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Multi-Objective Real Power Loss and Voltage Deviation Minimization for Grid Connected Micro Power System Using Whale Optimization Algorithm

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Abstract – *In this paper, a whale optimization algorithm (WOA) is applied to solve the multi-objective real power loss and bus voltage deviation (VD) minimizations for grid connected micro power system with non-firm small power plants. The control variables are the voltage magnitude at voltage control buses and the transformer tap changers. The methods were tested with IEEE 6 and 14 buses systems comparing to genetic algorithm (GA), artificial bee colony (ABC), and particle swarm optimization (PSO). The simulation results shown that WOA can successfully provide the minimum the multi-objective real power loss and bus VD solution than those computed by GA, ABC, and PSO. Moreover, the applied methods use the minimum computation time among all methods.*

Keywords – loss minimization, optimal power flow, voltage deviation, whale optimization algorithm.

1. INTRODUCTION

The main aim of utility in power system is to provide the electricity with the reliability, quality, sustainability, and in cheap price. After emerging of economic concern in the electrical power system, the researches in power system has been developed continuously. Since the 1920s, the optimality of operation and transmission in power flow sector has been proposed by the French scholar Carpentier and it has been called optimal power flow (OPF) [1]. OPF is regarded as a development and upgrade of the class power flow in order to get economically and safely operation together with optimization of total operating cost, active power loss, reactive power injection, and transformer tap-changer. It has been considered as an effective optimization tool for power system sector after further research by many scholars [2].

OPF is a highly nonlinear optimization and complex multi constraint problems with a combination of various variables. Moreover, it is a process to investigate the optimal solution in an electrical power system in order to get the highest benefit and it is ensured that all the variables are in the constraints. Furthermore, OPF aims to optimise such objectives which subject to the network power flow equation and variable operating limits [3]. The objective of OPF can be formulated in various ways. For example, real power loss minimization, total operating cost, total emission minimization, or voltage deviation minimization. This also includes maximum and minimum output of the various variables such as bus system voltage, injected reactive power, and transformer tap-changer within the specified ranges.

Many methods have been applied to solve OPF problems up to now. It is grouped as conventional and intelligent methods. The well-known conventional methods are Newton method [4], Gradient method [5], linear programming [6], quadratic programming [7], and Interior point method [8] have been widely used. These methods are preferred for fast calculation and online computation [2]. On the other hand, these methods are not suitable for some optimization problems with discrete variables due to their difficulties to reach the convergence and global solution.

Due to continuously developed technology in the last decade, many novel intelligent techniques have been developed for dealing with complex OPF problems. Those recent intelligent methods include genetic algorithm [9], particle swarm optimization [10], artificial bee colony [11], and whale optimization algorithm (WOA) [12]. Heuristic search algorithm likes GA was considered as the most suitable one for solving simultaneous multi-dimensional problems for global optimum solution. Furthermore, GA can reach convergence easily and it has complex encoding and decoding operation [2]. PSO is a heuristic method which bases on the behaviour of swarms of fish, bird, etc. has better convergence than GA due to its combination of social psychology principle and better calculation to enhance the behaviour of the swarms. ABC which was proposed by Karaboga in 2005 was recognized as the most efficient and novel swarm intelligent technique. It is based on the intelligent behaviour of the honey bee to find the nectar sources. Also, ABC was successfully applied to solve all kinds of optimization problems so it has better performance to numerical optimization than GA, PSO.

The earlier optimizations developed are population based stochastic algorithms. Some novel well-known algorithms for single objective problems are moth-flame optimizer (MFO) [13], bat algorithm (BA) [14], ant colony optimization (ACO) [15], cuckoo search (CS) [16], mine blast algorithm (MBA) [17], krill herd (KH) [18], interior search algorithm (ISA) [19], etc. However, these algorithms have limited capabilities to handle uncertainties [20], local minima [21], misleading global solutions [22], better constraints handling [23], *etc*. Emerging algorithms were proposed to overcome these difficulties.

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The most recent meta-heuristic; therefore, was proposed in 2016, by Mirjalili Seyedali and Andrew Lewis. It is basically stochastic population based, nature inspired algorithm which mimics the bubble-net feeding in the foraging behavior of the humpback whales [12]. WOA is a sole objective algorithm that is equipped with powerful operators to provide them a capability to solve multi-objective and complex problems. Meanwhile, [24] presented the multi-objective version of the WOA which was known as non-dominated sorting whale optimization algorithm (NSWOA). It was proved that NSWOA performed efficiently in solving multi-objective functions when compared to other multi-objective algorithms. Moreover, the computational complexity of NSWOA is in order of $0(mn^2)$ where n is the number of individuals in the population and m is the number of objectives. It is much better than some of the algorithms such as non-dominated sorting genetic algorithm (NSGA) [25] and strength-pareto evolutionary algorithm (SPEA) [26] which are $0(mn^3)$. Another developed WOA which involves the crossover and mutation operators in the WOA was known as WOA-CM [27] which has the same computational to PSO. Furthermore, the computation of GA and ant lion optimizer (ALO) [28] is worse than those of WOA-CM and PSO due to the need to sort the solutions in each iteration. WOA was also developed to improve global convergence speed and to get better performance which was known as chaotic whale optimization algorithm (CWOA) as explained in [29].

Recently, non-firm power plant or distributed generation (DG) is widely preferred in the micro grid due to its potential solution for loss minimization, reliability improvement, and voltage profile enhancement. DG is given the definition of on-site small scale power generations which are interconnected or connected directly to the distribution network. It refers to electrical power production closed to consumer location integrating with renewable and non-renewable energy sources. Micro network connected to the grid may be operated in various modes which are grid connected, islanding, and virtual power plant modes. The objective function of the system is, therefore, different from conventional OPF.

The optimization techniques using the analogy of swarm behavior of natural creature emerged at the beginning of the 1990s [30]. Kumari at al. used GA and PSO for optimal power flow including FACTS devices which were mentioned for comparative purposes [31]. ABC was used to solve optimal power flow while generation cost was the objective function applied to IEEE 14 and 30 buses test system as described in [32]. The modified differential evolution (DE) algorithm for optimal power flow was presented in [33]. The authors in [3] used four algorithms based on swarm intelligence (GA, PSO, ABC, and DE) to solve optimal power flow considering loss minimization. The application of the key cutting algorithm to optimal power flow was applied in [34]. In [2], [35], a method to solve multi-objectives in optimal power flow using the algorithms based on swarm intelligence with considering voltage stability index was developed. Application of harmony search to optimal power flow in generation cost minimization was proposed in [36].

A hybrid of WOA and pattern search method for solving optimal power flow was developed in [37] considering multi-objectives functions, such as generating fuel cost, voltage profile improvement, minimization of total power losses and emission reduction are also considered. WOA was used to find the optimally distributed generation (DG) and filter placement and sizing in distribution network [38], [39]. Following, [40] presented voltage profile improvement in distribution systems using WOA considering optimal capacitors. WOA was proposed to control automatic generation of interconnected modern power systems including renewable energy sources based on the optimal proportional–integral–derivative (PID) controller [41]. The comparison of GA and WOA was investigated in [42] for fault location estimation in power system.

In optimization literature, almost no any algorithms which logically prove no-free lunch theorem [43] for solving all optimization problems. However, WOA which is a novel nature inspired meta-heuristic optimization algorithm was proved to be usable for all optimization problems. To the best knowledge of authors, WOA has not been used in literature for multi-objective function in optimal power flow considering voltage deviation.

This paper illustrates the application and performance of heuristic optimization methods (GA, PSO, ABC, and WOA) to OPF. The objective function is to minimize power loss with controllable variables of voltage magnitude, reactive power, and transformer tap-changer. The IEEE 6 and 14 bus systems are used to convey the efficiency and robustness of the algorithms.

The paper was organized into 5 sections. The problem formulation of multi-objective OPF problems of which objective function involves minimization of active power loss and minimization of voltage deviation was described in the next section. Section 3 provided the brief description of the algorithms (GA, PSO, ABC, and WOA) applied to solve OPF problems for comparative purpose. Moreover, it gave the algorithm procedure of working by flow chart step-by-step. The simulation result and discussion were placed in Section 4. Finally, the conclusion and future work of the paper were included in Section 5.

2. PROBLEM FORMULATION

The main purpose of this research is to minimize transmission power loss and voltage deviation power system. The multi-objective function for loss and voltage deviation minimization can be written as,

$$Minimize \;\; f_i(x,u) \quad i = 1, 2, ..., N_{obj}\,, \tag{1}$$

$$Subject\,to \;\; g(x,u) = 0, h(x,u) \le 0, \tag{2}$$

where,

f_i	is the objective function i,
N_{obj}	is the number of objective function,
g	is the equality constraints,
h	is the inequality constraints,
x	is the vector of dependent variables, and
u	is the vector of independent variables.

2.1 Active Power Loss Objective Function

The loss can be obtained by computing the power flow between two buses as illustrated in figure 1 and it can be formulated in the following equations.

Where V_i and V_k are the bus voltage at bus *i* and *k* respectively. The power flow between buses *i* and *k* at bus *i* is given as;

$$S_{ik} = P_{ik} + Q_{ik}\,, \tag{3}$$

$$S_{ik} = V_i I^*_{ik}\,, \tag{4}$$

$$S_{ik} = V_i(V^*_i - V^*_k)^* Y_{ik} + V_i V_i^* Y_{ik0}\,. \tag{5}$$

Similarly, the power flow between buses k and i at bus k is given as,

$$S_{ki} = V_k(V^*_k - V^*_i)^* Y_{ki} + V_k V_k^* Y_{ki0}\,. \tag{6}$$

Hence, the loss between these two buses is the sum of power flow in Equation 5 and 6.

$$S_{Total\ loss} = S_{ik} + S_{ki}\,. \tag{7}$$

The total power loss in a system is obtained by summing all the power flow of bus. The power loss in the slack bus can be obtained by summing the power flow at the terminated bus [44]. In this paper, the reactive power loss is neglected, so the objective function of total real power loss reduction is obtained as,

$$F_{Loss} = real\left(\sum_{i=1}^{n} S_{i\,Total\ loss}\right), \tag{8}$$

where,

n	is the number of the bus branches, and
$S_{Total\ loss}$	is the total complex power loss.

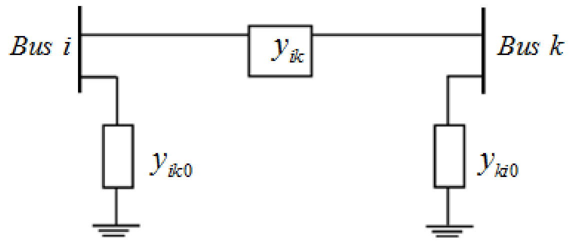

Fig. 1. Diagram of power flow between two buses.

2.2 Voltage Deviation Objective Function

Voltage Deviation (VD) is one among the various objective functions in OPF and it aims to mitigate the voltage deviation in the system. Also, [45] it can be formulated as,

$$F_{VD} = \sum_{j=1}^{N_{Load\ bus}} \left|V_j - V_{ref}\right|, \tag{9}$$

where,

$N_{Load\ bus}$	is the number of load bus or PQ bus,
V_j	is the actual voltage magnitude at load bus *i*, and,
V_{ref}	is the reference voltage magnitude at load bus *i*, which it is considered $V_{ref} = 1.0\,p.u.$.

2.3 System Variable Constraints

System variable constraints are considered as inequality constraints which comprise of reactive power injected (MVAR), voltage magnitude, and transformer tap-changer. These variables are optimized and they are limited to be in the constraints during the optimization process. The system variable constraints are expressed as,

$$\left|V_{i\min}\right| \le \left|V_i\right| \le \left|V_{i\max}\right|, \tag{10}$$

$$Q_{i\min} \le Q_i \le Q_{i\max}\,, \tag{11}$$

$$T_{i\min} \le T_i \le T_{i\max}\,, \tag{12}$$

where,

$\left|V_i\right|$	is the voltage magnitude,
Q_i	is the injected reactive power, and
T_i	is the transformer tap-changer setting.

2.4 Power Flow System Constraints

OPF problem must satisfy the system power flow equations and they can be formulated as,

$$P_{G,i} - P_{D,i} - \sum_{k=1}^{n}\left|V_i\right|\left|V_k\right|\left|Y_{ik}\right|\cos(\delta_i - \delta_k + \theta_{ik}) = 0, \tag{13}$$

$$Q_{G,i} - Q_{D,i} - \sum_{k=1}^{n}\left|V_i\right|\left|V_k\right|\left|Y_{ik}\right|\sin(\delta_i - \delta_k + \theta_{ik}) = 0, \tag{14}$$

where,

$P_{G,i}, Q_{G,i}$	are real and reactive power generation at bus *i*,
$P_{D,i}, Q_{D,i}$	are real and reactive demands at bus *i*,
V_i, V_k	are voltage magnitudes at bus *i* and *k*,
δ_i, δ_k	are voltage angles at bus *i* and *k*,
Y_{ik}	is the magnitude of the *ik*th element in bus admittance matrix,
θ_{ik}	is the angle of the *ik*th element in bus admittance matrix, and
n	is number of the total buses.

2.5 Overall Objective Function

In this paper, two objective functions of loss and VD minimization are considered. Thus, the overall objective function can be written in the form below. The two objective function descriptions are shown in Figure 2. The best fitness value of the overall function can be determined by the shortest vector from the origin.

$$F^2 = F^2_{Loss} + F^2_{VD}, \tag{15}$$

$$F = \sqrt{F^2_{Loss} + F^2_{VD}}. \tag{16}$$

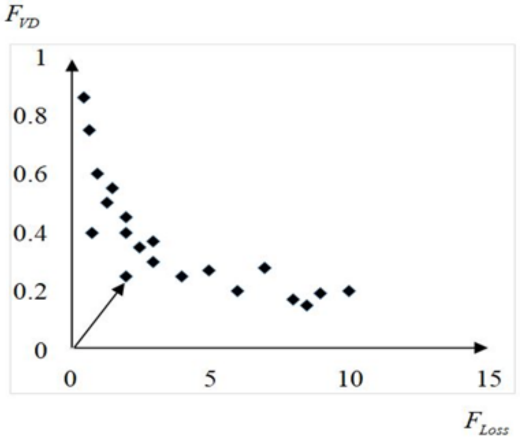

Fig. 2. Multi-Objective functions of loss and VD minimization.

3. ARTIFICIAL INTELLIGENCE TECHNIQUES

Recently, many intelligent search methods have been developed to solve the optimization works which are complex problems instead of traditional optimization techniques due to their accuracy and robustness. In this paper, four different algorithms are implemented on real power loss and VD minimization in order to figure out its efficiency and performance. The brief detail of each intelligent search methods is mentioned in this section.

3.1 Genetic Algorithm

There are many optimization algorithm techniques for solving the optimization problems. Due to the limitation of classical optimization methods in finding global minimum value, the heuristic optimization methods are widely used because of their reliability, flexibility, and robustness in seeking optimum value in recent years [46].

GA was proposed by John Holland in 1975; moreover, it can find the global optimal solution in complex multi-dimensional search space [47], and it is a heuristic search method which mimics the biological process of natural evolution such as mutation, crossover, selection, etc, GA is very well- known and widely used in many research areas where an intelligent is applied. Like others methods, GA needs the initial value and randomly generates the solutions to find the best fitness value [48]. GA working can be summarized as shown in Figure 3.

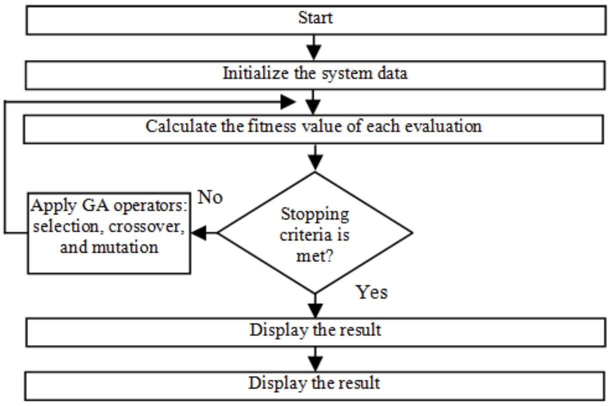

Fig. 3. Flowchart of GA.

3.2 Artificial Bee Colony

Artificial Intelligence techniques can be obtained from natural behaviour or phenomenon of animals such as fish, ants, and birds. Swarm intelligence has become an interesting research method to many researchers in the related field in recent years. The swarm intelligence method can be defined as any attempt to develop or design algorithms the problem solving by inspiring the natural behaviour of social insect colonies and other animal species. Currently, a new intelligent search algorithm which mimics the natural behaviour of honey bee swarm in searching food sources is called Bee algorithm and it was considered as an efficient method in solving optimization problems as other swarm-based intelligent approaches [49]. It was introduced by Karaboga in 2005. The food sources location which foraged by a honey bee represent a feasible solution of the optimization problem and the amount of nectar and pollen of food sources represent the fitness value of the associated solutions [20]. A bee colony is divided into employed bees, onlooker bees, and scout bees. Employed bees represent the first half of the colony and the second half is the onlooker bees. Onlooker bees are placed on the foods by using "roulette wheel selection" method. The employed bees whose food sources were exhausted become scout bees. In the ABC optimization process, it includes the initial phase, employed bee phase, onlooker bee phase, and scout bee phase [50], [51] and the flowchart of ABC is illustrated in Figure 4.

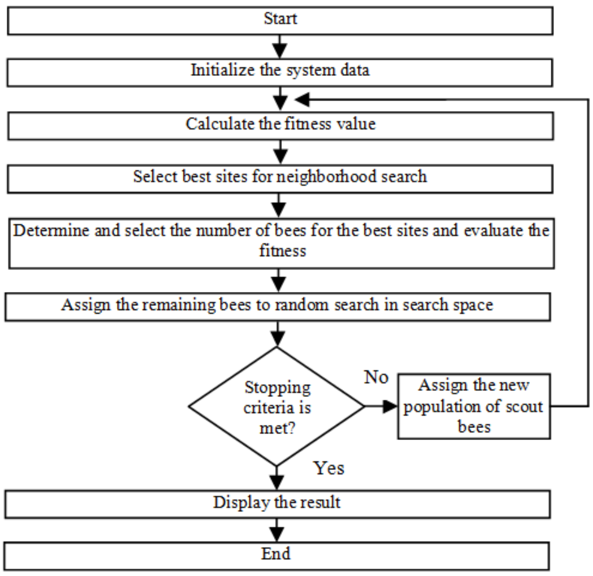

Fig. 4. Flowchart of ABC.

Initial phase: the numbers of feasible solutions is randomly generated by the following formulas.

$$X_{ij} = X_{ij\min} + rand(X_{ij\max} - X_{ij\min}), \tag{17}$$

where,

$j = 1, 2, ..., D$. D is the dimension of the problem,

X_{ij} is the $j\,th$ dimension parameter of the solution X_i,

$X_{ij\max}, X_{ij\min}$ are the upper and lower bounds respectively for dimension *j*, and $rand$ is the random number between 0 and 1.

Employed bee phase: the employed bees search the food source which is the solution X_k with dimension j in search space from one place to another better place which is the new feasible solution X'_{ij} as shown in Equation 18. The best food source location is kept in the memory.

$$X'_{ij} = X_{ij} + R_{ij}(X_{ij} - X_{kj}), \tag{18}$$

Where,

$j = 1, 2, ..., D$ and $k = 1, 2, ..., N_e$ are randomly generated ($k \neq i$), X'_{ij} is the *j*th dimension parameter of candidate solution of X'_i, X_{kj} is the *j*th dimension parameter of the feasible solution, and R_{ij} is a random number between -1 and 1.

The fitness value of the feasible solution can be calculated by the formula in Equation 19.

$$fit_i = \frac{1}{1 + f_i}, \tag{19}$$

where,

fit_i is the fitness value of the feasible solution and

f_i is the objective function.

Onlooker bee phase: The employed bees share the information of the food source to the onlooker bees waiting on the hive by the special dace which is known as "waggle dance" and then onlooker bee chooses a food source which is a solution by probability depending on the information from employed bees [32]. The probability is given as;

$$\eta_{fit,i} = \frac{fit_i}{\sum_{n=1}^{N_e} fit_i}. \tag{20}$$

where,

fit_i is the fitness value of the solution.

Scout bee phase: Every bee colony has scouts which are considered as the colony's explorers. Also, the explorers don't have any guidance to find the food sources. Eventually, the scouts can discover rich in entirely unknown food sources. Nevertheless, the artificial scouts can have rapid discovery in a feasible solution. When the food source is abandoned and the scout bees find a new food source without any guidance with Equation 20.

3.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is the most popular one among the most recent intelligent optimization search methods. It was proposed by Eberhart and Kennedy in 1995 [52]. It was imitated the behaviour of individual swarms which are a flock of bird, school of fish and other insect groups. PSO is the intelligent method which is inspired by individual movement in the group to share the information with each other in order to increase the efficiency of the group [3], [35]. Each particle is moved based on best personal position (Pbest) and best global position (Gbest) through the information. Moreover, PSO uses the parallel computation method to search. Each individual corresponds to the candidate solution of the problem in each iteration. Current speed, previous experiences, and information of its neighbour are the things which lead to getting the optimum point. In n-dimensional search space, speed vectors represent as the position and individual velocity which participant *i* and its velocity can be modified by the following equations and the working of PSO can be described in the flowchart as shown in Figure 5. The mathematical expression of the algorithm is also expressed in the following equations.

$$x_i^{(k+1)} = x_i^k + v_i^{(k+1)}, \tag{21}$$

$$v_i^{(k+1)} = v_i^k + \alpha\left(\left(x^{Pbest} - x_i^k\right) + \beta\left(x^{Gbest} - x_i^k\right)\right), \tag{22}$$

where,

x_i^k is the current individual position of particle i at iteration k,

v_i^k is the velocity of the particle i of the previous vector at iteration k,

α, β are random number between 0 and 1,

x^{Pbest} is the personal best position of the particle, and

x^{Gbest} is the global best position of the particle.

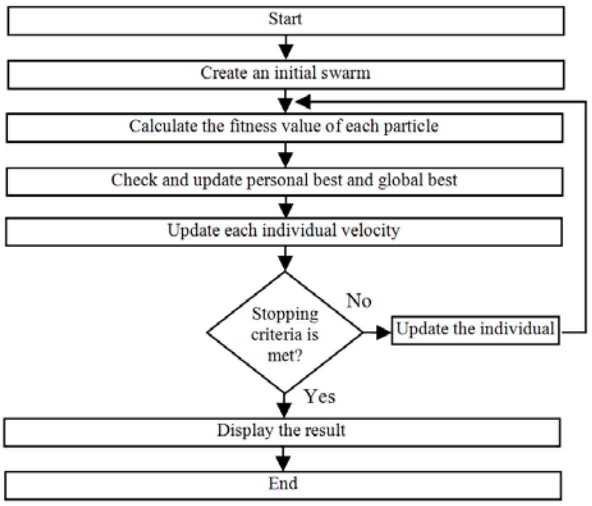

Fig. 5. Flowchart of PSO.

3.4 Whale Optimization Algorithm

Meta heuristic optimization algorithms are becoming more and more popular in engineering application since it is easy to implement, do not require gradient information, can bypass local optima, can be utilized in a wide range of problem covering a different discipline, and . Similar to the algorithms based on swarm intelligence, rely on a simple concept. WOA is the most recent meta-heuristic optimization search techniques which have just proposed by Seyedali Mirjalili and Andrew Lewis in 2016. It is an intelligent search method which mimics the prey hunting behaviour of a humpback whale. The whale is considered as an intelligent animal in the world with motion [53]. Humpback whale is the biggest mammals in the sea and it is also a predator which hunts small fish as its prey. Moreover, the whale is the animal which never sleeps at all in its whole life because it needs to breath from the surface of the ocean and the only haft of its brain sleeps [54]. Naturally, humpback whale hunts the small fishes which are closed to the ocean surface by producing the bubble [55]. This hunting behaviour is called bubble-net feeding. When it encounters the prey, it produces bubble circularly or in a spiral shape around the prey and swims up toward the surface as shown in [12]. The mathematical modelling of WOA can be described in three operators [56], [57]. It includes encircling prey, bubble -net hunting, and search for prey and the flowchart of WOA is shown in Figure 6.

Encircling prey: the location of prey is determined and circled them. In this phase, the current best position is assumed as the best candidate solution and the rest of search agent try to update their position toward the best search agents. Furthermore, the process can be expressed by the following equations.

$$\vec{D} = \left|\vec{C}\cdot\vec{X^*}(t) - \vec{X}(t)\right|, \tag{23}$$

$$\vec{X}(t+1) = \vec{X^*}(t) - \vec{A}\cdot\vec{D}, \tag{24}$$

$$\vec{A} = 2\vec{a}\cdot\vec{r} - \vec{a}, \tag{25}$$

$$\vec{C} = 2\vec{r}, \tag{26}$$

where,

t is the current iteration,

$\vec{A}, \vec{C}$ are the coefficient vectors,

$\vec{X^*}$ is the best solution obtained so far,

X is the vector position,

$\vec{a}$ is the linearly decrease from 2 to 0,

$\vec{r}$ is the random vector from 0 to 1, and

$\vec{D}$ refers to the distance between whale and preys which is the best position obtained.

Bubble-net hunting method (exploitation phase): there are two approaches to form the mathematical problem of bubble hunting method.

- Shrinking encircling prey: the process is contributed by Equation 26, so it means that $\vec{A}$ is decreased when $\vec{a}$ decreases linearly. Thus, $\vec{A}$ is the random value in the interval [-a , a] that a decrease from 2 to 0. The new position of a search agent can be obtained from the original position of the agent and position of current best agent.
- Spiral updating position: the helix-shape movement of humpback whales can be formed as the spiral equation as below. It is created between the position of whale and preys.

$$\vec{X}(t+1) = \vec{D'}\cdot e^{bl}\cdot\cos(2\pi l) + \vec{X^*}(t), \tag{27}$$

$$\vec{D'} = \left|\vec{X^*}(t) - \vec{X^*}(t)\right|, \tag{28}$$

where,

b is the constant, and

l is the random number from -1 to 1.

During preys hunting, humpback whale swims around within shrinking circle and along spiral shape path simultaneously. During optimization, only 50% of assumption is chosen between either shrinking encircling or spiral shape to update the position of a whale. Moreover, it can be modelled as two equation system below.

$$\vec{X}(t+1)=\begin{Bmatrix} \vec{X}^*(t)-\vec{A}\cdot\vec{D} & if \quad p<0.5 \\ \vec{D}'\cdot e^{lb}\cdot\cos(2\pi l)+\vec{X}^*(t) & if \quad p\geq 0.5 \end{Bmatrix}, \tag{29}$$

where,

p is the random number from 0 to 1.

Search for prey (exploration phase): In this phase, the vector $\vec{A}$ is used to search randomly for preys. It means that it upgrade the position based on chosen search agents instead of best search agents to get the optimum point. Furthermore, this can be expressed in mathematical form as below.

$$\vec{D}=\left|\vec{C}\cdot\vec{X}_{random}-\vec{X}\right|, \tag{30}$$

$$\vec{X}(t+1)=\vec{X}_{random}-\vec{A}\vec{D}. \tag{31}$$

where,

$\vec{X}_{random}$ is the random position vector or random whale chose from the current population.

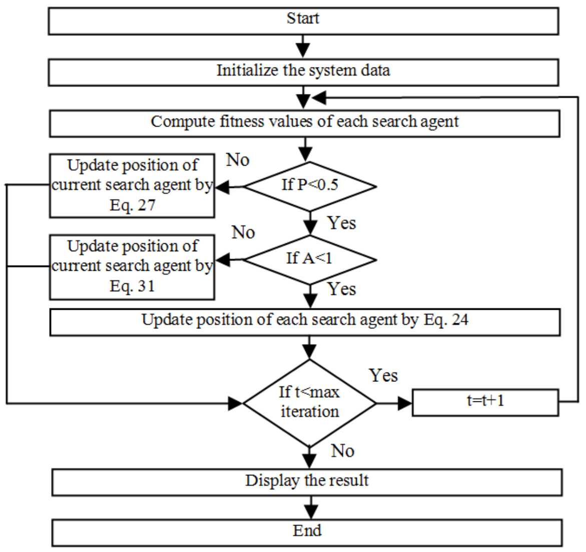

Fig. 6. Flowchart of WOA.

3.5 Algorithm Application for the Objective Function Minimization

The application of the applied algorithms in multi objective function for the active power loss and VD minimization using GA, ABC, PSO, and WOA can be described as shown in Figure 7. Moreover, the working process of the applied algorithm is also addressed.

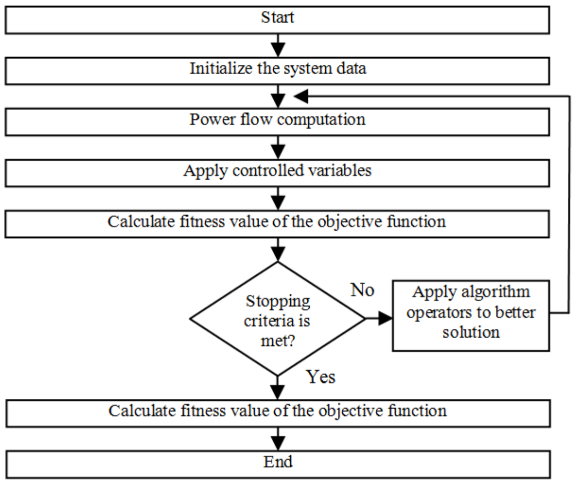

Fig. 7. Flowchart of loss and VD minimization.

4. SIMULATION RESULT AND DISCUSSION

In this section, the IEEE 6 and 14 buses test system was employed in order to verify the effectiveness and robustness of the used proposed methods. To compare the accuracy of the algorithm, fours methods (GA, ABC, PSO, WOA) of optimization techniques were applied to solve the problems. Also, the limitation of the controlled variables was shown in Table 1. All the four algorithms were set the same value of the parameters in order to compare the efficiency and computation time. The setting of the parameters of each method was expressed in Table 2.

Table 1. Controlled variable constraints.

Variables	Limitation	
	min	max
V (p.u.)	0.90	1.1
T (p.u.)	0.90	1.1
Q (Mvar)	0	50

Table 2. Parameters setting values of each method.

Parameters	Algorithms			
	GA	ABC	PSO	WOA
Population	30	30	30	30
Maximum iteration	200	200	200	200
Maximum error	$1x10^{-6}$	$1x10^{-6}$	$1x10^{-6}$	$1x10^{-6}$

4.1 IEEE 6 Bus System

The 6 bus standard tested system was employed with the algorithm. The figure of the system was illustrated in Figure 8 and the loss and VD comparison of before and after simulation including deduction rate and computation time were displayed in Tables 3 and 4. Moreover, the optimal solutions were obtained as shown in Table 5 and the voltage profile improvement comparison was also shown in Figure 9. In the 6 bus system, bus 6 and bus 5 are slack and voltage controlled bus respectively. Bus 1, 2, 3 and 4 are load buses which have totally 10.53MW and 5.99MVAR of loads. Bus 5 is connected to a small power plant with 20MW of fixed capacity. After simulation, the result shows that the total active power loss of the system is 14.80MW before minimization.

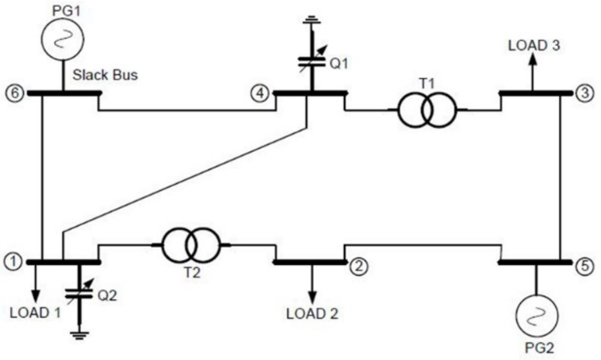

Fig. 8. IEEE 6 bus standard test system.

Table 3. Loss reduction comparison of 6 bus system.

Case	Before (MW) Loss	After (MW) Loss	Saving	Deduction %	Computed time (s)
GA	12.46	7.697	4.763	38.22	36.76
ABC		7.695	4.765	38.24	98.03
PSO		7.695	4.765	38.24	112.85
WOA		7.695	4.765	38.24	32.86

Table 4. VD reduction comparison of 6 bus system.

Case	Before VD	After (MW) Loss	Saving	Deduction %
GA	0.44	0.295	0.145	32.95
ABC		0298	0.142	32.97
PSO		0.297	0.143	32.50
WOA		0.296	0.143	32.50

Table 5. Optimal solutions of 6 bus system.

Variables		Bus	GA	ABC	PSO	WOA
Q (Mvar)	Q1	1	45.63	46.36	45.80	47.1
	Q2	4	30.48	30.66	30.75	29.85
T (p.u.)	T1	1-2	1.09	1.1	1.1	1.1
	T2	4-3	1.07	1.07	1.07	1.07

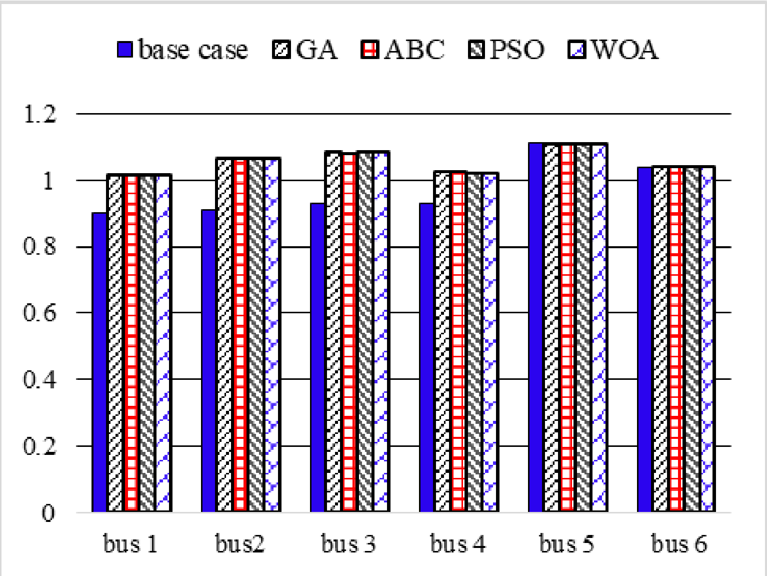

Fig. 9. Voltage profile comparison of 6 system.

The results showed that the minimum loss was 7.695MW which was achieved by ABC, PSO, and WOA, while GA provided 7.697MW which was a bit higher. However, GA was the method which provided the better solution followed by WOA, PSO, and ABC when considering the minimum VD. Moreover, the computation time spent by each method to find the optimal solutions showed that WOA consumed the least computational time effort. According to the result of power loss and VD, WOA gave the least power loss and spent less time to reach the optimal solutions. As a result, the power loss of the entire system could be improved with 38.24% reduction.

The voltage profile of the base case before improvement was to be closed to the lower limit of the specified range. Nevertheless, the voltage profile was improved significantly to be within specified boundary after adjusting the control variables to the optimal values as shown in Figure 9. The convergence characteristics of GA, ABC, PSO, and WOA were shown in Figure 10. It was observed that WOA converged with the minimum iterations.

According to Figure 11, it could be concluded that WOA provided the better fitness values than others since it has the shorter vector distance from the origin due to the lowest loss and VD function which could be considered as a great benefit for the network. GA gave the minimum VD function with higher power loss function while ABC and PSO provided the minimum loss function to those of GA with higher VD function.

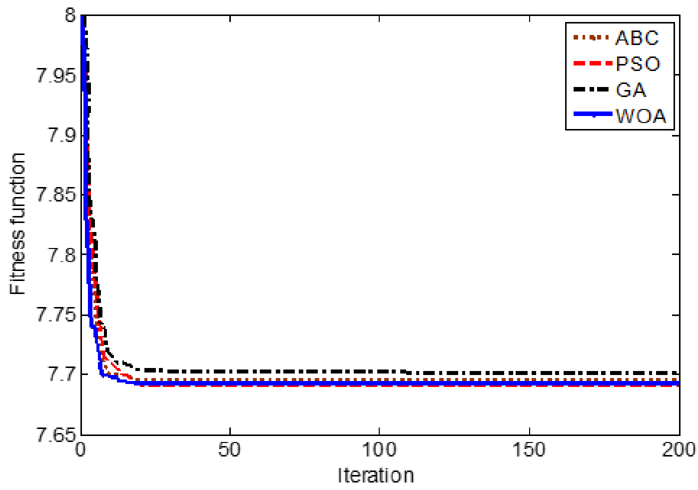

Fig. 10. Convergence characteristic of 6 system.

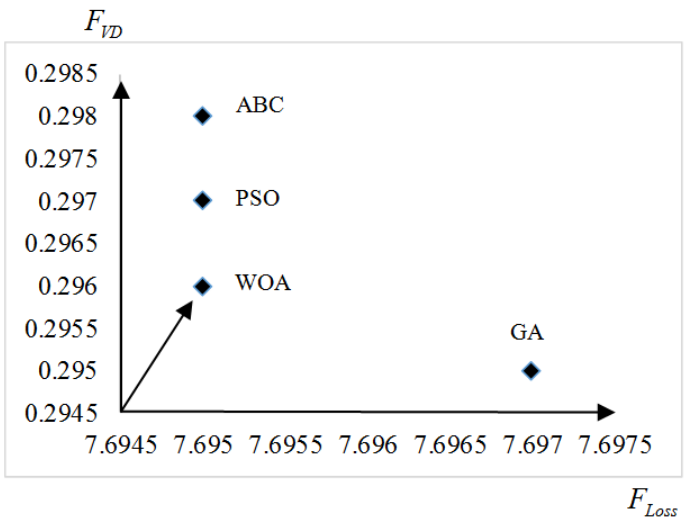

Fig. 11. Fitness function value comparison of 6 system.

4.2 IEEE 14 Bus System

The second tested system to verify the performance and effectiveness of the algorithms was the IEEE14 bus system. There are 12 load buses which are bus 3 to 14 and bus 1 and 2 were considered respectively slack and PV bus. In this system, there is a small power plant which connected to the voltage controlled bus with a fixed capacity of 40MW. The total active power loss before minimization is 14.72MW. The test case was carried out by solving the optimal power flow problem of power loss and VD objectives with the variable limits used as the system constraints as shown in Table 1. Loss and VD minimization comparison are expressed in Tables 6 and 7. Furthermore, the optimal solution is also shown in Table 8, including the voltage profile comparison shown in Figure 12.

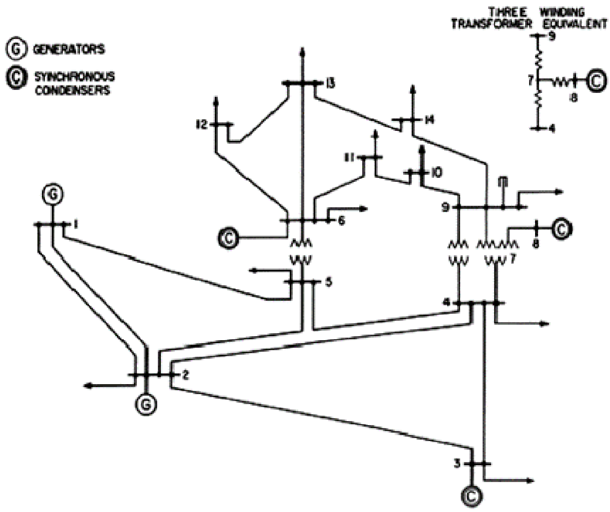

Fig. 12. IEEE 14 bus standard test system.

Table 6. Loss reduction comparison of 14 bus system.

Case	Before (MW)	After (MW)			Computed time (s)
	Loss	Loss	Saving	Deduction %	
GA	14.72	13.91	0.81	5.50	186.57
ABC		13.87	0.85	5.77	765.07
PSO		13.85	0.87	5.91	950.39
WOA		13.70	1.02	6.92	136.65

Table 7. VD reduction comparison of 14 bus system.

Case	Before	After (MW)		
	VD	Loss	Saving	Deduction %
GA	0.66	0.86	-0.20	-30.30
ABC		0.89	-0.23	-34.85
PSO		0.97	-0.31	-46.97
WOA		0.84	-0.18	-27.27

Table 8. Optimal solutions of 14 bus system.

Variables		Bus	GA	ABC	PSO	WOA
Q (Mvar)	Q1	3	11.11	11.34	9.35	2.83
	Q2	6	39.39	38.88	24.98	25.76
	Q3	8	10.40	10.32	14.84	20.32
T (p.u.)	T1	4-7	1.07	1.07	1.09	1.04
	T2	4-9	1.09	1.10	1.09	1.08
	T3	5-6	1.01	1.02	1.03	1.05

The results showed that WOA provided the best results when compared with those obtained by PSO, ABC, and GA. For the 14 bus system, the obtained minimum loss solutions were 13.91MW, 13.87MW, 13.85MW, and 13.70MW for GA, ABC, PSO, and WOA respectively. When considering the minimum loss, WOA was the method which gave the least loss followed by PSO, ABC, and GA, respectively. Furthermore, the minimum VD was achieved by WOA and it was followed respectively by GA, ABC, and PSO. WOA spent the less time to reach the optimal solutions when compared to other algorithms in regarding of computational time effort. As a result, the power loss was improved with 6.92% reduction with WOA of the entire system.

Before improvement, the voltage profile was poor since most of the bus voltage was closed to the lower boundary of the specified range. However, it was resumed obviously after adjusting the control variables to their optimal points as illustrated in Figure 13.

Moreover, the convergence characteristic was also shown in Figure 14. Additionally, the WOA could reach the convergence rapidly when compared to ABC, PSO, and GA in term of the iterations.

Based on Figure 15, WOA was still the method which gave the best fitness value due to its shortest vector distance from the origin since it could provide the least loss and VD function. It was followed by ABC, GA, and PSO, respectively.

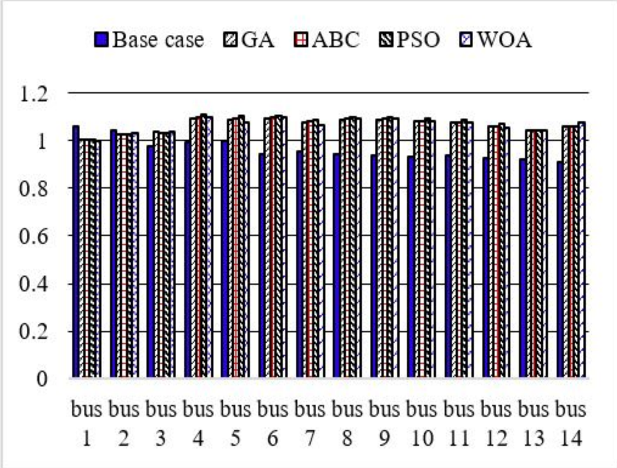

Fig. 13. Voltage profile comparison of 6 system.

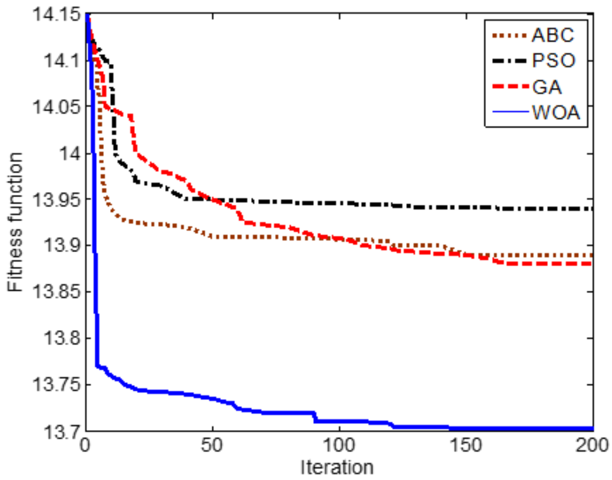

Fig. 14. Convergence characteristic of 14 system.

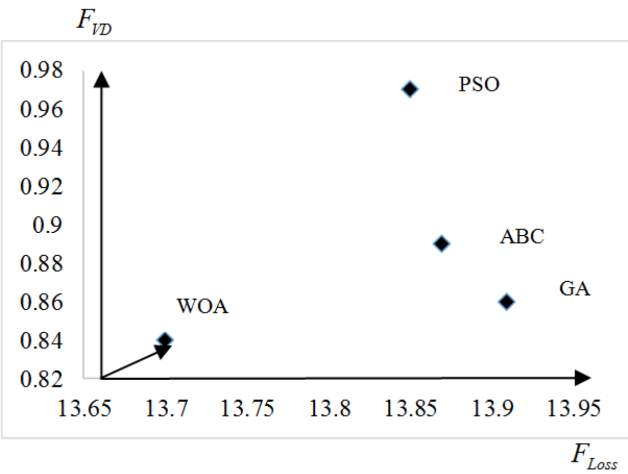

Fig. 15. Fitness function value comparison of 14 system.

5. CONCLUSION AND FUTURE WORK

In this paper, the methods for solving OPF problems with transmission loss and voltage deviation minimization were described. The four algorithms including GA, ABC, PSO, and WOA were applied to solve the multi-objective problem for comparative purpose. The IEEE of 6 and 14 bus systems were employed with the algorithms to show the accuracy and effectiveness. The obtained outcome are compared with each algorithm and it was shown that the loss and VD have been minimized together with controlled variables were in the limitation. Furthermore, it could be recognized that WOA resulted in the best solution in providing minimum power loss and VD. Therefore, the methods can be effectively applied to the grid connected micro power system in optimal operation. The proposed method can be further extend to apply the emerging power system with high penetration distributed energy resources.

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