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Enhancing Voltage Stability with a Hybrid BWO-RL-Based PI Controller

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Abstract

The traditional methods of PI tuning are based on trial and error, which can be inefficient for complex networks that have limited system information. To solve this problem, this paper makes use of a hybrid technique using Reinforcement Learning (RL) and black Widow Optimization (BWO). Development of a simulation model for a hydropower plant using PI control has been done in MATLAB Simulink & the tuning of PI parameters has been accomplished with the aid of a hybrid BWO-RL technique, thus utilizing BWO's capacity to tackle non-linear & non-convex optimization problems & potential of RL technique to allow the PI controller to adapt and learn from the system's real-time feedback. The purpose of this study is to evaluate how well the model of hydropower plant functions & voltage is stabilized while using the proposed controller. By utilizing the proposed technique, the model voltage profile succeeded in becoming better, and errors (MSE, MAE, MAPE, and RMSE) have been reduced to a significantly low range. Overall, this research informs practices for reliable, eco-friendly hydropower operation, benefiting the energy industry and the environment.

Keywords: Reinforcement learning (RL), BWO (Black Widow Optimisation), PI controller, and a hydroelectric plant.

1 Introduction

Small Hydropower plant is the most cost-effective way to provide electricity to rural areas in underdeveloped nations. Hydroelectricity is a sustainable energy source. As in the winter & spring, pure mountains streams, & lakes can be used to create power. Hydropower plants provide low-cost electricity & have more durability [1] [2]. The main objective of this research is an enhancement of voltage stability of a hydropower plant, which is very important. Major potential Benefits and Implications of this work are as follows:

1. To ensure a consistent energy supply, benefiting industries, businesses, and households.
2. To make the hydropower plants operate at peak efficiency, maximizing energy output.
3. To reduce the risk of equipment failures and associated environmental hazards.
4. To reduce operational costs and downtime and decrease maintenance expenses, increasing overall economic benefits.
5. To enhance the grid's resilience against disruptions, improving overall reliability.
6. To delay the need for costly grid upgrades.
7. To reduce backup power source usage during outages, minimizing environmental impact.

For controlling voltage, the majority of hydraulic power facilities are controlled by PI (Proportional-Integral) controllers. PI controller's function is to regulate the system's output by adjusting the input in response to the deviation from a desired value. Water flow and turbine speed in hydro plants are controlled using PI controllers. This could be accomplished by regulating the flow of water into the turbine by opening or closing the turbine's gates. The wicket gates' opening is regulated by the PI controller, which receives data from sensors monitoring the water flow and turbine speed. Many more renewable sources are used day by day [3]. The performance of an isolated small hydropower plant using conventional control algorithms like Proportional, PI & PID control are depicted in some studies [4].

The creation of hydraulic power includes complicated and dynamic processes, necessitating the tunning PI controller. Tuning a PI controller primarily involves adjusting the proportional gain (K_P) & integral gain (K_i). Different from integral gain, which affects the steady-state error, proportional gain affects the controller's response to changes in error output. Control performance objectives can only be reached by careful tweaking of these parameters. Integral control is useful for reducing steady-state error and speeding up reaction times. However, instability and oscillations could occur from the integral gain that is too high. Optimal control performance requires a combination of proportional and integral gain. PI tuning aims to fine-tune the controller's settings to produce the required response characteristics and maximize the system's performance. The use of PI tuning in a Hydropower plant gives the following advantages [2];

a) Because the water flow and turbine speed can be tuned using PI controllers, the efficiency of the hydro plant may be increased. This ensures the facility is running as efficiently as possible and reduces waste.
b) The control system is secure and reliable since the PI controllers have been tuned to be accurate and can react rapidly to a variety of changes. This is crucial for ensuring the plant's security and avoiding costly repairs to machinery.
c) Hydro plants must be able to adjust to a broad variety of operational circumstances and external influences, including weather and water level fluctuations. The plant's stability can be maintained by the use of

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properly calibrated PI controllers that can respond to these variations.

d) Since the unneeded or excessive movement of the turbine wicket gates may be mitigated with a well-tuned PI controller. This has the potential to extend the lifespan of the machinery and reduce maintenance/operational expenses.

In brief, PI tuning is crucial for small hydro plant control system design and maintenance for dependable, efficient, and safe operation. A tuned PID controller employed in the excitation system has been proposed by [5]. Optimal PID Controllers for AVR systems considering Excitation Voltage Limitations Using a Hybrid Equilibrium Optimizer have been proposed in [6].

Rule-based, heuristic, & optimization-based (or model-based) PID tuning approaches are the main categories [7]. Having a firm understanding of the function of each PI parameter is essential for achieving the intuitive tuning that may be attained via trial and error. Simple to construct, this method might be time-consuming and uncertain in its output [7]. To estimate processes from step tests based on rule-based tuning, Ziegler-Nichols, Cohen-Coon, Kappa-Tau, and Lambda tuning use simple models [8]. First-order plus dead-time models are typical. Despite their popularity, these techniques are vulnerable to modifications for both the real process and the approximation model.

PID values may be optimized with the use of optimization-based methodologies if an exhaustive technical specification and accurate process model are available. However, to be effective, such strategies need a comprehensive model [8] [9], which may be challenging to develop in practice. The innovative PI tuning method described here was created by solving an optimization problem. However, it does not restrict the user from using any PID controller or process model of their preference. Using the water hammer effect as an example, [10] suggests a PID controller based on an improved Iterative Sliding Mode Control (IMC). It was discovered that the proposed tuning technique improved the hydraulic unit's steadiness. This research delves further into metaheuristic algorithms [11]. Parameter adjustment for a PID controller is described in detail, using the most advanced metaheuristic approaches, in [12]. Both traditional and state-of-the-art optimization methods were discussed at length, and their salient points were outlined in this paper's debate. Through the use of simulation results based on transient response characteristics, new optimization methodologies for the optimum tuning of PID controllers have been proven to provide better results than the traditional approach, as well as the other optimization strategies[13] [14] [15].

Using PID and I-PD controllers, a multi-source, multi-area linked power system achieves effective Automatic Generation Control (AGC) [16]. The Fitness Dependent Optimizer (FDO) algorithm helps these controllers work best. An FDO-PID & FDO-I-PD two-area reheat thermal, gas, along with a hydropower system evaluates FDO-based controllers. An electrohydraulic servo control system is stabilized by selecting PID controller settings utilizing Barrier Failure Analysis (BFA), PSO, GA, and ACO (Ant colony optimization) [17]. Step response uncertainty reduction led to the discovery of stability. In contrast to GA, this method necessitates the use of a high-end, current desktop or workstation PC-improved solution with faster response. To further improve computational efficiency, it is advised that a BFA technique be used instead of the PSO method, which suffers from premature convergence.

Some of the optimization algorithms used to fine-tune PID controllers for artificial insulin regulation include BOMA (Brain Storm Optimization Algorithm), CTOA (Class Topper Optimization Algorithm), GA (Genetic Algorithm), GSA (Gravitational Search Algorithm), GWOA (Gray Wolf Optimization Algorithm), PSO (Particle Swarm Optimization), and SRA (Sequential Randomized Algorithm) [18]. It has been established that a GWOA technique works better when simulating in MATLAB-Simulink and then in real-time assessing the results. In [19], PID controller parameters for two processes are tuned using two different optimization techniques, and it is found that the PSO-based adjusted values outperform the GA-based values in a CSTR (Continuous Stirred-Tank Reactor). Despite some minor differences in peak overshoot values, the responses are indistinguishable between the two different QTP (Quick Test Professional) optimization techniques. In [20], GA, FA (Firefly Algorithm), and PSO algorithms optimize system parameters before using a PI controller. The importance of optimization methods in frequency and voltage regulations in power systems is well described in [21] [22] [23].

Integral Time Square Error (ITSE) & Integral Time Absolute Error (ITAE) are two examples of cost functions that may be used to evaluate controller settings in optimization approaches. It has been shown [20], that analytical and conventional tuning methodologies for controllers were less effective than optimization tactics.

The recent optimization method Black Widow Optimisation (BWO) is inspired by black widow spider hunts. Meta-heuristic BWO can tune hydro plant PI controllers for global optimization. BWO's capacity to tackle non-linear & non-convex optimization problems that converge swiftly to global optimal provides it with a good choice for hydro plant PI tuning. Unlike other optimization approaches, BWO is less likely to remain stuck in local optima.

More recently, [24] [25] [26] [27], suggested Deep RL algorithms for the control of discrete-time nonlinear systems. A controller in each of these systems takes the form of a deep NN, making them actor-critic approaches. RL is based on the concept of learning through trial and error, where an agent interacts with an environment to learn an optimal policy that maximizes a reward signal. In the context of PI tuning in hydro plants, RL can be used to learn optimal controller parameters that minimize an error function, which is typically based on the performance metrics of a control system. Overall, RL approach for PI tuning in hydro plants, and has the potential to improve performance & efficiency of a control system, & ensure safe as well as reliable operation of a plant.

To take benefit of BWO as well as the RL technique, a hybrid method is used in this work to tune parameters of PI controller used for a small hydropower plant. The following is an outline of the most significant contributions provided by this work:

1. Development of MATLAB model of PI control Hydropower plant & tuning of PI controller by using conventional techniques and intelligent methods like Cuckoo, Firefly, Particle Swarm Optimization, and Grey Wolf Optimization.
2. Tuning of the PI controller by using BWO algorithm, which effectively optimizes the controller's parameters by simulating the black widow concept. This optimization process ensures that the PI controller is tuned to the specific dynamics and operating conditions

of the hydropower plant, maximizing its effectiveness in voltage regulation.

3. Incorporation of Reinforcement Learning techniques to allow the PI controller to adapt and learn from the system's real-time feedback. The controller can continuously update its control strategy based on the observed performance and the desired voltage targets, leading to improved response time and stability.
4. Use of a hybrid approach of combining BWO and RL (for PI tuning) to benefit from the strengths of both algorithms. It results in enhanced performance, reduced computational effort, and increased robustness. This controller can effectively handle the nonlinearities, uncertainties, and disturbances present in hydropower plant systems, leading to improved voltage regulation and system stability.
5. Comparison of performance of the proposed technique with other techniques in terms of error functions.

In rest of the paper, a complete methodology is explained in section 2. Performance measures used for the evaluation of the proposed method are described in section 3. Section 4 briefly describes the simulation results followed by the conclusion and list of references.

2. Methodology

The Black Widow Optimisation is the first step in the proposed method. This step determines the proportional and integral gains (KP and Ki, respectively) of the PI controller that is utilized in the hydropower plant. The initial population for BWO is the result of the classical Z-N method. MSE error is the fitness function. The best candidates from BWO are further tuned by using Reinforcement learning. The overall methodology is shown in Figure 1. The results of the hybrid method are compared with Black Widow Optimization & Reinforcement Learning when used independently as well and the comparison is also made for a few more nature-based optimization techniques.

The proposed BWO-RL-based PI Controller for voltage stability in hydropower plants uses two techniques in cascade, i.e., BWO for initial tuning and Reinforcement Learning (RL) for real-time adaptation & final tuning of PI controller parameters as shown in flowchart of Figure 1.

The BWO-optimized PI controller gains provide a strong starting point, while RL ensures the controller adapts to changing conditions and disturbances to maintain voltage stability. Properly designing the RL reward function and training the RL agent to optimize voltage stability are critical steps in this implementation. Details of BWO & RL for PI tuning are given in the following subsections.

2.1. BWO (Black Widow Optimization)

The BWO algorithm is intended to function in a manner that is analogous to the hunting strategy employed by black widow spiders. This strategy comprises searching for food in an environment that is packed full of limitations. To locate the most nutritious food, the spiders employ a methodology that is equal parts exploration and exploitation. These techniques are put to use in a BWO algorithm to investigate the search space and get closer & closer to the optimal solution.

The PI tuning process in hydro plants can be accomplished with the help of the BWO algorithm by treating controller settings as optimization decision variables. For purpose of determining how efficient a control system is, this method incorporates a fitness function. This is accomplished by the utilization of the metrics of ascent, settlement, overshoot, and steady-state error. A fitness function is used to measure how well each entity solution performs, and it also helps find the best possible solution globally

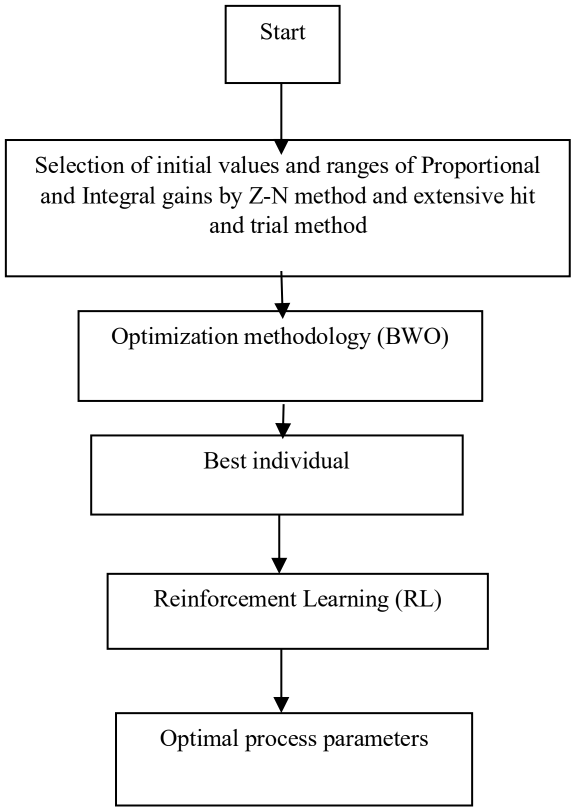

Fig. 1. Flow chart of proposed hybrid optimization method

BWO algorithm is an excellent choice for both exploitation and exploration stages because it has a fast time to converge and can avoid issues that are related to problems with local optimization. It is also essential to keep in consideration that BWO may be able to strike an appropriate harmony between their exploratory and exploitative activities. BWO is a promising alternative since it can study a large region, which makes it applicable to several different optimization issues that might each have numerous local optimum solutions. Compared to existing meta-heuristic algorithms such as GA, PSO, BBO (Biogeography-Based Optimization), ALO (Antlion Optimization) [28], MFO (Moth Flame Optimization) [29], GWO [30], WOA (Whale Optimization Algorithm) [31], SHO (Spotted Hyena Optimizer) [32], MVO (Mean-variance optimization) [33], and HS (Head Space) [34], gathered data shows that BWO method provides improved results. Figure 2 illustrates a flowchart of a BWO process.

It aims to find the optimal values for the PI controller gains (`Kp` and `Ki`) that minimize a predefined objective function related to voltage stability. Here's a simplified representation of the BWO algorithm: The objective function used in BWO should be designed to represent the voltage stability problem, incorporating factors like voltage deviations and system constraints.

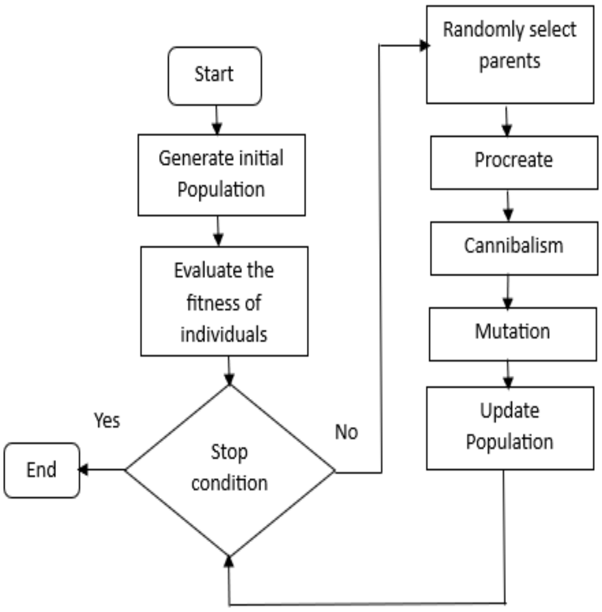

Fig. 2. Flow chart of BWO Optimization technique

Initialize a population of black wolves with random positions
Evaluate the fitness of each wolf based on the objective function
While the stopping criterion is not met:
Sort the wolves by fitness
Select alpha, beta, and delta wolves (the best, second best, and third best)
Update the positions of other wolves using mathematical equations
Apply constraints to the positions (e.g., within predefined bounds)
Evaluate the fitness of the updated positions
Update the alpha, beta, and delta wolves if necessary
End While
Return the best position found as the optimal PI controller gains

2.2. RL (Reinforcement Learning)

Some of the most prominent applications of Reinforcement Learning (RL), a branch of machine learning, are in the realm of control, namely in the calibration of PID controllers and other similar tasks. RL algorithms typically work by estimating the value function or the Q-function, which provides an estimate of the expected reward given a particular state and action.

The RL agent interacts with an environment by taking actions (i.e., adjusting controller parameters) and observing resulting state and reward. The agent then updates its policy based on the observed state and reward, using methods such as Q-learning, policy gradient methods, or actor-critic methods. One of the main advantages of RL for PI tuning is its ability to handle non-linear & non-convex optimization problems, which are common in control systems. RL can also adapt to changes in the system dynamics and environmental conditions, which makes it well-suited for complex and dynamic systems like hydro plants. The successful application of RL for PI tuning in hydro plants requires careful design and tuning of the RL algorithm, as well as careful consideration of the error function, the state representation, and the action space [35] [36].

Understanding the evolving two-way interaction between the agent and environment is crucial to RL. If an agent's actions are rewarded by the environment, it will be more likely to act. In RL, the concepts "agent," "environment," "action," "state," and "reward" are fundamental. To transform circumstances into actions, the learner functions as the agent interacting with the environment. The decision to complete the assignment is the agent's action. When we say something "returns to its state," we mean that the surrounding environment is put back into its original condition after an action is taken. In [37] [38], shows the result of the environment that provides feedback. The agent in real life does not know what to do ahead of time. The magnitude of the rewards increases as it gains knowledge. When evaluating the data collected from its surroundings, an agent is either rewarded or punished. The agent makes adjustments to its action policy to get closer to the optimal policy. State activity is represented through policy. One RL paradigm is trial and error. After making assessments of the environment at each time step T within a state S_t, the agent gets a credit or punishment according to the rules in force [39] [40]. A recognizable pattern of RL is shown in Figures 3 and, 4 and the comparison of conventional and RL-based controllers is shown in Figure 5. Table 1 shows the details of Reinforcement learning parameters.

The RL component complements the BWO-tuned PI controller by enabling real-time adaptation. Here's an overview of integrating with the PI controller:

i. State Representation: Define the state space for the RL agent. It typically includes voltage measurements, system load, and other relevant variables that affect voltage stability.
ii. Action Space: Define the action space, which corresponds to adjustments in the PI controller's output. Actions could involve changing `Kp`, `Ki`, or the reference voltage.
iii. Reward Function: Design a reward function that quantifies the system's voltage stability. This function should encourage the RL agent to take actions that maintain stable voltage levels. A possible reward function could be based on minimizing voltage deviations or deviations from a desired reference voltage.
iv. Real-Time Adaptation: During actual operation, the RL agent uses its learned policy to select actions based on current states. These actions are applied to the PI controller, allowing it to adapt to changing conditions in real time.

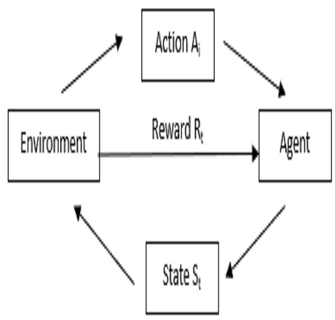

Fig. 3. Working of Reinforcement Learning technique

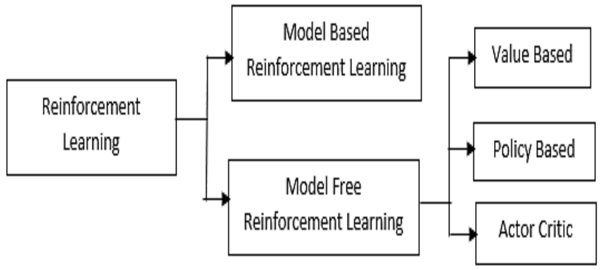

Fig. 4. Classification of Reinforcement Learning Technique

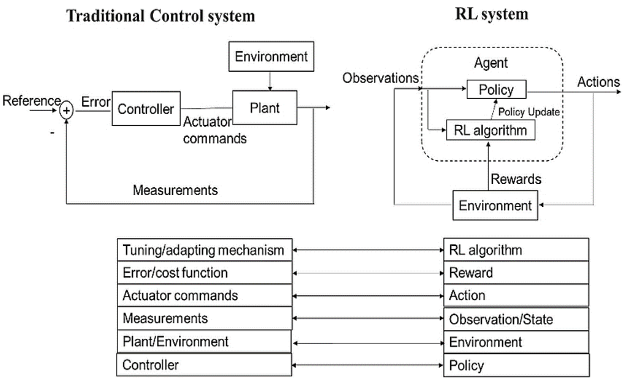

Fig. 5. Comparison of traditional and RL-based controller

Table 1. Basic terms used in RL Model

Terms	Description
Agent	It behaves in a specific manner to gain something from its surroundings.
Environment	It's a hypothetical predicament that the agent must solve.
Status	The "state" of an entity describes its current surroundings.
Action	When anything happens in the world, that's action.
Reward	When anything is rewarded monetarily for doing a desirable behavior in its environment, we call that incentive.
Policy	It's the agent's plan for getting from where it is now to wherever it has to go to complete the next set of objectives.
Value	Value is an incentive that lasts a long time or comes at a lower cost.
Value Function	It is the sum of all benefits and is used to quantify a nation's worth.

3. Hydropower Plant PI Tuning & Performance Measures

"PI tuning" refers to the process of adjusting the settings of a Proportional-Integral (PI) controller based on physical characteristics and characteristics of a system that are being controlled within the context of this study. The premise upon which this method rests is that both dynamics of a controlled system & interaction between the system & controller greatly affect the PI controller's performance. It is predicated on idea that performance of PI controller is significantly influenced by dynamics of system being regulated as well as by interaction that takes place between system & controller. Figure 6 depicts the PI Controller.

Tuning the PI requires creating a problem, which may be done by defining the optimization's objective function & constraints. The objective function is typically expressed in terms of some measure of the PI controller's performance, such as the settling time or the steady-state error of the variable under control [41]. Limits may be placed on the proportional and integral gains, as well as the other PI controller parameters.

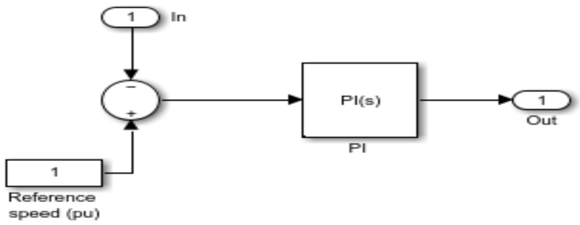

Fig. 6. Structure of PI controller

As shown below, this work used different optimization methods to determine hydropower plant PI controller proportional (Kp) and integral gain (Ki). Fitness function is MAE, MSE, MAPE, and RMSE errors.

3.1. MSE (Mean Square Error)

Mean squared error, or MSE, is a common measure of performance for evaluating a model's predictive power in a regression setting. It is determined by taking the square root of the average discrepancy between a dataset's expected and actual values [42]. Calculating MSE is as simple as:

$$\text{MSE}=\frac{1}{n}*\Sigma(\text{desired o/p value}-\text{actual o/p value})^2 \tag{1}$$

Where, n = number of items

3.2. MAE (Mean Absolute Error)

Mean Absolute Error, abbreviated as MAE, is another common measure of performance used to assess the precision of regression models. Instead of measuring the squared difference between the expected and actual values in a dataset, as MSE does, MAE takes an absolute measure of the discrepancy [43]. A measure of the consistency between two independent accounts of the same event is the mean absolute error (MAE). When the average error is both zero and positive and negative, MAE is employed. The MAE, or average absolute error, is the average error when examining data from multiple periods.

$$\text{MAE}=\frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{2}$$

3.3. MAPE (Mean Absolute Percentage Error)

It is usual practice to use a statistic known as Mean Absolute Percent Error (MAPE) to measure the precision of regression models, particularly when making predictions. Mean Absolute Prediction Error (MAPE) is a metric that is used to quantify the usual percentage difference that exists between the data that was expected and the data that was collected. One of the most widely used metrics for evaluating accuracy is the mean absolute percentage error, or MAPE, which is also commonly referred to as the average [43]. The formula for MAPE is:

$$\text{MAPE}=\frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \tag{3}$$

3.4. RMSE (Root Mean Square Error)

Root Mean Square Error (RMSE) is another common measure of performance used to assess the robustness of regression models. A comparable measure to MSE, RMSE is calculated by taking the square root of the average squared difference between the anticipated and actual values in a dataset, yielding a metric with the same units as the variable being forecasted. Predictions' accuracy is sometimes measured using a statistic called Root Mean Square Error [44], which is also known as Root Mean Square Deviation. To get the RMSE, we take the norm, mean, and square root of each data point's residual. In supervised learning applications, RMSE is often utilized since it relies on and needs exact measurements at every projected data point. The formula for RMSE is:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{t=1}^{n} e^2{}_t} \quad (4)$$

4. Simulation Results of Hydro Power Plant

A simulation model is a representation of the plant that was constructed to mimic its performance under various climatic and mechanical conditions. Typical power plant models comprise mathematical equations that describe the operation of the facility's turbines, generators, penstocks, and water storage reservoirs [41].

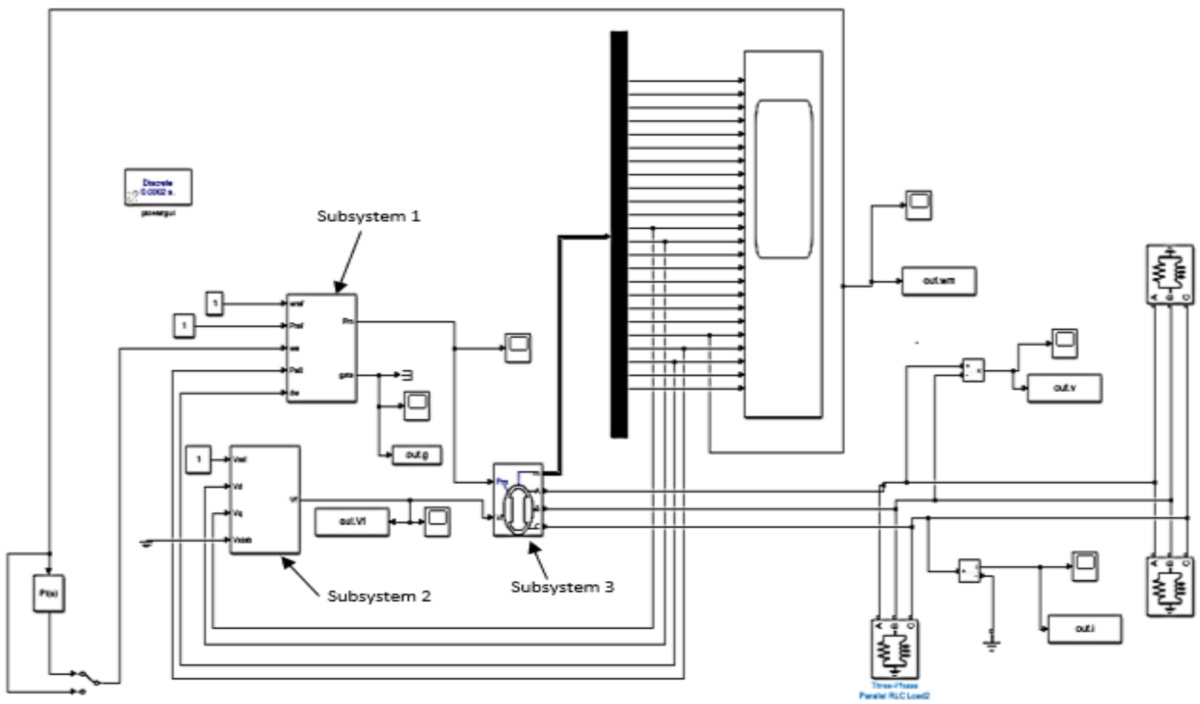

Fig. 7. Basic Hydropower plant Simulink model

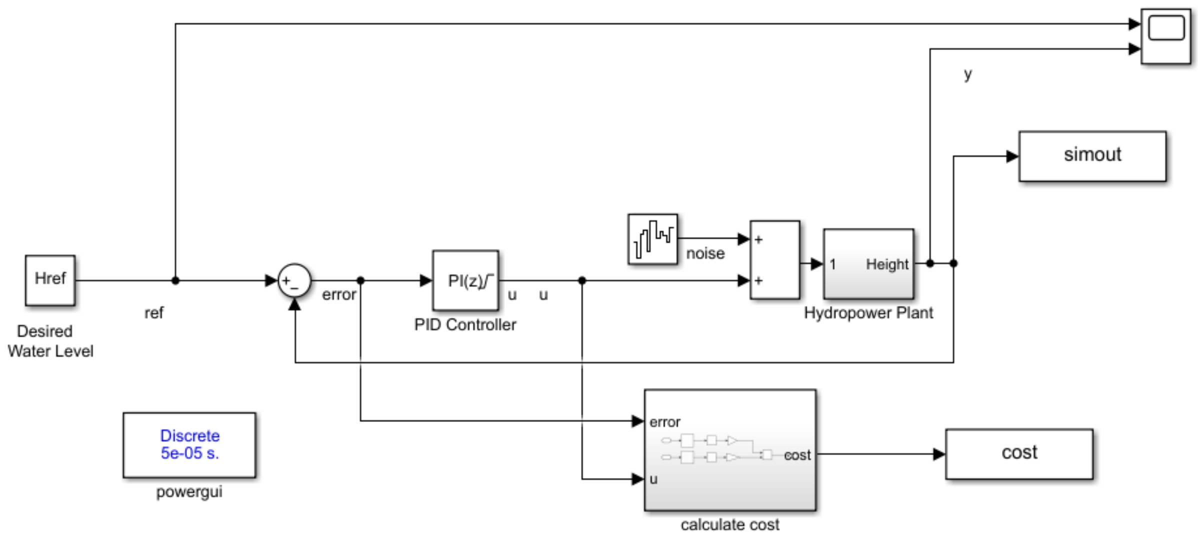

Fig. 8. Hydropower plant with PI controller

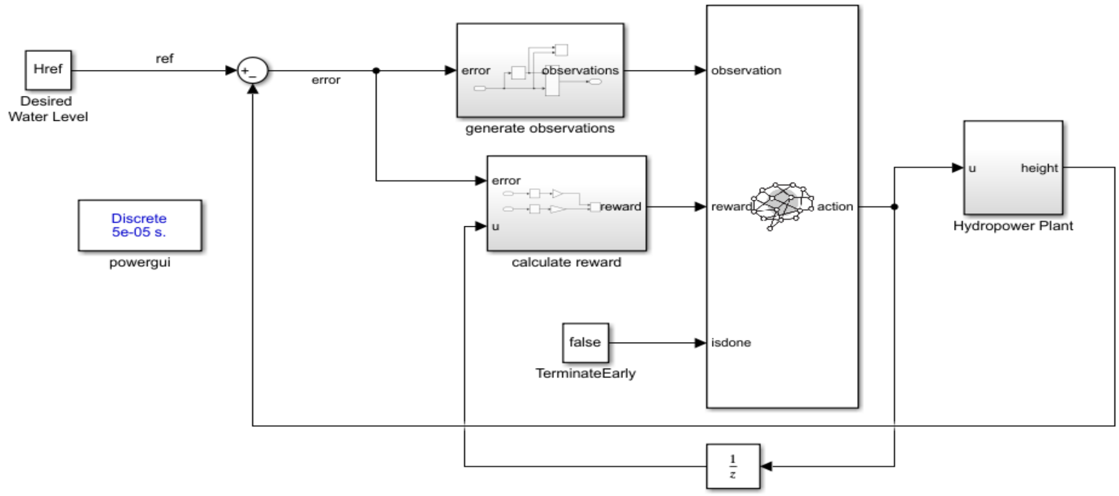

Fig. 9. Hydropower plant with RL controller

Hydropower plant production and efficiency can be forecasted using the simulation model as water flow rates, operational schedules, and maintenance needs are modified. The performance of a power plant can be improved by adjusting the operating parameters of turbines and streamlining the flow of water through penstocks. System layouts were simplified and recreated using subsystems. Subsystem 1 is the hydraulic turbine, Subsystem 2 is the excitation system, and Subsystem 3 is the synchronous generator. Figure 7 illustrates the interplay between three distinct systems.

Figure 8 depicts a pi controller in operation to regulate the hydropower plant's production. The difference between the target and the actual water level is used to generate the actuator's input. In Figure 9, an RL controller is used for the same purpose. The proposed approach integrates PI control with Reinforcement Learning for use with a hydroelectric generator. Hydraulic transients are simulated for several scenarios using all available plant data. The specifications of these units are given in Table 2 [45].

Table 2. Hydropower plant Parameters

Hydro Power Plant Parameters	
1. Parameters of Turbine & Governor	Tw= 3 ωref = 1p.u. Ta = 0.07, Ka =10/3 Rp =0.05, Td =0.02, Kp = 3, Ki = 0.10, Kd = 3.26 $gmin$ =0.01, $gmax$ =0.97518, v$gmin$ =-0.1, v$gmax$ =0.
2. Parameters of Exciter	Vref & Vter = 1 Tb and Tc = 0.00001, 0.00001 V$rmax$ = -15, V$rmin$ = 7.3 Tr=0.87 Ka =200, Ta =0.02 Ke =1, Te = 0.08 Kf =0.03, Tf =1 Vf =1.2911
3. Parameters of Synchronous Generator	Pn= 1.3 MW, L-L voltage=415V f =50 Reactance's; Xd =0.911, Xd' =0.408, Xd'' =0.329, Xq =0.580, Xq'' =0.350, X1 =0.3. Td' =0.7, Td'' =0.035, T$q0''$ =0.033, Rs =0.03 H =1, P =4, Vf =1
4. Parameters of PID Controller	Kp = 0.01, Ki = -0.88, Kd = 0.

4.1. Results Discussion

Simulation results for the hydropower plant using several methods for PI tuning are given in this section. The load is connected to the plant's synchronous generator through a transmission line, as shown in Figure 7. The generator is highly potent, capable of taking on a 1.2 MW load. The gate and mechanical input of the generator are disturbed by the massive oscillations that occur during the transient phase. PSO,

FA, CC, GWO, BWO, RL, and Hybrid BWO-RL are the seven approaches that are utilized in the process of modifying the K_P and Ki parameters of the PID controller. This is done to reduce the number of errors that occur. Mean squared error, mean absolute error, mean absolute percentage error, and root mean square error are the four-performance metrics used to evaluate and compare the various methods. MAPE is returned as a percentage instead of an absolute value, as with MAE. RMSE gives more importance to the highest errors. RMSE and MSE work on the principle of averaging the errors while MAE calculation is based on the median of the error. The lower value of MAE, MSE, MAPE, and RMSE implies a better voltage profile and better performance of the controller. Table 3 represents the optimal valves of the proportional and integral gain obtained by using various methods, with initial values being the result of Z-N tuning method.

Table 3. K_P & K_i values from different optimization techniques

Techniques	K_p	K_i
PI	0.0100	-0.8800
PSO	0.0361	-0.0257
CC	7.5812	-3.0092
FA	0.1260	-0.0934
GWO	9.9851	-3.0086
BWO	3.4620	-6.6867
RL	0.0456	0.0119
BWO-RL	0.0418	0.0248

Table 4 gives a comparison of the performance of various techniques in terms of 4 different error measures. Bar graphs given in Figures 10-13 give a representation of the same graphically.

Table 4. Different errors Comparison results

Techniques	MAE	MSE	MAPE	RMSE
PI [K_p, K_i]	0.18082839	0.05377593	0.18082839	0.23189637
PSO	0.00805725	0.00009674	0.01191551	0.00980553
FA	0.00802079	0.00009549	0.00801867	0.00976469
CC	0.02752624	0.00080418	0.02752262	0.02969827
GWO	0.02752263	0.00080415	0.02752263	0.02835751
BWO	0.00799788	0.00009485	0.00799787	0.00973888
RL	0.00764117	0.00007146	0.00795024	0.00845309
BWO-RL	0.00760912	0.00007063	0.00760911	0.00840441

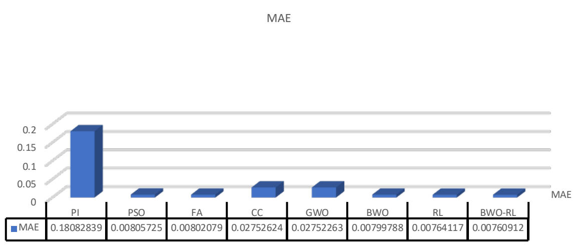

Fig. 10. Bar graph for MAE

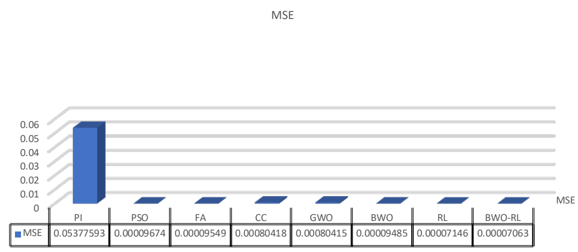

Fig. 11. Bar graph for MSE

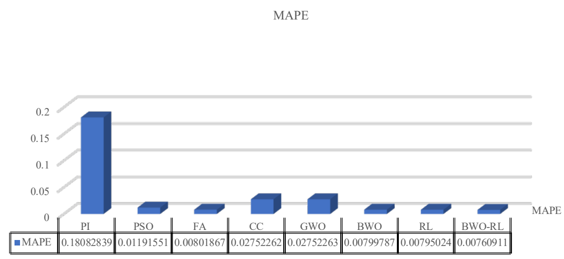

Fig. 12. Bar graph for MAPE

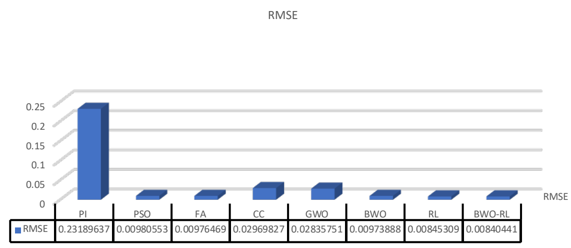

Fig. 13. Bar graph for RMSE

When the plant was first connected to its load, there were several problems with the working of the gates and the mechanical power that was fed to the generator. The MSE, MAPE, MAE, and RMSE errors have been reduced to almost negligible levels by utilizing a PID controller with PSO, FA, CUCKOO, GWO, BWO, and BWO-RL. In comparison to the other methods (PI, FF, GWO, CUCKOO, PSO, and BWO), the Hybrid BWO-RL methodology produced the highest quality output, as is demonstrated in Table 4. While simulating the model, it was discovered that employing BWO-RL reduced the number of oscillations and errors that occurred during the period of transition.

5. Conclusion and Future Directions

This work uses a Hybrid BWO-RL (Black Widow Optimization-Reinforcement Learning) based PI (Proportional-Integral) controller to improve the voltage profile in hydropower plants. By combining the optimization capabilities of BWO and the RL, this controller has shown better performance as compared to traditionally tuned PI controllers. Its ability to optimize controller parameters and adapt in real-time makes it a valuable tool for improving voltage stability, ensuring efficient and reliable operation of hydropower plants. Enhancing voltage stability in hydropower plants using a

Hybrid BWO-RL-based PI Controller has made significant contributions to the field of hydropower plant control systems in following ways:

1. Improved Reliability: The controller has improved the reliability of hydropower plants by maintaining stable voltage levels, reducing the risk of power outages, and ensuring continuous energy supply.
2. Efficiency Gains: Voltage stability enhancements have led to increased energy efficiency, reducing energy losses during power generation and transmission.
3. Environmental Impact Reduction: By preventing equipment failures and disturbances, the controller has contributed to a reduction in environmental impacts associated with power generation.
4. Innovative Integration: Reinforcement Learning (RL) represents an innovative integration technique, paving the way for further AI-based control system developments in hydropower.
5. Real-Time Adaptability: The controller's real-time adaptability to changing conditions and disturbances is valuable, ensuring stability during dynamic events.

The Hybrid BWO-RL-based PI controller represents a significant advancement in the field of hydropower plant control systems. In future, the performance of the hybrid controller can be tested for the hydro plant used as a source of a Hybrid microgrid system. Some other future research directions include:

1. Complexity Management: Addressing the complexity introduced by
the hybrid BWO-RL-based PI Controller to make it more manageable and efficient.
2. Data Challenges: Overcoming challenges related to obtaining sufficient and representative training data for RL-based controllers, especially in real-world environments.
3. Computational Resources: Finding ways to make RL training computationally more efficient and scalable for broader implementation.
4. Generalization: Ensuring that the controller can handle a wide range of operating conditions and disturbances through improved generalization.
5. Multi-Objective Optimization: Considering multiple objectives, such as voltage stability, grid integration, and economic factors, for more balanced control strategies.
6. AI Integration: Exploring additional AI techniques beyond RL, such as deep reinforcement learning and neural network-based controllers.
7. Real-World Validation: Extensive testing and validation of the controller in real-world hydropower plants to ensure its practical applicability and effectiveness.
8. Robustness Testing: Rigorous testing of the controller's robustness to various disturbances and extreme scenarios.

In summary, enhancing voltage stability in hydropower plants through innovative control systems represents a promising avenue for improving grid reliability, energy efficiency, and sustainability in the hydropower industry. Future research will continue to refine and expand upon these advancements.

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