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A hybrid algorithm of ABC variant and enhanced EGS local search technique for enhanced optimization performance

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ABSTRACT

A hybrid algorithm for optimizing a complex power system-based problem, economic environmental dispatch (EED) is proposed. The algorithm hybridizes a recently proposed artificial bee colony (ABC) variant referred to as JA-ABC3 and a local search technique, evolutionary gradient search (EGS) which has been enhanced i.e., augmented. The enhanced EGS has been inserted into JA-ABC3's framework and the resulting hybrid algorithm, known as EGSJAABC3 is expected to exhibit robust optimization performance by showing the capability to reach the global optimum in less number of generations. JA-ABC3 which is generated through few modifications towards the standard ABC algorithm is the best candidate as it has exhibited better performance than the standard ABC and other ABC variants. Since JA-ABC3 is a global search algorithm, a local search technique, EGS that has been augmented is selected to be its hybrid partner as it also exhibits better or same performance than its kind. The task of the augmented EGS is to enhance the exploitation capability of the algorithm and thus, guides the solution faster towards the global optimum. In other word, the enhanced EGS is taking part in the exploitation process while JA-ABC3 takes role in exploration and some parts of the exploitation processes. Then, a number of benchmark functions are used to evaluate the robustness of EGSJAABC3 in terms of convergence speed and global optimum achievement. Next, the main significant output of this research is a robust optimization algorithm (i.e., EGSJAABC3) later applied to solve complex real-world problems that is known for their uncertainty. In this paper, EGSJAABC3 is tested to minimize EED on three test generator systems; 6, 10 and 40 units. The acquired outcome on both benchmark functions and EED application demonstrate the robustness of EGSJAABC3 as an optimization algorithm and therefore, provide other researchers and engineers a tool for solving optimization problems.

1. Introduction

Bio-inspired algorithms (BIAs) that are inspired by the biological phenomenon of surrounding nature (Binitha and Sathya, 2012; Sandhya, 2012), have been employed to solve various problems. For instance, artificial bee colony applied to solve optimal reactive power flow (Ayan and Kılıç, 2012), bat algorithm for robot manipulator (Rahmani et al., 2016) and pigeon-inspired optimization algorithm used in automatic carrier landing system (Dou and Duan, 2017). Among them, artificial bee colony (ABC) algorithm is one of the popular BIAs as many researchers have been trying to work on it to generate robust optimization algorithms. This is because ABC is known for its simplicity and flexibility in comparison with other prominent optimization algorithms such as ant colony optimization (ACO), evolutionary algorithms (EA) and particle swarm optimization (PSO) algorithms. Most importantly, ABC has shown to perform better or the same in comparison to those algorithms (Brownlee, 2011; Karaboga and Basturk, 2007, 2008).

The standard ABC, being good at exploration only is one of its limitations as it tends to converge slower on any unimodal functions (Karaboga and Akay, 2009) due to its incapability to robustly search the search space to find the global optimum. On the other hand, as it is good at exploration, it becomes poor at exploitation, making it prematurely converges towards local minima of multimodal functions as it has improper guidance towards the global optimum. In addition, it has slower convergence. Theoretically, one of the key success of a robust optimization algorithm is how balanced its exploration and exploitation capabilities are. Exploration process basically is the ability of an algorithm to search and examine various unknown space to obtain an optimal solution while exploitation process refers to the ability of

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the algorithm to make use of previous knowledge of good solutions and relate and apply the information to find the optimal solution (Gao and Liu, 2012).

The most critical problem faced by ABC is mainly caused by its mutation equation. Its mutation equation only make used of self and neighbor solutions, thus making it good at exploration but poor at exploitation (Gao et al., 2012; Gao and Liu, 2012; Zhu and Kwong, 2010). The other problem faced by ABC is that it also portrays extreme self-reinforcement that makes ABC exhibits less capabilities in exploitation.

To overcome the aforementioned problems, a number of ABC variants with few modifications to the standard ABC have been developed. To mention a few, they are enhanced probability-selection ABC (EPS-ABC) (Abro and Mohamad-Saleh, 2014), modified ABC variant (JA-ABC3) (Sulaiman et al., 2015a), new enhanced ABC (JA-ABC5) (Sulaiman et al., 2015b), ABC with memory (ABCM) (Li and Yang, 2016), ABC rate of change (ABC-ROC) (Anuar et al., 2016), improved ABC (IABC) (Gao et al., 2016), robust modified ABC variant (JA-ABC5b) (Sulaiman et al., 2016) and many others.

Nevertheless, almost all existing variants do not have the capability to simultaneously solve the problems. Hence, hybrid or memetic solutions have been proposed. Such solutions generate robust optimization algorithms with balanced exploration and exploitation processes by combining the strength of evolutionary algorithms (EAs) operators with local search techniques (Krasnogor and Smith, 2005). Various hybrid algorithms such as genetic local searchers (Merz, 2000), hybrid GAs (Yew-Soon and Keane, 2004; Jaddi and Abdullah, 2013), hybrid ABC and DE (Zorarpaci and Ozel, 2016) and many others have shown to be able to solve a wide range of optimization problems efficiently compared to the global or local search alone (Kang et al., 2013, 2011; Pandey and Kumar, 2013; Tien and Li, 2012; Yildiz, 2013).

Inspired by the powerful performance of the existing hybrid algorithms, the hybridizations of ABC with local search techniques have become an attractive area of research. The development of these techniques can be observed in the works of Kang et al. (2011), Tien and Li (2012), Kang et al. (2013), Pandey and Kumar (2013) and Yildiz (2013). Their works have shown efficiencies of proposed hybrid algorithms as robust optimization algorithms outperforming other kinds of optimization algorithms. Nonetheless, there are in fact challenges faced by the researchers regarding hybrid algorithms. The challenges are on how the selected global search techniques affect the performance of hybrid algorithms and their universality to solve diverse real-world applications (Wang et al., 2013). Moreover, few of the existing memetic ABC algorithms have been found to converge slower and are computationally intensive (Kang et al., 2013, 2011, 2009; Tien and Li, 2012; Yildiz, 2013).

Based on the above-mentioned facts, a hybrid optimization algorithm which hybridizes an ABC variant with a local search technique is proposed to solve the problems faced by the existing variants and hybrid algorithms; slow convergence rates, prone to local minima traps and computationally intensive.

In this study, a recently modified ABC variant referred to as JA-ABC3 is employed, owing to its simplicity attribute besides portraying excellent performance than other variants including the global best ABC (BABC1), improved ABC (IABC), enhanced ABC (EABC) as well as the standard ABC as shown in the work of (Sulaiman et al., 2015a).

This paper is organized into four sections. A review on JA-ABC3 and EGS local search technique is presented in Section 2. In Section 3, the proposed hybrid optimization algorithm is explained in detail. To assess the robustness of the proposed hybrid algorithm, a series of experiments is conducted using various benchmark functions and the obtained results and discussions are presented in Section 4. In Section 5, a description regarding EED is explained and the results and analysis are presented. Lastly, conclusion and suggestions for future research work are presented in Section 6.

2. Background

2.1. Standard artificial bee colony (ABC) algorithm

By mimicking the foraging behavior of honeybees, Karaboga proposed artificial bee colony (ABC) algorithm in 2005. ABC consists of five phases which are initialization, employed-bees, onlooker-bees, scout-bees and termination phases.

First, during initialization phase, food sources, which represent the possible solutions are being randomly initialized. The number of food sources to be initialized (i.e. *FoodNumber*) is based on the parameter *population-size* which is half of the size. Then, the food sources are randomly assigned to the employed-bees around the hive. After the assignment, the nectar amounts which are the fitness values of each of the food sources is calculated. Next, in the employed-bees phase, the neighborhood of food sources associated with the employed-bees is explored using the following mutation equation (Karaboga and Akay, 2009).

$$z_{ij} = y_{ij} + \phi_{ij}\left(y_{ij} - y_{kj}\right) \tag{1}$$

where z_{ij} is the new candidate solution of new food sources, y_{ij} is the food source to be updated, y_{kj} is the neighborhood food source and ϕ_{ij} is the random numbers in the range $[-1, 1]$.

The equation suggests that the new candidate solution is being updated based on the values of the food source itself and randomly chosen food source. Then, greedy-selection mechanism is employed to select the best food sources between the candidate solution and the old food source y_i. The best food source among them (i.e. fitter fitness value) is called potential fitter food source. This potentially fitter food sources are then shared with onlooker-bees in the onlooker-bees phase.

The onlooker-bees do not update all potential food sources shared by the employed-bees. The onlooker-bees use fitness-proportion selection scheme to further select the potential food sources to be updated. Greedy-selection is also applied to choose the best food source between the potential food source and the updated one. This food source is called best-so-far food source the current generation and is memorized.

In the scout-bee phase, the scout-bee is the employed-bee who's its food source does not show improvement over a certain number of preset generations called *limit*. Thus, its food source is to be abandoned (Zhu and Kwong, 2010). The scout-bee will explore search space randomly for discovering a new food source. The replacement of the abandoned food source with the new one is essential in order to balance out the number of food source in the population (Karaboga and Akay, 2009).

Lastly, in the termination phase the termination criterion, *maximum-generations* is checked whether to repeat or terminate the algorithm's processes. More details on the standard ABC algorithm can be found in (Karaboga, 2005; Karaboga and Akay, 2009).

2.2. Modified ABC variant (JA-ABC3)

JA-ABC3 is an ABC variant proposed by Sulaiman et al. in 2015. Since its introduction, it had very well improved the performance of the standard ABC algorithm (Sulaiman et al., 2015a) as illustrated in their work. JA-ABC3 is developed through some modifications to the standard ABC. JA-ABC3 procedures are given as follows:

Step 1: Initialize food sources randomly
Step 2: Calculate fitness of each of the food sources
Step 3: *Identify a percentage of poor food sources*
Step 4: *Update the poor sources around global best food source*

$$z_{ij} = y_{best,j} + \varphi_{ij}\left(y_{pj} - y_{kj}\right)$$

Step 5: *Explore for neighborhood of all food sources assigned to employed-bees randomly using modified mutation equation*

$$z_{ij} = y_{kj} + \varphi_{ij}\left(y_{ij} - y_{pj}\right)$$