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Power Flow Optimization in Cyber-Physical Systems Using Jellyfish Optimization Technique

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Abstract: Cyber-physical systems (CPS) are under increasing strain, which has created a number of problems for the power system, including voltage instability, line overloads, and rising power losses. In order to solve these problems, it is essential to strategically deploy energy resources at the right nodes to maximise real and reactive powers, hence lowering losses and enhancing the voltage profile, especially in crowded networks. Grid operators can more effectively meet the demand for electricity while preserving the stability of the power system thanks in large part to power flow optimisation. However, because they are unpredictable, integrating intermittent renewable energy sources (RESs) presents particular difficulties. The power flow model put out in this study includes four different kinds of energy sources: thermal power plants (which stand in for traditional energy sources), wind power plants, battery charging stations, and solar photovoltaic power plants (which represent renewable energy sources). The goal is to assess the efficiency of the upgraded IEEE 30-bus test system through optimisation utilising an integrated strategy integrating fuzzy logic and jellyfish search optimizer (JS). Practical factors like the thermal generators' ramp rate restrictions and the erratic generation patterns of renewable energy sources are taken into account by the suggested algorithm. The algorithm effectively solves the optimum power flow (OPF) problem by minimising overall generating costs and reaching solution convergence, as shown by simulation results. The suggested method demonstrates its effectiveness in solving the difficulties of power flow optimisation by taking into account real-world scenarios and adding the complexities associated with RESs. The algorithm's effectiveness in assuring an ideal and affordable power flow solution is demonstrated by its ability to handle the intermittent nature of renewable energy sources and the limitations of thermal generators.

Keywords: Cyber-Physical System's (CPS); Fuzzy; Jellyfish; Optimum Power Flow (OPF); Smart Grid

1 INTRODUCTION

The main tool for designing and managing electric networks is now OPF [1]. The goal of the Optimal Power Flow (OPF) problem is to find the optimum solutions for a number of objectives while abiding by a number of equality and inequality conditions, system security restrictions, and the operational limitations of electrical equipment [2]. The active power outputs of generators, bus voltages at power plants, transformer tap settings, and reactive power contributions from VAR compensators are just a few of the control variables that are adjusted to achieve this. The OPF problem's main goals are to minimize total emissions (TE), minimize network losses, and minimize economic fuel costs (EFC) [3]. These goals combine technological, environmental, and economic factors to meet the expanding needs of the energy industry. Recently, academics have become increasingly eager to investigate OPF, a problem with two to three objectives. OPF remedy the purpose is to identify the best options for distinct objective functions. While also upholding a set of equity and limitations of inequality constraints, a solitary best option [4]. There must be trade-offs among two or more opposing aims. As in actuality, there is a collection of the best options, not a single one, unique best OPF solution. Consequently, the choice only the maker's preferences can determine the best course of action, and nobody else can be better to disregard alternative solutions. That is context, one of the well-known Pareto-optimal solutions dependable instruments for multi-objective optimization issues, can gather a group of ideal options.

Numerous traditional optimization techniques have been put forth since the OPF problem was first presented [5]. These techniques include of quadratic programming, mixed-integer mathematical optimization, non-linear programming, and interior-point methods [6-8].The composition of power systems is growing more complicated due to the ongoing integration of computing, communication, and control innovations in smart grids, transforming them into cyber-physical power systems (CPPS) with a close combination of data and physics. It consists of both the conventional physical grid and the power network connectivity created by data acquisition, control, and decision-making units, among other things.

Due to their quick convergence and ability to produce an ideal solution, some of these techniques have been successfully applied by the industry sector. But to use these optimization techniques, the optimization function must first be linearized. For this problem, various properties, such as the quasi, non-differentiable, and non-smooth ones, are frequently estimated for the optimization function.

Heuristic optimization approaches have also been proposed [9-12] as a remedy to this issue. In this way, the OPF is solved using a variety of heuristic methods. In [13], a sequential GA solution strategy was used to solve the OPF issue using a simple genetic algorithm (SGA), resulting in an appropriate control variable resolution that did not violate the system's restrictions. A hybrid genetic algorithm (GA) is introduced in Reference [14], integrating the capabilities of MATPOWER software's linear programming (LP) and sequential quadratic programming (SQP) techniques. This approach enhances the optimization process by leveraging both heuristic and mathematical programming methods.

Additionally, Reference [15] presents a refined genetic algorithm (RGA) designed to efficiently encode multiple control variables within a power system while maintaining a practical chromosomal length, ensuring computational feasibility and effectiveness. However, based on the analogy from nature, various global algorithms have been developed. A number of population-based heuristic techniques, including as genetic algorithms (GA), particle swarm optimization (PSO), teaching-learning-based optimization, evolutionary algorithms, and differential evolution, are frequently used to solve optimization problems. Various variations of these techniques have been investigated for the

Optimal Power Flow (OPF) problem. An electromagnetism-like mechanism optimizer, for example, has been updated and adapted for OPF. Specifically, modifications were made to the local search and force estimating phases, adding two randomly selected particles while maintaining the initialization phase. Furthermore, convergence properties for the OPF issue were improved by combining a Gaussian mutation operator with an adaptive biogeography-based optimization (BBO). To handle the same problem, a modified salp swarm algorithm (SSA) was used in another method, illustrating the variety of approaches used to optimize OPF solutions [21] that exhibited chaotic behaviour. In those reference [22-23], the management of various objective functionalities has been made possible by combining them into a single optimization problem using weighting factors, making the achieved operating point particularly sensitive to the choices of weight factors. For the best placement of fault current limiters and distributed generators in distribution networks, the coyote optimization technique (COA) has been dedicated in Ref. [24]. In this study, a fuzzy based model was used to activate the single objective optimization for the minimization of energy losses, short circuit currents, and installed devices.

The goal of this study is to complete the efforts made to identify the best solution to the OPF problem. This article's contribution can be succinctly summed up as follows:

- The jellyfish search (JS) metaheuristic optimization algorithm, which is brand-new and recently created, is integrated with fuzzy in this study to provide an efficient OPF in cyber-physical systems.
- To test the proposed algorithm's viability in finding the best solution for the OPF problem using renewable energy sources under ideal and realistic settings, it is applied to an IEEE 30 parallel coupled with communication bus system that includes two wind turbines and one solar Photovoltaic generator.

The remainder of this essay is organised in the manner below. The mathematical formalism and related appropriate restrictions used for the Objective functions are shown in Section 1.1. The new idea for applying JS and fuzzy to OPF that incorporates the indeterminate RES is established in section 2. For the four methods under consideration, Section 3 presents the simulation results of various practical case studies. Section 4 and Section 5 offers this paper's conclusions and references at the end.

1.1 Objective Function and Problem Formulation

The working parameters of the IEEE 30-bus system are listed in Tab. 1. Three separate power production resources, namely thermal power generators (TGs) with fixed outputs, solar PV generators (SPGs) with variable outputs, and wind generators (WPGs) with variable outputs, are included in the modified network. The mix of all sources and reserve power must be used to balance this variance in PV and wind outputs, therefore the total generation cost consists of operating expenses for all units, reserve expenses, and penalty expenses.

Table 1 IEEE 30 bus system details

Component	Quantity	Description
Total Buses	30	30 buses are interconnected connected
Communication Points (Wireless)	10	At Bus 1, 2, 8, 5, 11, 15, 17, 21, 22 & 28
Branches	41	These branches are connecting load, sources and buses
Steam based Generator	3	SG1, SG2, SG3, in which Bus 1 is swing bus, other at 2 & 8
Wind Turbine Source	2	WTS1, WTS2 at Bus 5 & 11
Solar Source	2	SS1, SS2 both at Bus 15
Physical Control Variables	05	Voltage of Bus 2, 5, 11, 17, 21
Cyber Control Variables	10	Weight of each communication point

A. **Cost Model for different sources used**. Fossil fuel is used to power thermal power plants. The relationship between steam generator power output in MW and the cost of fossil fuels in \$/Hr is provided by Eq. (1).

$$C_{\mathrm{T}}(SG)=\sum_{i=1}^{NTG} x_i+y_i P_{SG}+z_i P_{SG}^2. \tag{1}$$

Where x, y, z shows the cost coefficient of the steam generators while i indicate the i^{th} element of the steam turbine. If the generator units are owned by the Independent System Operator (ISO), the cost function might not apply in the same way when an Independent Grid Operator (IGO) chooses to include compensation costs in the ongoing maintenance and renewal expenses or assigns these costs to the initial investment in solar PV or wind generators. In contrast, the ISO is required to pay costs based on the scheduled power contracts with private owners of solar PV or wind generators if they are privately owned. Depending on how the renewable energy assets are owned, this distinction has an impact on how costs are handled and recorded. The following is how planned power affects the actual costs of the j^{th} wind based renewable power generator:

$$C_{\mathrm{WT}S}=f_j P_{\mathrm{WTS},j}. \tag{2}$$

In a similar manner, the k^{th} solar Photovoltaic PV generator's direct cost is:

$$C_{\mathrm{SS}}=f_k P_{\mathrm{SS},k}. \tag{3}$$

Where $P_{\mathrm{WTS}}/P_{\mathrm{SS}}$ and f, respectively, stand for the planned wind/solar power and the direct cost coefficient associated with the j^{th} wind power/solar power plant.

B. **Uncertainty in the model.** Due to the sporadic nature of wind energy, two situations are possible. The first situation occurs when the wind farm's production power is lower than what was anticipated. Overestimating output power is the word used to describe this circumstance. In this instance, the grid operators uses spinning reserve to give its customers a dependable power supply [26]. Reserve cost is the price necessary to commit the reserve producing units in order to correct the overestimation problem. The j^{th} wind energy plant's reserve cost is calculated using:

$$C_{\mathrm{WTS,\,RC}} = \\ = P_{\mathrm{WTS},j} \int_0^{P_{\mathrm{WTS}}} (\textit{relative power} \times \textit{power distribution function}). \tag{4}$$

Solar energy also has erratic and sporadic output, just as wind energy. In general, the method used to address under- and overstatement of solar power output should be the same as that used to address wind output power. For solar Photovoltaic PV plant k, the reserve cost is provided by:

$$C_{\mathrm{SS,\,RC}} = \\ = P_{\mathrm{SS},\,i} \times \textit{relative power} \times \textit{power distribution function}. \tag{5}$$

C. **Cyber layer interaction with grid**. In, the above cases all consist of physical layer model and uncertainty. The cyber layer model indicates the interaction with the communication network of the system. In this research will use the weight of each Communication Points and it will impact the system directly. If the weight of the communication point is more than 0.8 then will consider as trusted healthy network and if the value is less than this means unhealthy network.

$$W_{\mathrm{cp}} = \begin{cases} > 0.8 & \text{Healthy} \\ < 0.8 & \text{Unhealthy} \end{cases}. \tag{6}$$

D. **Problem statement objective**. As shown in Eqs. (1)-(5), the goal optimum for OPF is generated by incorporating all cost function models. Emission cost is disregarded in the objective function ($F1$). The objective function ($F2$) is constructed with the effect of communication points to better understand the variation in generation scheduling when uncertainty is taken into account.

Consequently, reducing overall cost is the objective function:

$$F1 = C_{\mathrm{SG,\,Total}} + C_{\mathrm{SS}} + C_{\mathrm{WTS}} + C_{\mathrm{SS,\,RC}} + C_{\mathrm{WTS,\,RC}}, \tag{7}$$

$$F2 = W_{\mathrm{cp}} \times \sum_{b=0}^{b=10} \textit{Bus power}. \tag{8}$$

The OPF objective functions are formulated while incorporating both equality and inequality constraints within the system. Notably, achieving power convergence to an optimal solution ensures that the equality constraints are inherently satisfied through power balance equations. Among the inequality constraints, generator bus voltages and active power outputs—excluding those from the swing or slack generator, which is typically assigned to bus 1—serve as self-regulating parameters.

The optimization method employed determines an optimal value for each control variable within its allowable range. Consequently, careful attention is required for inequality constraints related to the slack generator's active and reactive power limits, the reactive power output of other generators, voltage constraints on PQ buses, and transmission line capacity limitations.

In the context of a cyber-physical system (CPS), interactions between the cyber and physical layers must be considered. While cyber-layer disruptions can directly impact the physical system's performance, the reverse influence is typically constrained and does not exhibit the same level of impact.

2 PROPOSED METHEDOLOGY

The three pillars of the JFS optimizer are based on the movements of jellyfish. The first pillar holds that the jellyfishes' movements might be in their swarm or on their journey to the ocean current, and that the temporal control (TC) function can regulate these two forms by shifting between them. The second tenet is that jellyfish are attracted to certain areas once there is enough food available. The numerical objective function is used to characterise food quantity as the third pillar [27, 28]. The jellyfish colony is randomly initialised in chaotic logistic mapping, and can be expressed as follows:

$$X_i(t+1) = 4P_0(1 - X_i) \tag{9}$$

Where P_0 denotes the beginning jellyfish population, which has the potential to produce a value of P_0, and X_i conveys the i^{th} jellyfish based on chaotic value. Their motions in the ocean complete the quest for food.

In areas where there is an abundance of food, they are extremely prone to mobility. This approach is used in this situation because it can explore more effectively. This characteristic is used to determine the global optimal point. According to the flowchart for this modification in Fig. 1, the jellyfish can move in a jellyfish swarm using either passive motion or active motion. In a swarm, jellyfish move both actively (type B) and passively (type A) [29]. Jellyfish start moving passively right after the swarm forms, then after a short while, they start moving actively.

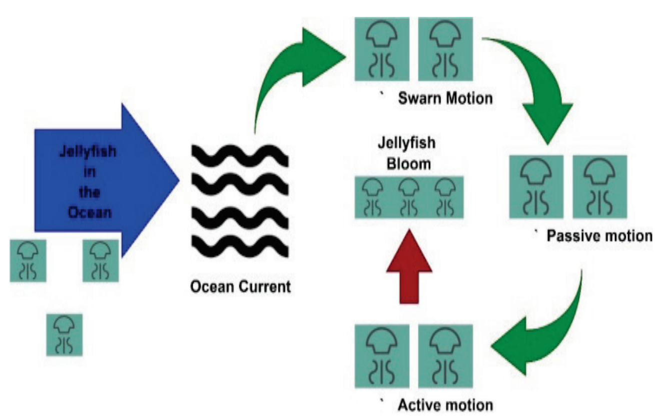

Figure 1 Jellyfish search optimization flow

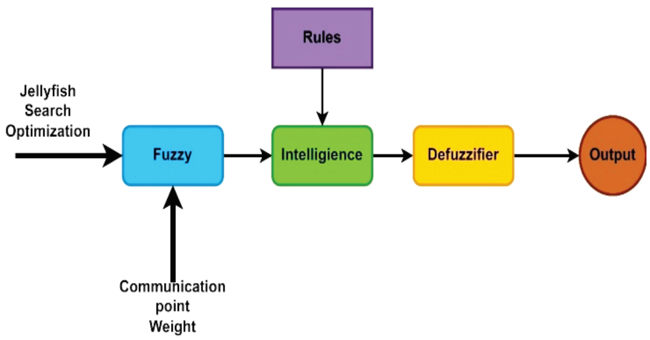

Figure 2 Integration of fuzzy with JS

Table 2 Fuzzy rule for the proposed methodology

Rule	Identification	Description
JS is H and CPW is H	Their optimal values	Healthy system with OPF
JS is H and CPW is L	Individual values	Healthy OPF with cyber disturbance
JS is L and CPW is H	With respect to Rule 1	Unhealthy
JS is L and CPW is L	With respect to Rule 1	Unhealthy with possibility of cyber disturbance
H = High; L = Low		

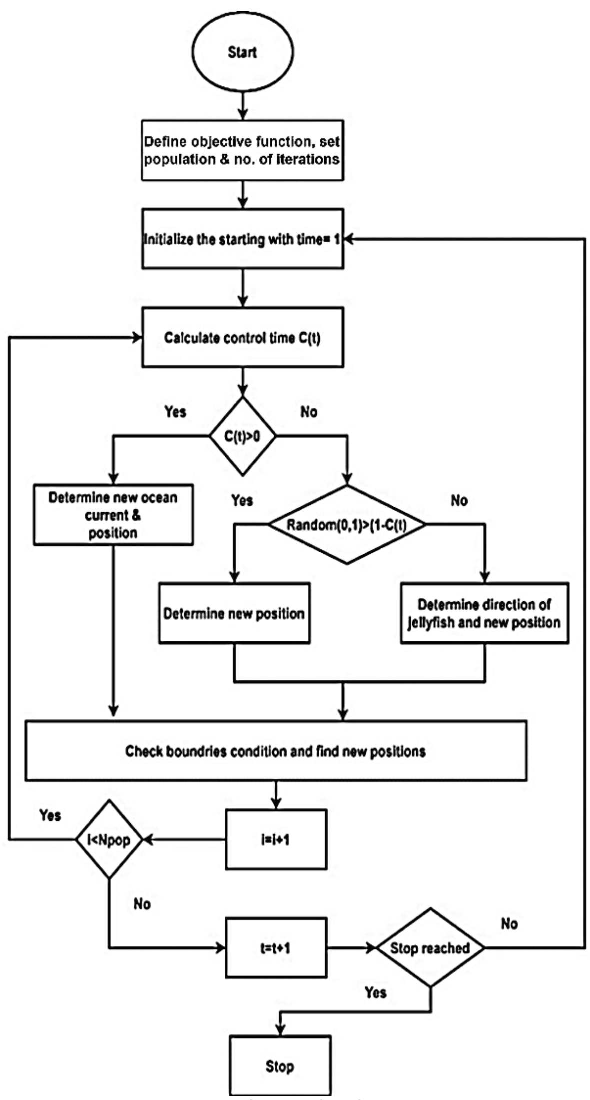

Figure 3 JS based OPF flow chart

The TC mechanism determines whether to choose type A or type B. When compared to a random number in the range [0-1], the phrase $(1 - CF(t))$ is significant in this context. The jellyfish exhibits type A motion if this value is higher than the $(1 - CF(t))$ calculation's result. When the pseudo random is less than the computed value stated, jellyfish, on the other hand, follows type Bmotion If. This concept is further explained by the fact that type A motion is favoured at start point, when the TC function rapidly decreases from 1 to 0, and type B motion is chosen as time advances.

Now the JS OPF output will serve as input for the fuzzy. The final status of the line or bus will be obtained by the interaction with fuzzy and cyber layer of the system.

3 RESULT AND DISCUSSION

When dealing with the OPF issue as previously explained, the equality and inequality requirements are taken into account. The equality conditions, which serve as load flow balancing equations, are effectively upheld by applying the Newton-Raphson algorithm (NRA). The NRA method in this article maintains the uncertainty of (4) and (5) since it establishes the program's steady state for power system operators. Since MATPOWER is employed, the NRA algorithm serves as an effective tool for visualising three-phase networks [30].

Any other limits, such as decision-making constraints and dependent variable constraints, are expressed by two operating limitations. The decision variables of the first type continue to reach their limits, and if either of them is beyond evaluation, they are arbitrarily recreated within their suitable ranges. Additionally, the objective function prolongs and penalises the second type's restrictions (dependent variables). As a result, the jellyfish solution could not be chosen in the following iteration if there were any violations of these criteria.

Table 3 System parameters used

Parameters	Values
Nominal bus voltage	100 V (L-L)
Rated frequency	60 Hz
Source Impedance	1+j1.5 Ω
Non-linear load R-L	20+j79 Ω
dc-link voltage	800 V
Coupling Inductor, L_f	3.5 mH
Overloading factor, a	1.2
DC bus voltage recovery time, t	90 ms
Variation of energy during dynamics, k	20%
Current ripple, ΔI	25% of I
Overshoot voltage, V_{os}	15% of V_{dc}
Switching frequency, f_s	5 kHz
C_{dc}	3.3 mF
L_f	4.2 mH
r_f	0.5 Ω
L_c	0.6 mH
r_c	0.425 Ω
C_f	15 µF
R_d	2.025 Ω
ω_c	50.26 rad/s
ω_n	377 rad/s
$\omega_{c,\ PLL}$	7853.98 rad/s

A well-known test case used in power systems research and analysis is the IEEE 30-bus system. It is frequently used to examine how electrical power systems behave and to evaluate different algorithms and approaches to power system analysis. This system is portrayed as a network of transmission lines and buses that act as reduced versions of an electrical grid. Please be aware that compared to actual power grids, which can be much larger and more complex, the IEEE 30-bus system is a comparatively modest and simplified model. However, it provides a useful benchmark for evaluating and creating methods and methodologies for power system analysis. Fig. 4, shows the actual model used for the simulation in the MATLAB environment.

Parameters used in the model is stated in the Tab. 3.

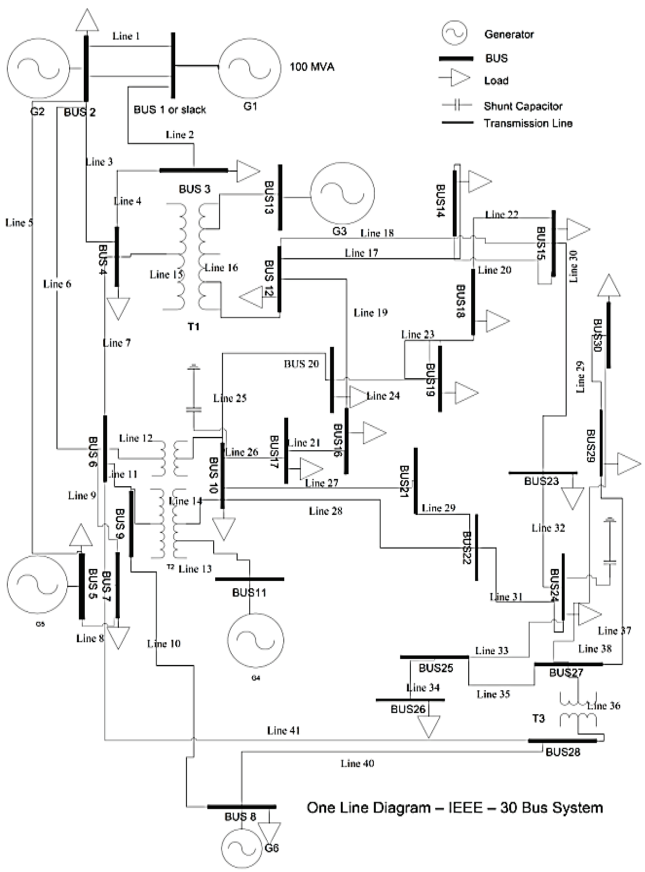

Figure 4 Simulation MATLAB model

3.1 Simulation Results

Various case studies are carried out for the modified IEEE-30 bus system in this section. The outcomes of the various case studies utilising the suggested Jellyfish search (JS) optimization technique is shown and described. ABC, CGO, FPA, and GPC are used as four distinct optimization techniques to test the efficacy of the JS optimization process. Apart from these two cases will be consider:

- Case A: Only Physical layer is taken into consider putting cyber layer at 1.
- Case B: Considering cyber and physical layer both.

The effects of changing the schedule for wind and solar power as well as PDF parameters on generation costs are investigated using case studies A and B. The goal of the subsequent case studies is to maximise the schedule generation across all sources under ideal and realistic circumstances. A minimum of 1000 iterations are used as the finishing condition after the algorithm has been run vs times, the optimal value of the optimization problem of each case study has been identified, and control variable settings have been listed.

3.1.1 Case A

In Case A, we consider only the OPF with a normal cyber layer. Figs. 5 and 6 show the simulation results for the JS. At iteration 100, we obtain the best results with a value of 15,116 for the five inputs. Ideally, when the cyber layer weight is set to 1, it implies no faults in the communication system. However, in reality, this is not the case, leading to a higher global best value. During the simulation, some parameters were affected due to misinterpretations in the communication channel.

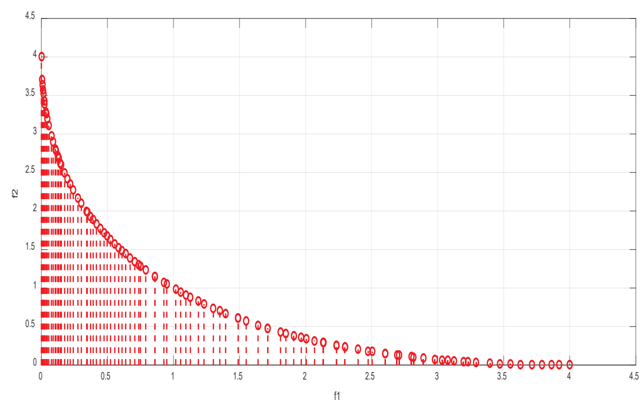

Figure 5 Plot of the objective functions

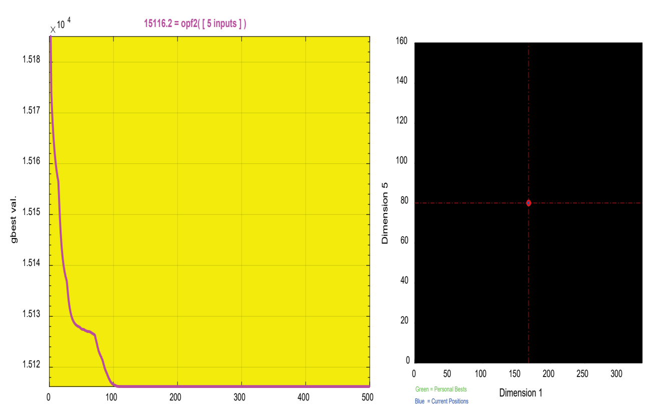

Figure 6 OPF for the case A using JS

3.1.2 Case B

In this case CPS system is consider and for every simulation the weight of the communication point is taken into consideration. So, the effect and OPF will be correctly monitored. So, Fig. 6, shows the results of the simulation by taking into CPS system. The tuning parameters for the other methods with the proposed method is stated in the Tab. 4. Control variables with the results for the case A and B is shown in the Tab. 4. The overall cost for the simulation is shown in the Fig. 8.

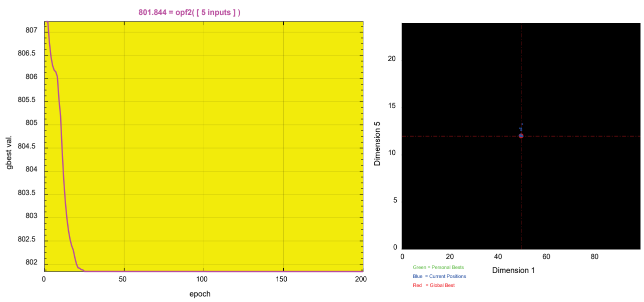

Figure 7 OPF of CPS using JS+Fuzzy

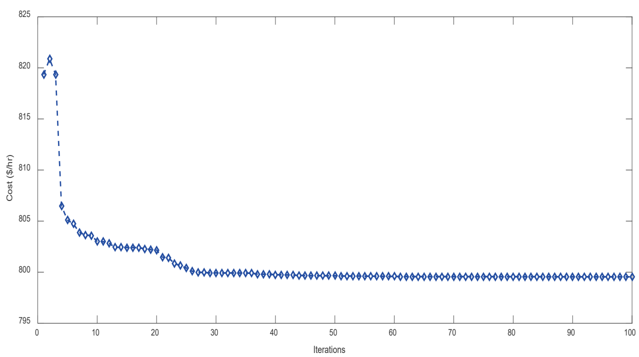

Figure 8 Cost iteration for CPS system

Table 4 Simulation parameters

Parameters	PSO	GA	ABC	JS+Fuzzy
Population	15	15	15	15
Iteration	200	200	200	200
Other parameters	Constriction factor 0.75	Mutation rate 0.1	Limit 100	Not required

Table 5 Case A simulation result

Control Variable	PSO	GA	ABC	JS+Fuzzy
CV1	1.042	1.0332	1.062	1.048
CV2	1.064	1.0414	1.034	1.069
CV3	1.053	1.0510	1.053	1.071
CV4	1.066	1.0676	1.036	1.069
CV5	1.032	1.0332	1.072	1.037

Table 6 Case B simulation result

Control Variable	PSO	GA	ABC	JS+Fuzzy
CV1	1.021	1.054	1.089	1.068
CV2	1.052	1.067	0.99	1.073
CV3	1.067	1.032	1.012	1.035
CV4	1.042	1.048	1.068	1.022
CV5	1.031	1.073	1.011	1.057

Table 7 Computational time for case A and Case B

Technique	Case A (Sec)	Case B (Sec)
PSO	2.24	2.33
GA	2.11	2.21
ABC	1.98	1.99
JS+Fuzzy	1.52	1.47

The control variable for the voltage in P.U is shown in the Tabs. 5 and 6 for both cases. The Computational time for case A and case B is shown in the Tab. 7. Fig. 9, shows the effect of CPS weight of communication point for case A and case B.

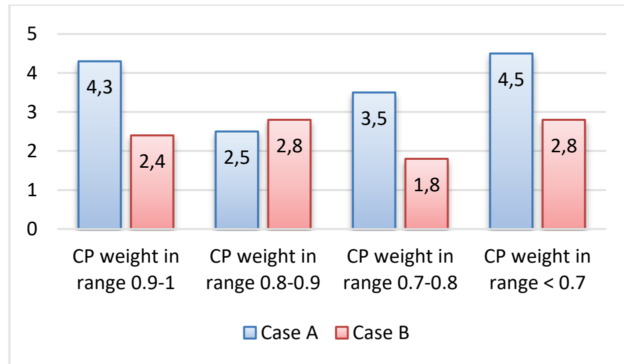

Figure 9 Case A and Case B response as per the weight change in CPS

3.2 Discussion

A comparison on different parameters is stated in the Tab. 8. The comparison is done on 5 major parameters which are stated below:

- Parameter 1: Fast convergence
- Parameter 2: Time taken
- Parameter 3: Is able to deal with CPS system
- Parameter 4: Is possible to extend to other system
- Parameter 5: Accuracy.

Table 8 Comparison [30-32]

Parameter	PSO	GA	ABC	JS+Fuzzy
P1	••	••	•••	••••
P2	•••	••	•••	••••
P3	•	•	•	••••
P4	••	••	••	••••
P5	•••	•••	•••	••••
Four dot means highest value				

4 CONCLUSION

To sum up, this research presents a new metaheuristic optimization approach that addresses the Optimal Power Flow (OPF) problem in a complex power system scenario with stochastic wind and solar energy sources by combining jellyfish optimization with a fuzzy search optimizer. The suggested algorithm provides a reliable method to minimize generation costs while taking into account variable cost coefficients and carbon emission fees. It does this by modeling the unpredictable nature of these renewable sources using Weibull and log-normal probability density functions. The thorough comparison of the suggested JS integrated Fuzzy algorithm with established techniques like ABC, PSO, and GA shows how much better it performs in terms of cost savings and convergence of the solution. These findings highlight how well the JS integrated Fuzzy approach optimizes the OPF problem, indicating that it is a useful tool for managing and planning energy systems in the future.

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