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Enhanced Artificial Bee Colony with Savings Algorithm for Inventory Routing Problem

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ABSTRACT

Inventory Routing Problem (IRP) is a critical component of Supply Chain Management, where it is a coordination of inventory management and transportation. It aims to balance the trade-off between transportation costs for delivering products and holding costs for maintaining inventory. Several real-world problems faced nowadays require effective optimization and logistical solutions, where this problem arises in various industries and has become increasingly complex. The problem addressed in this study is based on an automotive parts supply chain that consists of a depot, an assembly plant, a set of homogeneous capacitated vehicles, and multi-suppliers on a finite horizon with multi-periods. Artificial Bee Colony (ABC) is a swarm intelligence algorithm that is based on the behaviour of bees in a colony, where information is shared through waggle dance. ABC consists of three phases, which are employed bee phase, onlooker bee phase, and scout bee phase. This study proposed an enhancement in the initialization phase and in onlooker bee phase of the ABC algorithm. Clarke Wright savings algorithm was implemented in the initialization phase to determine the best feasible delivery routes while minimizing the total transportation cost. 2-opt and 2-opt were used to improve the routes in the onlooker bee phase. Results showed that 7 better total cost were found out of 14 benchmark datasets when compared to the previous literature. The enhanced ABC algorithm obtained better results with 5.59% at most, which demonstrated the effectiveness of the algorithm.*

Keywords: Artificial Bee Colony, Clarke Wright Savings Algorithm, Inventory Routing Problem

1 INTRODUCTION

An efficient distribution network is critical for Supply Chain Management (SCM) as it enables cost minimization and enhances overall productivity [1]. The activities of SCM include purchasing, production and scheduling, marketing, location, transportation, and inventory control [2]. SCM is defined as strategically coordinating these activities to improve long-term performance [3]. The

Inventory Routing Problem (IRP) is a variation of the Vehicle Routing Problem (VRP), which coordinates two activities of SCM, inventory and transportation. The decision of inventory and routing management must be optimized at the same time to improve the performance of the system [4]. The IRP involves finding the optimal solution among many possible combinations of routes and inventory levels, which becomes computationally exhaustive as the problem size increases. Routing or transportation is the heart of the IRP, which enables the movement of goods and ensures product availability. The transportation cost contributes a significantly large amount to the logistics. Hence, optimizing transportation will yield significant savings.

Many optimization algorithms successfully demonstrated the effectiveness of metaheuristics in approximate solutions of IRP such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing, and Artificial Bee Colony (ABC). The ABC is an algorithm based on a honeybee's swarm's unique behaviour. ABC is a simple and efficient algorithm that is proven to perform better compared to other algorithms [5]. Initially proposed for numerical optimization, the application of ABC has been extended by many researchers to tackle combinatorial optimization problems, for example, the application to Capacitated VRP [6].

The main contribution of this study is in the enhancement of ABC for solving the IRP. A modified Clarke Wright savings algorithm was proposed to generate better sequences. As the IRP was constrained by vehicle capacity, the modification of savings is designed to ensure that the suppliers will be assigned to a new route once capacity is full. This study is organized as follows. The following section explore the literature focussed on enhancing and modifying existing algorithm. The IRP is described in the next section followed by the solution methodology proposed, enhanced ABC. Then, results and throughout discussion were presented, and the last section conclude our work.

2 LITERATURE

Artificial Bee Colony (ABC) has gain significant interests especially in solving combinatorial optimization problems due to its flexibility [7] and simplicity. There are various combinatorial problems successfully proposed ABC as their solution strategies, for example assembly line productions, DNA sequencing and modelling, network problems and routing problem [8]. However, it is known that many combinatorial optimization problems are NP-hard, which often results in ineffective polynomial-time solutions.

Despite the promising results shown by ABC algorithm in addressing various optimization problems [5], it does have drawbacks including convergence especially in larger and complex problems [9], [10] getting trapped in local optimal, lack of diversity in the population [11], limited scalability results in less effective search as the problem size increases and lack of theoretical foundations which makes it difficult to understand and analyse the behaviour of the algorithm [12]. Hence, enhancement and modification of the algorithm is usually proposed to overcome these weaknesses and improve its performance.

Enhancements of an algorithm are proposed mainly to improve efficiency and effectiveness of an algorithm. There are instances where the basic algorithm struggles to handle larger datasets and complex problems that involve strict constraints. As the problem size increase, the performance of ABC deteriorates gradually [13]. This is critical as most real problems involved large datasets and time sensitive. Hence, embedding a fast local heuristic helps in decrease computational time. Another concern of inefficiency is in the accuracy of results in especially in forecasting, where small errors could cause serious consequences.

There are few techniques of enhancements. Among them are hybridizing two algorithms, or by modifying/adding phases, and operators of an algorithm, and combining mathematical formulation with metaheuristic algorithm, named *Mat-heuristic* [14]. [15] utilize the qualities of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) by hybridizing both algorithms to solve benchmark problem. A set of rules derived from the analysis of swarm intelligence was used inside the GA. Results showed to be robust and effective. Similarly, studies by [16] on global optimization, [17] on location and sizing distribution, [18] enhanced GA by adaptive mutation operator, [19] on embedded feature selection for hyperspectral image analysis, a fully informed PSO presented by [20] for multi-mode resource-constrained project scheduling problem, and [21]on finding optimal reactive power flow.

Different combinations of metaheuristic have also been done. For instance, [22] hybridized Variable Neighbourhood Search (VNS) with simulation for the Stochastic Inventory Routing Problem, achieving rapid solutions compared to previous studies. [23] presented reduced computational time results by combining VNS with GA for the Profitable VRP with Cross-Docking.

In the context of the VRP, researchers have made enhancements to improve the accuracy of the basic algorithms. [24] enhanced Clarke Wright savings algorithm (or savings algorithm in short) for VRP by considering the combination of distance and customer demand. They obtained fast results with 5.23% improved accuracy. [25] then further improved the solution quality in [24] by proposing a robust enhancement to the savings formulation by implementing a three-parameter savings function. The enhancement is aimed to merge customers with both small and large demand in the same route to reduce capacity losses.

[26] studied Capacitated VRP and proposed enhanced savings algorithm in terms of route post-improvement and tested the algorithm on 90 benchmark datasets. Out of the 90 datasets, 76 has shown optimal results indicating a percentage of 84% and a small deviation of 0.049%. Research by [27] enhanced the savings algorithm by implementing a *stop assignment procedure*, inter-route improvements similar to [28]. Superior results were obtained when implemented to real-life problems compared to the basic savings algorithm. Also, [29] solved real-world problem with lower number of vehicles and 30.57% distance savings.

Pre-seeding in the initialization, [30] improved the ABC to accelerate convergence speed and to avoid the local optima, where they were inspired by previous authors such as [31], [32], [33], [34], and [35]. By introducing a new initialization approach and a novel search mechanism, [30] were able to show high performance in accuracy and the proposed algorithm could be used for complex numerical optimization problems.

Recently, [36] enhanced ABC to solve multi-products IRP that focused on balancing the exploration and exploitation process, where the study was able to give an average of 2.25% improvement to the results. However, vehicle utilization can be further improved, which will have a direct impact on the distance. Previous literatures have proved that an enhancement is required to further improve the results from benchmark datasets. Motivated by the literature, an enhancement of ABC is proposed in this study that focuses on route improvement to obtain more efficient routes.

3 PROBLEM DESCRIPTION

This study considered an IRP with multi-periods and multi-products. The network is a many-to-one distribution network defined on a finite planning horizon that comprises of a depot, an assembly plant, and N suppliers each supplying a distinct product. A set of homogeneous capacitated vehicles available at depot travels and starts collecting products from suppliers to the assembly plant and return to the depot. The assumptions include no backordering, immediate product availability when vehicle arrival, variable demand over time (which can be zero), unlimited vehicles, and subject to vehicle capacity constraint.

If collection is more than demand, the excess inventory incurs product-specific holding costs at the assembly plant. It is also assumed that there are no storage limitations at the assembly plant. The objective of this study is to provide the optimal collection strategy that minimizes the total cost, which includes the inventory cost and transportation cost. The mathematical formulation of the IRP in this is based on a previously literature [37] with a modification made to ensure a supplier cannot be visited by more than one vehicle.

4 METHODOLOGY

This study implemented a metaheuristic method, ABC, for the problem. The ABC consists of three phases, which are employed bee phase, onlooker bee phase, and scout bee phase. In the employed bees, a mechanism to update inventories was implemented where deliveries were transferred between periods to increase/decrease the inventories and balance with the routing part. Employed bees then shared the information of the beneficial food source with the onlooker bees through waggle dance. The onlooker bees will decide which employed bees to follow based on the nectar values. The onlooker bees will exploit the same food source. The value of food source will be improved according to the control parameters decided and if the value is not improved after the pre-determined number of iterations, the employed bee assigned will abandon the food source, and become a scout bee. It will then begin to search for new food source.

An enhancement of the ABC that targeted on routing part of IRP was proposed in this study. The enhanced algorithm is denoted as ABCSA. The enhancement was done in the initialization phase and in the onlooker bee phase. A construction heuristic, Clarke Wright savings algorithm is utilized in the initialization phase to generate a feasible route that minimizes distance. This algorithm calculates the savings achieved by combining two suppliers, i and j into a single route, based on a distance matrix. The savings values between the suppliers, denoted as s_{ij}, are then sorted in descending order [38]. The routing process begins by selecting the top value from the savings list, which corresponds to the highest savings. If the total demand collected does not exceed the vehicle capacity and there are no route constraints, the route for both suppliers will be combined into a single route. As the IRP considered is constrained by vehicle capacity, the savings algorithm is modified to ensure feasible solution. The capacity of the vehicle is determined concurrently while building the routes using savings algorithm. The ABCSA described is presented by flow chart in Figure 1.

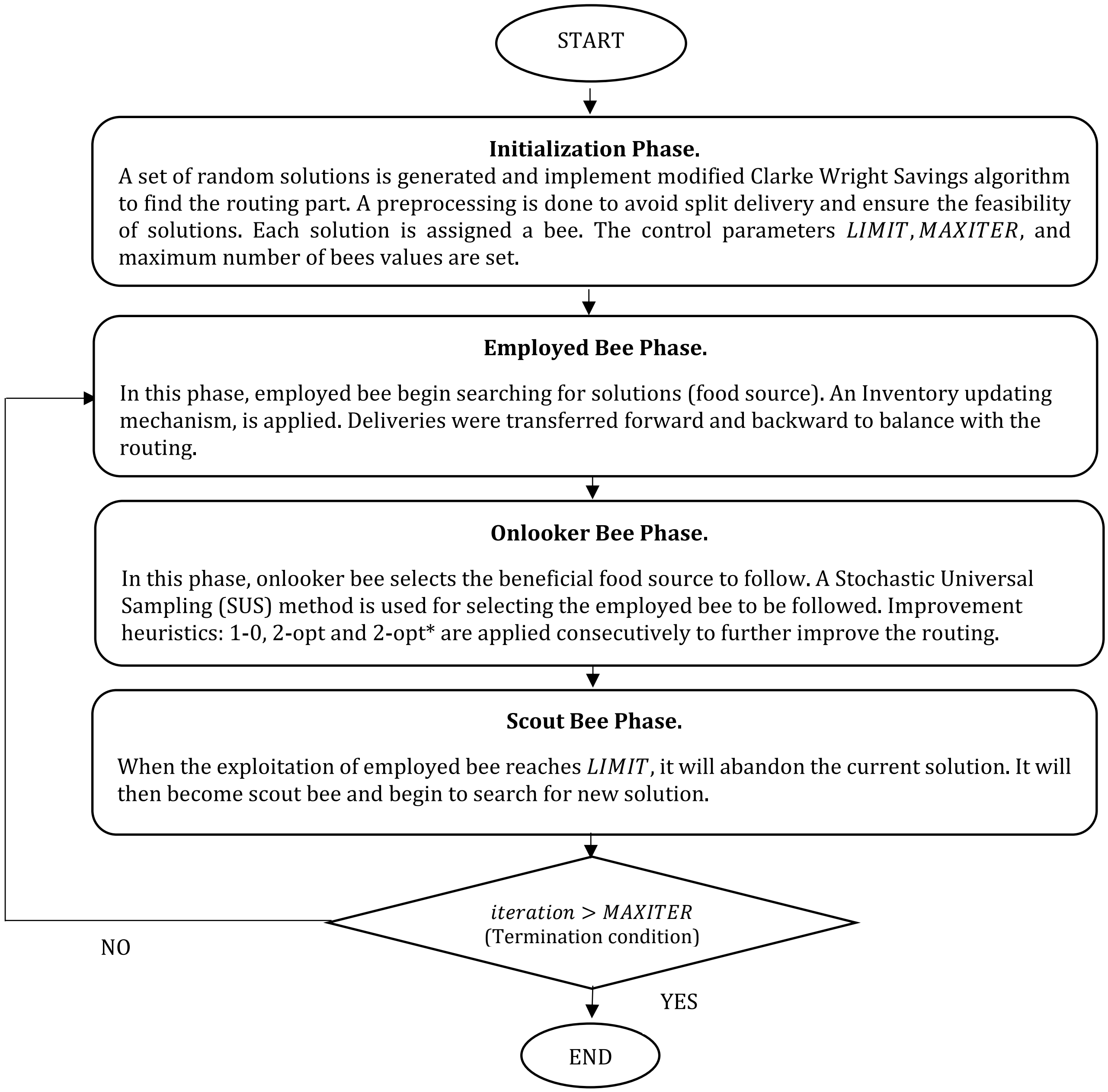

Figure 1: Flowchart of ABCSA

In addition to the embedded $1-0$ swap and $2-opt$, an inter vehicle heuristic, $2-opt^*$ was employed in the onlooker bee phase. The $2-opt^*$ finds better routes by swapping suppliers between two different vehicles. This is done exhaustively for all vehicles within the same period and eventually collapses vehicle. As a trade-off, the ABCSA took longer time to run. Therefore, similarly to the previous literature, ABCSA is terminated after 3600 seconds even though the maximum number of iterations, $MAXITER$ have not reach the predetermined value 250.

5 RESULTS AND DISCUSSIONS

The performance of the Artificial Bee Colony enhanced with Savings algorithm (ABCSA) developed was tested on a benchmark dataset [36]. The dataset consists of various combinations of suppliers and periods. Each dataset is enumerated by Sx Ty such that S indicates supplier and T is period/time. x takes on the values of 12, 20, 50, and 98, while y takes on the values of 5, 10, 14, and 21. For instance, S20T5 refers to a dataset with 20 suppliers and 5 periods. It should be noted that the datasets for S12 and S98 are limited to a maximum of 14 periods. The ABCSA was run on 16GB of RAM computer and 3.6GHz. The enhanced algorithm is coded in MATLAB 2020a.

The ABCSA was set to run 10 independent runs until optimality based on pre-determined values of control parameters. For comparison purposes, the bee population is set at 50 (25 employed bees and 25 onlooker bees) following the previous literature, The control parameters, LIMIT, and maximum number of iterations (MAXITER) are set at 25×maximum supplier and 250 respectively. Table 1 tabulates the best costs and the percentage difference (%Δ) between the ABCSA and [36]. Note that previous literature embedded the Giant Tour procedure in the initialization phase. The best solution of both algorithms is given in bold. The ABCSA works better for medium size dataset (S20 and S50) with 7 better results out of the 14 datasets tested. In average, the ABCSA performs slightly better by 0.31% indicating the effectiveness of the algorithm developed.

Table 1: Best costs and number of vehicles

Dataset	**ABCSA**	**#veh**	**[36]**	**#veh**	**%Δ**
S12 T5	1983.95	15	**1961.71**	*14*	1.13
S12 T10	4313.05	33	**4012.65**	*29*	7.49
S12 T14	6072.54	44	**5645.57**	*41*	7.56
S20 T5	3004.78	23	**2987.73**	*22*	0.57
S20 T10	**5923.64**	*43*	6221.23	46	-4.78
S20 T14	**8678.69**	69	8751.05	*65*	-0.83
S20 T21	**13142.67**	100	13233.06	*97*	-0.68
S50 T5	**5134.54**	48	5355.01	*47*	-4.12
S50 T10	**10755.38**	103	11392.59	*101*	-5.59
S50 T14	**15348.97**	146	15600.78	*137*	-1.61
S50 T21	**23364.70**	223	24535.92	*219*	-4.77
S98 T5	587242.88	60	**585854.63**	60	0.24
S98 T10	1174564.37	120	**1165316.11**	*11*9	0.79
S98 T14	1646132.31	168	**1642123.06**	168	0.24
Average					-0.31

It is interesting to note that for S20 and S50 found better solution with a higher number of vehicles, and the maximum vehicle gap is 9 in the medium dataset of S50 T14. Better vehicle number is given in italic. Dataset S50 obtained a better solution with a slightly higher number of vehicles, which indicates that the routing sequences found by savings algorithm are better in distances. Note that previous literature focused on reducing the number of vehicles while ABCSA saved distances.

The average of cost, inventory, transportation costs and standard deviation were tabulated in Table 2. The S50 and S12 dataset (T5 and T10) consistently perform well based on the standard deviation. Furthermore, the transportation cost has a significant impact on the overall cost, indicating that maintaining excessive inventory is not beneficial according to the distribution strategy of ABCSA.

Table 2: Average costs, inventory, transportation, and standard deviation

Dataset	**Total Cost**	**Inventory**	**Transportation**	**Standard Deviation**
S12 T5	2043.83	102.60	1941.23	37.47
S12 T10	4387.31	124.20	4268.11	48.40
S12 T14	6234.43	314.40	5920.63	136.81
S20 T5	3096.59	91.80	3004.79	46.68
S20 T10	6247.88	468.00	5779.88	260.69
S20 T14	8885.39	308.70	8576.69	266.64
S20 T21	13419.92	309.30	13110.62	223.96
S50 T5	5158.49	34.00	5124.49	19.06
S50 T10	10798.34	50.80	10747.54	32.29
S50 T14	15441.37	89.00	15352.37	142.85
S50 T21	23703.83	413.60	23290.23	242.69
S98 T5	594537.41	6456.52	588080.89	7402.06
S98 T10	1179839.47	2613.27	1177226.20	11105.87
S98 T14	1683271.42	26958.82	1656312.60	39106.71

Table 3 tabulates the average running time in seconds for both algorithms. It is observed that S50 and S98 make use of the second termination condition, which is in 1 hour. It is worth noting that both algorithms run on different specifications of computer.

Table 3: Average running time in seconds

Dataset	**ABCSA**	**[36]**
S12 T5	252.71	242.95
S12 T10	459.90	432.53
S12 T14	641.05	590.77
S20 T5	788.40	1466.77
S20 T10	1478.36	1399.13
S20 T14	2065.21	1906.02
S20 T21	3114.63	2849.31
S50 T5	3600.00	3600.00
S50 T10	3600.00	3600.00
S50 T14	3600.00	3600.00
S50 T21	3600.00	3600.00
S98 T5	3600.00	3600.00
S98 T10	3600.00	3600.00
S98 T14	3600.00	3600.00

6 CONCLUSION AND RECOMMENDATIONS

An Artificial Bee Colony enhanced with Clarke Wright savings algorithm (ABCSA) is proposed for solving the inventory routing problem (IRP). The enhancement was made targeting to improve the routing part; hence savings algorithm was implemented in the initialization phase while 2-opt* and 2-opt in the onlooker bee phase. ABCSA performed well in medium dataset, with 7 better solutions compared to previous literature. ABCSA showed significant improvement of at most 5.59% and 0.31% on average, in expense of computational time. It is interesting to emphasize that ABCSA found solutions with lower distance but higher number of vehicles. This indicates the capability of savings algorithm in finding efficient routes. Future works can explore IRP as a multi-objective and embedding a fast algorithm to reduce the computational time.

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