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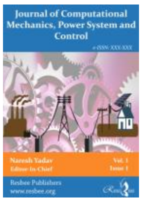

A Hybrid Learning Algorithm for Optimal Reactive Power Dispatch under Unbalanced Conditions

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Abstract: In the power system, optimal reactive power dispatch problem is very challenging optimization problem. Various researches have solved the issues related to optimal reactive power dispatch by minimizing the transmission loss or by optimizing the bus voltage. These researches were immune to voltage fluctuations. The main intention of this paper is to develop a novel approach to lessen the voltage deviation and power loss in optimal reactive power dispatch under unbalanced conditions. This minimization of voltage deviation and power loss were accomplished using a hybrid optimization algorithm referred to as WOA+FF that hybridizes the concept of Whale Optimization Algorithm (WOA) and Firefly algorithm (FF). The proposed WOA+FF operated on the control variables like the voltage and transformer tap settings as well as load reactance with the intention of achieving optimum results. The IEEE 14 and the IEEE 39 benchmark bus systems are the two IEEE benchmark test bus systems that are used to evaluate the entire experiment. Finally, the proposed WOA+FF model is compared with the existing models like Genetic Algorithm (GA), FF, WOA, and Particle Swarm Optimization (PSO) to exhibit the enhancement in the performance of ORPD operation.

Keywords: Optimal reactive power dispatch; active power loss minimization; voltage profile improvement; Inequality and equality constraints; WOA+FF based optimization algorithm

1. Introduction

The Power industry of a nation shapes the basic national infrastructure of that nation's economy as it is the capitalist and technologically intensive industry. In the early 80's the demand for power was low and hence small power stations were available in the locality [6] [7]. The present-day power system is large with multiple generating stations, as it has a higher demand for agricultural, commercial and domestic consumers. In these power technologies, the major issue is power system stability [8] [22] [23]. The main factor causing voltage instability is the inability of the power system in meeting the reactive power demand at heavily stressed systems, and this prevents it from maintaining the desired voltages [9] [10] [11]. The reactive power/voltage control limits, reactive power compensating devices as well as the load characteristics are the factors contributing to the voltage collapse. It is essential to optimize the reactive power dispatch in order to maintain the voltage stability, power system losses and to control the operations of the power system [12] [13].

The active power regulation and the reactive power dispatch are the two major constraints for the economical operation of a power system [14] [15]. The cost of production of reactive power is typically low, but it introduces huge drawbacks on the active power transmission loss as well as active power production. In the transmission line, the active power flow in terms of the transmission as well as distribution voltage needs to be controlled with reactive power [20] [21]. The Optimal Power Flow (OPF) is efficient in determining the optimal settings for a few of the variables concerning the power system control in order to determine the objective functions regarding the system parameters [16]. The sub-problem of OPF is the Optimal Reactive Power Flow (ORPF) and its major objective is to diminish the Real Power Loss (RPL) with the aid of power system control variables adjustments like minimization of active power loss and maximization of voltage profile and stability. In the conventional approaches, several classic optimization techniques like linear programming, quadratic programming, and interior point method were employed to override the issues related to optimization of the reactive power dispatch

[17] [18] [19] [29] [30]. But, they failed in attaining the global minima and suffered from complexity. Thus, it is essential to have an optimal technique, to overcome these challenges.

This paper intends to diminish the voltage deviation and power loss in the system under unbalanced conditions by means of employing two major optimization concepts like Whale Optimization Algorithm (WOA) and Firefly Algorithm (FA). Thus, this model is simply referred to as WOA+FF model. The proposed WOA+FF algorithm operates on the variation of the control variables like load reactance as well as voltage and transformer tap settings to achieve optimal results. The IEEE 14 and the IEEE 39 benchmark bus systems were utilized as two IEEE benchmark test bus systems for conducting the experiment. Finally, the proposed WOA+FF model was compared with the existing models like GA, FF, WOA, and PSO in order to find the evaluation in the improvement of ORPD operation with the proposed model.

The leftover sections of this research work are organized as: Section 2 portrays the literature works undergone in the field of optimal reactive power dispatch under unbalanced conditions. Section 3 depicts the proposed optical reactive power dispatch learning. The results obtained and their corresponding discussion is shown in Section 4. Section5 provides a strong conclusion to this research work.

2. Literature Review

2.1 Related Works

In 2015, Srivastava and Singh [1] formulated Hybrid Multi-Swarm Particle Swarm Optimization (HMPSO) algorithm with the intention of solving the issues related to Reactive Power Dispatch (RPD) in an electrical power system. Power losses and voltage deviation were minimized to solve RPD problem and to enhance the power system efficiency as well as voltage profile. This model used Separate swarms for generating local and global solutions. But, it suffered from the drawback of high computing time.

In 2015, Liang et al. [2] introduced an enhanced Firefly algorithm with the objective of solving the issues related to multi-objective optimal active and reactive power dispatch with load and wind generation uncertainties. Here, the active power optimal dispatches, as well as the reactive power optimal dispatches, were considered at the same time. In the load bus, the position of the load tap changer in the transformer and the reactive power injection of capacitors were considered in addition to reducing the transmission line losses. In the thermal generating unit, the active power outputs were obtained using the economic dispatch in the active power dispatch. The advantage of this research was, it avoided the trapping of solution into local minimum and it required less count of iterations. The major drawback of this research was its CPU time, which was higher than the Firefly algorithm.

In 2016, Basu [3] formulated Multi-objective differential evolution with the aim of solving multi-objective ORPD (MORPD) problem by diminishing the voltage deviation as well as active power transmission loss and enhancing the voltage stability. The IEEE 30-bus, 57-bus, and 118-bus systems were utilized to test the performance of the proposed model. The merits of this model were Good convergence rate and the demerit was higher computationally complexity.

In 2015, Robbins and Garcia [4] proffered branch power flow modeling approach for solving OPF problem in radial power systems. On the basis of Alternating Direction Method of Multipliers (ADMM), a distributed algorithm was constructed to solve the convex quadratic program. In addition, the unbalanced three-phase formulation was used in Distributed Energy Resources (DERs) to solve OPF in balanced network case. The Pareto optimal problems were solved and have high computational efficiency as an advantage. Apart from this, it required a diverse searching procedure and the success rate was low.

In 2014, Zhou et al. [5] projected Strength Pareto Multigroup Search Optimizer (SPMGSO) for solving Multiobjective ORPD (MORD). The Non-Dominated Front (NDF) was effectively strengthened with enhancement mechanisms like crowding entropy constraint treatment, chaotic logistic dispersion as well as ring-migration synergistic cooperation in both diversity and distribution. In addition, the hierarchical clustering, as well as equilibria-based multicriteria decision-making scheme, was employed to achieve the final best compromise solution. The proposed model was verified using benchmark IEEE 30-bus and 162-bus power systems. This approach was efficient in solving the Pareto optimal problems. But, the convergence rate was low.

3. Proposed Optical Reactive Power Dispatch Model

3.1 ORPD Model Under Unbalanced Condition

The main objective of ORPD is to diminish the active power loss as well as to enhance the stability as well as voltage profile. Eq. (1) depicts the vector of the dependent variables. The slab bus power is represented using the notation Pi_G and the term R_{1j} depicts the voltage bus ST, where $j=1,2,\cdots,NPQ$. The reactive power output of the generator is represented as T_{Gj}, where $j=1,2,\cdots,NG$. The count of the generator bus and the count of ST bus depicted using the term NG and NPQ, respectively. The mathematical formula for the vector of the control variables is expressed in Eq. (2).the voltage controller bus terminal voltage is represented as R_{Gj}, where $j=1,2,\cdots,NG$ and the resultant of shut VAR compensator is represented using the term T_j .in which $j=1,2,\cdots,NC$. In the tap changing transformer, the setting of the tap is denoted as M_j ,where $j=1,2,\cdots,NG$. The quantity of shut VAR compensator and the quantity of tap changing transformer is depicted using the notation NG and NC, respectively. The equality, as well as the inequality constraints, is generated by the chosen variables and the mathematical formula for the objective function is represented in Eq. (3). The voltage deviation and the active power loss are denoted as Q_a and Q_b, respectively.

$$Z = S_{G1}R_{1-1},\cdots,R_{1-NPQ},T_{G-NG} \tag{1}$$

$$J = R_{G-1},R_{G-NG},T_{C-1}\cdots,T_{C-NC},M_1,\cdots,M_{NM} \tag{2}$$

$$f_j = \alpha Q_a + (1-\alpha)Q_b \tag{3}$$

3.2 Active Power Loss and Voltage Deviation

The active power or true power is the power that is consumed by the AC circuit. In the LLC-RC, the actual power is the actual outcome of the converter that is utilized to run the load. The mathematical representation for the active power minimization is shown in Eq. (4), in which the active power loss of the system and the Active Power Loss and Voltage Deviation

Active Power Loss: The active power or true power is the power that is consumed by the AC circuit. The actual power is the actual outcome of the system that is utilized to run the load. If the total generated power by the system is more than the total power supplied to the load, then an imbalance condition takes place in the system and makes the system frequency to rise. So, it is necessary to reduce the active power loss. The mathematical representation for the active power minimization loss is shown in Eq. (4). The active power loss of the system and the count of the transmission loss in the system is represented using the term p_{loss} and N, respectively. In between m and n bus, k^{th} branch conductance takes place and it is represented as h_k. The voltage phase angle of m^{th} bus is denoted as χ_m and voltage phase angle of n^{th} bus is specified as χ_n.

$$D_a = p_{loss} = \sum_{k=1}^{N} h_k\left[Vo_m^2 + Vo_n^2 - 2Vo_m Vo_n\left(\cos\chi_m - \chi_n\right)\right] \tag{4}$$

Voltage Deviation: The most important parameter of the power system is the voltage deviation as it determined the system security in terms of bus voltage. In general, the difference between the actual bus voltage and the nominal voltage is referred to as voltage deviation. If the deviation of bus voltage is smaller than the nominal voltage, the voltage condition and the power quality of the system gets enhanced. Further, to boost the voltage profile, the voltage magnitude of bus Vo_j at different system loads need to be minimized from a pre-specified voltage magnitude reference value Vo_{ref}. The mathematical formula for voltage profile improvement is depicted in Eq. (5), in which the notation $\psi(x)$ is the step function that is mathematically given in Eq. (6). The count of load buses is denoted as N_{LB} and under the balanced condition, the voltage from the load flow is specified as Vo_j. The active and the reactive power is denoted using the term P and Q, respectively. Moreover, the resistance and the susceptance of the line is denoted as R and x, respectively. It is the necessity of a every buses in the power system to withstand the voltage that are below the normal operating conditions and these buses need to adapt themselves to the disturbance like change in load and system configuration. At present most of the major networks deteriorate due to the instability in voltage. Further, to enhance the voltage stability, the voltage stability indicator need to be minimized and in each of the buses, the voltage collapsed condition is indicated by L-index value Li_m and the L-index value of n^{th} bus is determined using Eq. (15), where $n = 1,2,\cdots,NPQ$. The count of PV bus is indicated as NPQ. In Eq. (16), the submatrices are represented as A_a and A_b. Further, after the separation of the parameters of PQ and PV bus, YBUS is indicated in Eq. (17). For all PQ bus, the L-index value Li_m is determined by setting Li_m =0 or 1 on the basis of voltage collapse as well as n^{th} bus no-load condition. Eq. (18) manifests the objective function in which $Li_m = 1,2,\cdots,NPQ$.

$$D_a = Vo_{Dev} = \sum_{j=1}^{N_{LB}} P_f \psi(Vo_{min} + Vo_m) + 2P_f \psi(Vo_m - Vo_{min}) \tag{5}$$

$$\psi(x) = \begin{matrix} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{matrix} \tag{6}$$

$$|Vo_m|^2 = |Vo_j|^2 - 2\left(\underset{im}{\tilde{R}} P_{im} + \underset{im}{Rx} Q_{im} \right) + C_{im}(P,Q) \tag{7}$$

$$\underset{im}{\tilde{R}} = \operatorname{Re}\left[aa^H\right] \otimes R_{im} + \operatorname{Im}\left[aa^H\right] \otimes x_{im} \tag{8}$$

$$\underset{im}{\tilde{x}} = \operatorname{Re}\left[aa^H\right] \otimes x_{im} - \operatorname{Im}\left[aa^H\right] \otimes R_{im} \tag{9}$$

$$a = \left[1 - e^{-j2\Pi/3} \; e^{j2\Pi/3} \right] \tag{10}$$

$$C_{im} = \left[Z_{im} \left[H^*_{im*} / Vo^*_j \right] \right] \otimes \left[Z_{im} \left[H^*_{im0*} / Vo_j \right] \right] \tag{11}$$

$$Z_{im} = R + jx \tag{12}$$

$$H_{im} = \left[P_{im} + jQ_{im} \right] \otimes \left[\underset{im}{\tilde{Z}} \left(P_{im} - jQ_{im} \right) \right] \tag{13}$$

$$\underset{im}{\tilde{Z}} = Z_{im} \otimes \left(a_j \bar{a}_j^{\,H} \right) \tag{14}$$

$$L_m = 1 - \sum_{m=1}^{NPV} D_{nm} \frac{Vo_m}{Vo} \tag{15}$$

$$D_{nm} = \left[A_a\right]^{-1} \left[A_b\right] \tag{16}$$

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} A_a & A_b \\ A_c & A_d \end{bmatrix} \begin{bmatrix} Vi_{PQ} \\ Vi_{PV} \end{bmatrix} \tag{17}$$

$$D_c = \max(Li_m) \tag{18}$$

3.3 Inequality and Equality Constraints

The power system, the constrained optimization problem is solved with the help of two constraints, namely equality and inequality constraints. The equality constraints are binding constraints and they need to be enforced. For illustration, in an OPF system, the real and reactive power balance equations at system buses must always be satisfied within user-specified tolerance. The inequality constraints are-non binding constraints and there is no necessity for the real power output to stay within its maximum limit. Here, the equality constraints are exploited by physical law in order to regulate the power system. The load flow equations are the equality constraints and they are mathematically represented in Eq. (19), where $m = 1,2,\cdots,NB$. The count of buses is represented as NB. At m^{th} bus, the generation of active and reactive powers is denoted using the term P_{Gm} and Q_{Gm}, respectively. In the same m^{th} bus, the demand related to active and reactive powers is specified as P_{Dm} and Q_{Dm}, respectively. In between m^{th} bus and n^{th} bus, the transfer conductance is denoted using the parameter B_{mn}. The upcoming section portrays certain constraints of the power system.

$$\begin{aligned} P_{Gm} - P_{Dm} - Vo_m \sum_{n=1}^{NB} Vo_n G_{mn} \cos(\chi_m - \chi_n) + \\ B_{mn} \sin(\chi_m - \chi_n) = 0 \end{aligned} \tag{19}$$

$$Q_{Gm} - Q_{Dm} - Vo_m \sum_{n=1}^{NB} Vo_n G_{mn} \cos(\chi_m - \chi_n) + B_{mn} \sin(\chi_m - \chi_n) = 0 \tag{20}$$

It is the obligation of the design statement to maintain the magnitude of the output voltage as well as the generator reactive power within the limit. The mathematical formula for the lower and upper limits is expressed in Eq. (21) and Eq. (22). Further, on the basis of Eq. (23), the shunt VAR compensators reactive output power upper and lower limits are made. Eq. (24) exhibits the physical considerations of the transformer tap settings in terms of upper and lower limit values. In terms of security constrain in PQ buses, the voltage magnitude and transmission lines loadings are considered. Eq. (25) and Eq. (26) depicts the concerned limit flow of each line for the voltage of the buses.

$$Vo_{Gm}^{min} \le Vo_{Gm} \le Vo_{Gm}^{max}, \ m = 1,2,...,NG \tag{21}$$

$$Q_{Gm}^{min} \le Q_{Gm} \le Q_{Gm}^{max}, \ m = 1,2,...,NG \tag{22}$$

$$Q_{Cm}^{min} \le Q_{Cm} \le Q_{Cm}^{max}, \ m = 1,2,...,NC \tag{23}$$

$$T_m^{min} \le T_m \le T_m^{max}, \ m = 1,2,...,NT \tag{24}$$

$$Vo_{Lm}^{min} \le Vo_{Lm} \le Vo_{Lm}^{max}, \ m = 1,2,...,NPQ \tag{25}$$

$$H_{im} \le H_{im}^{max}, \ m = 1,2,...,N \tag{26}$$

3.4 Proposed WOA+FF Approach

In general, conventional WOA is a simple defined procedure [24]. The main problem faced by WOA is slow convergence speed and suffers from the drawbacks of local optima stagnation. FA has the capability of dealing with highly, non-linear optimization problems [27]. But, here the speed of the optimization is low. In order to overcome these drawbacks, the current approach intends to merge both FF and WOA together (WOA+FF). In WOA during the spiral updating of the position of the whales, the updating is based on the attractiveness of FF. The mathematical formula for WOA spiral updating is shown in Eq. (27) and Eq. (28). In which S depicts the position vector and a refers to the current iteration. The distance between the whale and the prey is manifested as R, a random number in the limit [−1, 1] is k and the logarithmic spiral is a constant value is represented as c. Further, the attractiveness in between two FF is depicted as per Eq. (29) the maximum attractiveness is indicated as M_0 and it is the light absorption coefficient. The newly formulated equation mathematical formula for proposed WOA+FF is shown in Eq. (30).

$$S\ (a+1) = R' e^{ck}.Cos(2\pi k) + S^*(a) \tag{27}$$

$$R = \left| S^*(a) - S(a) \right| \tag{28}$$

$$M = M_0 e^{-\gamma x} \tag{29}$$

$$S\ (a+1) = R' e^{ck}.Cos(2\pi k) + S^*(a) + M \tag{30}$$

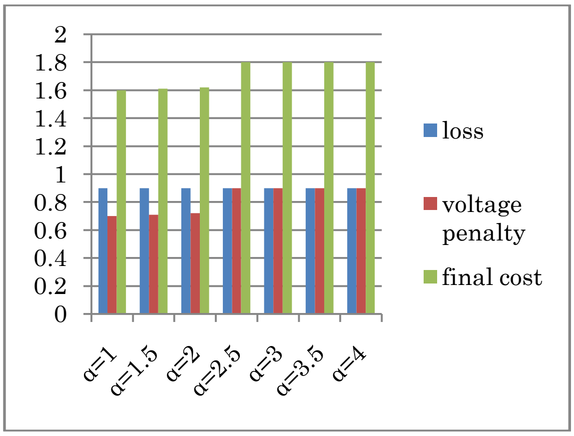
4. Result and Discussion

4.1 Experimental Setup

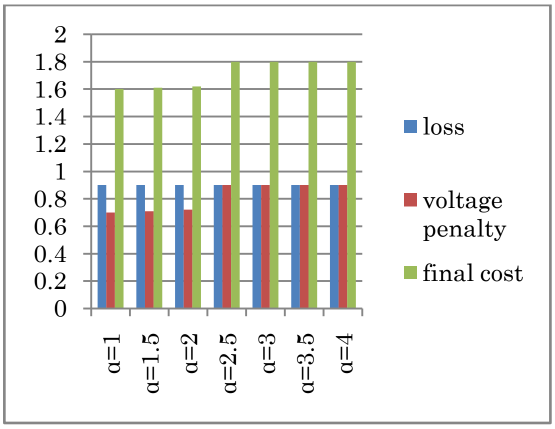
The proposed automatic video watermarking model was carried out in MATLAB, and the results related to the corresponding simulation were observed on IEEE 14 and the IEEE 39 standard bus systems. The proposed model WOA+FF model is verified over the existing models like GA [26], FF [27], PSO [28], GWO [25] and WOA [26] in terms of convergence and statistical analysis.

4.2 Convergence Analysis

Fig.1 exhibits the convergence analysis of the proposed model by varying the parameter α (fitness function) from α=1, α=1.5, α=2, α=2.5, α=3, α=3.5 and α=4 and the corresponding values of loss, voltage penalty and the final cost function are measured for both the IEEE 14 and the IEEE 39 bus systems. In Fig. 1(a) relating to IEEE 14 bus systems, the loss function here is constant and it stays in the level 0.9 for all varying α values. The voltage penalty is 0.7 at α=1, 0.71 at α=1.5, 0.72 at α=2, α=2.5 at 0.9 and α=3, α=3.5 and α=4. The final cost function is 1.6 in α=1 and 1.61 in α=2, 1.62 in α=2, 1.8 in α=2.5, 1.8 in α=3, 1.8 in α=3.5 and 1.8 in α=4.In Fig. 1(b), the values of loss, voltage penalty and the final cost function is measured for IEEE 39 bus systems. The loss is 0.9 when α=1, α=1.5 and it is 0.89 when α=2, 0.86, 0.85, 0.84 and 0.81, for α=2, α=2.5, α=3, α=3.5 and α=4, respectively. The voltage penalty is 0.9 for α=1, 0.6 at α=1.5, 0.4 at α=2, 0.41 at α=2.5, 0.42 at α=3, 0.7 at α=3.5 and 1 at α=4.The final cost value is 1.8, 1.5, 1.29, 1.27, 1.27, 1.54 and 1.81 at α=1, α=1.5, α=2, α=2.5, α=3, α=3.5 and α=4, respectively.



(a)

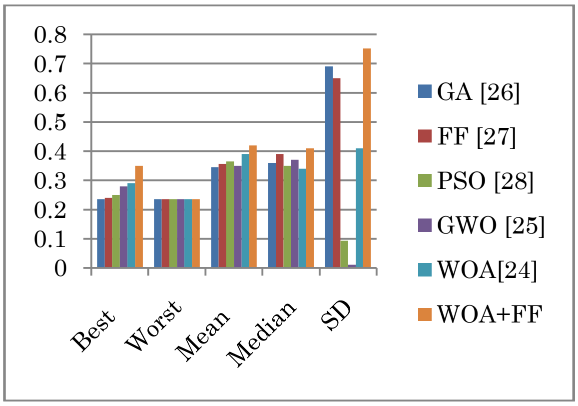


(b)

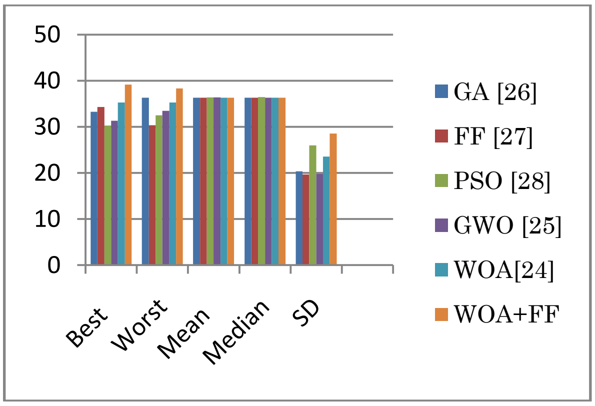
Fig. 1. *Convergence analysis in terms of loss, voltage penalty and final cost for (a) IEEE 14 bus systems and (b) IEEE 39 bus systems*

4.3 Statistical Analysis

Fig.2 denotes the Statistical report of the IEEE 14 bus system for the proposed WOA+FF over the existing algorithms like GA, FF, and ABC algorithms. Here, the reactive power of all 5 generator buses (buses no: 1, 2, 3, 6 and 8) and transformer tap settings of 3 buses namely, bus 8, 9 and 10 as well as voltage magnitudes of buses 13 and 3 are optimally fixed with the aid of proposed WOA+FF and other conventional buses in order to accomplish the ORPD. The value of the voltage is maintained in the limit of 0.97 pu–1.06 pu. The voltage penalties are added to the voltage when the voltage level crosses above the limit or goes below the limit. Fig. 2(a) exhibits the statistical analysis of the proposed WOA+FF model over the existing models like GA, FF, PSO, GWO and WOA models for IEEE 14 bus system. The highest best value is 0.35 and it is 48.5%, 45.3%, 40%, 25%, and 20.6% better than the extant models like GA, FF, PSO, GWO, and WOA, respectively. The worst value recorded by the proposed WOA+FF model is 0.2356. The mean of the proposed model is 0.42 and it is 7.3 %, 10.11%, 12.3%, 8.5% and 3.9% superior to conventional models like GA, FF, PSO, GWO, and WOA, respectively. The median of the proposed model is 0.41, which is the highest among all other models. The standard deviation of the proposed model is 0.752. Fig. 42(b) manifests the statistical analysis of the proposed WOA+FF model over the existing models like GA, FF, PSO, GWO and WOA models for IEEE 39 bus system. The best value recorded by WOA+FF is 0.35 and it is 17.7%, 14.2%, 29.4%, 25.2%, and 11% better than the existing models like GA, FF, PSO, GWO, and WOA, respectively. The worst case of the proposed model is 0.2356 and it is 5.5%, 26.4%, 17.9%. 14.4% and 8.5% better than existing models like GA, FF, PSO, GWO, and WOA, respectively. The median of the proposed model is 0.41 and it is 0.013%, 0.005%, 0.4%, 0.06% and 0.016% better than existing models like GA, FF, PSO, GWO, and WOA, respectively.



(a)



(b)

Fig. 2. *Performance analysis of WOA+FF over existing models for (a) IEEE 14 bus systems and (b) IEEE 39 bus systems*

5. Conclusion

This paper focused on solving the ORPD problem by means of using the hybrid algorithm WOA+FF using both Whale Optimization Algorithm (WOA) and Firefly Algorithm (FF). The inequality and equality constraints were used for solving the non-linear optimization problem and the active power loss and the voltage deviation minimization was the major objective of this research. The performance of the proposed WOA+FF model was verified with other existing algorithms like WOA, GWO, GA and FF for both the IEEE 14 and the IEEE 39 benchmark bus systems. The resultant of the analysis from the GWO|+FF model exhibited minimum cost function and reduced voltage deviation as well as power loss. The median of the proposed model for IEEE 39 benchmark is 0.41 and it is 0.013%, 0.005%, 0.4%, 0.06% and 0.016% better than existing models like GA, FF, PSO, GWO, and WOA, respectively. The highest best value is 0.35 and it is 48.5%, 45.3%, 40%, 25%, and 20.6% better than the extant models like GA, FF, PSO, GWO and WOA, respectively for IEEE 14 benchmark bus system. The resultant of the analysis from GWO+FF model exhibited minimum cost function and reduced voltage deviation as well as power loss.

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