and each has its own pros and cons that change based on the case. Artificial Neural Networks (ANN) are the most common type of network and are great at predicting the input/output of a turbine. Furthermore, people say they are hard to understand, but they are praised for being able to fake complicated systems. It has been shown that using ANNs instead of regular autoregressive models can cut the Root Mean Square Error (RMSE) by up to 25% when it comes to predicting floods. To find flaws and vibrations in turbines, Support Vector Machines (SVMs) and Support Vector Regression (SVR) are often used. They can handle small datasets well, which makes them good for SHP sites that do not get a lot of tracking [15]. But they need to be carefully tuned, which can make them less useful in real time. Random Forests (RF) can handle noisy or overfitted data well, which makes them good at finding outliers. However, when working with big datasets, they might not work as well as deep learning methods [45].

Long Short-Term Memory (LSTM) networks are about 25% more accurate than ARIMA baselines in places where rain falls a lot [48]. More than 95% of the time, Convolutional Neural Networks (CNNs) can find problems from shaking and sound data, which is a lot better than traditional signal processing methods [10]. Reinforcement Learning (RL) has a lot of promise for real-time dispatch improvement by changing how the rotor works as the water level changes.

Many individuals are looking at hybrid methods as a good middle ground. For example, ANN combined with Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO). These models keep the good things about machine learning for making predictions while using optimization methods to make them more accurate and consistent. The classification accuracy of mixed systems is usually the best (92% to 97%), as in Table 3. These systems strike a good balance between performance and processing efficiency.

Table 3. Comparative performance of AI models in SHP applications

AI Model	Details
Artificial Neural Network (ANN)	Typical Application in SHP: Inflow forecasting; Turbine efficiency prediction Strengths: Captures nonlinear relationships; Widely used; Flexible Limitations: Requires large datasets; “Black box” nature reduces interpretability Reported Accuracy: RMSE reduction of 20%-25% compared to ARIMA [45]
Support Vector Machine (SVM) / Support Vector Regression (SVR)	Typical Application in SHP: Turbine fault detection; Vibration pattern classification Strengths: Performs well with small datasets; Good generalisation. Limitations: Sensitive to kernel choice; Computationally intensive for large datasets Reported Accuracy: Fault detection accuracy 88%-94% [46]
Random Forest (RF)	Typical Application in SHP: Sensor anomaly detection; Classification of operational states Strengths: Robust against overfitting; Works with noisy data Limitations: Less accurate than deep learning for large datasets Reported Accuracy: Classification accuracy 84%-90% [47]
Long Short-Term Memory (LSTM) Networks	Typical Application in SHP: River inflow and load forecasting Strengths: Handles sequential and seasonal data; Outperforms ANN in time-series tasks Limitations: Requires long training times and large datasets Reported Accuracy: 25% lower forecasting error than ARIMA [48]
Convolutional Neural Network (CNN)	Typical Application in SHP: Vibration and acoustic-based fault detection Strengths: Automatically extracts features; High accuracy in condition monitoring Limitations: Requires large, labelled datasets; High computational demand Reported Accuracy: Fault detection accuracy above 95% [49]

Hybrid Models (e.g., ANN+GA, ANN+PSO)	Typical Application in SHP: Efficiency prediction; Fault classification; Optimisation tasks Strengths: Combines predictive modelling with optimisation; Improved accuracy Limitations: Higher complexity; May require fine-tuning for convergence Reported Accuracy: 92%-97% [50]

To support clearer comparison across the reviewed literature, the following summary Table 4 consolidates key patterns related to AI models, application domains, dataset characteristics, and methodological limitations in SHP research. This table provides a consolidated view of the methodological landscape in SHP-AI research and highlights recurring patterns that inform the critical analysis presented in the subsequent sections.

This comparative evidence indicates that no single AI model is universally superior. Instead, model selection must balance accuracy, interpretability, data availability, and computational resources. For SHP plants in rural or resource-constrained settings, hybrid and ensemble methods may currently provide the most practical solutions.

Table 4. Summary of SHP tasks addressed in the literature

Task	Common AI models	Limitations
Inflow forecasting	ANN, LSTM	Small datasets, short time series, missing data
Turbine optimisation	GA, PSO, hybrid methods	Often based on simulated conditions; limited real-site validation
Fault detection	SVM, ANN	Lack of standard performance metrics; minimal testing on real devices
Sedimentation modelling	ANN	Few studies; high sensitivity to data quality

5.3. Economic and Technical Feasibility of AI Adoption in SHP

Both economic and technical factors affect how likely it is that SHP will be able to use AI. When it comes to the economy, SHP projects often have trouble because they have a limited budget. This is especially true for rural electricity projects that depend on small energy sales to cover their costs [46]. To add AI, you need to buy sensors, data storage systems, and computing power, which could make the initial costs higher [47]. But these costs can be recovered over time by making operations more efficient, lowering the need for upkeep, and making tools last longer. For instance, using AI for fault detection in predictive maintenance has been shown to cut down on unplanned plant breakdowns by up to 30%, which saves a lot of money in the long run [7]. The amount and quality of data provided determine how useful AI is in SHP. Most solar and wind farms use high-tech SCADA systems, but many SHP sites, especially those in low-income areas, lack them. As a result, it is not always possible to obtain the large datasets required to train deep learning models [17]. As an alternative, mixed methods such as physics-informed models or transfer learning can be used. These approaches work well with smaller datasets and require fewer large training samples [48]. Cloud and edge AI tools also help get around problems with data and hardware. Cloud platforms can process data without having strong computers on-site, and small edge devices put in place at SHP plants can help with making decisions in real time [49].

In the end, it is up to each SHP site to decide if adopting AI is worth it based on its own technology needs and budget. Larger SHP plants that get more money from revenue and the government are more likely to invest in advanced AI systems. Smaller community-based projects, on the other hand, might like low-cost blend types that balance efficiency and cost [50]. While adding AI to SHP can be hard at first, the long-term benefits make it an investment that is worth making.

6. Discussion

Beyond reviewing specific AI models, the discussion must consider how AI fits with SHP's technical, economic, environmental, and social or policy realities. These four dimensions determine how effectively AI can support SHP. As shown in Figure 6, AI contributes through technical optimisation, economic benefits, environmental sustainability, policy, and social factors.

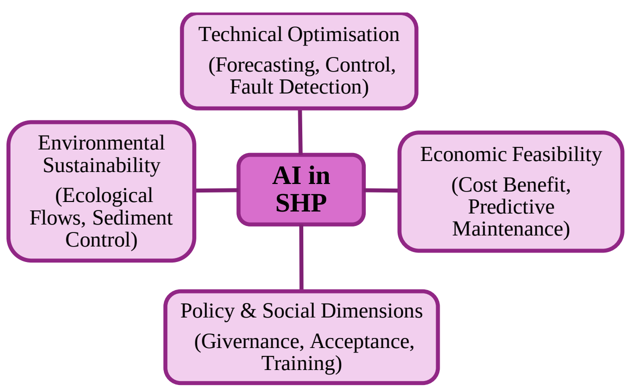

Fig. 6 Conceptual framework: AI contributions to SHP

6.1. Balancing Technical Feasibility with Economic Constraints

AI in SHP should be judged on both how well it works and how much it costs. There are not many funds for SHP projects, especially in the country [51]. To add AI, companies often need to buy new sensors, computer tools, and supervisory control and data acquisition (SCADA) systems [52]. This can make the cost of capital rise by 10% to 20% [47]. AI can still save money, as shown by predictive maintenance. Using AI to find faults can cut down on rapid turbine breaks by as much as 30% [7], which saves money on fixes and energy. It is easier to plan how to use energy, save water, and keep the grid safe when they know how much water will come in. These benefits come in slowly, but they cut down on the time it takes to get the money back. Though it takes longer to see results, ecological flow management is worth it because it helps people follow the rules and protect the environment more than it makes money. Table 5 shows that the costs and benefits of each AI application are different.

Table 5. Cost-benefit considerations of AI in SHP

AI Application	Upfront Cost	Long-Term Benefit	Payback Horizon
Inflow Forecasting	Medium (sensors, data acquisition)	• Improved load matching; • Reduced spillage	2-3 years
Predictive Maintenance	High (sensors, vibration monitoring)	• Reduced unplanned outages; • Extended equipment life	3-5 years
Ecological Flow Optimisation	Medium (environmental sensors, modelling)	• Balanced electricity generation with ecosystem protection	4-6 years
Energy Management & Dispatch	Low–Medium (software integration)	• Higher plant efficiency; • Better grid integration	2-4 years

In several cases, AI models like ANNs paired with planning methods are a good compromise because they require less computer power while still making accurate predictions. Costs are also cut by cloud and edge AI platforms, which do not need as many expensive tools on-site [48]. Taking care of these technical and financial trade-offs is important for making AI use in SHP sustainable and scalable.

6.2. AI and Environmental Sustainability in SHP

SHP is often viewed as a more environmentally friendly option than large hydropower, yet it is not entirely free from environmental impacts. Even at smaller scales, SHP installations can influence river ecosystems, alter sediment movement, and affect how water is shared and used locally. In practice, many Environmental Impact Assessments (EIAs) still depend on simplified hydrological models and manual field surveys, which may overlook gradual or long-term changes. With the ability to support continuous monitoring and informed decision-making, AI offers a more adaptive approach to managing SHP systems in ways that better align with environmental sustainability. [37].

Controlling flow in the environment is a huge application. AI models can guess how different flow rates will affect fish and other species by using past biology and hydrological data. RNNs and LSTMs can predict how things will move during different times of the year, which helps operators change how much water they release [38]. Also, CNNs combined with drone images can easily find different types of fish and changes in the plants along the banks of rivers, which cuts down on the need for hard work in the field [39].

AI also makes it easier to handle sediment, which is especially helpful in rivers that have a lot of it. Based on weather and water conditions, machine learning can predict when sand will enter a system. This lets workers plan when to flush [40]. This keeps the rotor from wearing out and stops the release of dangerous sediment.

In addition to making things more efficient, AI can also help people accept it by using tools that help them make decisions that take environmental, social, and economic issues into account. This helps SHP projects meet their environmental goals while still making money [41]. Overall, AI helps make things run more smoothly, protect the environment better, and be more in line with what the community wants.

6.3. Institutional, Policy, and Social Dimensions

Adoption of AI in SHP is also affected by how ready institutions are, how the government sets laws, and how well the community accepts AI. Institutionally, SHP does not always have clear rules about how to use technology. Large wind or hydropower farms use standard SCADA systems, but small SHP plants often use equipment from different manufacturers. This means that the data forms are not always the same, which makes it harder to integrate AI [50]. Setting clear rules for sharing data would help with tracking and make the adoption of AI go more smoothly.

From a policy point of view, funding for green energy has mostly gone to solar and wind, leaving SHP with fewer reasons to make digital changes. Countries that include SHP in their national energy plans are more likely to use AI because digital tracking is required in order to get financial help [53].

Cybersecurity must also be covered by regulations, as digital strikes can happen on SHP plants that use AI. Before AI can be used on a large scale safely, it needs to be protected by strong data safety and security rules [51]. Social acceptance is equally important. People who live in rural areas may be afraid that technology will take away work or make it harder for them to control the power system. In order to fix this problem, AI plans should include communities in making choices and offer training to improve local skills [54]. Long-term SHP success depends on making sure AI helps both scientific progress and balance in society.

6.4. Future Outlook for AI in SHP

The future of AI in SHP is closely tied to the need for scalable, sustainable, and context-specific solutions. While pilot projects have demonstrated AI's technical feasibility, wider deployment will require approaches that address data scarcity, cost constraints, and environmental considerations. A great approach is to use hybrid models, such as Physics-Informed Neural Networks (PINNs), which mix hydrology equations with data-driven learning. This makes them more accurate while cutting down on the need for big datasets. This means they can be used for SHP sites that are remote or not well watched [48].

A big part is also likely to be played by collaborative learning methods. Transfer learning lets models that were learnt on big hydropower or green datasets be used on smaller SHP plants. Federated learning, on the other hand, lets many operators train the same models without sharing private data [52]. Edge AI can help remote SHP sites even more by running simple, real-time algorithms on nearby devices, so they do not have to rely on the expensive cloud [55].

It is also important that AI in SHP fits in with bigger goals for sustainability. AI should not only improve technical performance and economic efficiency, but it should also help protect ecosystems and make communities stronger. It will be important to use multi-objective planning that takes into account things like ecology, the need to share water, and social acceptance. Inflow forecasting, predictive maintenance, ecological flow control, and energy management are some of the AI applications shown in Table 6. These directly help reach several UN Sustainable Development Goals, such as SDG 7 (Clean Energy), SDG 9 (Innovation and Infrastructure), SDG 13 (Climate Action), and SDG 15 (Life on Land) [56]. Connecting the use of AI to these global goals can help SHP projects get more support from policymakers and get money for growth.

Table 6. Alignment of AI applications with Sustainable Development Goals (SDGs)

AI Application	Related SDG	Impact Pathway
Inflow Forecasting	SDG 7 (Affordable and Clean Energy)	• Improves the reliability of the electricity supply for rural communities; • Reducing reliance on fossil fuels.
Predictive Maintenance	SDG 9 (Industry, Innovation, and Infrastructure)	• Enhances infrastructure resilience and reduces downtime. • Enabling sustainable energy access.
Ecological Flow Optimisation	SDG 15 (Life on Land)	• Protects river ecosystems and biodiversity while maintaining energy production.
Energy Management & Dispatch	SDG 13 (Climate Action)	• Enables efficient integration of SHP into grids. • Reducing carbon emissions and supporting decarbonization.

The chosen studies were very different in terms of datasets, water sources, model design, and evaluation methods, even though a thorough review method was used. A meta-analysis could not be done because of this difference. Instead, an organised story method was used, which is often used in reviews of engineering and AI, where the data is not all the same.

6.5. Ethical and Socio-Environmental Considerations

When AI is used in SHP, there are also important moral, social, and environmental issues to think about. Strong data control and privacy rights are needed for AI systems because they use operating and environmental data gathered from whole communities. On a social level, AI may make rural SHP systems more reliable by reducing the need for constant human control. However, this could lead to job loss, overdependence on technology, and less local preparation. To ensure fair acceptance and community trust, planning must be open, the community must be involved, and efforts must be made to build people's skills all the time. In terms of the environment, methods that are not well thought out could hurt ecosystems without meaning to, for example, by messing up biological flows or making sediment stress higher.

For responsible implementation, AI needs to be used with expert knowledge, clear biological boundaries, and rules about protecting the environment. Closer consideration must be given to the quality of the examined research, in addition to the more general insights already stated. Many SHP-AI works use small or very site-specific datasets, which makes it hard for their models to be used in other situations. It is common for cross-validation and stability tests to be missing, which raises the risk of overfitting. Different performance measures and not enough information about trial sets are also used in different ways when reporting. Even though this review was organised in a way that made sense, the studies that were looked at were very different from one another in terms of the datasets, water inputs, model designs, performance measures, and validation methods. It was not possible to do a formal summary or meta-analysis because the data were so different. An organised story synthesis was used instead, which is good for reviews in engineering and AI, where data uniformity is not great. A quick look at possible bias was also done, and common issues were found, such as small datasets, poor cross-validation, uneven reporting, and the heavy use of generated flow data. These problems show that future SHP-AI research needs to use more uniform datasets and better ways to compare results.

7. Conclusion

In conclusion, this review looked at the role that AI plays in SHP and pointed out both its pros and cons. A lot of people in solar and wind have used AI for forecasts, predictive repair, and energy management, but not many people in SHP have done the same. Because of problems like sediments, changing low-head conditions, and the need for natural flow, SHP cannot just copy methods from other sources. Instead, AI needs to be mixed with water models based on physics to make sure that they work well in all places.

There are three main reasons why this review goes into more detail about the analysis than other state-of-the-art studies. First, it combines AI applications from several areas, such as hydrology, optimising turbines, predictive maintenance, environmental tracking, and connecting to the smart grid. Most earlier SHP reviews were limited to predicting input or finding faults. Second, the study shows how AI techniques can be used in different fields by comparing SHP to solar and wind energy. It also explains why some methods work better than standard SHP models when there isn't enough data. Third, it combines scientific, economic, environmental, and policy views into a single framework. This gives us a fuller picture than studies that only focus on model correctness or computational performance. This review highlights several overarching insights:

- AI offers strong potential for improving inflow forecasting, predictive maintenance, and environmental monitoring in SHP.
- Hybrid physics-AI approaches are the most promising for data-scarce environments, and
- Technical progress must be paired with digital infrastructure, policy support, and community acceptance to achieve meaningful impact.

A number of important problems are also brought up by the study. Because each study used different datasets, modelling techniques, and review methods, it is not possible to do a full meta-analysis. A lot of studies used fake data or weak validation, which raised the risk of bias. Because of this, uniform data, consistent reporting, and better review methods should be at the top of the list for future study. It is also important for researchers to keep working on mixed physics-AI models, transfer and shared learning, and edge-AI tools for SHP sites that are far away.

Supporting technologies that watch the climate, setting clear rules for sharing data, and spending in digital infrastructure are all important steps that policymakers need to take. Giving people reasons to update their SHP systems and making institutional support stronger will help make sure that AI not only improves technical performance. It also helps achieve bigger goals, such as giving people in rural areas access to energy and protecting the environment. Overall, this review emphasised that AI in SHP must be evaluated within a framework.

It must consider scientific, economic, environmental, and social factors. If AI solutions are too expensive, do not care about the environment, or are socially unacceptable, technical feasibility alone does not mean they will work. Cost-benefit studies show that some applications pay for themselves quickly, while others provide long-term benefits that make the investment worthwhile.

In the same way, AI can be very helpful in taking care of the environment by helping to improve biological flow and control silt, which makes SHP projects more in line with larger conservation goals. For building trust and allowing the growth of AI-enabled SHP systems, it is important that institutions are ready, that policies are clear, and that the community is involved.

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