Comparisons of Energy Loss Reduction by Phase Balancing in Unbalance Distribution Networks via Metaheuristic Algorithms

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Three-phase balancing can improve the operation efficiency of distribution networks. The common approach is phase arrangement of each tapped-off point in unbalanced distribution networks. This complex problem requires searching for an optimal combination. Metaheuristic algorithms can efficiently solve this complicated problem. In this study, 10 common metaheuristic algorithms are applied in the IEEE 37-bus test system for optimal phase arrangement, and the performance of each of them is compared and discussed. The outcomes of this work are helpful for realizing energy loss reduction by phase balancing, which applies metaheuristic algorithms in unbalanced distribution networks.

Keywords—Metaheuristic, Optimization, Load phase arrangement.

I. INTRODUCTION

Optimization of the operation of power distribution systems can enhance energy efficiency, power quality, and system reliability, and many studies have been conducted on this subject. The operation of distribution systems can be divided into three stages, namely, long-term energy planning, mid-term operating planning, and short-term operating control. Topology design, sizing, and allocation of power elements, such as the capacitor and distributed generator (DG), belong to the long-term stage. Phase arrangement at the tapped-off point belongs to the mid-term stage, and the short-term stage covers feeder switching, on-load tap changer (OLTC) control, capacitor control, dispatch of the energy storage system (ESS), and others. Phase arrangement is the common approach for improving inherently unbalanced distribution networks. The phase connection between distribution transformers or laterals and the main feeder in the distribution network is changed to balance three-phase loads on the entire feeder. Phase arrangement essentially reduces voltage unbalance, neutral current, and line loss, thus improving operation efficiency. Moreover, the reduction of zero- and negative-voltage unbalance improves the derating operation of three-phase induction motors [1]. Thus, phase arrangement at the tapped-off point in the operation planning stage improves energy efficiency.

In general, system operators conduct phase arrangement manually on the basis of their experience. This approach is inefficient and unsystematic. The problem of phase arrangement is difficult to formulate as a mathematical function because of the availability of many possible combination solutions. Metaheuristic algorithms are used to solve these problems. Many methods are utilized to solve different problems in mathematical optimization. A heuristic uses experience in a certain behavior to solve problems, whereas a metaheuristic is a higher-level self-learning technique for solving a problem quickly when classic methods are too slow or for finding an approximate solution when classic methods fail to find any feasible solution. This kind of algorithm is solved by trading optimality, completeness, accuracy, or computing time. Any search problem has b variables, and each of them has d choices; an unskilled algorithm has to search for bd solutions. Metaheuristic searches by a certain mechanism can improve efficiency and reduce bd to b'. The global best may not be found, but a nearly global best can be obtained easily. To some degree, it can be considered a shortcut. Metaheuristics are inspired by nature and based on real-world observations or experiences, such as biological behavior and evolution, even without a theory.

Reference [2] proposed a two-stage optimal phase arrangement approach for minimizing the energy losses of distribution networks by using the particle swarm optimization (PSO) algorithm. Reference [3] used an immune algorithm to create three-phase balancing in distribution feeders. Reference [4] combined PSO and the ant colony algorithm (ACO) to optimize network reconfiguration in a distribution system for loss reduction and voltage-profile improvement. Meanwhile, Reference [5] utilized PSO and the genetic algorithm (GA) to develop a load balancing scheme.

The current study examines common metaheuristic algorithms for energy loss reduction by phase arrangement and compares their performance, calculation speed, and convergence.

II. PROBLEM DESCRIPTION

The three-phase imbalance in distribution networks is caused by single-phase distribution transformers or laterals, symmetrical three-phase distribution transformers with unbalanced loads, and asymmetrical three-phase distribution transformers (U-V and V-V connections). The U-V connection, which is also known as an open-wye and open-delta connection, is a three-phase arrangement that uses only two phases instead of three; it is a modification of the wye-delta connection. The V-V connection, also known as an

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open-delta connection, is modified from the delta-delta connection. These asymmetrical connections are sometimes used in distribution transformers to reduce costs and save space; however, the problems of three-phase imbalance are exacerbated.

The possible connection schemes for three-, two-, and single-phase transformers and laterals are different, as shown in Fig. 1. To solve this problem, all transformer connections in the feeders must be rearranged to evenly distribute the loads to each phase. The six types of three-phase transformer connection schemes are shown in Fig. 2. An optimization algorithm is used to identify the optimal arrangement for all transformer connections among these connection types.

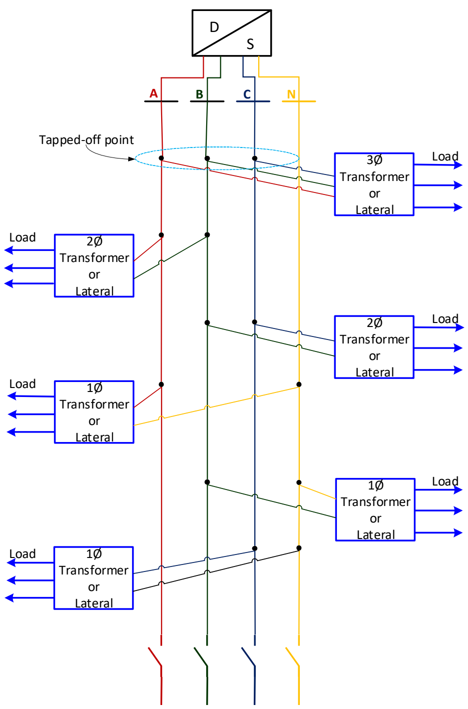

Fig. 1 Various connections of the tapped-off points in three-phase, four-wire distribution networks

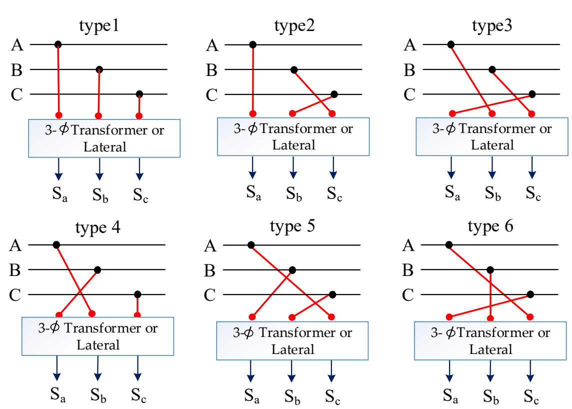

Fig. 2 Six types of three-phase transformer connection scheme

In this study, a phase arrangement scheme is implemented in the IEEE 37-bus test system. Fig. 3 shows the system's single-line diagram. It is a 4.8 kV distribution network with single-phase and unbalanced three-phase loads. The power flow is solved with the distribution system simulator software OpenDSS. The algorithms search for an optimal or sub-optimal solution by using the objective function of system total losses and negative-sequence voltage unbalance ratios in accordance with the results of steady-state power flow solutions in OpenDSS.

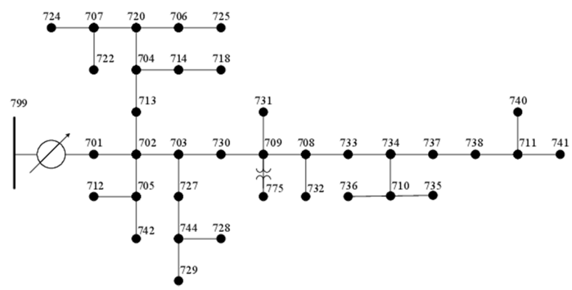

Fig. 3 Single-line diagram of the IEEE 37-bus test system

III. Metaheuristic Algorithms

Metaheuristics can be categorized into single-agent, multi-agent, and dynamic-agent algorithms. The single-agent algorithm is mainly used to determine the local optimal solution. The multi-agent algorithm searches for the solution by using a number of individuals simultaneously. The global optimal solution can be identified easily, but the process is time consuming. The dynamic-agent algorithm can change the number of agents in different cases. Meanwhile, metaheuristics can also be roughly divided into algorithms inspired by bio-intelligence and natural phenomena. The following text introduces 10 popular metaheuristic algorithms, and all of them are applied in the IEEE 37-bus test system to compare their performance.

A. Artificial Bee Algorithm

The artificial bee algorithm (ABA) was introduced by Karaboga in 2005 for optimizing numerical problems [6]. It was inspired by the intelligent foraging behavior of honey bees. The algorithm is specifically based on the model proposed by Tereshko and Loengarov in 2005. The mathematic function is described as follows:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n}, \tag{1}$$

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}), \tag{2}$$

$$x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j), \tag{3}$$

where p_i is the foot source function and v_{ij} and x_i^j are the velocity and position of the bee colony, respectively. The detailed functions of ABA were presented in Reference [6].

B. Bat Algorithm

The bat algorithm (BA) was inspired by the echolocation behavior of microbats, with varying pulse rates of emission and loudness, and it was developed by Xin-She Yang in 2010 [7]. The mathematic function is described as follows:

$$f_i = f_{min} + (f_{max} - f_{min})\beta, \quad (4)$$

$$v_i^t = v_i^t + (x_i^{t-1} - x_*)f_i, \quad (5)$$

$$x_i^t = x_i^{t-1} + v_i^t, \quad (6)$$

Bats fly randomly with velocity v_i^t at position x_i^t and with frequency f_i and loudness A^0 to search for prey. They can automatically adjust the frequency of their emitted pulses and the rate of pulse emission r ∈ [0, 1] depending on the proximity of their target. The detailed functions of variations in loudness and pulse rates were examined in Reference [7].

C. Cat algorithm

The cat algorithm (CA) was developed by observing the behaviors of cats; it is composed of tracing and seeking modes, which are modeled upon the behaviors of cats. It was proposed by Chu et al. in 2006 [8]. The mathematic function is described as follows:

$$v_k^d = v_k^d + r_1 \times c_1 \times \left(x_{best}^d - x_k^d\right), \quad (7)$$

$$x_k^d = x_k^d + v_k^d. \quad (8)$$

The position of cat swarm x_k^d is updated by velocity v_k^d. Then, the point to move to is randomly selected from the candidate points, and the position of the cat is replaced as

$$P_i = {|FS_i - FS_b|}\Big/{FS_{max} - FS_{min}}. \quad (9)$$

D. Cuckoo Search Optimization

The cuckoo search optimization (CSO) algorithm was developed by Yang and Deb in 2009 [9]. It was inspired by the obligate brood parasitism of several cuckoo species that lay their eggs in the nests of other host birds. Several host birds engage in direct conflict with the intruding cuckoos. CSO idealizes such breeding behavior and can thus be applied to various optimization problems. The algorithm was described by a pseudo code in Reference [9]. The position function of the cuckoo is

$$x_{t+1} = x_t + sE_t. \quad (10)$$

The random walk and abandon procedures were described in detail in Reference [9].

E. Gravitational Search Algorithm

The gravitational search algorithm (GSA) was proposed by Nobahari and Nikusokhan in 2009 [10], and it is based on the law of gravity and the notion of mass interactions. GSA uses the theory of Newtonian physics, and its searcher agents are the collection of masses. The mathematic function is described as follows:

$$a_p(t) = G(t)\sum_{q=1}^{n_m} rand_q \frac{M_q(t)}{R_{pq}(t)+\epsilon}\left(x_p - x_p\right), \quad (11)$$

$$v_p(t+1) = rand_q \times v_p(t) + a_p(t), \quad (12)$$

$$x_p(t+1) = x_p(t) + v_p(t+1), \quad (13)$$

where $a_p(t)$ is the total gravitational acceleration and $v_p(t)$ and $x_p(t)$ are the velocity and position of each agent, respectively. The detailed functions of GSA were discussed in Reference [10].

F. Grey Wolf Optimizer

The gray wolf optimizer (GWO) algorithm mimics the leadership hierarchy and hunting mechanism of gray wolves in nature, and it was proposed by Mirjalili et al. in 2014 [11]. The position vector of a gray wolf $\vec{X}(t)$ is described as follows:

$$\vec{D} = \left|\vec{C}\overrightarrow{X_p}(t) - \vec{X}(t)\right|, \quad (14)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}\vec{D}. \quad (15)$$

The detailed functions of GWO were presented in Reference [11].

G. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm was proposed by Kennedy and Eberhart in 1995 [12]. It is inspired by bird flock migration and forage behaviors. The two fundamental behaviors are concluded to be cognition-only and social-only models by observation. The velocity and position function of a particle swarm are described as follows:

$$v_n^{i+1} = \omega v_n^i + \varphi_p rand()\left(p_{bestn}^i - s_n^i\right)$$
$$+\varphi_g rand()\left(g_{bestn}^i - s_n^i\right), \quad (16)$$

$$s_n^{i+1} = s_n^i + v_n^{i+1}. \quad (17)$$

H. Firefly Algorithm

The firefly algorithm (FA) was proposed by Yang in 2008, and it was inspired by the flashing behavior of fireflies [13]. The algorithm was described by a pseudo code in Reference [13]. The position function of any pair of two fireflies x_i^t and x_j^t is

$$x_i^{t+1} = x_i^t + \beta e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \epsilon_t. \quad (18)$$

The detailed functions of FA were shown in [13].

I. Firework Algorithm

The firework algorithm (FWA), which was proposed by Tan and Zhu in 2010 [14], was inspired by fireworks explosion. In the algorithm, two types of explosion (search) processes are employed, and the mechanisms for keeping the diversity of sparks are well designed. The number of sparks generated by each firework x_i is defined as

$$s_i = \frac{y_{max} - f(x_i) + \xi}{\sum_{i=1}^{n}(y_{max} - f(x_i)) + \xi}. \quad (19)$$

The amplitude of explosion for each firework is defined as follows.

$$A_i = \hat{A} \times \frac{f(x_i) - y_{min} + \xi}{\sum_{i=1}^{n}(f(x_i) - y_{min}) + \xi}. \quad (20)$$

The general distance between location x_i and other locations is defined as

$$R(x_i) = \sum_{j\in K} d(x_i, x_j) = \sum_{j\in K} \|x_i - x_j\|. \quad (21)$$

Then the selection probability of location x_i is defined as

$$p(x_i) = \frac{R(x_i)}{\sum_{j\in K} R(x_i)}. \quad (22)$$

The detailed functions of FWA were presented in Reference [14].

J. Whale Swarm Algorithm

The whale swarm algorithm (WSA) was proposed by Zhen et al. in 2017 [15], and it was inspired by the communication of whales with one another via ultrasound for hunting. The random movement of a whale *X* guided by its better and nearest whale *Y* can be formulated as

$$x_i^{t+1} = x_i^t + rand(0, \rho_0 e^{-\eta d_{X,Y}}) \times (y_i^t - x_i^t). \quad (23)$$

The detailed functions of FWA were discussed in Reference [15].

IV. Comparison and Discussion

All of the 10 metaheuristic algorithms mentioned above are used to search for the solution of phase arrangement in the IEEE 37-bus test system to reduce the energy loss. The objective functions are total power loss and average voltage unbalance ratios of the symmetrical component (zero- and negative-sequence voltage unbalancing rates, respectively), as shown in Eqs. (24) to (26).

$$P_{loss} = \sum_{i=1}^{n} I_i^2 R_i, \quad (24)$$

$$d_0 = \frac{\sum_{j=1}^{n} \frac{V_0^j}{V_1^j}}{n} \times 100\%, \quad (25)$$

$$d_2 = \frac{\sum_{j=1}^{n} \frac{V_2^j}{V_1^j}}{n} \times 100\%, \quad (26)$$

where P_{loss}, d_0, and d_2 are the total loss, average zero-sequence voltage unbalance ratio, and average negative-sequence voltage unbalance ratio, respectively. I_i and R_i are the current magnitude and resistance of each element (line sections and transformers), respectively. V_0^j, V_1^j, and V_2^j are the zero-, positive-, and negative-sequence voltages of each bus, respectively.

TABLE I shows the performance of the 10 metaheuristic algorithms introduced in Section III. The number of agents and number of iteration times are set to 100. Objective functions P_{loss} and d_2 are optimized by the algorithms (the value of d_0 is too small, so it is not discussed here). The optimization results, calculation time, and convergence time (time of iteration) are listed in TABLE I.

The results show that GSA cannot find a feasible optimization solution. FWA obtains the best solution among the algorithms, but its process is time consuming. CA and PSO devote the least time on obtaining the feasible solution. Moreover, CSO and WSA achieve convergence early, and CA and GWO achieve convergence late. BA and FWA do not achieve convergence.

The d_2 convergence characteristics of all the metaheuristic algorithms are shown in Fig. 4. FWA improves d_2 from its initial value of 2.79% to the best solution of 0.09%. Similarly, the power loss convergence characteristics of all the metaheuristic algorithms are shown in Fig. 5. FWA improves the power loss from its initial value of 152.4 kW to the best solution of 138.9 kW.

TABLE I Performance of the 10 metaheuristic algorithms

Algorithm	Performance			
	P_{loss} (kW)	d_2 (%)	Time spent (s)	Convergence time
ABA	139.8	0.156	237.5	<20
BA	139.6	0.189	233.4	-
CA	140.2	0.243	80.8	40~60
CSO	139.6	0.155	388.1	<10
GSA	140.2	0.349	241.1	20~40
GWO	139.4	0.138	80.6	40~60
PSO	139.8	0.235	80.4	0~20
FA	141.0	0.348	7854.0	-
FWA	138.9	0.083	17186.6	40~60
WSA	140.0	0.176	15705.4	0~20
Original	**152.4**	**2.79**	**-**	**-**

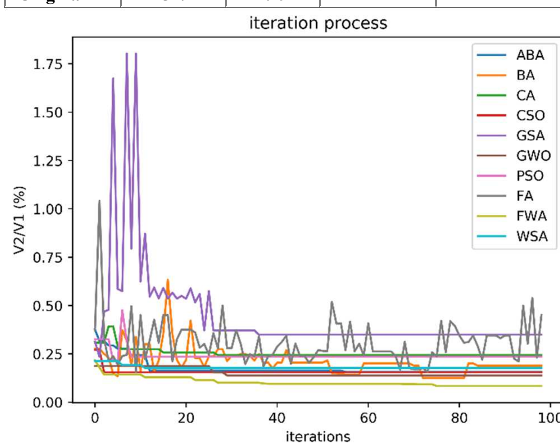

Fig. 4 d_2 convergence characteristics of the metaheuristic algorithms

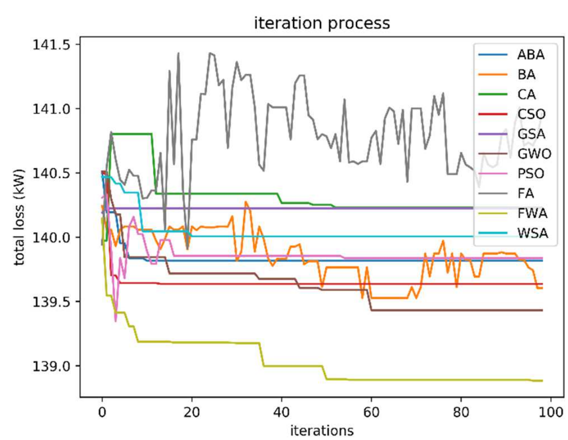

Fig. 5 Power loss convergence characteristics of the metaheuristic algorithms

V. Conclusion

Ten common metaheuristic algorithms are applied in this work to solve the energy loss reduction and improve the operation efficiency of distribution networks by phase arrangement. The performance of the algorithms is compared in terms of power loss, negative-sequence voltage unbalance ratio, iteration number, and computing time. The simulation results demonstrate that the metaheuristic algorithms can reduce the power loss and negative-sequence voltage unbalance ratio under the specific test system and parameter setting. FWA has the best solution among the algorithms, but its process is time consuming. The results of this study are helpful for realizing energy loss reduction by phase balancing, which applies metaheuristic algorithms in unbalanced distribution networks.

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