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Review on bio-inspired algorithms approach to solve assembly line balancing problem

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Abstract. Bio-inspired algorithms that have been introduced by mimicking the biological phenomenon of nature have widely implemented to cater various real-world problems. As example, memetic algorithm, EGSJAABC3 is applied for economic environmental dispatch (EED) optimization, Hybrid Pareto Grey Wolf Optimization to minimize emission of noise and carbon in U-shaped robotic assembly line and Polar Bear Optimization to optimize heat production. The results obtained from their research have clearly portrayed the robustness of bio-inspired algorithms to cater complex problems. This paper highlights the efficiencies of bio-inspired algorithms implemented to cater problem relate to assembly line balancing. This kind of problem is very crucial to counter since it involves minimizing the time of the machines and operators or cost that required optimal task distribution. The outcome of this paper shows the effectiveness of bio-inspired algorithms in solving assembly line balancing problem compared to traditional method.

1. Introduction

Bio-inspired algorithms (BIAs) are approaches that have been developed based on the biological phenomenon of nature [1]. BIAs can be categorized as metaheuristic method and swarm-intelligence-based (SI) algorithms are among the most prominent classes in BIAs classes. This is because they have been discovered the exhibit the capability to solve various optimization problems including optimizing economic environmental dispatch [2], optimal reactive power dispatch [3] and cutting parameters optimization [4]. With the increasing of the complexity of problems, BIAs seems to be the most effective methods to solve those problems [5]. One of the problem that been meticulously studied by researchers in literature is assembly line problem.

Assembly line, which is normally the last step of production that involves final assembly of the products. An assembly line generally consists of several workstations placed in sequential order. Each of the workstation is in charge to complete certain specific jobs [6]. Hence, it is a must to make the best use of the efficiency of the assembly line by minimizing the time of the operators and machines for each workstation. This is the challenge faced by the researchers in catering the problem as it is a combinatorial problem due to the correlation between each job in each workstation. In other words, the idle time of the operators caused by the different loads in each workstation are to be minimized as well as required optimal task distribution [7].

This paper highlights the implementation of BIAs to cater assembly line problem. The main objective is to analyse the efficiency of BIAs as a problem solver to solve assembly line problem in which later can be used as a guidance for manufacturing companies specifically. The paper is organized into 4 section. Then, few prominent BIAs are highlighted to provide ideas on what is BIAs itself. Section 3 then provide the review on the application of BIAs in solving assembly line problem before concluding remarks are presented in section 4.

2. Bio-Inspired Optimization Algorithms (BIAs)

There are thousands of BIAs that have been established by optimization researchers to solve various optimization problems. The most important element in developing BIAs is to have balanced exploitation and exploration process of the algorithm. Having balanced exploration and exploitation process, it means that the algorithm has the capabilities as a robust algorithm. Among the most prominent BIAs are:

2.1. Ant colony optimization (ACO) algorithm

ACO algorithm was suggested by Dorigo et. al in 1996. ACO is adopted the cooperative communications among ants facilitated by pheromones. Pheromones is an artificial trail that works as a guide for the ants to their destinations. It works by using collective behaviour which means that as the trail is followed by more ants, the trail become attractive to be followed. Besides that, ACO uses constructive greedy heuristic besides having positive feedback and distributed computation [8].

2.2. Particle swarm optimization (PSO) algorithm

The other BIAs is PSO algorithm. PSO has been created by Shi and Eberhart in 1998 is based on the collective behaviour of creatures such as fish schooling or birds flocking. The creatures or call as particles fly or swarm in the population with the aim to reach the optimum position and velocity. The algorithm works in a sequence. First, within the search space, the fitness of each particle is being evaluated. Then, the algorithm updates the individual and global-best particle in the population. Lastly, the velocity and positions each particle is being updated [9].

2.3. Artificial bee colony (ABC) optimization algorithm

ABC was being introduced by Karaboga in 2005. This algorithm adopted the foraging behaviour of honey bees. There are three types of bees in the population which are employed-bees, onlooker-bees and scout-bee. Employed-bees and scout-bee are in charge with the exploration process while onlooker-bees are in charge with the exploitation process. In other words, ABC is possessing both exploration and exploitation capabilities. First, after initialization, each employed-bees have been assigned with food sources that represent the potential solutions. Then, the employed-bees shared the fitness values information of each of the food source with the onlooker-bees in the hive through waggle dance as a medium of communication. Onlooker-bees select only the best-so-far food source for further exploring to find the best food source. Then, the food source that cannot be updated through predetermined time, its respective employer-bee will be abandoned. New bee will be recruited to replace the abandoned employed-bees prior to stabilize the number of the population. The new bee is referred as scout-bee [10].

2.4. Raven roosting optimization (RRO) algorithm

RRO algorithm has been proposed by Brabazon et al. in 2016. This global search algorithm was stimulated from the foraging and social roosting behaviour of raven. Generally, ravens live and socialize in groups of 200 to ten thousand during the non-breeding seasons called roost. Hence, they interacted among each other to perform task like foraging for food sources [11]. The algorithm starts with random selection of a roost in the search space. Then, the fitness value of the position of each raven is calculated after each population of the members is being placed randomly in the search space. Next, the raven with the finest solution is selected as leader. After the selection, a portion of the population follows the leader to gain the food source while the others take a flight to their best-so-far personal position to forage. In each cycle, raven will stop its flight at the location that is better location than the current best position's bird, and forage. The processes of evaluating and updating the location are continued until the stopping criterion is met [12].

2.5. Modified ABC variant (JA-ABC5) algorithm
Another example of optimization algorithm is modified artificial bee colony (ABC) named as JA-ABC5. JA-ABC5 is introduced by Sulaiman *et. al* in 2015. Basically, JA-ABC5 is the extended and modified version of two other ABC; JA-ABC3 [13] and JA-ABC4b [14]. There are four modifications that have been implemented into the standard ABC algorithm. The first modification happens after initialization phase which is the insertion of new stages, aimed to improve the exploitation process of the algorithm by improving the average fitness of the population. The first stage identifies few poor food sources and update the poor food sources around global-best food source. The process has improved the exploitation capability of the algorithm. This is because the recent population now consist of fitter food sources. Also, the random selection of food sources has created diverse population as well [15].

3. BIAs Approach in Assembly Line Balancing Problem
There are not many BIAs found in the literature that have been applied to particularly solve assembly line problem. Most of researchers are fond to use other methods to solve the problem such as exact methods [16][17], constraint programming [18], goal programming and many others. One of the example is the application of bees algorithm (BA) and ABC algorithm to solve one type of assembly line balancing problem by Tapkan et. al in 2016. In their research, they have introduced assembly line balancing problem with parallel two-sided that associates the strength of two-sided and parallel and lines. Besides that, they have also included walking times that is necessary to be considered when involving large assembly line system. This is because the larger the assembly system, the longer the walking distances between each production line. In the end, they have concluded that both BA and ABC algorithm have shown better performance than other existing optimization algorithms which is Tabu search algorithm [19].

Another example is the implementation of PSO algorithm in robotic assembly line balancing problems by Janardhanan *et. al* in 2017. In their research, their objective is to minimize the cycle time. PSO has been applied to solve two configurations of robotic assembly line which are straight and U-shaped configurations. PSO has shown excellent performance in computational time in comparison to other algorithms [20].

The other example is the implementation of hybrid algorithm based on genetic algorithm to solve cost-oriented robotic assembly line problem (cRALBP) by Pereira *et. al* in 2018. In their research, they are more focusing on cost-oriented assembly line problem. They have proposed a hybrid algorithm to cater two case studies. For the first case study, the memetic algorithm is able to create feasible solution to the problem by encoding individuals as ordered lists of tasks. For the other case study, the method gives suggestion for an effective local search technique and give guidance on the strong NP-hardness of a number of assembly line balancing problems [21].

Besides that, in 2018, Babazadeh *et. al* have introduced an algorithm called as an enhanced non-dominated sorting genetic algorithm II (NSGA II) to cater straight and U-shaped assembly line balancing problems. Before applying the algorithm to solve the problem, they have tested the algorithm on several benchmark functions. The obtained results have clearly portrayed the excellent performance of the algorithm in comparison to others. Later, after implementing the algorithm on the straight and U-shaped assembly line balancing problems, they have concluded that their proposed algorithm has shown the capability in dealing with the problem that consists of several conflicting objective functions. Lastly, they have mentioned the gap that can be fulfilled by other researchers which is to apply the algorithm to solve problem with high complexity such as mixed-model assembly line balancing problem since they are more focusing on single-model [22].

Later, in 2019, Şahin and Kellegöz have developed a new hybrid method for multi-manned workstations that involved solving a resource constrained assembly line problem. The new hybrid method, which is the hybridization of PSO with a special constructive heuristic has been used for that purpose and it is being compared with tabu search and cuckoo search algorithm. Lastly, they have concluded that their proposed hybrid BIAs are able to produce results that have acceptable deviations from the lower bounds [23].

Then, in 2019 as well, Zhang *et. al* have designed hybrid pareto grey wolf optimization (HPGWO) algorithm to solve assembly line problem that having multi-objective because it involves with minimizing cycle time, noise and carbon emission. They have also compared the performance of their designed BIAs with other five algorithms. The results showed their proposed algorithm is able to achieve promising results in minimizing cycle time and noise and carbon emission [24].

4. Conclusion

Based on the above review, it can be concluded that, although there are not many literatures found regarding the implementation of BIAs in solving assembly line problem, the efficiency of the BIAs in solving the problems tremendously show a good sign that BIAs is perfect choice as the problem solver. Hence, more study on the applications of BIAs to optimize assembly line balancing problem should be conducted to further analyze and prove the effectiveness of BIAs as the best method at solving assembly line balancing problem.

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