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Investigation of the Glimn-Kirchmayer Input-Output Method for Hydropower Plant Modelling using Swarming Intelligence Computing Techniques

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Abstract: In order to model a modern power system generation, optimization is typically performed with the aim of improving the relative Input-Output (I-O) performance such as the efficiency, energy, and input-output response while considering certain underlying constraints and system objectives. While the Nigerian hydro power plants have been proven to be a somewhat more reliable and more enviro-friendly energy base with some recent improvement in generation capacity, the system has been reported to operate sub-optimally leading to huge power losses and systems malfunction. In this research paper, the optimization of an existing Nigerian Hydro-Power Plant – the Shiroro Hydro Power Station (SHPP) is simulated using the MATLAB programming language and considering several swarm intelligence hybridized optimizers – the PSO, SMO, BBO and the ABCO. The reported results showed the BBO as the best method while the SMO as the least performing.

Keywords: Hydro Power, Intelligence, Optimization, Simulation, Swarm.

I. INTRODUCTION

Renewable energy refers to energy obtained from natural sources that are not depleted through use. It can be broadly defined as energy harnessed from naturally replenishing resources occurring within a human timescale, including solar radiation, wind, tides, rainfall, geothermal heat, and ocean waves. These sources are continuously regenerated through natural processes and are therefore considered sustainable for long-term energy production [1]. Unlike conventional fossil fuels, the availability of renewable energy is generally not significantly affected by consumption rates, making its depletion unlikely in the foreseeable future. Although excessive or poorly managed utilization may temporarily reduce the availability of certain renewable resources, natural replenishment processes ensure their continued supply. In the context of Nigeria, several renewable energy resources are readily available and can be effectively harnessed for national development. Renewable energy technologies play a vital role in various applications, including water heating and cooling, transportation, electricity generation, and the provision of off-grid energy services, particularly in rural communities.

Hydro (water) energy as we all know is a form of renewable energy that utilizes the directed flow of water due to difference in potentials (heights) on a prime mover such as turbine to generate electrical energy – the combined system being referred to as a hydro plant.

In a hydro power plant, certain constraints will influence the level of accuracy a hydro optimization scheme can attain. Some of these constraints include the plant operational data (head, power output and discharge rate), reservoir and plant constraints. Thus, to attain good planning in the schedule program, good quality in the optimization processes is highly desired.

In this research paper, several swarm intelligence optimization strategies are employed to support the hydro plant in attaining desired power matching output considering the aforementioned constraints.

II. LITERATURE REVIEW

Research on hydropower generation and optimization modelling has attracted considerable attention in recent years. For instance, study [2] investigated the feasibility of enhancing the electricity output of the Shiroro Hydropower Station

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through the integration of hydro-kinetic turbines. Similarly, Ajibola et al. [3] proposed the incorporation of pumped storage systems combined with optimization models to improve the operational efficiency and reliability of hydropower systems. In another related work, Response Surface Methodology (RSM) was applied to improve the accuracy of power generation estimation at the Jebba Power Station [4].

Yuan et al. [5] developed an optimization framework based on a chaotic genetic algorithm for hydropower generation scheduling under ecological constraints. Their results showed that the proposed model effectively optimized power production while maintaining environmental sustainability requirements.

Niu and Zhang [6] employed the LINGO optimization platform to enhance the operational performance of a municipal water supply system in China. The findings demonstrated high computational precision, with only a negligible difference between the predicted and actual service flow rates.

Likewise, Dutta [7] applied a linear programming approach to determine the optimal storage capacity of the Gadana Dam reservoir in India. The model was implemented using LINGO software, where relevant reservoir characteristics were incorporated to estimate the required storage volume for efficient dam operation.

III. METHODS

Several analytical models have been developed to represent the input–output (I–O) relationships governing hydropower generation systems [8-10]. In this study, the Glimm–Kirchmayer and Hamilton–Lamont models are considered for describing these relationships. Operational data obtained from the Shiroro Hydropower Plant were used for model development and evaluation. The methodological framework adopts the Glimm–Kirchmayer input–output model, which is further optimized using swarm intelligence optimization techniques to improve predictive performance and operational efficiency.

A. *Daily Power Output Data of Shiroro Power Turbine*

To conduct the optimization simulations, operational data from the Shiroro hydropower turbine were collected, including the water discharge rate and the hydraulic head. These parameters were used to estimate the net daily power output of the turbine. The computed results derived from the operational data are presented in Table 1.

Table.1: Daily Estimate of Power Output (10 days observation)

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

In this approach, the estimated power P (MW), flow rate Q, and head H constitute the primary inputs to the objective function, which was solved using swarm intelligence-based evolutionary optimizers.

A.1. Glimn-Kirchmayer Model

The I-O flow model according to Glimn-Kirchmayer is described as follows:

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

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Where:
$a_{0i}, a_{1i}, a_{2i} b_{0i}, b_{1i} b_{2i}$- are the parameters of the Glimn-Kirchmayer model for unit, i
H_i- the effective head in metres for unit, i
P_i- electrical power produced by unit, i
K_i- proportionality constant for unit, i

A.2. Objective Function Representation

A vector state representation of the hydro-plant parameters with respect to the generation units may be described in a sequence notation form as:

$$X = [a_{0i}, a_{1i}, \dots, a_{D-1}] \quad (2)$$

Where:
D - dimension of the model (i.e., the number of parameters)

The parameters arranged in the sequence shown in (2) are commonly referred to as the decision set, decision variables (DV), or optimization variables (OV). Based on this set of decision variables, an objective function is formulated to produce values that an optimization algorithm seeks to either minimize or maximize. The optimizer identifies the parameter set that yields the most optimal value of the objective function, and the corresponding parameters are selected as the optimal solution. Other parameters within the fitted set are similarly determined through this optimization process.

In this study, the objective function is formulated using the Absolute Sum of Errors (ASE) criterion, as expressed in (3), which differs from the Sum of Absolute Errors (SAE) approach adopted in [9]. The ASE-based metric has been observed to provide greater robustness in identifying hidden inconsistencies within optimization algorithms.

$$ASE = \left|\sum_{j=1}^{O} ASE_j\right| = \left|\sum_{j=1}^{O} Z_{actual,j} - Z_{estimated,j}\right| \quad (3)$$

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

B. *Description of the used Swarm Intelligence Optimizer Methods*

B.1. The Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is derived from the concept of collective swarm behaviour initially proposed in [11]. The method is inspired by the natural dynamics observed in biological swarms, where individuals coordinate their movements through simple interaction rules. Such behaviours are commonly observed in phenomena such as bird flocking, fish schooling, the motion of air particles, and the cooperative organization of bee colonies. These natural systems provide the conceptual foundation for PSO, where a population of particles collectively searches for optimal solutions within a defined problem space.

The PSO model is as provided in Algorithm 1.

Algorithm 1: *The Algorithm for PSO*

i. Initialize the size of the particle swarm say, n

ii. Initialize the positions and velocities for all swarm particles randomly

iii. **While** end criterion false **do**

  a. t = t+1

  b. Compute fitness value of each particle

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iv. $xx *= arg\, min_{t-1}^{n}(f(x*(t-1)), f(x_1*(t)), f(x_2*(t)), \dots \dots f(x_t(t)), \dots \dots f(x_n(t)))$;

v. For I = 1 to n

vi. $x_t^{\#}(t) = arg\, min_{t-1}^{n}\left(f\left(x_t^{\#}(t-1)\right), f(x_1(t))\right)$

vii. For j = 1 to Dimension

viii. Update the *j-th* dimension value of x_t and v_t

ix. $v_{ij}(t+1) = wvi_j(t) + c_1r_1\left(x_{ij}^*(t) - x_{ij}(t)\right) + c_2r_2\left(x_j^*(t) - x_{ij}(t)\right)$

a. $x_{ij}(t+1) = x_{i_j}(t) + v_{ij}(t+1)$

b. $v_{ij} = sign(vi_j)mn(|v_{ij}|, v_{max}())$

x. End For

xi. End For

xii. End While

B.2. Artificial Bee Colony Optimization (ABCO)

The Artificial Bee Colony Optimization (ABCO) algorithm was developed in 2005 by Dervis Karaboga and his research group at Erciyes University. The algorithm draws inspiration from the cooperative foraging behaviour of honey bee colonies during their search for food sources [12]. It is founded on the natural strategies employed by bees, where collective intelligence and information sharing enable the colony to identify, evaluate, and exploit the most productive food sources with high efficiency [13].

The ABCO modelling is as provided in Algorithm 2.

Algorithm 2: *The Algorithm for ABCO*

i. Generate initial population X_i, $i = 1 \dots, SN$

ii. Evaluate the population

iii. Set cycle to 1

iv. Repeat

v. FOR each employed bee

a. Produce new solutions v_i by using (1)

b. Calculate the fitness

c. Apply a greedy selection process

vi. FOR each onlooker bee

a. Choose a solution xi depending on a probability say, p_i

b. Produce new solutions v_i

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c. Calculate the fitness

d. Apply the greedy selection process

vii. If there is an abandoned solution then

a. Replace it with a new solution produced by a scout using (3).

viii. Memorize the best solution achieved so far

ix. cycle = cycle + 1

x. Until cycle = MCN

xi. END FOR

xii. END FOR

B.3. Biogeography Based Optimization (BBO)

BBO is another emerging population-based bio-inspired Evolutionary Algorithm (EA) technique that deals with the creation of species, movement of species from one habitat to another and the extinction of the species themselves [14]. In BBO solution process, species (population of random numerical units) may simply drift (emigrate) from one habitat to another or enter (immigrate) into a habitat from another one. This drifting or floating and immigrating or entering phenomenon is what gives the BBO an interesting diversity.

In BBO, an emigration rate, μ and an immigration rate, λ are typically computed as in equations (4) and (5) as:

$$\mu_s = \frac{s}{s_{max}} \quad (4)$$

$$\lambda_s = 1 - \mu_s \quad (5)$$

Where:

s - specie number at unit time step, $s = 1, 2, 3 \ldots s_{max}$

s_{max}- maximum possible number of species i.e. the population size of the BBO

Considering the emigration and immigration effects, the probability of a habitat having the maximum species s_{max} may be computed as provided in equation (6).

$$P_s(t + \Delta t) = (1 - \lambda_s \Delta t - \mu_s \Delta t)P_s(t) + P_s - \Delta t - \lambda_s + P_s + \mu_s + \Delta t \quad (6)$$

B.4. Spider Monkey Optimization (SMO)

SMO is based on collective behaviour of monkey agents which are actually spider monkeys – a class of spider looking animals that form communication networks in groups or sub-groups based on a fission-fusion social structure (FFSS) [15].

FFSS is defined by four key features namely:

i. The FFSS SMO agents are social forage competitive and form groups of between 40-50 individuals which may form smaller divisible groups to reduce competition and whilst the search for food is taking place.

ii. The presence of a female (global) leader responsible for global food forage sourcing and sub-group formation (about 3 to 8 members) where the sub-group support an independent food search in the absence of enough supply.

iii. The presence of a female (local) leader responsible for local food forage sourcing and sub-group decision making.

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iv. Communication between members of sub-groups within and outside the sub-groups and basing on the presence of food sources and in order to maintain their respective boundaries.

Implementing the SMO requires a total of 6 phases namely [15 -18]:

i. Local leader phase
ii. Global leader phase
iii. Local leader learning phase
iv. Global leader learning phase
v. Local leader decision phase
vi. Global leader decision phase

IV. RESULTS AND DISCUSSIONS

A. *Simulation Results*

The simulation results using the combined swarm optimizers for 1000 iterations are as presented in Tables 2 through 4 showing the estimated parameters for 3 different trial runs. The corresponding simulation fitness plots are equally provided in Figures 1 through 3 for the first 3 trials.

Table.2: Estimated Coefficients for Trial 1

Parameter	PSO	ABCO	BBO	SMO
a0	-2.69	-10.21	4.25	-3.88
a1	15.14	0.00	10.20	63.82
a3	-0.04	0.09	-0.03	-0.17
b0	0.50	0.00	0.62	-40.90
b1	0.53	0.00	0.67	0.52
b3	0.60	0.00	0.0	0.046

Table.3: Estimated Coefficients for Trial 2

Parameter	PSO	ABCO	BBO	SMO
a0	10.77	-3.28	-0.80	-4.19
a1	22.44	20.48	23.14	451.86
a3	-0.06	0.15	-0.06	-1.18
b0	0.71	0.01	0.46	0.89
b1	0.09	0.00	0.76	-46.95
b3	0.37	0.00	0.12	0.02

Table.4: Estimated Coefficients for Trial 3

Parameter	PSO	ABCO	BBO	SMO
a0	0.63	11.00	0.94	-1.36E+5
a1	25.12	0.00	9.99	436.63
a3	-0.07	15.00	-0.03	8.36
b0	0.13	0.00	0.95	243.34
b1	0.59	0.00	0.00	-200.96
b3	0.00	0.00	0.00	0.09

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From the Tables 2 to 4, it can be seen that the BBO optimizer results were more consistent compared to that of the PSO, BBO and SMO. In particular, the consistency in the ABCO results were clearly observable for coefficients b1 and b3 for all trial runs; the coefficients b1 and b3 were also approximately consistent for the BBO results. The results using SMO was also highly inconsistent when compared to the optimizer techniques.

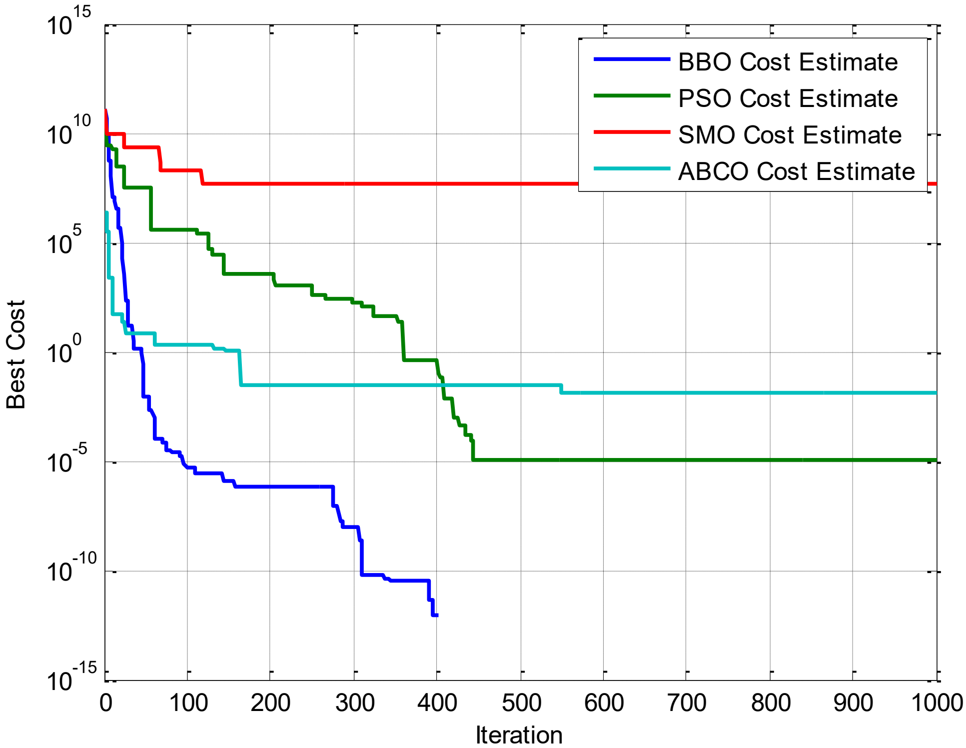

Fig 1: Comparative Fitness Response of Swarm Optimizers (Trial 1)

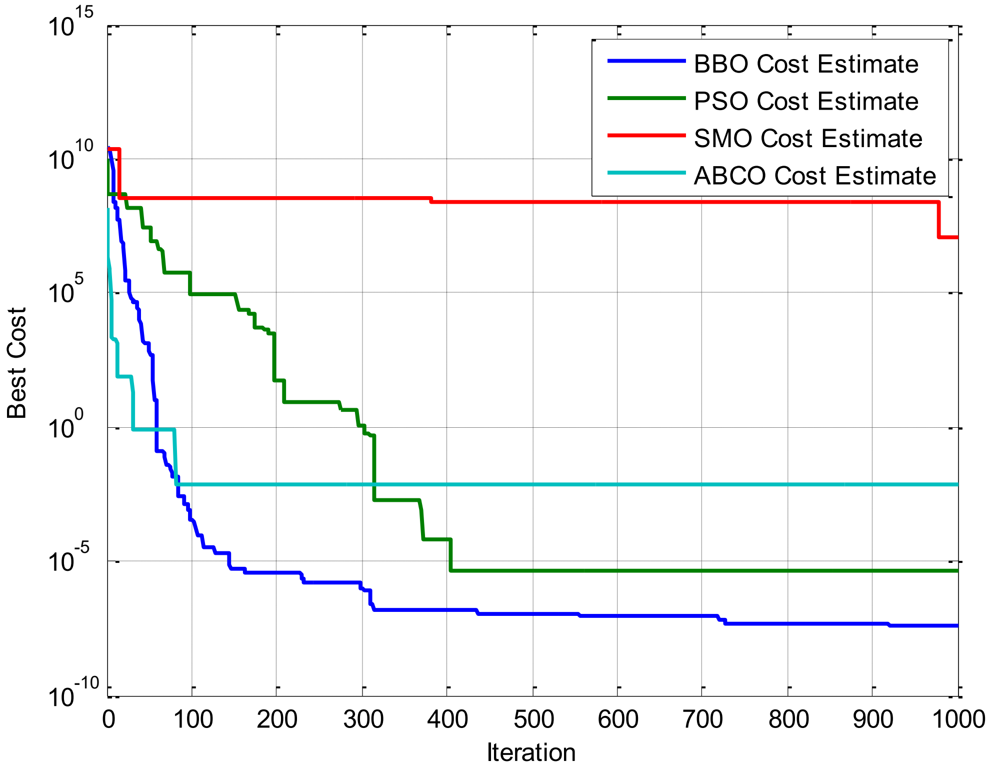

Fig 2: Comparative Fitness Response of Swarm Optimizers (Trial 2)

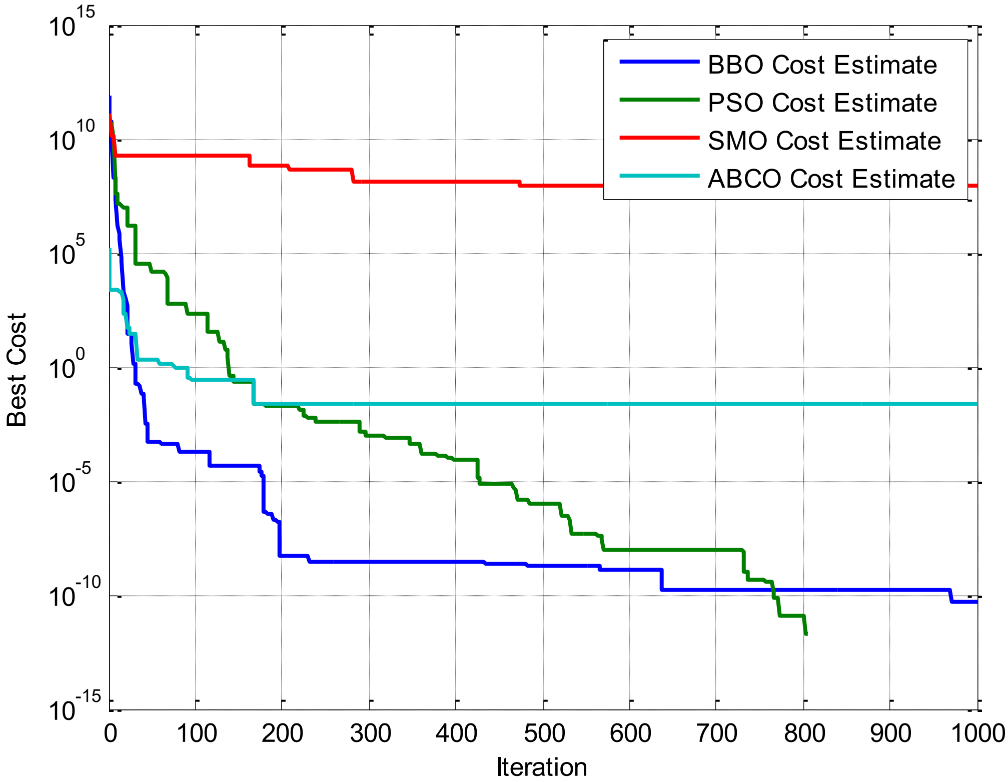

Fig 3: Comparative Fitness Response of Swarm Optimizers (Trial 3)

Furthermore, from the fitness response plots shown in Figures 1 to 3, it is clear that the BBO is the best method for the chosen problem; this implies its coefficients represent the most suitable configuration for the hydro-power plant set. Also, as clearly seen, the SMO performed very poorly making it a very unsuitable choice for the studied problem. However, as seen in Figure 3, the, PSO outperforms the BBO; but this occurs at around 800 iterations.

V. CONCLUSION

This research paper has presented a swarming intelligence solution based on hybrid set of swarm evolutionary optimizer techniques applied to the optimization of Shiroro power station hydro-turbine operational data. The proposed hybrid solution has considered Glimn-Kirchmayer quadratic model for operational function-fitting simulation experiments as well as the PSO, ABCO, BBO and SMO swarming techniques for the discovery of the optimizer that gives suitable coefficients in relation to best fitness responses. The research identified the best model to be the BBO.

The proposed solution can be well adapted to fit any given plant data provided the initial boundaries of the coefficients are well chosen. The research study can also be applied in the field of real time power systems optimization and modelling. In particular, the following key (recommended) research application areas are identified: adaptive plant-level simulators of hydro-turbine performance with sensitivity studies with respect to swarming optimizer parameters, novel data-driven dynamic methods of I-O model for energy management and control, hybrid or multi-agent control systems for power industry and other new forms of nature-inspired algorithms for the prediction of turbine power output.

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