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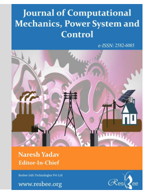

Enhancing Hydro Power Plant Efficiency through Hybrid-Optimization Approach

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Abstract: The inclusion of hydroelectric power is crucial to Nigeria's overall energy mix, playing a significant role in electricity generation. However, the Shiroro hydro plant, one of the main facilities located on the Kaduna River, is currently facing operational obstacles due to deteriorating infrastructure and inadequate maintenance practices. To overcome these challenges and improve efficiency within Nigeria's hydroelectric power sector, a hybrid-optimization approach has been proposed. This study sought to enhance the efficiency of the Shiroro hydro plant by implementing this innovative method. To achieve our objectives and address pertinent research questions, a mixed research method combining primary and secondary data was employed. The analysis included hydropower modeling and hydro-turbine input-output modeling. Three optimizer models, namely the particle swarm optimizer (PSO), Ant colony optimizer (ACO), and Artificial bee colony optimizer (ABCO), were utilized to formulate objective functions and task representations. The study involved comparing the daily output and fitness response of the Shiroro hydro plant through swarm optimizer iterations. The findings revealed a clear correlation between the turbine's power output and the water flow rate and water column height, suggesting that altering these factors could significantly improve the plant's performance. The comparison of the PSO, ACO, and ABCO models demonstrated that PSO and ABCO generated optimal or near-optimal solutions, while ACO produced suboptimal results. Consequently, the study concluded that enhancing the Shiroro hydro plant's output was feasible by increasing the water flow rate and column height. Additionally, the utilization of PSO and ABCO models proved to be an effective means of accurately predicting the turbine's output. As a result, the study recommended the integration of hybrid optimization techniques to monitor and identify any deviations in the Shiroro hydro plant's daily power output. This approach would enable prompt maintenance to be carried out, preventing significant damage to the plant. Ultimately, this research contributes valuable insights into improving the efficiency and performance of Nigeria's Shiroro hydro plant.

Keywords: Hydro Power; Hydro-Turbine; Shiroro Hydro Plant; Input-Output Modeling; Hybrid-Optimization.

Nomenclature

Abbreviations	Descriptions
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimizer
ABCO	Artificial Bee Colony Optimizer
I-O	Input-Output
DV	Decision Variables
OV	Optimization Variables
ASE	Absolute Sum of Errors
SAE	Sum of Absolute Errors
EB	Employed Bee
OB	Onlooker Bee
SB	Scout Bee
MW	MegaWatts
FV	Fitness Value
HPP	Hydroelectric Power Plants
MCS	Monte Carlo Simulation
ETAP	Electrical Transient Analyzer Program
HRES	Hybrid Renewable Energy Systems.

1. Background to the Study

Hydroelectric power plants are a critical component of the global renewable energy portfolio, harnessing the inherent potential energy of flowing water and converting it into electrical energy through turbines and control systems [20]. These plants play a vital role in reducing carbon emissions and promoting sustainable living environments. One notable example is the Shiroro hydro plant located in Niger State,

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Nigeria [1] [27]. With a capacity of 600 MW, it is the second-largest hydroelectric power station in Nigeria and supplies electricity to millions of people through the national grid [12] [19].

To optimize the efficiency and output of hydropower plants like Shiroro various factors come into play. The flow rate of water, head of water, and turbine size all influence the plant's performance [2]. Swarm intelligence-based optimization algorithms, such as PSO, ACO, and ABCO are utilized to achieve the best possible outcomes [11]. These algorithms handle complex optimization problems and converge on the global minimum, minimizing wasted energy while maximizing efficiency.

Mathematical models known as I-O models provide a common method for modeling hydropower plant output and performance [7][24]. The Glimn-Kirchmayer quadratic model is an advanced I-O model that effectively represents the non-linear relationship between water flow rate, head height, and turbine efficiency, enabling control over output and performance [24]. To optimize the Glimn-Kirchmayer quadratic model's parameters, the PSO, ABCO, and/or ACO algorithms can be employed [9]. Combining these algorithms in a hybrid optimization approach enhances the accuracy and efficiency of the models, reducing the required optimization time [5].

The optimization of hydroelectric power plants remains a significant issue in global communities. Therefore, this study proposes integrating swarm intelligence with I-O mathematical models for hydropower plants, specifically targeting the Shiroro hydro plant in Nigeria. By optimizing the plant's efficiency and output while minimizing wasted energy. This hybrid approach aims to enhance its overall performance and contribute to sustainable energy production.

1.1 Statement of the Problem

In Nigeria, hydropower plants play a vital role in electricity supply but they face various challenges. One of the biggest obstacles is accurately identifying risks and anticipating potential problems for these structures, putting their safety and stability at risk and leading to power cuts. Additionally, finding the ideal operational parameters is challenging, resulting in suboptimal system performance and expensive maintenance. To address these difficulties, we plan to implement hydropower plant I-O mathematical models with the integration of swarm intelligence. These optimizer objective functions use operational and performance data to predict system failures and provide insights to enhance efficiency and decrease costs. We anticipate significant improvements in effectiveness, ranging from moderate to very high levels.

1.2 Aim and Objectives of the Study

This study was aimed at enhancing the efficiency of the Shiroro hydro plant located in Nigeria through a hybrid-optimization approach. Specifically, the objectives were to:

1. Estimate the actual daily power output of the Shiroro hydro plant for 10 days.
2. Determine the Shiroro hydro plant’s swarm optimizers for 100 iterations.
3. Ascertain the comparative fitness response of the Shiroro hydro plant’s swarm optimizers for trials 1 and 2.

1.3 Research Questions

1. What is the actual daily power output of the Shiroro hydro plant for 10 days?
2. What are the Shiroro hydro plant’s swarm optimizers for 100 iterations?
3. What could be the comparative fitness response of the Shiroro hydro plant’s swarm optimizers for trials 1 and 2?

2. Literature Review

The world's increasing population and industrialization have led to a heavy reliance on energy for development. However, exclusive dependence on fossil fuels is not sustainable due to their limited availability and environmental impact [22]. Countries in East, Central, and West Africa have significant potential for generating renewable energy, particularly hydropower. Hydropower systems harness kinetic energy from water to generate electricity and generally consist of infrastructure, such as a reservoir and turbine. A global transition towards renewable energy may be the ideal solution [16].

Hydroelectricity involves using flowing water to turn turbines, essentially converting the kinetic energy of falling water from a higher elevation to a lower one into electricity. Hydropower is a successful source of renewable energy, and small-scale projects are especially useful for providing sustainable electricity in remote areas. Moreover, hydropower can play a significant role in supplying consistent, eco-friendly energy on a much larger scale. Hydropower is available in around 150 countries worldwide, with China ranking as the leading global producer. Hydropower offers numerous benefits, including competitive advantage, flexibility to meet evolving energy needs, minimal environmental impact, and the generation of zero waste [16].

However, the accuracy of a hydro optimization scheme may be affected by various constraints, such as plant operational data, plant and reservoir constraints, discharge rate, head, and other factors [23]. Thus, it is essential to attain high-quality optimization plans to achieve good scheduling programs effectively. For instance, in a regulated market, the optimization plan might prioritize minimizing power generation costs while considering fixed power generation and market price [26]. Therefore, the optimizer must efficiently combine specific limits and the set of parameters to attain the lowest power generation cost possible, considering a predetermined generation capacity and market price [30].

This aligns with [15], who submitted that optimization, generally referred to as mathematical programming, involves a set of mathematical principles and methodologies to solve quantitative problems across various disciplines. In almost every aspect of human endeavor, there is a drive to achieve the most favorable outcome with the least amount of resources or input. The authors admitted that optimization is integral in designing efficient and cost-effective production systems. It identifies the conditions for the highest or lowest value of a function by solving mathematical and physical problems. Unconventional optimization techniques, such as genetic algorithms and particle swarm optimization, are gaining popularity for solving complex engineering problems [15].

2.1 Theoretical Framework

[3] reinvigorated hybrid optimization techniques theory through a study in 2012 to enhance the efficiency of solid rocket motor design using hybrid optimization techniques. The researchers combined optimization algorithms including GA, PSO, and simulated annealing to optimize key parameters such as propellant composition, nozzle geometry, and chamber pressure [3]. The study revealed that the hybrid optimization approach outperformed individual optimization algorithms, producing optimal solid rocket motor designs. Furthermore, a similar hybrid optimization approach can improve the efficiency and performance of hydropower plants by optimizing various parameters such as water flow rate, generator efficiency, and turbine blade geometry. The implementation of such capabilities can enhance hydropower plant output and contribute to sustainable energy.

2.2 Review Table

S/N	Authors	Objective	Methodology	Key Findings	Contribution
1	Twaha and Ramli [25]	Reviewing optimization approaches for hybrid distributed energy generation systems.	Literature review and analysis.	Optimization approaches improve hybrid energy systems.	Provides an overview of optimization techniques for hybrid energy systems.
2	Banos *et al* [6]	Reviewing optimization methods in renewable and sustainable energy.	Literature review and analysis.	Optimization methods enhance renewable energy systems.	Provides insights into optimizing renewable energy systems.
3	Oladepo *et al* [17]	Maximize the utilization of renewable energy sources in a grid-connected hybrid power system.	Hybrid particle swarm optimization/whale optimization algorithm.	Optimal sizing and scheduling of renewable energy sources and storage systems for minimum cost and maximum reliability.	A novel optimization algorithm that improves the performance of grid-connected hybrid power systems.
4	Ajao *et al.* [1]	Assess the feasibility of large-scale combined-cycle hydroelectric power generation at Shiroro hydroelectric power station.	Technical and economic analysis of the potential project.	The project is technically and economically feasible, with the potential to increase the power output of the station by 30%.	A comprehensive assessment of the feasibility of large-scale combined-cycle hydroelectric power generation at Shiroro hydroelectric power station.
5	Oliveira *et al.* [18]	Obtain availability projections for HPP.	MCS	Optimal maintenance scheduling reduces financial costs.	Efficient statistical analysis for risk analysis and decision-making in HPP operations.
6	Dimkpa *et al.* [8]	Optimization of power generation of an existing power plant (Omoku gas turbine) in Nigeria.	Analyzing bus, branch, generator, and load data using ETAP 12.6.0.	Optimization slashed power losses, boosted branch voltage, and increased profit.	The research enhances power generation from the Omoku gas turbine.
7	Fathima and Palanisamy [10]	Investigating optimization methods for microgrids with hybrid energy systems.	Literature survey and review.	Diverse objectives and optimization approaches for microgrids with hybrid energy systems.	Outlining a framework for optimization in microgrids with hybrid energy systems
8	Jyoti-Saharia *et al.* [13]	Improve energy management in hybrid renewable energy systems.	Analyzing algorithms for optimization and control.	Effective strategies for power management in HRES.	Potential applications of advanced algorithms for HRES optimization.

2.3 Identified Research Gap

This study dives deep into Nigeria's Shiroro hydro plant, addressing a research gap that has long been overlooked. While previous studies have explored hybrid optimization approaches in hydropower plants, Nigeria's hydro plants have been neglected. This study was aimed at bridging this gap by evaluating the effectiveness of hybrid-optimization techniques like PSO, ABCO, and ACO in boosting the efficiency of the Shiroro hydro plant. By combining these optimization techniques, the study strives to achieve unprecedented levels of efficiency, surpassing recent studies in this field. Hence, this research becomes crucial, as it sheds light on the potential benefits of hybrid optimization techniques in Nigeria's hydro plants, ultimately improving energy generation and sustainability.

3. Materials and Methodology

To achieve the objectives of this research, a systematic approach involving hydropower modeling, hydro-turbine I-O model parameter estimation, objective function formulation, task representation, optimizer modeling, PSO model, ABCO model, and ACO model.

3.1 Hydro Power Modeling

This study uses the systems optimization architecture that shows the components needed to establish interdependencies as shown in Fig.1

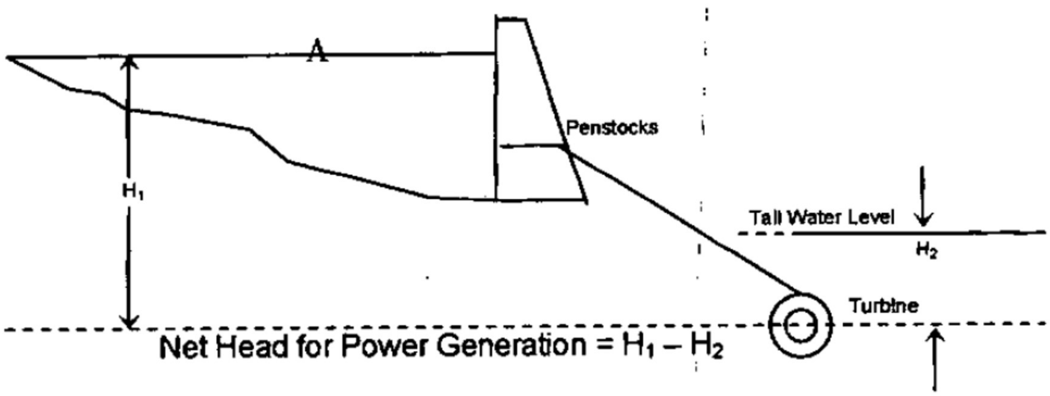

Fig 1. *Systems Architecture for Hydro Power System Optimization*

For a typical storage reservoir plant, its head, flow, and storage all exhibit interdependency relationships. To obtain a steady energy source in the reservoir, the flows must be routed through the reservoir to periodically stimulate the energy-generating processes.

For the aforementioned procedure, the following data are needed:

i) Series of inflows at the reservoir
ii) Storage-Elevation-Area relationships for the reservoir, and
iii) Power plant efficiency.

In essence, the reservoir continuity is consistently applied to simulate steady power generation. The steady-state power in MW is calculated as:

$$P_{ht} = 0.003785 \times R_i \times H_i \times \eta \tag{1}$$

Where,

R_i = is the release into penstock in mm³ for the unit, i

H_i = is the net head in meters for the unit, i

η = is the plant efficiency

For strong plants, the steady state power Pht can be increased because the stream flows stored during the high-flow seasons can be discharged during dry seasons at a higher-than-normal flow rate. To optimize the parameters of the hydropower reservoir, the maximization of Pht can be considered an objective function.

3.2 Hydro-turbine I-O Model Parameter Estimation

For a hydropower generation system, several models exist to describe I-O relations [24]. This study investigates the Glimn-Kirchmayer and the Hamilton-Lamont models.

The I-O flow models are described as follows:
Glimn-Kirchmayer Model:

$$Q_i\left(H_i, P_i\right) = K_i \cdot \psi\left(H_i\right) \cdot \phi\left(P_i\right) = K_i\left(a_{0i} + a_{1i}H_i + a_{2i}H_i^2\right)\left(b_{0i} + b_{1i}P_i + b_{2i}P_i^2\right) \tag{2}$$

Hamilton-Lamont's Model:

$$Q_i\left(H_i, P_i\right) = {A\left(P\right) \cdot B\left(H_i\right)} \big/ {H} = \left(a_{0i} + a_{1i}P_i + a_{2i}P_i^2 + a_{3i}P_i^3\right)\left(b_{0i} + b_{1i}H_i + b_{2i}H_i^2\right) \tag{3}$$

Where,

$a_{0i}, a_{1i}, a_{2i} b_{0i}, b_{1i} b_{2i}$ = the parameters of the Glimn-Kirchmayer or Hamilton-Lamont's model for the unit, i.

a_{3i} = an additional parameter due to the cubic representation of Hamilton-Lamont's model for the unit, i.

H_i = the effective head in meters for the unit

i P_i = electrical power produced by the unit, i

K_i = proportionality constant for unit, i

3.3 Objective Function Formulation and Task Representation

The process of estimating the parameters of the I-O model of a hydro-power plant may be construed as an optimization problem. In this regard, the task will be to minimize the objective subject to the parameter boundary constraints or limits. To achieve this purpose, a vector state representation of the parameters for the generation units may be described in a sequence notation form:

$$X = \left[a_{0i}, a_{1i}, \ldots, a_{D-1}\right] \tag{4}$$

Where,

D = dimension (number of parameters) of the model

The sequence parameters as presented in Eqn (4) are typically referred to as the decision set, DV, or OV. Using the DV set in an objective function yields the values that the optimization algorithm tries to minimize or maximize; one of these values is then selected as the most optimal of the fitted set that corresponds to a given parameter. The other fitted parameters are correspondingly selected in this way. The objective function considered in this study follows the ASE criterion as represented in Eqn (5) which is different from the SAE employed in [24]. This proposed metric is more robust in revealing hidden inconsistencies in optimization algorithms.

$$ASE = \left|\sum_{j=1}^{O} ASE_j\right| = \left|\sum_{j=1}^{O} Z_{actual,j} - Z_{estimated,j}\right| \tag{5}$$

Where,

O = total number of considered observations of the state values, Q, H, and P

$Z_{actual,j}$ = actual measured value of the state values, Q, H, and P at observation, j

$Z_{estimated,j}$ = optimizer's estimated value of the state values, Q, H, and P at observation, j

3.4 Optimizer Modelling

In this context, the PSO, ABCO, and ACO are considered for the multi-agent optimization solution. The mathematical models of these optimizers are elaborated in the following sub-sections.

3.5 PSO Model

The PSO model was proposed in 1995 by Kennedy and Eberhart and uses synchronized movement and coordination observed in swarming particles to solve optimization problems. It iteratively improves solutions by mimicking particle behavior in a swarm. During the iteration process, the PSO model updates the velocities and positions of the particles based on the following equations:

Velocity update equation:

v_i(t+1) = w * v_i(t) + c1 * rand() * (pbest_i(t) - x_i(t)) + c2 * rand() * (gbest(t) - x_i(t))

Position update equation:

x_i(t+1) = x_i(t) + v_i(t+1)

In these equations:

- `v_i(t)` is the velocity of particle 'i' at iteration 't'
- `x_i(t)` is the position of particle 'i' at iteration 't'

- `w` is the inertia weight, which controls the impact of the previous velocity on the current velocity
- `c1` and `c2` are the acceleration coefficients, which control the impact of the personal best position and the global best position on the velocity update
- `pbest_i(t)` is the personal best position of the particle 'i' at iteration 't', representing the best position the particle has found so far
- `gbest(t)` is the global best position found by any particle in the swarm at iteration 't'
- The PSO model follows the following steps:

1. Initialization:
   - Set the size of the particle swarm, denoted as 'n'.
   - Randomly initialize the positions and velocities of all particles within the swarm.
2. Iterative Optimization:
   - Continuously iterate through the following steps until a predefined end criterion is met.
     a. **Time update (t = t + 1):** Increment the time variable 't'.
     b. **Fitness computation:** Compute the fitness value of each particle by evaluating the quality of the potential solution represented by the particle.
     c. **Particle movement:** For each particle 'i' (from 1 to 'n') in the swarm, perform the following steps:
     d. Update the position and velocity of the particle based on the velocity update and position update equations.
     e. **Termination Criterion:** The iterative optimization process continues until a predefined termination criterion is met, such as reaching a desired fitness value or a specific number of iterations.

3.6 ABCO Model

ABCO is a novel swarm intelligence technique that combines the strengths of PSO with the concept of Artificial bee colonies. Introduced by Karaboga in 2005, ABCO draws inspiration from the organization and foraging abilities of honey bee swarms. This algorithm utilizes three types of bees: EB, OB, and SB. EB discovers and communicates food sources through dancing, while OB selects the best sources with minimal effort. Once employed bees deplete their sources, they become scouts, tasked with finding new food. ABCO encompasses exploitative and explorative functions performed by EB, OB, and SB. The operational principle of ABCO is detailed:

a) A sequence of food sources (position or points of real values) is randomly generated:

$$x_{ij} = x_{\min j} + rand\left[0, 1\right]\left(x_{\max j} - x_{\min j}\right) \tag{6}$$

This is called the initialization phase.
Where:

x_{ij} = location of ABCO food sources i in direction j

$x_{\min j}$ = lower boundary point of xi in direction j,

$x_{\max j}$ = upper boundary point of xi in direction j

An EB updates her position by replacing the fitness (nectar information) or simply the FV of an old solution with a new one if the new solution FV is better. The update equation for all EBs is defined as:

$$x_{ij}^{j} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{7}$$

Where

ϕ_{ij} = a random number between -1 and +1

b) An OB analyzes all the solution FVs obtained from the EBs and selects a solution based on a fitness-related-probability as:

$$prob_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \tag{8}$$

c) An SB replaces an abandoned food source (i.e. a food source that is not updated) with a randomly chosen food source within the search space after a predetermined number of limit trials;

$$x_{ij} = x_{\min j} + rand\left[0, 1\right]\left(x_{\max j} - x_{\min j}\right), for\ j \in \{1, 2, \ldots, D\} \tag{9}$$

SN = the total number of food sources considered.
D = size of the optimization problem.
$fitness_i$ = objective (fitted) values of solutions i.

3.7ACO Model

The ACO technique draws inspiration from the intelligent foraging behavior of ants to solve complex problems. Introduced by Dorigo in 1992, it has found numerous applications in both theory and practice. The technique involves two main steps: constructing a solution and updating pheromone trails. In practice, a set of solution vectors is obtained from an initial partial solution subset. The second step utilizes ant pheromone trails to enhance good solutions. For continuous domains, the primary operations follow specific equations, and a Monte Carlo operation handles critical steps, such as sampling a Gaussian function during the construction process:

$$p_i = \frac{\omega_l}{\sum_{r=1}^{k} \omega_r} \quad 10)$$

Computing a weighted standard deviation:

$$\sigma_l^i = \xi \sum_{e=1}^{k} \frac{\left| s_e^i - s_l^i \right|}{k-1} \quad (11)$$

4. Results and Discussions

4.1Answers to Research Questions

Research Question 1: What is the actual daily power output of the Shiroro hydro plant for 10 days?

To perform optimization simulations, operational data from the Shiroro power turbine comprising water flow rate and the water column height were used to estimate the actual daily power output of the turbine. The numerical results are shown in Table 1.

Table 1. *Estimated Daily Power Output (10 days observation)*

O	P(MW)	Q(m³/s)	H(m)
1	2151.20	192	377.57
2	2049.98	183	377.50
3	2172.80	194	377.43
4	4535.52	405	377.39
5	2284.26	204	377.34
6	2194.21	196	377.26
7	1869.26	167	377.20
8	1869.01	167	377.15
9	2394.77	214	377.11
10	2696.34	241	377.03

The estimated power P, in MW, the flow rate, Q, and head, H are all used to implement the objective function solutions as obtained by the swarm evolutionary optimizers.

Research Question 2: What are the Shiroro hydro plant's swarm optimizers for 100 iterations?

The results using the swarm optimizers for 100 iterations are presented considering the fitness costs of the swarm optimizers and their corresponding solved optimal parameter (coefficient) settings that describe the I-O model of the hydro turbine. The results show the estimated parameters for 2 different trial runs as in Tables 2 to 4 for the PSO, ABCO, and ACO optimizers.

Table 2. *PSO Estimated coefficients for 2 trial runs (10 days observation)*

8.5	PSO_1	PSO_2
a0	0.45	7.18
a1	14.47	9.87
a3	-0.035	-0.03
b0	0.36	0.35
b1	0.00	0.29
b3	0.00	0.57

Table 3. *ABCO Estimated coefficients for 2 trial runs (10 days observation)*

Parameter	$ABCO_1$	$ABCO_2$
a0	-4.51	7.00
a1	6.60	12.53
a3	0.25	0.17
b0	0.01	0.01
b1	**0.00**	**0.00**
b3	**0.00**	**0.00**

Table 4. *ACO Estimated coefficients for 2 trial runs (10 days observation)*

Parameter	ACO_1	ACO_2
a0	-4.49	-7.64
a1	0.36	2.39
a3	0.09	0.02
b0	0.04	0.11
b1	0.18	0.15
b3	0.01	0.03

The ABCO optimizer consistently outperforms PSO and ACO, as shown in Tables 2 to 4. Notably, ABCO's results for coefficients b1 and b3 exhibit clear consistency across all trial runs, while ACO's results are highly inconsistent compared to both ABCO and PSO.

Research Question 3: What could be the comparative fitness response of the Shiroro hydro plant's swarm optimizers for trials 1 and 2?

The fitness costs and optimal parameter settings of swarm optimizers for 100 iterations are shown, along with fitness results for trials 1 and 2.

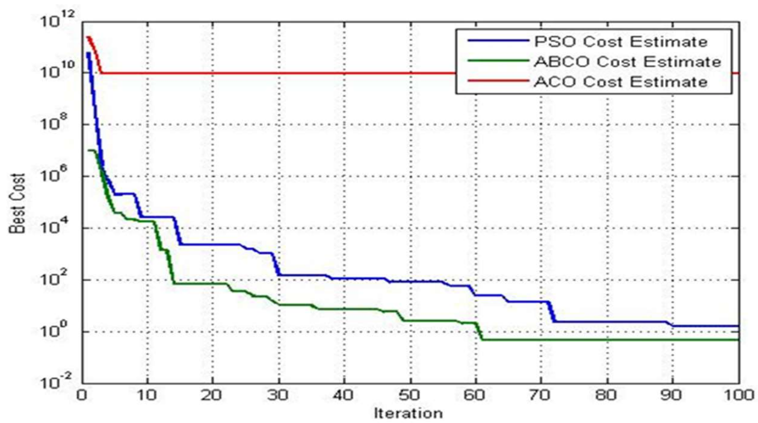

Fig. 2. *Comparative Fitness Response of Swarm Optimizers (Trial 1)*

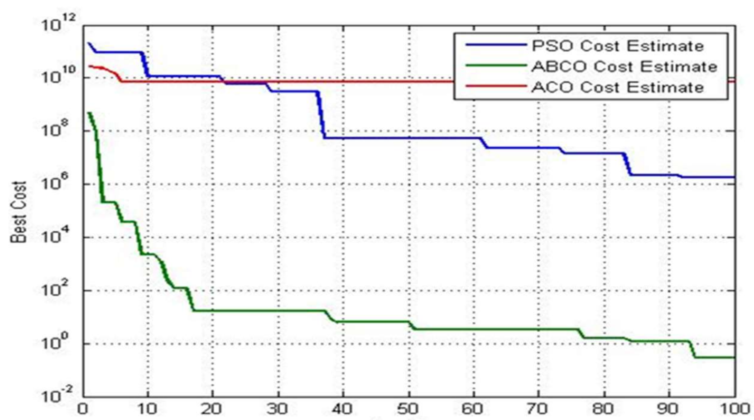

Fig. 3. *Comparative Fitness Response of Swarm Optimizers (Trial 2)*

As can be seen from the fitness response graphs (Figures 2 to 3), the ABCO performance is much better than that of the PSO and ACO. Also, the performance of the ACO is very disappointing as it got stuck in local optima.

4.2 Discussion

Table 1 presents the daily power output estimations of the Shiroro power turbine over a ten-day observation period. The results demonstrated a correlation between the water flow rate, water column height, and the power output of the turbine. As these factors increase, so does the power output of the turbine. However, the power output fluctuated significantly during the ten days, with day 4 recording almost double the power output of any other day. This suggests that specific operating conditions or factors may influence the turbine's power output.

Meanwhile, Tables 2 to 4 exhibited the estimated coefficients for different parameters of hydro turbines using three distinct swarm optimizers: PSO, ABCO, and ACO. These estimated coefficients play a crucial role in predicting the hydro turbine's output (power) for various inputs, such as water flow rate and head. For example, Table 2 showcases parameters such as a0, a1, and a3 coefficients, which represent the intercept, slope, and third-order coefficient of the I-O model (a0+a1Q+a3Q^3), where Q is the input (water flow rate). Similarly, Table 3 and Table 4 present similar parameters for different inputs.

The accuracy of the prediction depends on the precision of the I-O model and the accuracy of the estimated coefficients. To obtain the optimal parameter settings that describe the I-O model of the hydro turbine, the study conducted 100 iterations for each optimizer. The results indicated that the estimated coefficients vary depending on the swarm optimizer used. PSO and ABCO consistently generated optimal or near-optimal solutions, while ACO generally produced suboptimal solutions. However, it is crucial to note that these findings are based on a limited ten-day observation period. Different optimization parameters or an increased number of observations may yield different results.

4.3 Advantages and Disadvantages of Enhancing Hydro Power Plant Efficiency through Hybrid-Optimization (PSO, ABCO, and ACO) Approach

Advantages:

1. **Improved Efficiency**: The hybrid-optimization approach can lead to improved efficiency in hydropower plants. By combining different optimization techniques such as PSO, ABCO, and ACO, it is possible to find optimal solutions for power plant operations, leading to increased efficiency in power generation.
2. **Cost Reduction**: Optimal operation of hydropower plants can lead to cost reductions. The hybrid-optimization approach can help minimize operational costs, such as maintenance and fuel costs, by finding the best operating conditions for the plant.
3. **Enhanced Power Output**: By optimizing the operation of hydropower plants, the hybrid approach can increase power output. This can be achieved by finding the optimal scheduling of turbines, considering factors such as water availability and demand.
4. **Environmental Benefits:** The hybrid-optimization approach can contribute to environmental sustainability by reducing the environmental impact of hydropower plants. By optimizing the operation, it is possible to minimize water wastage and reduce the ecological disturbance caused by power plant operations.
5. **Flexibility:** The hybrid-optimization approach allows for flexibility in adapting to changing conditions. By using a combination of different optimization techniques, the approach can be adjusted to suit specific requirements and constraints.

Disadvantages:

1. **Complexity**: Implementing a hybrid-optimization approach using multiple techniques can be complex. It requires expertise in the different optimization techniques and their integration. This complexity may result in longer development and implementation times.
2. **Increased Computational Requirements:** The hybrid-optimization approach may require increased computational resources compared to simpler optimization methods. This can include higher processing power and longer computation times to find optimal solutions.
3. **Algorithm Tuning**: The effectiveness of the hybrid-optimization approach heavily relies on the appropriate tuning of the algorithms used. Finding the right parameters and configurations for each technique can be challenging and time-consuming.

5. Conclusion and Recommendation

In conclusion, the study delved into the Shiroro power turbine's power output correlation with water flow and column height. Increasing these factors enhances output. Three optimizers provided varied coefficient estimates in predicting turbine output, with PSO and ABCO providing optimal solutions, while ACO produced suboptimal solutions. The results of the study are important in predicting turbine output accurately. It is recommended that additional observations be conducted beyond the ten days to improve the accuracy of the results and test the model's stability. Furthermore, it is crucial to continuously monitor the turbine's daily power output to identify any deviations from normal operation and conduct maintenance immediately to prevent significant damage to the equipment.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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