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An improved artificial bee colony optimization algorithm based on orthogonal learning for optimal power flow problem

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ABSTRACT

The increasing fuel price has led to high operational cost and therefore, advanced optimal dispatch schemes need to be developed to reduce the operational cost while maintaining the stability of grid. This study applies an improved heuristic approach, the improved Artificial Bee Colony (IABC) to optimal power flow (OPF) problem in electric power grids. Although original ABC has provided robust solutions for a range of problems, such as the university timetabling, training neural networks and optimal distributed generation allocation, its poor exploitation often causes solutions to be trapped in local minima. Therefore, in order to adjust the exploitation and exploration of ABC, the IABC based on the orthogonal learning is proposed. Orthogonal learning is a strategy to predict the best combination of two solution vectors based on limited trials instead of exhaustive trials, and to conduct deep search in the solution space. To assess the proposed method, two fuel cost objective functions with high non-linearity and non-convexity are selected for the OPF problem. The proposed IABC is verified by IEEE-30 and 118 bus test systems. In all case studies, the IABC has shown to consistently achieve a lower cost with smaller deviation over multiple runs than other modern heuristic optimization techniques. For example, the quadratic fuel cost with valve effect found by IABC for 30 bus system is 919.567 $/hour, saving 4.2% of original cost, with 0.666 standard deviation. Therefore, IABC can efficiently generate high quality solutions to nonlinear, nonconvex and mixed integer problems.

1. Introduction

In electric power grids, the optimal power flow (OPF) problem is of great importance for power system operators (SO) to maintain a reliable and economic power system operation. The main goals of OPF are to optimize the fuel cost, power losses, voltage stability, and emission cost, while satisfying system constraints. Traditional OPF involving conventional fossil-fuel power plants is a highly nonlinear, nonconvex and mixed integer problem (Adaryani & Karami, 2013; Bai, Abedi, & Kwang, 2016). For example, the cost function of a fossil-fuel power plant can be quadratic or in other nonlinear form when the valve effect is considered. An overview of OPF can be found in (Cain, O'Neill, & Castillo, 2012; Gan, Thomas, & Zimerman, 2000; Momoh, Koessler, Bond, & Stott, 1997).

In all, the OPF is a non-linear, non-convex optimization problem due to the cost functions and constraints of a large number of power plants integrated into the power grid. A wide range of traditional optimization techniques such as quadratic programming, nonlinear programming, interior point method, mixed integer programming (Alsac & Stott, 1974; Burchett, Happ, & Vierath, 1984; Hua, Sasaki, Kubokawa, & Yokoyama, 1998; Shoults & Sun, 1982) have already been implemented in this field. Some of the techniques have even been adopted by industry because of their fast convergence and robustness. However, those approaches linearize the OPF problem first, and fail to consider the non-smooth, non-differentiable and non-convex properties of the system.

To circumvent such problem, various modern heuristic optimization algorithms have been developed for power system optimization (Lee & El-Sharkawi, 2008) because such techniques tackle the original problem without modifying it. In general, heuristic algorithms are developed based on two categories which are single-solution based and population based approaches. Several examples of single-solution based approach are tabu search and simulated annealing (Abido, 2002; Soares, Vale, Morais, & Faria, 2011), while population based approaches include particle swarm optimization (PSO), gravitational search algorithm (GSA), differential evolution (DE), genetic algorithm (GA), harmony search, and artificial bee colony (Abou, A, Abido, & Spea, 2010; Adaryani & Karami, 2013; Bakirtzis, Biskas, Zoumas, &

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Petridis, 2002; Park, Jeong, Shin, & Lee, 2010; Sivasubramani & Swarup, 2011). In addition to these original heuristic methods, enhanced approaches based on the original ones have been developed for more efficient search. The authors in (Bakirtzis et al., 2002) improved basic GA to solve the OPF by introducing an advanced and problem-specific genetic operator. Such operator includes the fitness scaling and elitism features, and the algorithm was tested on IEEE-30 and IEEE RTS-96 system. Reference (Park et al., 2010) proposed an improved PSO to tackle the problem considering the valve point effect on the regular quadratic fuel cost function.

This study focuses on the artificial bee colony (ABC) method reported by Karaboga in 2005 (Karaboga, 2005). The ABC falls into the category of population-based optimization algorithms which have been demonstrated competitive to other methods because the ABC controls fewer parameters and is robust (Karaboga & Akay, 2009; Pan, Tasgetiren, Suganthan, & Chua, 2011; Zhan, Zhang, Li, & Shi, 2011). The balance between exploration and exploitation is an important issue for modern heuristic optimization techniques. The former is the capability of investigating various unknown regions in search space, and the latter is the ability to make the best decision given current information (Crepinsek, Liu, & Mernik, 2013). In reality, the two aspects are contradictory to each other and therefore a well balanced approach needs to be found. The search process of ABC performs well for exploration because the searching scheme is random enough for exploration; however, it performs poorly for exploitation and thus causes poor convergence (Gao, Liu, & Huang, 2013).

In order to enhance the ability of exploitation, researchers proposed a search mechanism which utilizes the information of current best solution inspired by differential evolution (DE). In such search mechanism, onlooker bees only search around the best solution formed in the previous iteration according to a predefined probability (Gao & Liu, 2012). Gao and Liu (2011) improved the initialization phase in that the chaotic system was utilized, and modified the search mechanism using the information of current best solution. Such work is able to improve the exploitation.

The search equation of the original ABC randomly selects a dimension of the solution vector and performs mutation with the same dimension of another solution vector. Here the dimension refers to the number of control variables in a solution vector. For example, if the solution vector consists of 24 control variables, it is interpreted as 24 dimensions in such solution vector. However, this search scheme falls short of effectiveness because one solution vector may contain useful information on some dimensions while the other solution may contain good information on its other dimensions. In other words, merely concentrating on a specific dimension of the solution will be likely to lose other useful information for solution improvement. Therefore, in order to update the solution considering all the information of each dimension from two candidate solutions, inspired by the orthogonal experimental design (OED) Gao (2013) proposed an orthogonal learning (OL) technique to obtain better exploitation. The OED is utilized to determine the best combination out of two vectors via a relatively small number of experimental tests instead of exhaustive trials (Zhan et al., 2011; Zhang & Leung, 1999). The OL strategy is implemented with the help of OED, and details of such strategy will be described later.

In all, the previous works on OPF have either fallen short of the ability to tackle original problem without approximation or the balance in exploration and exploitation in modern heuristic techniques. Thus far, to the best knowledge of authors, the application of ABC based on orthogonal learning on power system operation problems has not been documented in the literature yet. Here, we first propose this method to handle the OPF problem, which is to be our main contribution. With that, better optimization solution can be found by improving the balance in exploration and exploitation. The performance was tested on modified IEEE 30 and 118 bus test systems and comparative analysis was conducted with other methods. For the case of minimizing fuel cost considering valve effect, the total cost can be reduced by 4.2% compared with the original ABC. Power system is a highly non-linear system and therefore many control and optimization become hard-to-solve problems without linearizing system. IABC is to possibly further improve the solutions of those problems such as controlling the Flexible Alternating Current Transmission System (FACTS) devices, optimizing the placement of distributed generators.

2. Problem formulation

2.1. Traditional OPF problem

The objective of traditional optimal power flow (OPF) is to minimize fuel cost for power generation by determining a setting of control variables while satisfying network constraints and operational requirements. Its mathematical formulation is:

$$\mathrm{Min}\, f(x, u) \tag{1}$$

$$s.\ t.\ \ g(x, u) = 0 \tag{2}$$

$$h(x, u) \le 0 \tag{3}$$

where vector u represents control variables and it includes generator real power P_G except at slack bus, generator bus voltage V_G, transformer tap TP (discrete variable), and shunt compensator Q_C (discrete variable) at selected buses; vector x represents state variables and it includes real power P_{G1} at slack bus, voltages V_L at load bus, reactive power Q_G at generator bus, and loadings S_L of transmission lines.

The objective functions f from (1) considered in the study are the real power losses and total fuel cost. Two different fuel cost functions are considered here, quadratic cost functions with and without the valve point loading (Park et al., 2010):

$$f_1 = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{4}$$

$$f_2 = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + |d_i \sin(e_i(P_{Gi,\min} - P_{Gi}))| \tag{5}$$

where a_i, b_i, c_i, e_i, and P_{Gi} denote for the fuel cost coefficients and real power of the i-th unit. Fig. 1 shows the effect of valve point loading on a quadratic cost function. In a real power plant, steam is controlled by valves to enter the turbine through separate nozzle groups. The best efficiency is achieved when each nozzle group operates at full output (Decker & Brooks, 1958). Therefore in order to achieve highest possible efficiency for given output, valves are opened in sequence and this results in a rippled cost curve, as shown in Fig. 1.

Resistance and reactance in transmission lines cause real power loss, and minimizing real power loss is one of the major concerns for system operation. The mathematical formation of the objective function is shown as follows:

$$f_3 = \sum_{k=1}^{N_l} \frac{r_k}{r_k^2 + x_k^2}[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)] \quad \forall\, i, \forall\, j \tag{6}$$

where N_l is the number of transmission lines, r_k and x_k represents the

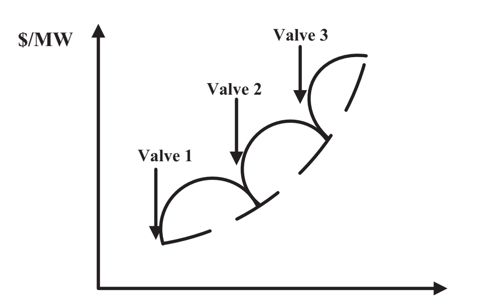

Fig. 1. Effect of valve point loading on a quadratic cost function.