Quasi-Reflection Jellyfish Optimizer for Optimal Power Flow in Electrical Power Systems

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Abstract: This paper suggests a new version of Jellyfish Optimizer (JFO) integrated with Quasi-Reflection (QR) in solving the Optimal Power Flow (OPF) problem, considering fuel costs, emissions and losses. Despite the high simplicity of the basic framework of the JFO with substantial features in intensifying and exploring the search space, it needs further assistance in improving its searching ability. The suggested QRJFO creates a uniformly chosen cluster inside the jellyfish population. It represents a shared network that exchanges knowledge in a cluster which is distinct from everyone else. Furthermore, the discovery process is facilitated by the advent of the learning strategy of QR points. The efficiency of the suggested methodology is measured by implementing it on IEEE 30 bus-system. The simulation outputs display the solution effectiveness and the applicability of the suggested QRJFO relative to JFO as well as other documented implementations.

Keywords: Jellyfish optimizer, Quasi-reflection point, Optimal power flow, Fuel costs, Power losses, Emissions.

1. Introduction

One of the nonlinear optimization issues is the Optimal Power Flow (OPF), where it has a specific objective to be optimized taking into consideration the electric physical constraints (El-Sehiemy et al., 2014). The total fuel cost, the pollutant emission level of power system components, and the active losses are the main pillars of the OPF issue (Mohamed et al., 2017). Its main goal is searching for the best operation and economic settings of generator voltages, transformer taps, power generation and reactive power outputs from both capacitors and reactors (Ramesh Kumar & Premalatha, 2015). For hybrid AC/DC power systems, the fuel cost minimization is enhanced with emissions minimization as mentioned in (Abdul-hamied et al., 2020). Economical operation of power systems is an important issue for minimizing the production costs as mentioned in (Ravichandran & Subramanian, 2020), (El-Sehiemy et al., 2021). In the previous studies, the power system operators aimed at working at the level of economical operations as well as at providing high quality and reliable services at a lower cost.

Besides, the control variables are adjusted with consideration of operational equality and inequality constraints of the power flow balance (El-Ela et al., 2021).

Earlier, numerous traditional optimizers have been implemented to solve the OPF such as the simplex method, Newton-based method (Pulluri et al., 2018). Despite the excellent convergence characteristics of some of these techniques, they suffer from some deficiencies. As they are not able to guarantee global optimality, some theoretical assumptions are considered for them such as differentiability, convexity, and continuity, which are not vital to OPF conditions (Duman, 2017). On contrary, in the last few recent years, diverse optimization algorithms have been implemented to handle the OPF such as Evolutionary Algorithm (EA) (Surender Reddy et al., 2014), Genetic Algorithm (GA) (Zhang et al., 2019), adaptive GA with adjusting population (AGAPOP) (Attia et al., 2012), Chaotic Self-Adaptive Differential Harmony Search Algorithm (CSDHSA) (Arul et al., 2013), Black-Hole-Based Optimization Approach (BHBOA) (Bouchekara, 2014), Improved Electromagnetism-like Optimization Algorithm (IEOA) (Jeddi et al., 2017), Modified DE algorithm (MDE) (Shaheen et al., 2016), heap-based optimizer (Ginidi et al., 2021), Imperialist Competitive Algorithm (ICA) (Ghanizadeh et al., 2011), Crow Search Optimizer (CSO) (Shaheen et al., 2021a), Novel Bat Algorithm (NBA) (Yang, 2013), coyote algorithm (Abou El-Ela et al., 2021) the renewable energy has been occupied a

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lot of attention around the world since it presents cheap and sustainable energy. Consequently, its presence in power systems becomes a fact that had to deal with. Hence, load frequency control (LFC, Modified Crow Search Optimizer (MCSO) (Shaheen et al., 2021b), Improved Moth-Flame Algorithm (IMFA) (Taher et al., 2019), multi-verse optimizer (Shaheen, 2019), multi-objective marine predator optimizer (Alharthi et al., 2021), (Shaheen et al., 2021d), and modified Teaching-Learning Algorithm (TLA) (Shabanpour-Haghighi et al., 2014).

The aim of this article is to solve the OPF issue using the proposed QRJFO algorithm. JFO has been proposed by Chou and Truong (2021) and it is inspired by the jellyfish movements. A Quasi-reflection learning is emerged into the standard JFO to deal with population diversity, the local search capability, and convergence speed. The JFO and the proposed QRJFO are implemented, with and without the effects of shunt Volt-Ampere-Reactive (VAR) compensation to get the optimal solution of fuel costs, losses, and emissions of OPF issue.

This paper is organized in 5 sections. The OPF issue problem formulation is described in Section 2. Next, the JFO and the proposed QRJFO algorithms are illustrated in Section 3. The establishment of the outcomes is depicted in Section 4. Section 5 denotes the conclusion of this work.

2. Problem Formulation

The OPF issue representation can be mathematically written (Elsayed et al., 2021) fuzzy decision making is employed to select the best compromise operating point for the hybrid AC/HVDC power systems. In these systems, the active and reactive power controllability of the voltage source converters (VSCs as depicted in equation (1):

Min FF(x,y)

$$\text{subjected to: } f(x,y)=0 \text{ and } g(x,y)\le 0 \tag{1}$$

where FF represents a certain objective function, while x and y are the states and control variables. Additionally, f and g denote the equality and inequality system constraints.

2.1 Problem Objectives

The quadratic equation of the fuel generation cost (FF1) is formulated as follows:

$$FF1=\sum_{i=1}^{N_g} a_i Pg_i^{\,2}+b_i Pg_i+c_i \tag{2}$$

where N_g is the number of generators; Pg_i denotes the active output power (MW) for each generator i, while the cost coefficients are illustrated by (a_i, b_i, and c_i).

Another objective function which involves the total ton/hr emissions (FF2) discharged from the fossil-fuel generators in electrical systems can be expressed as follows:

$$FF2=\sum_{i=1}^{N_g}(Ea_i Pg_i^{\,2}+Eb_i Pg_i+Ec_i)/100+Ed_i e^{Ee_i Pg_i} \tag{3}$$

where the coefficients (Ea_i, Eb_i, Ec_i, Ed_i, and Ee_i) demonstrate the atmospheric pollutants emission.

Another objective function which minimizes the power losses of the transmission network can be formulated as follows:

$$FF3=\sum_{i=1}^{NB} P_i=\sum_{i=1}^{NB} Pg_i-Pd_i \tag{4}$$

where Pd_i expresses the active power demand at each bus i. N_b establishes the number of buses.

2.2 System Constraints

The load flow balance equations (equality constraints) are the following:

$$Pg_i-PL_i-V_i\sum_{j=1}^{N_b}V_j(G_{ij}\cos{,}_{ij}+B_{ij}\sin{,}_{ij})=0,\ i=1,\ldots N_b-\text{slack} \tag{5}$$

$$Qg_i-QL_i+Qc_i-V_i\sum_{j=1}^{N_b}V_j(G_{ij}\sin{,}_{ij}-B_{ij}\cos{,}_{ij})=0,\ i=1,2,\ldots NPQ \tag{6}$$

The active and reactive power demands are specified by PL and QL respectively, whereas the mutual conductance and susceptance between bus i and j are expressed by G_{ij} and B_{ij}, respectively. Qg_i is the VAR injected at bus i; V_i refers to the voltage at bus i; Qc_i indicates the reactive power injection of switched capacitors at bus i; slack and NPQ illustrate the slack bus and the number of load buses, respectively.

The operational variables and their corresponding constraints, denoted by the superscripts (max) and (min) bounds are expressed as follows:

1) The generator voltages:

$$Vg_i^{\min}\le Vg_i\le Vg_i^{\max},\ i=1,2,\ldots\ldots.Ng \tag{7}$$

2) The active generators' power outputs:

$$Pg_i^{min} \leq Pg_i \leq Pg_i^{max}, \; i = 1, 2, \ldots \ldots . Ng \tag{8}$$

3) Generator reactive power outputs:

$$Pg_i^{min} \leq Pg_i \leq Pg_i^{max}, \; i = 1, 2, \ldots \ldots . Ng \tag{9}$$

4) The transformer tap settings:

$$Tap_k^{min} \leq Tap_k \leq Tap_k^{max}, \; k = 1, 2, \ldots \ldots N \tag{10}$$

5) Load bus voltage magnitudes:

$$V_{L_i}^{min} \leq V_{L_i} \leq V_{L_i}^{max}, \; i = 1, 2, \ldots \ldots . NPQ \tag{11}$$

6) The switched (capacitors and reactors) reactive power injection:

$$Qc_q^{max} \leq Qc_q \leq Qc_q^{max}, \; q = 1, 2, \ldots \ldots . Nq \tag{12}$$

7) Transmission line loadings:

$$|S_F| \leq S_F^{max}, \; L = 1, 2, \ldots \ldots . NF \tag{13}$$

where Nq and Nt define the number of the VAR sources and the number of on-load tap changing transformers, respectively, while NF illustrates the number of transmission lines. S_F refers to the power flow through line F which may have a negative value which indicates that the flow is reversed. Therefore, the absolute symbol is used in equation (13). SF^{max} indicates the transmission line loading.

3. Proposed QRJFO optimization

In the beginning, the population of jellyfishes (X_i) is created using chaotic logistic mapping. In JFO, the motions of jellyfishes can be inside the swarm or in the direction of the ocean currents. The transition between such two modes is regulated by the process of time regulation (TR).

Inside the swarm, two types of behaviours are modelled: active (Form A) and passive (Form B). In Form A, the jellyfishes move towards the positions that are rich in food. Equation (14) illustrates the new location of the jellyfish.

$$X_i(t+1) = \begin{cases} X_i(t) + R \times (X_j(t) - X_i(t)) & \text{if } f(X_i) \geq f(X_j) \\ X_i(t) + R \times (X_i(t) - X_j(t)) & \text{if } f(X_i) < f(X_j) \end{cases} \tag{14}$$

where f is the objective value related to each jellyfish location and R is a random number that is changing at each instant, using uniform distribution, within the range [0-1]. In Form B, the position of every jellyfish shall be changed around its existed position as follows:

$$X_i(t+1) = 0.1 \times R \times (U_b - L_b) + X_i(t) \tag{15}$$

where L_b and U_b indicate the lower and upper limits in the considered problem, respectively.

On the contrary, the motions of jellyfishes can be in the direction of the ocean currents where their directions (trends) are estimated based on the average of all the positions of the jellyfishes. Thereby, the updated position of every jellyfish is represented as:

$$X_i(t+1) = R \times (X^* - 3 \times R \times \mu) + X_i(t) \tag{16}$$

where μ is the mean of the positions of the jellyfishes and X^* is the currently best jellyfish position in the swarm.

If the jellyfish passes past the restricted search field, the jellyfish will return to the boundary. This can be represented as depicted in equation (17):

$$\begin{cases} X'_{i,d} = (X_{i,d} - U_{b,d}) + L_b(d) & \text{if } X_{i,d} > U_{b,d} \\ X'_{i,d} = (X_{i,d} - L_{b,d}) + U_b(d) & \text{if } X_{i,d} < L_{b,d} \end{cases} \tag{17}$$

where X_i refers to i^{th} jellyfish position and d refers to each dimension of the control variables.

Each jellyfish chooses between the motions inside the swarm (forms A or B) or in the direction of ocean currents using the time regulation (TR) process. This process is based on a regulating function c(t) that is described in equation (18):

$$c(t) = \left| \left(1 - \frac{t}{Max_{iter}}\right) \times (2 \times rand(0,1) - 1) \right| \tag{18}$$

where *Maxiter* indicates the maximum number of iterations and *t* is the current iteration. When the value of the regulating function c(t) exceeds a chosen coefficient (C_o), each jellyfish takes the direction of the ocean current. Otherwise, it follows the motions inside the swarm. In this mode, a number inside the range [0-1] is randomly created, using uniform distribution, and if it exceeds the value (1 − c(t)), the jellyfish exhibits form A motion. Else, it follows form B.

In the standard JFO, the variation of c(t) in (18) depends on *Maxiter*. In the beginning of iterations, c(t) will be inside (-1,1), but with a decreasing tendency in a long run; near *Maxiter* the values will be close to zero. Based on that, the jellyfishes have higher tendency to move inside the swarm, in active and passive forms.

To improve the JFO's performance, a quasi-reflection JFO (QRJFO) variant is suggested. Two improvements are introduced in the typical JFO method. At first, the JFO calculates, in every iteration, the average of all the entities in the swarm. In the suggested variant, a cluster is arbitrarily chosen from the swarm population for every jellyfish. Each cluster has a variable scale that represents a shared network which exchanges knowledge inside the swarm cluster that is distinctive from each other.

Added to that, a learning strategy of quasi-oppositional method is developed from the JFO algorithm to improve the discovery feature (Bentouati et al., 2020) planning and energy management of power systems. OPF analysis aims to find the optimal solution of system nonlinear algebraic equations with satisfying operational constraints. Economic, environmental and technical objectives are considered for multi-dimensions efficient energy management. These objectives involve the reduction of the production costs, reduction of the environmental emissions, improving the voltage profile, reducing the power losses and enhancing the system stability. This paper presents a new high-efficiency technology that proposes a multi-objective version of the recently proposed moth swarm algorithm (MSA). If y is a particular value inside $[L_b, U_b]$, its quasi-opposite value (y_q) will be as follows:

$$y_q = \text{rand}\left[\left(\frac{U_b + L_b}{2}\right), (U_b + L_b - y)\right] \tag{19}$$

By using the concept of quasi-oppositional points, the reflected points are created and the locations of jellyfishes are replaced. Then, the quasi-oppositional concept is assessed only to preserve the same number of objective evaluations. Figure 1 displays the suggested QRJFO flowchart algorithm.

4. Simulation Results

In this section, the proposed QRJFO and JFO are implemented on the standard IEEE 30 bus to solve the OPF issue. Ten simulation runs are completed for the proposed QRJFO and JFO with a maximum iterations number of 300 whereas the population size is 50. This system involves 4 on-load tap changing transformers, 30 buses, 6 generators, 41 lines, and 9 capacitive sources. The data for buses, the limits of reactive power generations, and transmission lines are taken from (Liu et al., 2017). The generator voltages have a maximum and a minimum value of 1.1 and 0.95 p.u., respectively. Two scenarios are considered in this study. In the first scenario, the effects of the shunt

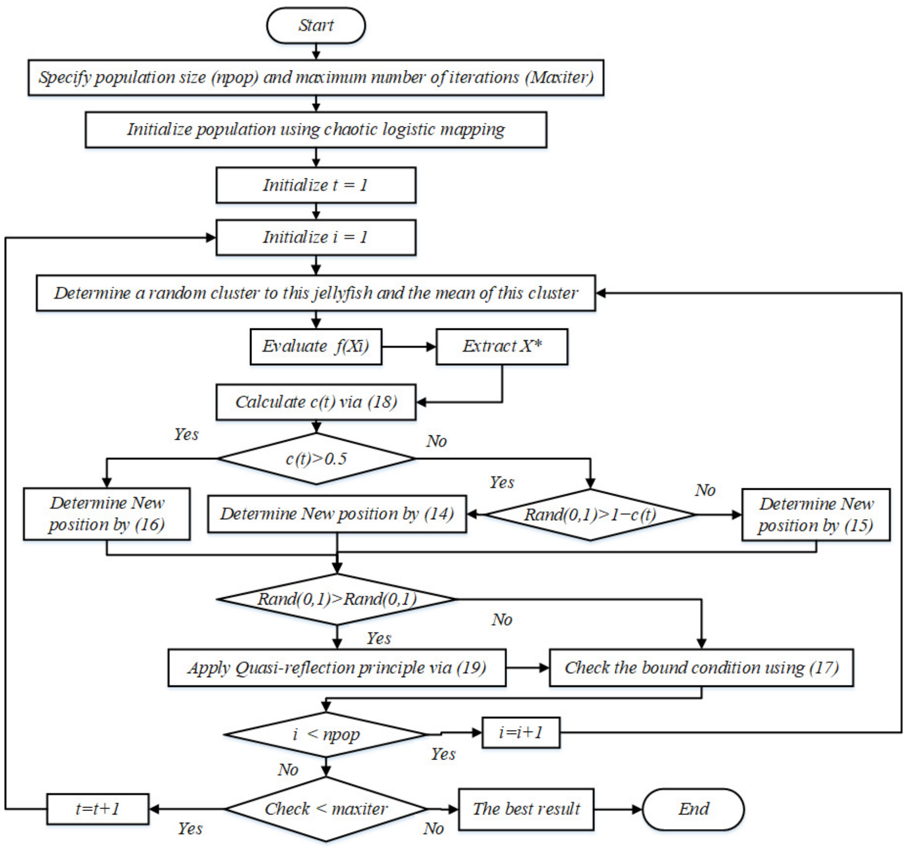


Figure 1. Flowchart of the proposed QRJFO optimization algorithm

VAR compensation and transformer tap settings are ignored. Thus, the control variables are active power outputs and voltages of the generation units. On the contrary, in the second scenario, the effects of the transformer tap settings and shunt VAR compensation are involved. For each scenario, three cases are studied as illustrated below:

Case 1: The Quadratic Fuel Costs (QFC) Minimization

Case 2: The Pollutant Emissions (PE) Minimization

Case 3: The Power Losses (PL) Minimization

4.1 Application for Scenario 1

Table 1 denotes the cost coefficients, while Table 2 describes the IEEE 30-bus test system emission coefficients. For the previously illustrated three cases studied, the JFO and the suggested QRJFO version are applied and their obtained outputs are recorded in Table 3. For the first case, the minimum QFC obtained by the suggested QRJFO is reduced from 901.96 $/hr to 800.2502 $/hr with respect to the initial case, however, the JFO minimizes the QFC to 800.254 $/hr. For the second case, the minimization of the PE is successfully achieved using both JFO and QRJFO. As shown, the PEs are minimized to 0.2047859 ton/hr and to 0.2047833 ton/hr using the JFO and the suggested QRJFO, respectively. The third case illustrates the minimization of System Power Losses (SPL) by applying the proposed JFO and QRJFO. Their acquired values of SPL are 3.173287 and 3.172604 MW, respectively. Also, the convergence characteristics of the JFO and QRJFO algorithms for minimizing the QFC, PE and PL are displayed in Figures 2-4, respectively. These figures illustrate the higher capability of the proposed QRJFO when compared to JFO in improving the best solution, particularly during the early stages of the 100 iterations.

Table 1. Cost coefficients for IEEE 30-bus system

Bus	a	b	c
1	3.75E-3	2.00	0.0
2	1.75 E-2	1.75	0.0
5	6.25 E-2	1.00	0.0
8	8.3 E-3	3.25	0.0
11	2.5 E-2	3.00	0.0
13	2.5 E-2	3.00	0.0

Table 2. Emission coefficients for IEEE 30-bus system

Bus	EA	Eb	Ec	Ed	Ee
1	4.0910	-5.5540	6.490	2 E-4	2.857
2	2.5430	-6.0470	5.638	5 E-4	3.333
5	4.2580	-5.0940	4.586	1 E-6	8.000
8	5.3260	-3.5500	3.380	2 E-3	2.000
11	4.2580	-5.0940	4.586	1 E-6	8.000
13	6.1310	-5.5550	5.151	1 E-5	6.667

Table 3. Optimal results of JFO and the proposed QRJFO for Cases 1-3, Scenario 1

Variables	Initial	Case 1 (U1 ($/hr))		Case 2 (U2 (ton/hr))		Case 3 (U3 MW))	
		JFO	QRJFO	JFO	QRJFO	JFO	QRJFO
Vg_1	1.050	1.0999980	1.1000	1.09990	1.09990	1.099990	1.10000
Vg_2	1.040	1.088680	1.089290	1.095020	1.097450	1.098410	1.099190
Vg_5	1.010	1.063390	1.06470	1.077810	1.081470	1.0823080	1.083120
Vg_8	1.010	1.072590	1.073690	1.087380	1.090030	1.090370	1.0914090
Vg_{11}	1.050	1.099410	1.099990	1.095790	1.099940	1.099220	1.099990
Vg_{13}	1.050	1.054060	1.056210	1.056140	1.061090	1.060860	1.062350
Pg_1	99.240	177.15	177.144	64.08580	64.10260	51.57950	51.57260
Pg_2	80.00	48.844	48.741	67.6254	67.6013	79.9976	79.99900
Pg_5	50.00	21.309	21.313	49.9989	49.999	49.9993	49.99900
Pg_8	20.00	20.947	21.218	34.999	34.999	34.9989	34.99900
Pg_{11}	20.00	11.877	11.943	29.9996	29.999	29.9992	29.99900
Pg_{13}	20.00	12.003	12.00	39.9995	39.999	39.9986	39.99900
Cost_Pg	901.96	800.254	800.2502	944.65	944.6074	967.8221	967.83570
Losses	0.23909633	8.959052	8.960326	3.30896	3.30395	3.173287	3.172604
Emissions	5.8324	1.176231	1.179199	0.2047859	0.2047833	0.207215861	0.207215686

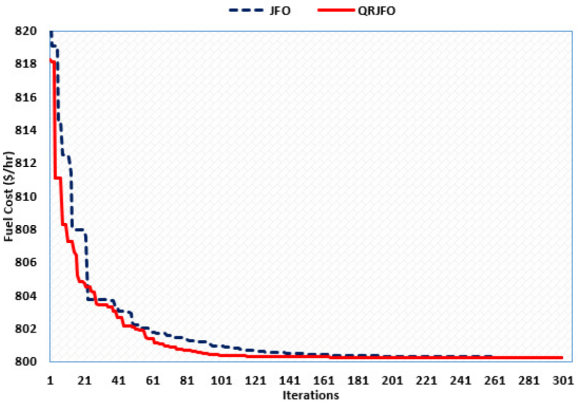


Figure 2. Convergence curves of JFO and QRJFO for Case 1, Scenario 1

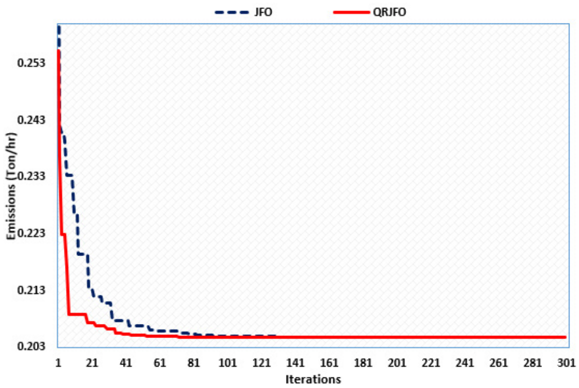


Figure 3. Convergence curves of JFO and QRJFO for Case 2, Scenario 1

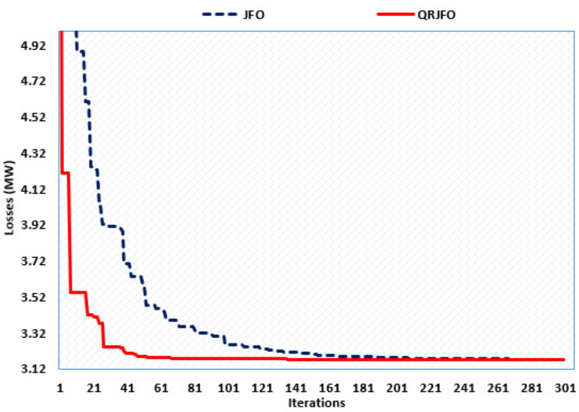
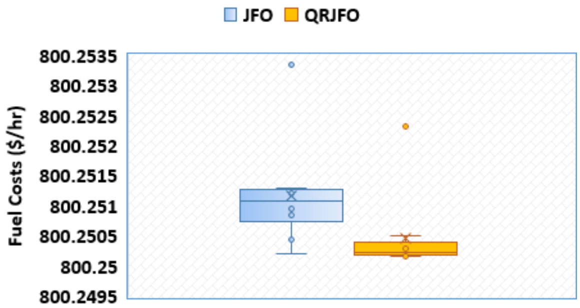


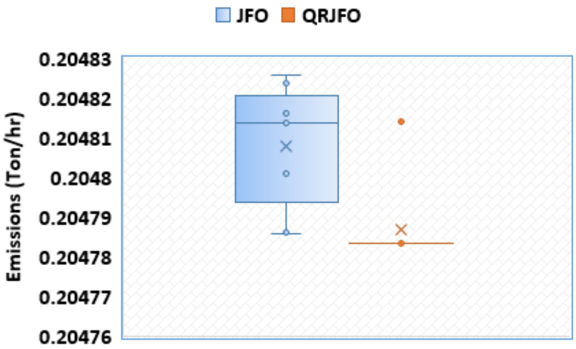
Figure 4. Convergence curves of JFO and QRJFO for Case 3, Scenario 1

4.1.1 JFO versus QRJFO: Robustness Analysis for Scenario 1

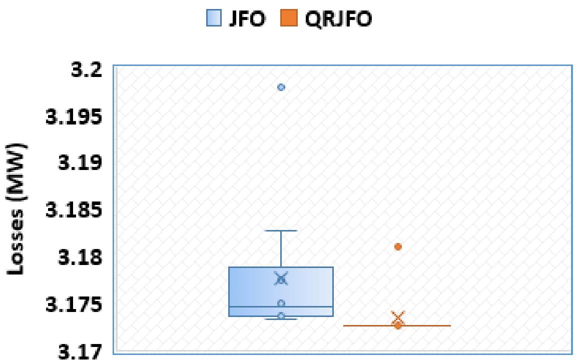
To evaluate the robustness analysis, the obtained minimum QFC, PE and PL of the 10-runs of JFO and of the proposed QRJFO are recorded. Their spread and centres for Cases 1-3 are displayed in Figure 5 via Box and Whiskers plot. As shown, the suggested QRJFO still follows the maximum, average and minimum values relative to the JFO for all the cases studied. Otherwise, the QRJFO provides the smallest standard deviations of QFC, PE and PL of 0.00084, 1.47E-05, and 0.0076, respectively relative to the JFO of 0.00066, 9.74161E-06, and 0.00266, respectively.



a - case 1



b - case 2



c - case 3

Figure 5. Box and Whiskers plot of JFO and QRJFO for Cases 1-3, Scenario 1

4.2 Application for Scenario 2

In this scenario, the effects of the transformer tap settings and shunt VAR compensation are involved. The tap changing transformer have a maximum and a minimum voltage of 1.05 and 0.95 p.u., respectively. However, the limitations of VAR injections for the capacitive sources are 5 MVA. The JFO and the suggested QRJFO version are applied for the three cases studied and their outputs are tabulated in Table 4.

Table 4. Optimal results of JFO and the proposed QRJFO for Cases 1-3, Scenario 2

Variables	Initial	Case (1) (U1 ($/hr))		Case (2) (U2 (ton/hr))		Case (3) (U3 MW))	
		JFO	QRJFO	JFO	QRJFO	JFO	QRJFO
Vg_1	1.0500	1.099980	1.0999990	1.0845460	1.0998840	1.0801280	1.0780150
Vg_2	1.0400	1.0856540	1.0886010	1.0811380	1.093460	1.0755390	1.07140
Vg_5	1.0100	1.0592020	1.0631540	1.0586270	1.0754470	1.0583810	1.05370
Vg_8	1.0100	1.0668530	1.0708280	1.0666110	1.0830010	1.0657750	1.0618780
Vg_{11}	1.0500	1.0997750	1.0997330	1.0816360	1.099880	1.0042520	1.059870
Vg_{13}	1.0500	1.0996350	1.0999680	1.0998370	1.0999950	1.0471360	1.0975430
Tap_{6-9}	1.0780	1.0407690	1.0245130	1.0336910	1.0296590	1.0621880	1.0130880
Tap_{6-10}	1.0690	0.9229740	0.9540090	0.9327810	0.9287530	1.0339520	0.9568230
Tap_{4-12}	1.0320	1.0028280	1.0036740	1.0179250	0.9841930	1.0615350	0.975850
Tap_{28-27}	1.0680	0.9726790	0.9769710	0.9864080	0.9746240	1.0369820	0.9577440
Qc_{10}	0	4.788078	4.952751	2.408265	3.242106	6.438482	12.18364
Qc_{12}	0	4.867021	4.893209	2.813026	2.460361	10.97369	9.498888
Qc_{15}	0	4.277636	4.787421	3.60315	2.640415	1.97545	4.859643
Qc_{17}	0	4.546313	4.984962	4.649712	4.937444	12.95008	8.960677
Qc_{20}	0	3.767055	4.386394	4.185922	4.481168	6.789432	3.552127
Qc_{21}	0	4.95365	4.898369	4.715191	4.997294	11.03702	12.95475
Qc_{23}	0	4.329351	2.674182	3.855241	3.606487	0.542298	1.247224
Qc_{24}	0	3.460546	4.984997	4.740595	4.99374	8.934137	6.984928
Qc_{29}	0	2.566404	2.844773	2.65091	2.631657	4.068645	2.272029
Pg_1	99.24	177.1974	177.0987	63.98755	63.94707	63.95811	63.83592
Pg_2	80	48.69343	48.69635	67.51098	67.45145	67.66739	67.6271
Pg_5	50	21.4438	21.29614	49.99908	49.99997	49.99674	49.99989
Pg_8	20	20.74069	21.04201	34.99943	34.9999	34.99611	34.9997
Pg_{11}	20	11.97215	11.89693	29.99918	30	29.99762	29.9999
Pg_{13}	20	12.00618	12.00758	39.99981	39.99893	39.99707	39.9999
Cost_Pg	901.96	799.1481	799.1065				
Losses	0.23909633					2.890692	2.856711
Emissions	5.8324			0.204719	0.204688		

For the first case, Table 4 illustrates that the minimum QFC obtained by the proposed QRJFO is reduced from 901.96 $/hr to 799.1065 $/hr, with respect to the initial case. Added to that, Table 5 illustrates comparative results for minimizing the fuel costs (Case 1) with several other algorithms which are Developed Grey Wolf Algorithm (DGWA) (Abdo et al., 2018), AGAPOP (Attia et al., 2012), EA (Surender Reddy et al., 2014), Symbiotic Organisms Search (SOS) (Duman, 2017), Moth Swarm Algorithm (MSA) (Mohamed et al., 2017), IMFA (Taher et al., 2019), Genetic Algorithm (GA) (Zhang et al., 2019), adapted GA (Attia et al., 2012), BHBOA (Bouchekara, 2014), DHSA (Arul et al., 2013), ICA (Ghanizadeh et al., 2011), Improved Electromagnetism-like Optimization Algorithm (IEOA) (Jeddi et al., 2017), CSO (Shaheen et al., 2021a), NBA (Yang, 2013), MCSO (Shaheen et al., 2021b).

Table 5. Comparison for Case 1-Scenario 2

Method	U1 ($/HR)	Method	U1 ($/hr)
Proposed QRJFO	799.1065	IMFA	800.3848
JFO	799.1481	TLA	800.4212
DGWA	800.433	SOS	801.5733
AGAPOP	799.8441	ICA	801.843
BHBOA	799.9217	DHSA	802.2966
MSA	800.5099	GA	802.1962
IEOA	799.688	CSO	799.8266
EA	800.0831	MCSO	799.3332
NBA	799.7516		

As shown, the JFO and the suggested QRJFO obtain the minimum QFC of 799.1481 $/hr and 799.1065 $/hr, respectively among other techniques. For the second case, the minimization of the PEs is obtained by the JFO and the proposed QRJFO as reflected in Table 4. As shown, the PE values are 0.204719 ton/hr and 0.204688 ton/hr, respectively. Table 6 shows a comparison with other optimizers.

Table 6. Comparison for Case 3-Scenario 2

Algorithm	PE	Algorithm	PE
QRJFO	0.204688	AGO	0.20484
JFO	0.204719	GO	0.20492
Stud KHA	0.2048	modified TLA	0.20493
ARBO	0.2048	IMRFO	0.204754
KHA	0.2049	NBA	0.2052063
CSO	0.2051355	MCSO	0.2048911

As the suggested ORJFO attains the minimum PE objective, it outperforms the other metaheuristics of Krill Herd Algorithm (KHA), Stud KHA (Pulluri et al., 2018), Adaptive Real Coded Biogeography-Based Optimization (ARBO) (Ramesh Kumar & Premalatha, 2015), modified TLA (Shabanpour-Haghighi et al., 2014), (Shaheen et al., 2021c). NBA, CSO, MCSO (Shaheen et al., 2021b). For the third case, the minimization of SPL is considered. From Table 4, the suggested QRJFO outperforms the standard JFO where it finds a lower SPL value of 2.85 MW compared to 2.89 MW for the JFO. Moreover, the convergence characteristics of the JFO and QRJFO algorithms are displayed for the three cases studied in Figures 6-8, respectively.

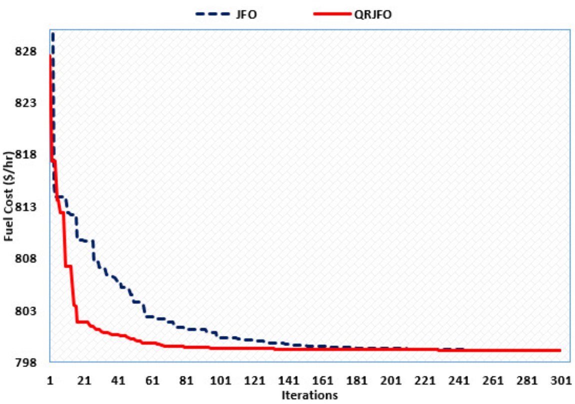


Figure 6. Convergence curves of JFO and QRJFO for Case 1, Scenario 2

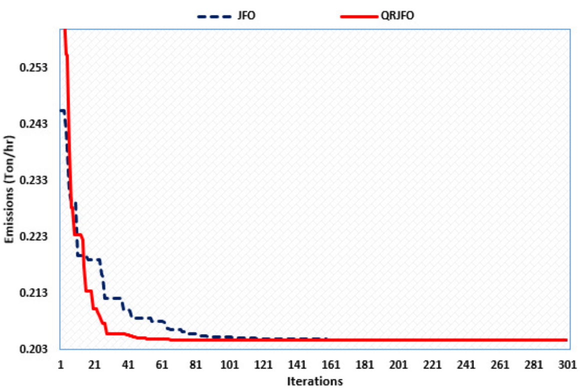


Figure 7. Convergence curves of JFO and QRJFO for Case 2, Scenario 2

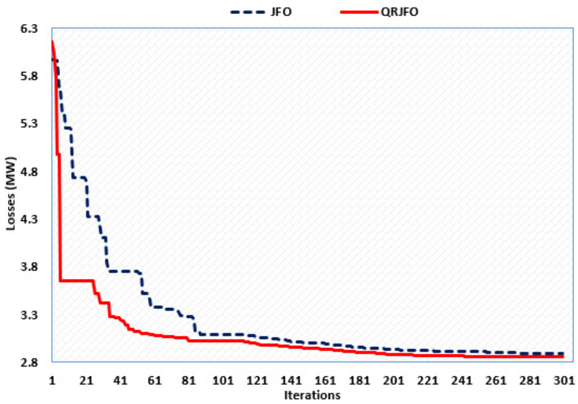
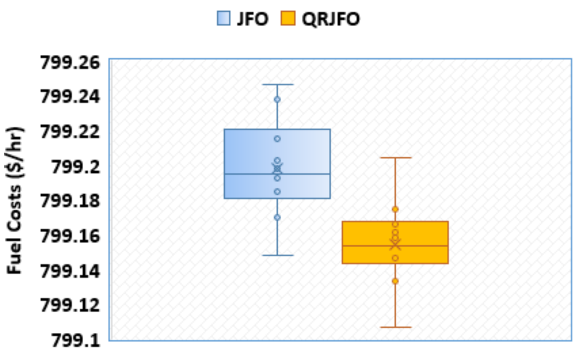


Figure 8. Convergence curves of JFO and QRJFO for Case 3, Scenario 2

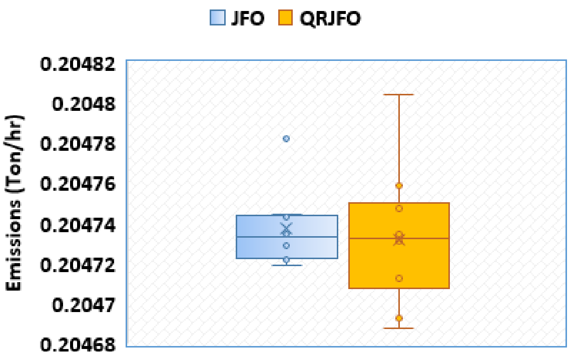
These figures indicate the greater efficiency of the suggested QRJFO relative to JFO to provide a better solution, especially in the early stages of 100 iterations.

4.2.1 JFO versus QRJFO: Robustness Analysis for Scenario 2

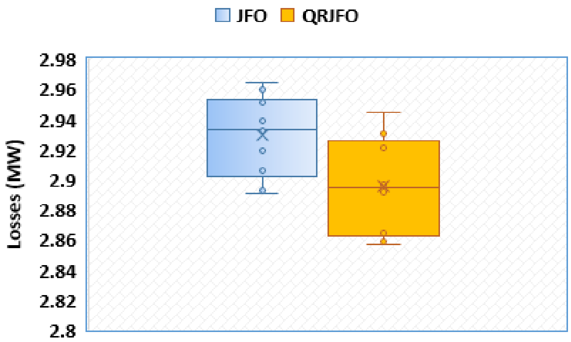
To evaluate the robustness analysis, the obtained minimum QFC, PE and PL of JFO and proposed QRJFO are displayed in Figure 9 via Box and Whiskers plot. The suggested QRJFO provides better robustness statistics relative to the JFO for all the cases studied. In case 1, the QRJFO provides the smallest maximum, average and minimum values of 799.204, 799.156 and 799.106$/hr with a smaller standard deviation of 0.0225 opposed to JFO of 0.0295. In case 2, the QRJFO acquires the smallest minimum and average PE values of 0.20468 and 0.20473, respectively. In case 3, QRJFO finds the smallest maximum, average and minimum values of 2.94, 2.895 and 2.856 MW whereas JFO finds the minimum, average and maximum values of 2.964, 2.93 and 2.891 MW, respectively.



a- case 1



b- case 2



c- case 3

Figure 9. Box and Whiskers plot of JFO and QRJFO for Cases 1-3, Scenario 2

5. Conclusion

This paper suggests and develops an improved Quasi-Reflection Jellyfish Optimizer integrated for solving the OPF problem. The QRJFO enhances the intensification and diversification features of the standard JFO. Both JFO and QRJFO are effectively implemented on two scenarios based on the IEEE 30 bus-system. The simulation outputs display the solution effectiveness and applicability of the suggested QRJFO relative to JFO. Also, the suggested QRJFO provides a great improvement in the convergence characteristics of the standard JFO, particularly during the early stages of the 100 iterations. Besides, the suggested QRJFO provides a great improvement in the degree of robustness of the standard JFO when achieving the optimal results and solution quality. Thus, the QRJFO shows superiority in comparison to several optimization algorithms with various objective functions reported in the literature.

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