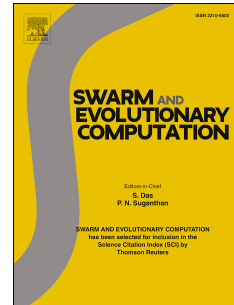# Accepted Manuscript

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An Artificial Bee Colony Algorithm with a Modified Choice Function for the Traveling Salesman Problem

Shin Siang Choong [a], Li-Pei Wong [b,*], Chee Peng Lim [c]

[a, b] *School of Computer Sciences, Universiti Sains Malaysia, Malaysia*
[c,] *Institute for Intelligent Systems Research and Innovation, Deakin University, Australia*

[a] css15_com047@student.usm.my, [b] lpwong@usm.my, [c] chee.lim@deakin.edu.au

Abstract

The Artificial Bee Colony (ABC) algorithm is a swarm intelligence approach which has initially been proposed to solve optimisation of mathematical test functions with a unique neighbourhood search mechanism. This neighbourhood search mechanism could not be directly applied to combinatorial discrete optimisation problems. In order to tackle combinatorial discrete optimisation problems, the employed and onlooker bees need to be equipped with problem-specific perturbative heuristics. However, a large variety of problem-specific heuristics are available, and it is not an easy task to select an appropriate heuristic for a specific problem. In this paper, a hyper-heuristic method, namely a Modified Choice Function (MCF), is applied such that it can regulate the selection of the neighbourhood search heuristics adopted by the employed and onlooker bees automatically. The Lin-Kernighan (LK) local search strategy is integrated to improve the performance of the proposed model. To demonstrate the effectiveness of the proposed model, 64 Traveling Salesman Problem (TSP) instances available in TSPLIB are evaluated. On average, the proposed model solves the 64 instances to 0.055% from the known optimum within approximately 2.7 minutes. A performance comparison with other state-of-the-art algorithms further indicates the effectiveness of the proposed model.

Keywords: hyper-heuristic; metaheuristic; bee algorithm; combinatorial optimisation problem; neighbourhood search; Lin-Kernighan.

1. Introduction

A computational optimisation methodology involves finding feasible solutions from a finite set of solutions, and identifying only the optimal solution(s). Swarm intelligence algorithms constitute a sub-class of computational optimisation methodology [1]. Swarm intelligence algorithms are developed based on emergence of collective behaviours pertaining to a population of interacting individuals in adapting to the local and/or global environments. Examples of swarm intelligence algorithms include Particle Swarm

* Corresponding author. Tel.: +604-6534751
E-mail address: lpwong@usm.my

Optimisation (PSO) [2], Ant Colony Optimisation (ACO) [3], Bat Algorithm (BA) [4], Firefly Algorithm (FA) [5], Cuckoo Search Algorithm (CSA) [6], and bee-inspired algorithms [7-9].

Bees are highly organised social insects. Their survival relies on assigning an important task to each bee in a cooperative mode. The tasks include reproduction, foraging, and constructing hive. Within these tasks, foraging is one of the most important tasks, because the bee colony must ensure an undisrupted supply of food to survive. The food foraging behaviours of bees can be computationally realised as algorithmic tools to solve various optimisation problems.

The Artificial Bee Colony (ABC) algorithm is one of the popular bee-inspired algorithms. Proposed by Karaboga [7], it is inspired by the foraging behaviours of honey bees in a colony. In the ABC algorithm, a food source represents a possible solution to the optimisation problem in the search space, and the nectar amount of the food source represents the fitness of that solution. The ABC algorithm defines three types of bees: employed bees, onlooker bees, and scout bees. An employed bee looks for new food sources around the neighbourhood of the food source that it has previously visited. An onlooker bee observes dances and selects a food source to visit. It tends to select good food sources from those found by the employed bees. A scout bee searches for new food sources randomly.

The mechanism of the ABC algorithm is as follows. The employed bees first perform a neighbourhood search nearby the food source in their memory (i.e. solution). Then, they go back to the hive and perform dances. The dances inform the onlooker bees about the fitness of each solution. Each onlooker bee observes and selects a food source to perform another neighbourhood search based on a probability proportional to the food source fitness (i.e. a roulette wheel selection). The onlooker bees tend to select good food sources from those found by the employed bees. The employed and onlooker bees perform neighbourhood search by perturbing an existing solution to produce a new solution. A greedy approach is applied to decide whether to accept the newly perturbed solution. If a solution could not be improved after a pre-determined number of trails (denoted as the *limit*), it is abandoned. The employed bee associated to that non-improving solution (i.e. local optimum) is abandoned, and it becomes a scout bee. The scout bee explores the search space at random and looks for a new solution.

This ABC algorithm has been used to solve optimisation of mathematical test functions [7]. Promising results have been reported by using a number of ABC variants [10-12]. To find the optimum solution of the mathematical test functions, the neighbourhood search performed by the employed and onlooker bees is formulated as follows (Eq. (1)):

$$v_{ij} = x_{ij} + \phi \ (x_{ij} - x_{kj}) \tag{1}$$

in which x_i is the solution associated to the i-th employed bee, x_{ij} is j-th element (i.e. dimension) of solution x_i, v_i is the new solution produced based on x_i, v_{ij} is j-th element of solution v_i, j is a random integer between 1 and dim (the dimensionality of the problem), ϕ is a random real number between -1 and 1, and k is a random integer between 1 and n (the number of employed bees).

In recent years, the ABC algorithm has been modified to solve combinatorial discrete optimisation problems, such as quadratic assignment problem [13], p-median problem [14-16], minimum spanning tree problem [17-19], clustering problem [20-22], uncapacitated facility location problem [23-25], Knapsack Problem (KP) [26-28], Job Shop Scheduling Problem (JSSP) [29-31], Vehicle Routing Problem (VRP) [32, 33], and Traveling Salesman Problem (TSP) [34, 35]. However, Eq. (1) cannot be directly applied when solving this set of problems. The employed and onlooker bees are prescribed with a perturbative heuristic (or a set of perturbative heuristics) to generate new solutions. These heuristics are problem-specific, for instance, the neighbourhood search heuristics for TSP include insertion mutation, swap mutation, random 2-opt, etc. In view of the availability of a large variety of problem-specific heuristics, the key question concerning the selection of a particular heuristic has been posed in the literature in recent years. This leads to the motivation of using hyper-heuristics for tackling such problem, which is the focus of our research in improving the ABC

algorithm.

A hyper-heuristic is a high-level automated methodology for selecting or generating a set of heuristics [36]. The term "hyper-heuristic" was coined by Denzinger et al. [37]. There are two main hyper-heuristic categories, i.e. selection hyper-heuristic and generation hyper-heuristic [38]. These two categories can be defined as 'heuristics to select heuristics' and 'heuristics to generate heuristics', respectively [36]. Both selection and generation hyper-heuristics can be further divided into two categories based on the nature of the heuristics to be selected or generated [38], namely either constructive or perturbative hyper-heuristics. A constructive hyper-heuristic incrementally builds a complete solution from scratch. On the other hand, a perturbative hyper-heuristic iteratively improves an existing solution by performing its perturbative mechanisms. The heuristics to be selected or generated in a hyper-heuristic model are known as the low-level heuristics (LLHs).

A typical selection hyper-heuristic model consists of two levels [36]. The low level contains a problem representation, evaluation function(s), and a set of problem specific LLHs. The high level manages which LLH to use for producing a new solution(s), and then decides whether to accept the solution(s). Therefore, the high-level heuristic performs two separate tasks i.e. (i) LLH selection and (ii) move acceptance [39]. The LLH selection method is a strategy to select an appropriate LLH from a set of available alternatives during the search process. The available LLH selection methods include simple random [40], choice function [41-43], tabu search [44], harmony search [45], backtracking search algorithm [46], and a set of reinforcement learning variants [47, 48]. The move acceptance method decides whether to accept the new solution generated by the selected LLH. Examples of move acceptance methods include Only Improvement [49], All Moves [43], Simulated Annealing [50], Late Acceptance [40], and some variants of threshold-based acceptance.

Striking a balance between intensification and diversification is important for a hyper-heuristic [36, 51]. Intensification encourages a hyper-heuristic to focus on the promising LLHs, which leads to a good performance. On the other hand, diversification serves as a forgive-and-forget policy which encourages attempts on those rarely used LLHs. Both intensification and diversification are crucial components as the capability of an LLH varies during different phases of the search process [52, 53]. An LLH with a good performance in one phase should not dominate the subsequent search process, while a poor performance in one phase should not lead to a permanent discrimination of an LLH in the later phases. In this study, an LLH selection method which is based on a choice function, namely the Modified Choice Function (MCF) [42], is integrated with the ABC algorithm. Specifically, MCF is used to select the neighbourhood search heuristic deployed by the employed and onlooker bees. The reason of choosing MCF is because it is able to adaptively control the weights of its intensification and diversification components during different phases of the search process. Besides that, to enhance the performance of the proposed MCF-ABC model, it is integrated with the Lin-Kernighan (LK) local search strategy [54]. The proposed model is denoted as MCF-ABC. It is tested using benchmark TSP instances provided in TSPLIB [55].

This article starts with a description of the related work in Section 2. Section 3 presents the proposed MCF-ABC model. The results and findings including performance comparison are presented in Section 4. Finally, concluding remarks are presented in Section 5.

2. Related Work

This section describes the related work of the study. Section 2.1 focuses on the applications of bee-inspired algorithms to solve TSP (or variants of TSP). Section 2.2 reviews some hyper-heuristic models which are based on a choice function. Section 2.3 introduces some local-search-based strategies for combinatorial optimisation problems.

2.1. Application of the Bee-inspired Algorithms to Solve TSP

TSP is an NP-hard discrete combinatorial optimisation problem [56]. When solving a TSP, the aim is to look for the shortest Hamiltonian path, which is the route that leads a person to visit each location once and only once, and to return to the starting location with the minimum total distance [57]. Suppose that the cities are located in some geometric region that the distances between two cities obey the usual axioms of a distance function of a metric space. TSP can be modeled as an undirected weighted graph. Let $G = (V, E)$ be an undirected weighted complete graph, in which V is a set of n cities ($V = \{v_1, v_2, \ldots, v_n\}$) and E is a set of edges ($E = \{(r, s) : r, s \in V \}$). E is usually associated with a distance matrix, $D = \{d_{r,s}\}$ where $d_{r,s}$ refers to the distance between city r and city s. Let $\prod$ represents all possible permutations of set V. A solution of a TSP is to determine a permutation $\pi \in \prod$, which has the minimum total round trip distance, as shown in Eq. (2), in which $\pi(i) \in V$ indicates the i-th element in π.

$$C_{TSP}(\pi \in \prod) = \sum_{i=1}^{n-1}[d_{\pi(i),\pi(i+1)}] + d_{\pi(n),\pi(1)} \tag{2}$$

A number of swarm intelligence algorithms have been employed to solve TSP, such as PSO [58, 59], ACO [60, 61], FA [62, 63], BA [64, 65], CSA [66, 67], and some hybrid algorithms [68-71]. In this study, we focus on bee-inspired algorithms to solve TSP. A discussion on the application of bee-inspired algorithms to solve TSP or its variants is presented. The associated neighbourhood search heuristic/mechanisms are also highlighted.

Marinakis et al. [72] proposed a Honey Bees Mating Optimisation (HBMO) model to solve TSP. The HBMO model employs a crossover heuristic and an Expanding Neighbourhood Search (ENS) method to perform neighbourhood search. The crossover heuristic is able to identify the common characteristics of the parents, while the ENS method combines multiple local search strategies, i.e. 2-opt, 2.5-opt, and 3-opt.

Wong [73] proposed a Bee Colony Optimisation (BCO) model. In the BCO model [73], a bee performs neighbourhood search on a selected dance (a solution constructed by another bee) based on a Fragmentation State Transition Rule (FSTR). The FSTR technique aids a bee in constructing a feasible solution under the influence of arc fitness and heuristic distance. Besides FSTR, the BCO model is equipped with three other components, i.e. waggle dance mechanism, local search, and pruning strategy. These components are bundled as a generic model [74] to solve multiple combinatorial optimisation problems, such as JSSP [75-77], Sequential Ordering Problem (SOP) [78], symmetric TSP [79-81], and asymmetric TSP [82].

Masutti and de Castro [9] proposed a bee-inspired algorithm known as TSPoptBees to solve TSP. The TSPoptBees model defines three types of bees, i.e. recruiter bees, scout bees, and recruited bees. The recruiter bees recruit other bees to exploit promising areas of the solution search space. Crossover heuristics are used to combine the solution associated with a recruited bee and its recruiter. The scout bees explore the search space by using mutation heuristics on randomly selected solutions from the population. Both the recruited and scout bees utilise a random method to select the heuristics.

Banharnsakun et al. [83] extended the ABC algorithm with a Greedy Subtour Crossover (GSX) heuristic [84] to solve TSP, which is denoted as ABC-GSX. Specifically, GSX is adopted as the neighbourhood search heuristic. In ABC-GSX, the new solutions generated during the neighbourhood search are further improved by using the 2-opt local search heuristic. GSX is able to improve the exploitation process of the ABC algorithm [83].

Karaboga and Gorkemli [85] proposed a combinatorial ABC algorithm to solve TSP. A Greedy Sub-tour Mutation (GSTM) heuristic serves as the neighbourhood search heuristic of the employed and onlooker bees. The resulting algorithm is denoted as ABC-GSTM. ABC-GSTM outperforms eight GA variants with different mutation operators [85].

Akay et al. [86] adopted a neighbour-based 2-opt move and a 2-opt local search in the ABC algorithm. The resulting algorithm is denoted as 2-opt ABC algorithm. During the neighbourhood search, an employed

or onlooker bee first performs a neighbour-based 2-opt move for the current solution. If the neighbour-based 2-opt move is not able to improve the solution, the solution undergoes a 2-opt local search. The experimental results show that the 2-opt ABC algorithm outperforms the 2-opt local search strategy.

Li et al. [87] applied an inner-over operator [88] as the neighbourhood search heuristic in ABC. The inner-over operator is a modified version of the inversion mutation. However, the selection of a sub-sequence to be inverted is related to the population, therefore the operator has some features of the crossover heuristic. The ABC algorithm with the inner-over operator outperforms the Bee Colony Optimisation in [8].

Zhong et al. [89] integrated the ABC algorithm with a threshold-based acceptance method. A new solution update equation and a greedy hybrid operator are proposed as the neighbourhood search mechanism. The new solution adds an edge based on another randomly selected solution to the current one. If the two solutions have a common edge, the edge to be added is formed based on a set of nearest cities. After an edge is added, the neighbour solutions are generated by applying reverse, insert, and swap heuristics. The best among the three solutions serves as the candidate solution. The empirical results show that the ABC algorithm with a threshold-based acceptance method outperforms that with a greedy acceptance.

Kocer and Akca [35] proposed an Improved ABC (IABC) algorithm with a loyalty and a threshold mechanisms to solve TSP. These two mechanisms form a decision making strategy which decides whether a bee serves as a worker or an onlooker. Besides that, a 2-opt local search strategy is integrated to avoid trapping in the local optimum [35].

Kıran et al. [34] analysed the effect of integrating single and multiple neighbourhood search heuristic(s) in a discrete ABC model. The heuristics include Random Swap (RS), Random Insertion (RI), Random Swap of Subsequences (RSS), Random Insertion of Subsequence (RIS), Random Reversing of Subsequence (RRS), Random Reversing Swap of Subsequences (RRSS), and Random Reversing Insertion of Subsequence (RRIS). The experiments in [34] can be divided into two categories. The first category consists of seven ABC models with a single neighbourhood search heuristic. The second category consists of two ABC models with multiple neighbourhood search heuristics (i.e. [RS, RSS, RRSS] and [RI, RIS, RRIS]). When multiple neighbourhood search heuristics are employed, a random selection strategy is applied. The empirical results show that the [RI, RIS, RRIS] model has a better performance on TSP instances with the number of cities ranging between 30 and 101. Comparatively, the RRS model performs better in two TSP instances with 225 and 280 cities.

Besides the classical TSP instances, bee-inspired algorithms have been adopted to solve different TSP variants. Karabulut and Tasgetiren [90] proposed a discrete ABC algorithm for solving the TSP with time windows (TSPTW). TSPTW involves a searching for a path with minimum cost that visits a set of cities once and returns to the starting city within a pre-defined time window (i.e. ready time and due date). A feasible solution of TSPTW requires a visit to each city to be made within the corresponding ready time and due date. A two-phase destruction and construction heuristic is adopted as the neighbourhood search heuristic in the discrete ABC algorithm proposed by Karabulut and Tasgetiren. During the destruction phase, a number of randomly selected cities are removed from the solution. In the construction phase, the NEH insertion heuristic [91] is applied to re-insert the removed cities back into the solution.

Pandiri and Singh [92] adopted the ABC algorithm for solving multiple TSP (MTSP) instances. There are more than one salesperson in an MTSP. The aim is to look for a path for each salesperson to visit the cities, subjected to a condition that each city must be visited exactly once by only one salesperson. The neighbourhood search mechanism in the ABC algorithm proposed by Pandiri and Singh [92] is as follows. Each city in a current solution has a certain probability to be copied to form a neighbourhood solution, otherwise the city is considered as an unassigned city. The unassigned cities are randomly inserted into the formed neighbourhood solution.

Pandiri and Singh [93] employed an ABC variant for solving a multi-depot TSP instance with load balancing. Besides having multiple salespersons, this problem considers multiple depots, in which each salesperson is stationed at a different depot. The task of a multi-depot TSP is to look for a route for each salesperson to start and end at his/her corresponding depot, such that each city is visited exactly once by one

salesperson. As such, the total distance traveled by the salespersons is minimised, and the workload among salespersons is balanced. Pandiri and Singh [93] applied a similar neighbourhood search mechanism as that in [92].

Zhong et al. [94] proposed a dynamic Tabu ABC model for solving MTSP with precedence constraints. MTSP with precedence constraints is a special case of MTSP whereby the cities need to be visited in a specific order. A dynamic Tabu list is designed to handle the constraints. Multiple probabilistic solution update mechanisms are implemented.

Based on the reviewed literatures in this section, it is noticed that bee-inspired algorithms can be integrated with a single or multiple neighbourhood search heuristic(s). This article proposes a new ABC model with multiple neighbourhood search heuristics. Specifically, the MCF is used to guide the selection of neighbourhood search heuristics (i.e. LLHs) in the proposed MCF-ABC model.

2.2. Modified Choice Function

Cowling et al. [41] proposed a hyper-heuristic based on a choice function. It is a score-based approach which measures the score of each LLH based on its previous performance. The score of each LLH is composed of three different measurements, i.e. f_1, f_2, and f_3. The first measurement, f_1, represents the recent performance of each LLH (Eq. (3)):

$$f_1(h_j) = \sum_n \alpha^{n-1} \frac{I_n(h_j)}{T_n(h_j)} \tag{3}$$

where h_j denotes the j-th LLH, $I_n(h_j)$ denotes the fitness difference between the current solution and the newly proposed solution by the nth application of h_j, $T_n(h_j)$ denotes the amount of time taken by the nth application of h_j to propose the new solution, $\alpha \in (0,1)$ is a parameter which prioritises the recent performance.

The second measurement, f_2, reflects the dependency between a consecutive pair of LLHs (Eq. (4)):

$$f_2(h_k, h_j) = \sum_n \beta^{n-1} \frac{I_n(h_k,h_j)}{T_n(h_k,h_j)} \tag{4}$$

where $I_n(h_k,h_j)$ denotes the fitness difference between the current solution and the newly proposed solution by the nth consecutive application of h_k and h_j (i.e. h_j is executed right after h_k), $T_n(h_k,h_j)$ denotes the amount of time taken by the nth consecutive application of h_k and h_j to propose the new solution, $\beta \in (0,1)$ is a parameter which prioritises the recent performance. Both f_1 and f_2 are the intensification component of the choice function. They encourage the selection of high performance LLHs.

The third measurement, f_3, records the elapsed time since the last execution of a particular LLH (Eq. (5)):

$$f_3(h_j) = \tau(h_j) \tag{5}$$

where $\tau(h_j)$ denotes the elapsed time (in seconds) since the last execution of h_j. Note that f_3 acts as a diversification component in the choice function. It prioritises those LLHs that have not been used for a long time.

The score of each LLH is computed as a weighted sum of the three measurements, f_1, f_2, and f_3, as shown in Eq. (6):

$$F(h_j) = \alpha f_1(h_j) + \beta f_2(h_k, h_j) + \delta f_3(h_j) \tag{6}$$

where α, β and δ are the respective weights of f_1, f_2, and f_3. In the initial model [41], these parameters were

statically fixed. Promising results have been reported when the proposed choice function (i.e. Eq. (6)) is paired with AM as its move acceptance method to solve the sales summit scheduling problem.

The parameters in Cowling et al. [41] need to be tuned and pre-determined. In order to have a more effective version of the hyper-heuristic, the parameters can be dynamically controlled during execution, as shown in Cowling et al. [95]. The values of α and β increase when the selected LLH is able to improve the solution. The growth is proportional to the magnitude of improvement over the previous solution. On the other hand, if the selected LLH performs a non-improving move, α and β are decreased proportionally to the fitness difference. This strategy is able to improve the model in Cowling et al. [41].

However, Drake et al. [42] stated some limitations of the strategy in Cowling et al. [95]. Firstly, rewarding/penalising the LLH proportionally to the fitness difference over the previous solution is arguable. During the early stages of optimisation, it is easier for a relatively weaker heuristic to obtain a great improvement from a poor starting solution, and a greater reward is assigned to this weaker heuristic. On the other hand, the improvement made in the later stages of optimisation is minor (due to convergence to an optimum solution, either local or global), and a lower reward is assigned. However, the improvement made in the later stages is more significant than the improvement made in the early stages, therefore this rewarding scheme might be misleading. Besides that, if no solution can achieve improvement for a number of iterations, this LLH selection method can descend into random selection due to the low α and β settings (i.e. the diversification component, f_3, dominates the score). Targeted at these limitations, Drake et al. [42] proposed a variant of choice function, namely MCF, to manage its parameters. In MCF, α and β are combined as a single parameter, μ. The score, F, is computed as follows (Eq. (7)):

$$F_t(h_j) = \mu_t[f_1(h_j) + f_2(h_k, h_j)] + \delta_t f_3(h_j) \tag{7}$$

If the selected LLH yields an improvement, intensification is prioritised by setting μ to a static maximum value close to one, at the same time δ is reduced to a static minimum value close to zero. When the selected LLH fails to improve the solution, μ is penalised linearly with a lower bound of 0.01, while δ grows at the same rate. This prevents the intensification components (i.e. f_1 and f_2) from losing their influence too quickly. Specifically, μ and δ are computed as follows (Eq. (8) and (9)), in which d denotes the fitness difference between the newly proposed solution and the previous solution.

$$\mu_t(h_j) = \begin{cases} 0.99, & d > 0 \\ max[0.01, \mu_{t-1}(h_j) - 0.01], & d \leq 0 \end{cases} \tag{8}$$

$$\delta_t(h_j) = 1 - \mu_t(h_j) \tag{9}$$

In Section 3, the proposed model which incorporates MCF into the ABC algorithm is presented. The main function of MCF is to help the employed and onlooker bees to select an appropriate neighbourhood search heuristic (i.e. LLH).

2.3. Local-Search-based Strategies

Local search strategies have been used widely in solving many combinatorial optimisation problems. Generally, the procedure of this category of strategies consists of the following steps:
1. Randomly generate a feasible solution, S.
2. Perform a transformation on S to produce S'.
3. If S' is found to be better than S, replace S with S'.
4. Repeat steps 2 and 3 until no improvement is observed. At this stage, S is said to be locally optimal.

A number of local search strategies that have been used for solving TSP include 2-opt [96], 3-opt [97], and LK local search [54].

In general, a local search strategy is able to yield a local optimal solution. However, its capability is limited to intensification, i.e., exploitation around the neighbourhood of the initial solution. One of the effective methods to increase the chance of a local search strategy to obtain the global optimal solution is to restart the search after a particular region of the search space is extensively exploited. A local search which adapts a restart mechanism is known as a Multi-start Local Search (MSLS) [98]. In MSLS, a local search is allowed to begin from different initial solutions. As such, it is able to yield a set of local optimal solutions. Ideally, the global optimum (or a near-global-optimal) solution can be found in the set of local optimal ones. Many MSLS variants have been developed to solve various combinatorial problems, such as permutation flow shop scheduling problem [99], generalised quadratic multiple KP [100], periodic VRP [101], and dynamic TSP [102].

In addition, diversification of a local search strategy can be improved by repeatedly performing a perturbation and a local search on a solution. One such method is Iterated Local Search (ILS) [103]. In ILS, an initial solution iteratively goes through a diversification phase and an intensification phase. During the diversification phase, a new solution is produced by performing a perturbation to the current solution. After that, the intensification phase is initiated to perform local search based on the newly produced solution. One ILS-based strategy for solving the TSP, i.e., the Chained Lin-Kernighan (CLK) heuristic, was proposed in [104, 105]. In the CLK heuristic, an LK local search is repeatedly performed on a TSP solution, which is followed by a double-bridge move [104] to exchange four arcs in the solution with the other four arcs. Besides TSP, ILS-based strategies have been used in various applications, i.e. variants of VRP [106, 107], bin-packing problem [108], and different scheduling problems [109-111].

Many swarm intelligence algorithms have good global search ability. As such, a balance between intensification and diversification can be achieved by integrating a local search strategy with a swarm intelligence algorithm. The usefulness of hybridising local search and swarm intelligence algorithms has been demonstrated in many publications [112-117]. Motivated by the research in this domain, the proposed MCF-ABC model is integrated with an LK local search strategy in this study. The local search takes place after each neighbourhood search performed by the employed or onlooker bees before applying the acceptance criterion.

With the inclusion of local search, the proposed MCF-ABC model has some similarities with the MSLS and ILS models. In the initialisation phase of MCF-ABC, a population of solutions is initialised to form multiple starting points of the local search process. During the activities performed by the employed and onlooker bees, each of these solutions undergoes an ILS procedure, i.e. repetitively goes through a perturbation using a selected LLH and an LK local search. During the activities performed by the scout bee, if a solution could not be improved after *limit* trials, a restart mechanism (i.e. a replacement of the solution with a random solution) takes place. Therefore, MCF-ABC shares some common features of MSLS during the initialisation phase and scout bee activities, while similarities between MCF-ABC and ILS are shown in the activities of the employed and onlooker bees.

3. The Proposed Model

The pseudo code of a classical discrete ABC model [34, 85] is shown in Algorithm I. The model consists of four phases: initialisation, employed bee phase, onlooker bee phase, and scout bee phase. In the initialisation phase, the maximum iteration (*maxIteration*), population size (*popSize*), the maximum number of trails of a solution (*limit*), and an LLH to be used for the neighbourhood search by the employed and onlooker bees (*llh$_x$*) are pre-determined. Then, the solution associated to each food source is initialised randomly. The employed and onlooker bees perform neighbourhood search using an LLH determined during the initialisation phase throughout the search process.

Algorithm I: Pseudo code of a classical discrete ABC model.

1 **Procedure** ABC()
  //initialisation
2 Initialise *maxIteration*, *popSize*, *limit* and *llh$_x$*
3 **for** i = 1 **to** *popSize*/2
4   *foodSource*[*i*] = initialiseSolutions()
5   *foodSource*[*i*].*counter* = 0
6 **end for**
7 **while** not reaching *maxIteration* **do**
    //Employed bee phase
8   **for** i = 1 **to** *popSize*/2
9   *newSol* = neighbourSeach(*foodSource*[*i*], *llh$_x$*)
10   **if** getFitness(*newSol*) < getFitness(*foodSource*[*i*])
11   *foodSource*[*i*] = *newSol*
12   *foodSource*[*i*].*counter* = 0
13   **else**
14   *foodSource*[*i*].*counter*++
15   **end if**
16 **end for**
    //Onlooker bee phase
17 **for** i = 1 **to** *popSize*/2
18   *k* = selectSolBasedOnRouletteWheelSelection(*foodSource*)
19   *newSol* = neighbourSeach(*foodSource*[*k*], *llh$_x$*)
20   **if** getFitness(*newSol*) < getFitness(*foodSource*[*k*])
21   *foodSource*[*k*] = *newSol*
22   *foodSource*[*i*].*counter* = 0
23   **else**
24   *foodSource*[*i*].*counter*++
25   **end if**
26 **end for**
    //Scout bee phase
27 **for** i = 1 **to** *popSize*/2
28   **if** *foodSource*[*i*].counter > *foodSource*[*i*].*limit*
29   *foodSource*[*i*] = initialiseSolutions()
30   *foodSource*[*i*].*counter* = 0
31   **end if**
32 **end for**
33 **end while**
34 **end Procedure**

The proposed MCF-ABC model is a bee algorithm with multiple neighbourhood search heuristics (i.e. LLHs). The seven perturbative LLHs for TSP proposed in [34], namely, Random Insertion (RI), Random Swap (RS), Random Insertion of Subsequence (RIS), Random Swap of Subsequences (RSS), Random Reversing of Subsequence (RRS), Random Reversing Insertion of Subsequence (RRIS) and Random Reversing Swap of Subsequences (RRSS), is adopted. Besides that, the proposed MCF-ABC model also includes three additional LLHs i.e. Shuffle Subsequence (SS), Random Shuffle Insertion of Subsequence

(RSIS) and Random Shuffle Swap of Subsequence (RSSS). Therefore, a total of ten LLHs are adopted in the MCF-ABC model. These ten LLHs involve four main types of operations, i.e. reverse, insert, swap and shuffle. Specifically, RRS performs a reverse operation, RI and RIS perform an insert operation, RS and RRS perform a swap operation, and SS performs a shuffle operation. Among the ten LLHs, four of the LLHs (i.e. RRIS, RRSS, RSIS, and RSSS) involve combinations of two types of operations. Note that the subsequence of a TSP solution considered by RRS, RIS, RSS, SS, and the four LLHs with combined operations covers size in a range of [2:*dim*], where *dim* denotes the TSP dimension. The details of the ten LLHs are shown in Table 1.

Table 1: Details of the ten integrated LLHs in the MCF-ABC model.

Operations	LLHs	Description
Reverse	Random Reversing of Subsequences (RRS)	Invert a randomly selected subsequence.
Insert	Random Insertion (RI)	Randomly pick a city from a solution, remove it from the solution, and reinsert it to a random position of the solution.
	Random Insertion of Subsequence (RIS)	Randomly pick a subsequence from a solution, remove it from the solution, and reinsert it to a random position of the solution.
Swap	Random Swap (RS)	Swap the position of two randomly selected cities in a solution.
	Random Swap of Subsequences (RSS)	Swap the position of two randomly selected subsequences in a solution.
Shuffle	Shuffle Subsequence (SS)	Re-order a randomly selected subsequence at random.
Combined Operations	Random Reversing Insertion of Subsequence (RRIS)	Invert a randomly selected subsequence, then remove the inverted subsequence from the solution, and reinsert it to a random position of the solution.
	Random Reversing Swap of Subsequences (RRSS)	Swap the position of two randomly selected subsequences in a solution. Each of the subsequences has a 0.5 probability to be inverted.
	Random Shuffle Insertion of Subsequence (RSIS)	Re-order a randomly selected subsequence at random, then remove the shuffled subsequence from the solution, and reinsert it to a random position of the solution.
	Random Shuffle Swap of Subsequence (RSSS)	Swap the position of two randomly selected subsequences in a solution. Each of the subsequences has a 0.5 probability to be shuffled.

The fitness function of the proposed MCF-ABC model is formulated as the round trip distance (i.e. tour length) to visit each city once and only once, and return to the starting city (as shown in Eq. (2)). The pseudo code is shown in Algorithm II. Similar to the classical discrete ABC model, the proposed MCF-ABC model consists of four phases: initialisation, employed bee, onlooker bee phase, and scout bee phase. In MCF-ABC, the solution associated with each employed bee is initialised randomly. In order for an employed bee or an onlooker bee to select an appropriate LLH, it is aided by the MCF as explained in Section 2.2. Each LLH has a score, F. Each employed bee or onlooker bee selects an LLH based on the F score (lines 9 and 22 in Algorithm II). The computation of F is shown in Eq. (7). The LLH with the largest F score is selected and ties are decided randomly. After performing a neighbourhood search, the generated solution by the neighbourhood search is improved using the LK local search [54] (lines 11 and 24 in Algorithm II). Then, a greedy acceptance method is applied to decide whether to accept the newly produced solution or otherwise (lines 12-13 and 25-26 in Algorithm II). After that, the F score of the selected LLH is updated using Eq. (7) (lines 18 and 31 in Algorithm II).

While the employed bees and onlooker bees perform neighbourhood search to exploit the promising areas of the search space, the scout bees focus on exploration of a new region in the search space [10, 24, 118]. As such, the scout bees are good for avoiding local optima. However, some studies suggest that random replacement of an abandoned solution decreases the search efficiency, because an abandoned solution could contains more useful information than a random solution [119, 120]. In this article, the same mechanism as proposed in the original ABC algorithm by Karaboga [7] is applied, i.e. if a particular solution (i.e. food source) has not been improved after the *limit* trials, it is abandoned. The employed bee associated to the abandoned food source becomes a scout bee, and it goes to search for a new food source (i.e. solution) at

random. The scout bee uses a random initialisation procedure to generate a new solution (line 35 in Algorithm II).

Algorithm II: Pseudo code of the MCF-ABC model.

1 **Procedure** MCF-ABC()
  //initialisation
2   Initialise *maxIteration*, *popSize*, *limit* and *LLHSet*
3   **for** i = 1 **to** *popSize*/2
4   *foodSource*[*i*] = initialiseSolutions()
5   *foodSource*[*i*].*counter* = 0
6   **end for**
7   **while** not reaching *maxIteration* **do**
      //Employed bee phase
8   **for** i = 1 **to** *popSize*/2
9   *selectedLLH* = selectLLH_BasedOnMCF()
10   *newSol* = neighbourSeach(*foodSource*[*i*], s*electedLLH*)
11   localSearch(*newSol*) //optional
12   **if** getFitness(*newSol*) < getFitness(*foodSource*[*i*])
13   *foodSource*[*i*] = *newSol*
14   *foodSource*[*i*].*counter* = 0
15   **else**
16   *foodSource*[*i*].*counter*++
17   **end if**
18   updateChoiceFunction(s*electedLLH*) //eq. (7)
19   **end for**
      //Onlooker bee phase
20   **for** i = 1 **to** *popSize*/2
21   *k* = selectSolBasedOnRouletteWheelSelection(*foodSource*)
22   *selectedLLH* = selectLLH_BasedOnMCF()
23   *newSol* = neighbourSeach(*foodSource*[*k*], *selectedLLH*)
24   localSearch(newsol) //optional
25   **if** getFitness(*newSol*) < getFitness(*foodSource*[*k*])
26   *foodSource*[*k*] = *newSol*
27   *foodSource*[*i*].*counter* = 0
28   **else**
29   *foodSource*[*i*].*counter*++
30   **end if**
31   updateChoiceFunction(s*electedLLH*) //eq. (7)
32   **end for**
      //Scout bee phase
33   **for** i = 1 **to** *popSize*/2
34   **if** *foodSource*[*i*].counter > *foodSource*[*i*].*limit*
35   *foodSource*[*i*] = initialiseSolutions()
36   *foodSource*[*i*].*counter* = 0
37   **end if**
38   **end for**
39   **end while**
40 **end Procedure**

4. Results and Discussion

The experimental setting, experimental results, and comparison studies are presented in this section.

4.1. Experimental Settings

All experiments were conducted using a computer with multiple Intel i7-3930K 3.20 GHz processors, and with 15.6GB of memory. At any particular time, each test was executed by one processor only. The proposed MCF-ABC model is implemented in C programming language. The implementation of the LK local search is obtained from Concorde [105].

The performance of the proposed model is investigated by using benchmark TSP datasets taken from TSPLIB [55]. A total of 64 instances are used, and their dimension ranges from 101 to 85900 cities. The numerical figure appears in the problem instance name denotes the dimension of the problem, e.g. eil101 is a 101-city TSP; d493 is a 493-city TSP.

Two key performance indicators are defined to measure the performance of the proposed MCF-ABC model as follows: the percentage deviation from known optimum, δ (measured in %) and computational time (measured in seconds) to obtain the best tour length. The formula for calculating δ is stated in Eq. (10) where C^* and $C(\pi)$ denote the best known tour length (or optimum tour length) and the obtained tour length of a particular TSP instance respectively:

$$\delta = \frac{C(\pi) - C^*}{C^*} \times 100 \qquad (10)$$

When an instance is solved by the proposed MCF-ABC model, a total of 30 test replications are conducted. The shortest tour length produced by each replication and the computational time to obtain such tour length are recorded. This leads to the creation of $C = \{c_1, c_2, \ldots, c_{30}\}$ and $T = \{t_1, t_2, \ldots, t_{30}\}$, in which C is a set of tour lengths and T is a set of computational time corresponding to the time to obtain the best tour length in C. For set C, the average of 30 tour lengths are identified and denoted as μ_C. Then, the average deviation percentages (i.e. δ_{avg}) from C^* are computed using Eq. (10). For set T, the average is computed and is denoted as μ_T.

4.2. Parameter Tuning

There are two parameters in MCF-ABC, i.e. *popSize* and *limit*. To determine both parameters, a structured design-of-experiment technique, i.e. the face-centred central composite design (CCD) [121], is employed. All 64 TSP instances are grouped into four classes according to their dimensions. Classes A, B, and C include instances with dimensions [1:500], [501:1000], and [1001:10000], respectively, while Class D includes instances with dimension >10000. For each class, one TSP instance is selected as a representative instance for the CCD experiments. Specifically, gil262, u724, fnl4461, and rl11849 are selected as the representative instances of Classes A, B, C, and D respectively. The resulting parameter settings from these representative instances are generalised to other TSP instances within the corresponding class.

In accordance with the face-centred CCD [121], each parameter is set at three different levels, i.e. low, medium, and high, as shown in Table 2. A total of $3^2 = 9$ combinations of these parameters at each level are generated. The experimental setting is illustrated in Figure 1. To have a fair comparison, all experiments are terminated after a fixed number of neighbourhood search operations (i.e. 10000 operations). For example, the experiment with *popSize* = 10 would be terminated after 1000 iterations, while the experiment with *popSize* = 20 would be terminated after 500 iterations. Table 3 shows the detailed configurations and results of the CCD design experiment.

Table 2: Low, medium, and high levels of *popSize* and *limit*.

	Low	Medium	High
popSize	10	20	30
limit	100	200	300
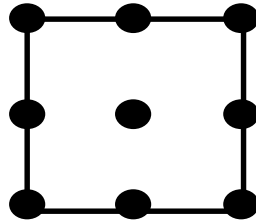
Figure 1: A face-centred central composite design with two parameters.

Table 3: Effects of *popSize* and *limit* on the MCF-ABC performance.

Configuration	*popSize*	*limit*	δ_{avg}			
			Class A gil262	Class B u724	Class C fnl4461	Class D rl11849
1	10	100	0	0.039	0.225	0.472
2	**10**	**200**	**0**	**0.007**	**0.213**	**0.447**
3	10	300	0	0.026	0.222	0.576
4	20	100	0	0.031	0.277	0.608
5	20	200	0	0.012	0.232	0.575
6	20	300	0	0.016	0.258	0.584
7	30	100	0	0.054	0.272	0.655
8	30	200	0	0.029	0.238	0.647
9	30	300	0	0.039	0.284	0.676

MCF-ABC is able to solve gil262 to the known optimum using all the nine configurations of *popSize* and *limit*. For Classes B, C, and D, the best results are achieved from the second configuration, i.e. *popSize*=10 and *limit*=200. With this configuration, *popSize* is set at the low level and *limit* is set at a medium level. Besides that, it is worth-noting that the configuration with *limit*=200 outperforms all other configurations with the same *popSize*. As such, 200 is selected for *limit*, which is in line with the setting in [122] as well. Based on the tuning results, MCF-ABC with *popSize*=10 and *limit*=200 is used in the following experiments to solve all 64 TSP instances.

4.3. Experimental Results of MCF-ABC

In order to examine the effect of the integrated LLH pool described in Table 1 listed in Section 3, the proposed MCF-ABC model with the ten integrated LLHs is compared with a variant denoted as MCF-ABC(4) which only integrates four LLHs with basic operations, i.e. RRS, RIS', RSS', and SS, whereby RIS' and RSS' consider subsequence with size [1:*dim*]. Besides, the proposed MCF-ABC model is compared with a Random-ABC model to examine the effectiveness of integrating the MCF hyper-heuristic in the ABC model. The Random-ABC model utilises the same sets of LLHs (i.e. ten LLHs) as MCF-ABC. In Random-ABC, a random strategy is used for the employed bees and onlooker bees to select an LLH for each neighbourhood search. For all the three algorithms (i.e. MCF-ABC, MCF-ABC(4), and Random-ABC), the stopping criterion is based on the pre-determined execution iterations (i.e. 1000 iterations). The average tour length (μ_C), average deviation percentages (δ_{avg}), and average computational time to obtain the best solution (μ_T) obtained by the three algorithms are shown in Table 4.

Table 4: Performance comparison of MCF-ABC, MCF-ABC(4), and Random-ABC based on 64 TSP benchmark instances.

	Optimum	MCF-ABC			MCF-ABC(4)			Random-ABC		
		μ_C	$\delta_{avg}(\%)$	$\mu_T(s)$	μ_C	$\delta_{avg}(\%)$	$\mu_T(s)$	μ_C	$\delta_{avg}(\%)$	$\mu_T(s)$
eil101	629	629.0	0.000	0.0	629.0	0.000	0.0	629.0	0.000	0.0
lin105	14379	14379.0	0.000	0.0	14379.0	0.000	0.0	14379.0	0.000	0.0
pr107	44303	44303.0	0.000	0.0	44303.0	0.000	0.0	44303.0	0.000	0.0
gr120	6942	6942.0	0.000	0.0	6942.0	0.000	0.0	6942.0	0.000	0.0
pr124	59030	59030.0	0.000	0.1	59030.0	0.000	0.1	59030.0	0.000	0.1
bier127	118282	118282.0	0.000	0.1	118282.0	0.000	0.1	118282.0	0.000	0.1
ch130	6110	6110.0	0.000	0.0	6110.0	0.000	0.0	6110.0	0.000	0.0
pr136	96772	96772.0	0.000	0.2	96772.0	0.000	0.1	96772.0	0.000	0.1
gr137	69853	69853.0	0.000	0.0	69853.0	0.000	0.1	69853.0	0.000	0.1
pr144	58537	58537.0	0.000	1.8	58537.0	0.000	2.2	58537.0	0.000	1.4
ch150	6528	6528.0	0.000	0.0	6528.0	0.000	0.1	6528.0	0.000	0.0
kroB150	26130	26524.0	0.000	0.0	26524.0	0.000	0.1	26524.0	0.000	0.0
kroA200	29368	26130.0	0.000	0.1	26130.0	0.000	0.2	26130.0	0.000	0.1
pr152	73682	73682.0	0.000	1.8	73682.0	0.000	2.0	73682.0	0.000	1.1
u159	42080	42080.0	0.000	0.0	42080.0	0.000	0.0	42080.0	0.000	0.0
si175	21407	21407.0	0.000	0.2	21407.0	0.000	0.2	21407.0	0.000	0.1
brg180	1950	1950.0	0.000	0.0	1950.0	0.000	0.0	1950.0	0.000	0.0
rat195	2323	2323.0	0.000	0.2	2323.0	0.000	0.2	2323.0	0.000	0.1
d198	15780	15780.0	0.000	1.3	15780.0	0.000	1.2	15780.0	0.000	0.9
kroA200	29368	29368.0	0.000	0.1	29368.0	0.000	0.1	29368.0	0.000	0.0
kroB200	29437	29437.0	0.000	0.0	29437.0	0.000	0.1	29437.0	0.000	0.0
gr202	40160	40160.0	0.000	0.6	40160.0	0.000	0.9	40160.0	0.000	0.5

	Optimum	MCF-ABC			MCF-ABC(4)			Random-ABC		
		μ_C	δ_{avg}(%)	μ_T(s)	μ_C	δ_{avg}(%)	μ_T(s)	μ_C	δ_{avg}(%)	μ_T(s)
tsp225	3916	126643.0	0.000	0.0	126643.0	0.000	0.1	126643.0	0.000	0.0
ts225	126643	3916.0	0.000	0.1	3916.0	0.000	0.1	3916.0	0.000	0.1
pr226	80369	80369.0	0.000	1.4	80369.0	0.000	3.4	80369.0	0.000	2.1
gr229	134602	134602.0	0.000	0.8	134602.0	0.000	1.3	134602.0	0.000	0.9
gil262	2378	2378.0	0.000	0.1	2378.0	0.000	0.2	2378.0	0.000	0.1
pr264	49135	49135.0	0.000	0.1	49135.0	0.000	0.1	49135.0	0.000	0.1
a280	2579	2579.0	0.000	0.0	2579.0	0.000	0.0	2579.0	0.000	0.0
pr299	48191	48191.0	0.000	0.2	48191.0	0.000	0.2	48191.0	0.000	0.2
lin318	42029	42029.0	0.000	1.5	42029.0	0.000	4.4	42029.0	0.000	1.6
rd400	15281	15281.0	0.0002	2.4	15281.0	0.000	4.1	15281.0	0.000	2.2
fl417	11861	11861.0	0.000	5.7	11861.0	0.000	4.8	11861.0	0.000	6.3
gr431	171414	171414.0	0.000	13.0	171414.0	0.000	15.1	171414.0	0.000	12.7
pr439	107217	107217.0	0.000	2.3	107217.0	0.000	2.7	107217.0	0.000	2.2
pcb442	50778	50778.0	0.000	1.6	50778.0	0.000	1.3	50778.0	0.000	1.5
d493	35002	35002.7	0.002	20.9	35002.9	0.002	21.6	35002.7	0.002	15.8
att532	27686	27686.5	0.002	11.4	27686.9	0.003	12.6	27686.7	0.003	11.9
ali535	202339	202339.0	0.000	10.6	202339.0	0.000	9.5	202339.0	0.000	8.4
si535	48450	48498.3	0.100	53.3	48535.1	0.176	55.2	48508.1	0.120	47.4
pa561	2763	2763.1	0.004	7.1	2763.3	0.011	7.5	2763.3	0.010	8.3
u574	36905	36905.0	0.000	2.1	36905.0	0.000	3.5	36905.0	0.000	3.6
rat575	6773	6774.3	0.020	6.3	6774.4	0.021	5.8	6774.3	0.020	5.5
p654	34643	34643.0	0.000	21.5	34643.0	0.000	19.2	34643.0	0.000	21.2
d657	48912	48915.1	0.006	15.5	48913.5	0.003	14.9	48914.1	0.004	11.9
gr666	294358	294404.1	0.016	32.1	294396.8	0.013	32.8	294389.7	0.011	31.8
u724	41910	41916.5	0.016	12.9	41917.4	0.018	12.9	41916.5	0.015	14.0
rat783	8806	8806.0	0.000	4.2	8806.0	0.000	6.5	8806.0	0.000	4.1
dsj1000	18659688	18661580.6	0.010	53.2	18663249.7	0.019	60.3	18662940.7	0.017	46.9
pr1002	259045	259073.0	0.011	16.6	259231.0	0.072	25.1	259173.4	0.050	29.7
si1032	92650	92650.0	0.000	4.4	92650.0	0.000	11.2	92650.0	0.000	5.5
vm1084	239297	239322.3	0.011	24.3	239321.6	0.010	21.5	239328.5	0.013	33.3
pcb1173	56892	56897.9	0.010	15.4	56899.0	0.012	12.1	56896.7	0.008	16.3
d1291	50801	50843.7	0.084	15.7	52383.2	3.115	49.3	51963.7	2.289	68.4
d1655	62128	62221.6	0.151	27.0	62246.9	0.191	37.8	62210.2	0.132	51.6
u1817	57201	57354.2	0.268	24.6	57377.6	0.309	22.7	57359.5	0.277	40.8

	Optimum	MCF-ABC			MCF-ABC(4)			Random-ABC		
		μ_C	δ_{avg}(%)	μ_T(s)	μ_C	δ_{avg}(%)	μ_T(s)	μ_C	δ_{avg}(%)	μ_T(s)
u2152	64253	64426.5	0.270	28.3	64433.9	0.282	28.7	64415.2	0.252	39.2
pr2392	378032	378549.6	0.137	28.9	378418.2	0.102	43.1	378559.5	0.140	41.0
fl3795	28772	28825.1	0.184	131.7	32294.8	12.244	258.2	31084.0	8.036	275.6
fnl4461	182566	183002.8	0.239	66.6	183019.3	0.248	48.7	183008.5	0.242	51.3
rl5915	565530	567990.2	0.435	94.2	573022.9	1.325	109.4	572285.2	1.194	109.4
pla7397	23260728	23324321.9	0.273	247.6	23328860.6	0.293	228.0	23323272.4	0.269	191.9
rl11849	923288	928015.1	0.512	308.9	934773.2	1.244	348.9	933587.4	1.116	368.5
pla85900	142382641	143484917.5	0.774	9082.5	144037897.2	1.163	5804.8	143851971.1	1.032	6453.7
	Average:		0.055	162.6		0.326	115.0		0.238	125.7

The average scores of δ_{avg} obtained by MCF-ABC, MCF-ABC(4), and Random-ABC in Table 4 are 0.055%, 0.326%, and 0.238%, respectively. On average, MCF-ABC yields better δ_{avg} than those of MCF-ABC(4) and Random-ABC. MCF-ABC solves all 64 instances to 0.055% from the known optimum within 2.7 minutes (≈162.6s). Besides that, MCF-ABC is able to consistently solve 40 out of 64 instances (i.e. 62.5%) to the known optimum for 30 replications.

To statistically compare the performance of each algorithm, the Wilcoxon signed-rank test [123] with 95% confidence interval is employed. In the Wilcoxon signed rank test, the difference between the δ_{avg} obtained by two compared algorithms is ranked. The tie instances are discarded, and N denotes the effective sample size (i.e. number of instances) after discarding the ties instances. The sum of ranks for the instances in which MCF-ABC outperforms its competitor is denoted as R^+, while R^- denotes the sum of ranks for the instances in which MCF-ABC is inferior to its competitor. According to the Wilcoxon signed rank test, the test statistic, W is compared with a critical value, $W_{cri,N}$ [123]. $W \leq W_{Cri,N}$ indicates that there is a significant difference between the performance of the two algorithms, while $W > W_{Cri,N}$ indicates otherwise. The results of the Wilcoxon signed ranks test are summarised in Table 5.

Table 5: The Wilcoxon signed ranked test for the comparison of MCF-ABC, MCF-ABC(4), and Random-ABC.

Comparisons (MCF-ABC vs …)	N	R^+	R^-	W	$W_{Cri,N}$	Significant Difference
MCF-ABC(4)	22	226	27	27	65	yes
Random-ABC	21	177	54	54	58	yes

The Wilcoxon signed rank test results show that, the proposed MCF-ABC model significantly outperforms MCF-ABC(4) and Random-ABC. The comparison with MCF-ABC(4) shows that the inclusion of more LLHs has positive effects on the performance, while the comparison with Random-ABC indicates that the MCF selection method performs better than the random selection method.

A convergence analysis is conducted based on a problem with the largest dimension in TSPLIB, i.e. pla85900. The best-so-far δ (computed using Eq. (10)) obtained in each iteration of the three algorithms are plotted in Figure 2. As shown in Figure 2, MCF-ABC(4) with four LLHs converges rapidly, but it is trapped in a local optimum, while Random-ABC and MCF-ABC with ten LLHs are more capable of escaping the local optimum. On the other hand, the proposed MCF-ABC model converges to a better solution than those of MCF-ABC(4) and Random-ABC in the later stage of the search process.
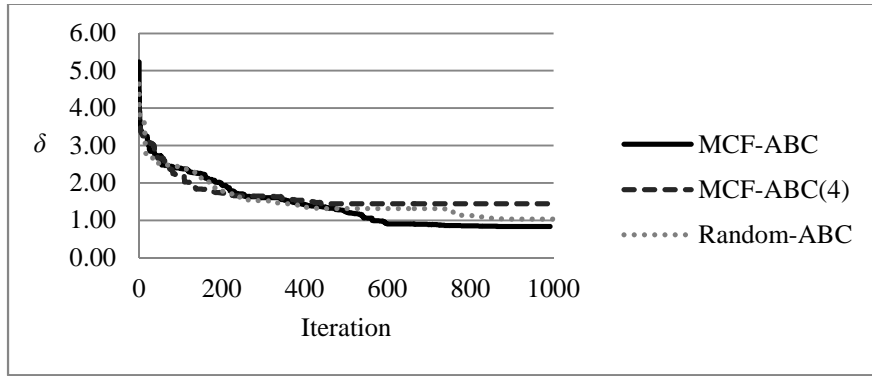
Figure 2: Convergence graph of MCF-ABC, MCF-ABC(4), and Random-ABC when solving pla85900.

To further analyse the experimental results of the proposed MCF-ABC model, the average execution distribution (in terms of percentage) of LLHs chosen by the MCF is recorded. In this analysis, the five classes which categorise the 64 TSP instances based on their dimensions described in Section 4.2 are utilised. Table 6 shows the average execution distribution of LLHs selected by the MCF when solving multiple instances in each class. Details about the categorisation of LLHs based on the type of operations can be found in Table 1 listed in Section 3.

Table 6: Average execution distributions (in percentages) of each LLH in MCF-ABC with local search.

Operations	Reverse	Insert		Swap		Shuffle	Combined Operations				$\delta_{avg}(\%)$
LLHs	RRS	RI	RIS	RS	RSS	SS	RRIS	RRSS	RSIS	RSSS	
Class A ($dim \in [101:500]$)	10.594	10.560	10.359	10.601	**12.184**	9.815	8.226	10.100	9.707	7.853	0.000
Class B ($dim \in [501:1000]$)	14.823	14.951	**15.347**	14.563	11.370	5.786	8.035	5.452	4.382	5.290	0.014
Class C ($dim \in [1001:10000]$)	16.549	16.596	**16.634**	16.534	10.184	4.392	6.851	4.636	3.250	4.374	0.159
Class D ($dim > 10000$)	**18.176**	17.738	17.746	17.458	16.452	2.342	3.046	2.232	2.254	2.556	0.643
Overall Average	12.833	12.834	12.800	12.764	11.759	7.724	7.749	7.873	7.164	6.500	0.055

Based on Table 6, RSS is selected most frequently when solving the instances in Class A ($dim \in [101:500]$). RIS is favoured when solving the instances in Class B ($dim \in [501:1000]$) and C ($dim \in [1001:10000]$). RRS yields the highest percentage when solving the instances in Class D ($dim > 10000$). For all classes, LLHs which perform single reverse, insert, and swap operations are more frequently selected than other LLHs (i.e. the top five selected LLHs with the highest percentage of each class are RRS, RI, RIS, RS, and RSS).

The intensification components of MCF (i.e. f_1 and f_2) generally evaluate the performance of an LLH based on the improvement it yields over its computational/execution time. Besides that, the influence of f_1 and f_2 are prioritised by the control mechanism of μ and δ (i.e. Eq. (8) and (9)), whereby μ and δ are set to constant maximum and minimum values, respectively, for an improved move. For a deteriorated move, μ is slightly decreased whereas δ is slightly increased. Therefore, in the proposed MCF-ABC model, RRS, RI, RIS, RS, and RSS are frequently selected as they are able to obtain good scores of f_1 and f_2 (i.e. bringing improvement within a relatively short computational time). If the control mechanism is modified such that a greater increment of δ for a deteriorated move is performed, the influence of the diversification component, f_3, is increased and other LLHs which are not frequently chosen would have a higher chance to be selected.

Besides that, an experiment that excludes the LK local search is conducted to investigate the execution distribution of LLHs in MCF-ABC without the local search strategy. The results are presented in Table 7. When the local search is excluded, the distributions of the selected LLHs for solving different classes of TSP instances are similar. MCF tends to concentrate on selecting RRS and RI, while other LLHs has less chance to be selected.

Table 7: Average execution distributions (in percentages) of each LLH in MCF-ABC without local search .

Operations	Reverse	Insert		Swap		Shuffle	Combined Operations				δ_{avg}(%)
LLHs	RRS	RI	RIS	RS	RSS	SS	RRIS	RRSS	RSIS	RSSS	
Class A (*dim*∈[101:500])	74.958	23.252	0.731	0.105	0.077	0.059	0.666	0.095	0.030	0.026	5.498
Class B (*dim*∈[501:1000])	71.239	26.104	1.075	0.149	0.112	0.072	1.035	0.138	0.040	0.035	10.115
Class C (*dim*∈[1001:10000])	70.836	28.564	0.199	0.024	0.019	0.011	0.311	0.023	0.006	0.005	18.061
Class D (*dim*>10000)	60.086	38.974	0.467	0.011	0.013	0.004	0.427	0.013	0.003	0.002	23.361
Overall Average	72.952	25.395	0.665	0.092	0.068	0.049	0.644	0.084	0.026	0.022	9.474

4.4. Competitiveness of MCF-ABC

This section compares the proposed MCF-ABC model with state-of-the-art algorithms. The comparison is conducted based on the following publications (the abbreviation of each publication is shown in parentheses):

- The analysis of discrete artificial bee colony algorithm with neighbourhood operator on traveling salesman problem (ABC) [34].
- A hierarchic approach based on swarm intelligence to solve the traveling salesman problem (ACO-ABC) [70].
- 2-opt based artificial bee colony algorithm for solving traveling salesman problem (2-opt ABC) [86].
- TSPoptBees: A bee-Inspired algorithm to solve the traveling salesman problem (TSPoptBees) [9].
- A generic bee colony optimisation framework for combinatorial optimisation problems (BCO) [73].
- Hybrid discrete artificial bee colony algorithm with threshold acceptance criterion for traveling salesman problem (HDABC) [89].
- Chained lin-kernighan for large traveling salesman problems (CLK) [105].
- Effective heuristics for ant colony optimisation to handle large-scale problems (ESACO) [60].
- Quantum inspired particle swarm combined with lin-kernighan-helsgaun method to the traveling salesman problem (QPSO) [115].
- Honey bees mating optimisation algorithm for the Euclidean traveling salesman problem (HBMO) [72].

In order to have a fair comparison, the *maxIteration* of the proposed MCF-ABC are set such that it uses equal or less number of neighbourhood search operations as compared with the benchmark algorithm (if stated) as shown in Table 8. Note that a ceiling function (i.e. [*Dim*/2]) is used to determine *popSize* in [34] and [70]. For example, if the problem is eil51, the value of *popSize* is [51/2]=[25.5]=26. In ACO-ABC [70], each of the ACO and ABC algorithms is executed for 250 iterations. TSPoptBees uses a dynamic population size, and its stopping criteria are based on the maximum number of iterations without improvement. The average final *popSize* and *maxIteration* for each instance are reported in Masutti and de Castro [9]. The average final *popSize* is varied between 99.60 and 177.00, while the average *maxIteration* used is varied between 1155.83 and 4271.83. As the source code of CLK [105] is available in the Concorde TSP solver software[*], CLK is re-

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[*] Available: http://www.math.uwaterloo.ca/tsp/concorde/

executed on the TSP instances in Classes C and D (as defined in Section 4.2) for comparison. CLK is a single-solution-based model (*popSize*=1), and it is allowed to run for 10,000 iterations. Except this maximum iteration, the default settings in Concorde are retained for other configurations, which include the level of backtracking (i.e. (4, 3, 3, 2)-breadth), choice of the kick (i.e. 50-step random-walk kick), and the initialisation method (i.e. Quick-Boruvka). For the comparison with ABC [34], ACO-ABC [70], 2-opt ABC [86], TSPoptBees [9], BCO [73], HDABC [89], and CLK [105], the *maxIteration* of MCF-ABC is set to 1000, while for the comparison with ESACO [60], QPSO [115], and HBMO [72], it is set to 300, 10000, and 5000 respectively. The δ_{avg} results obtained by the benchmark algorithms are shown in Tables 9-17. The Wilcoxon signed rank test with 95% confidence interval is conducted for statistical comparison between MCF-ABC and each benchmark algorithm.

Table 8: Experimental settings used by the compared algorithms and the proposed MCF-ABC model.

| Approaches [Citation] | Experimental Settings | | | |
| | Benchmark Algorithms | | MCF-ABC | |
	maxIteration	*popSize*	*maxIteration*	*popSize*
ABC [34]	100000	[*Dim*/2]×2		
ACO-ABC [70]	250+250	[*Dim*/2]×2		
2-opt ABC [86]	40	2000		
TSPoptBees [9]	varied from 1155.83 to 4271.83	varied from 99.60 to 177.00	1000	10
BCO [73]	10000	50		
HDABC [89]	1000	30		
CLK [105]	10000	1		
ESACO [60]	300	10	300	10
HBMO [72]	1000	50	5000	10
QPSO [115]	1000	100	10000	10

Table 9: Performance comparison among MCF-ABC and nine ABC variants [34].

	oliver30	eil51	berlin52	st70	pr76	kroA100	eil101	tsp225	a280
ABC [RS]	12.77	18.06	21.64	37.01	36.10	58.61	30.37	87.08	118.12
ABC [RSS]	**0.00**	0.50	0.24	1.48	1.58	3.74	5.22	26.12	42.46
ABC [RI]	4.88	8.02	11.29	14.21	15.04	21.47	12.78	27.40	38.04
ABC [RIS]	0.03	1.61	0.62	1.59	1.71	3.35	5.06	22.32	36.80
ABC [RRS]	0.33	2.59	3.05	2.67	1.53	2.63	5.30	8.07	11.27
ABC [RRIS]	**0.00**	0.35	**0.00**	0.55	0.62	1.89	3.51	21.62	33.48
ABC [RRSS]	**0.00**	0.32	**0.00**	0.80	0.64	1.89	3.59	20.93	38.01
ABC [RS, RSS, RRSS]	**0.00**	0.28	0.04	1.04	0.93	2.17	3.93	19.83	31.72
ABC [RI, RIS, RRIS]	**0.00**	0.39	**0.00**	0.56	0.45	1.04	2.90	12.41	23.92
MCF-ABC	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

Table 9 shows the performance comparison among MCF-ABC and nine ABC variants [34]. The neighbourhood search heuristic(s) used in each variant is stated in the parentheses. For example, ABC [RS] denotes an ABC variant with Random Swap as the neighbourhood search heuristic, while ABC [RI, RIS, RRIS] denotes an ABC variant with Random Insertion, Random Insertion of Subsequence, and Random Reversing Insertion of Subsequence as the neighbourhood search heuristics. The description of each LLH can be found in Table 1. Besides that, these nine ABC variants are integrated with a 2-opt local search strategy. The values shown in Table 9 are the δ_{avg} results obtained by the algorithms when solving each TSP instance. The results indicate that MCF-ABC consistently solves all the nine instances to the known optimum, and it outperforms all nine ABC variants reported in Kıran et al. [34].

Table 10: Performance comparison among MCF-ABC and ACO-ABC [70].

Instances	ACO-ABC	MCF-ABC
oliver30	0.00	0.00
eil51	3.39	0.00
berlin52	0.00	0.00
st70	3.47	0.00
eil76	2.31	0.00
pr76	6.39	0.00
kroA100	5.40	0.00
eil101	6.39	0.00
ch150	2.21	0.00
tsp225	7.74	0.00

Table 10 shows the performance comparison between MCF-ABC and ACO-ABC [70]. In ACO-ABC, ACO is applied to generate initial solutions for ABC and subsequently, the ABC algorithm utilises RI, RIS, and RRIS with a random selection method as its neighbourhood search mechanism. The proposed MCF-ABC model is able to consistently solve all the ten instances to the known optimum, and it outperforms ACO-ABC.

Table 11: Performance comparison between MCF-ABC and TSPoptBees [9].

Instances	TSPoptBees	MCF-ABC	Instances	TSPoptBees	MCF-ABC
att48	0.33	0.00	lin105	0.43	0.00
eil51	0.72	0.00	pr107	0.36	0.00
berlin52	0.32	0.00	pr124	0.84	0.00
st70	0.87	0.00	bier127	0.36	0.00
eil76	1.26	0.00	pr136	2.98	0.00
pr76	0.43	0.00	kroA150	1.51	0.00
kroA100	0.35	0.00	kroB150	1.54	0.00
kroB100	0.66	0.00	rat195	1.69	0.00
kroC100	0.70	0.00	kroA200	0.98	0.00
kroD100	1.18	0.00	kroB200	2.25	0.00
kroE100	0.57	0.00	tsp225	2.25	0.00
rd100	1.66	0.00	a280	2.02	0.00
eil101	0.77	0.00	lin318	2.34	0.00

Table 11 shows the performance comparison between MCF-ABC and TSPoptBees [9]. MCF-ABC is able to obtain better δ_{avg} as compared with TSPoptBees for all instances. Besides that, MCF-ABC consistently solves all the 26 instances to the known optimum for 30 replications.

Table 12: Performance comparison between MCF-ABC and BCO [73].

Instances	BCO	MCF-ABC	Instances	BCO	MCF-ABC
eil101	0.000	0.000	pr299	0.029	0.000
lin105	0.000	0.000	lin318	0.159	0.000
pr107	0.000	0.000	rd400	0.229	0.000
gr120	0.078	0.000	fl417	0.130	0.000
pr124	0.000	0.000	gr431	0.582	0.000
bier127	0.000	0.000	pr439	0.041	0.000
ch130	0.000	0.000	pcb442	0.423	0.000
pr136	0.018	0.000	d493	0.354	0.002
gr137	0.000	0.000	att532	0.351	0.002
pr144	0.000	0.000	ali535	0.103	0.000
ch150	0.000	0.000	si535	0.034	0.100
kroA150	0.000	0.000	pa561	0.948	0.004
kroB150	0.000	0.000	u574	0.697	0.000
pr152	0.000	0.000	rat575	0.537	0.020
u159	0.000	0.000	p654	0.048	0.000
si175	0.000	0.000	d657	0.445	0.006
rat195	0.198	0.000	gr666	0.553	0.016
d198	0.072	0.000	u724	0.622	0.016
kroA200	0.000	0.000	rat783	0.895	0.000
kroB200	0.002	0.000	pr1002	0.853	0.011
gr202	0.027	0.000	si1032	0.000	0.000
ts225	0.000	0.000	vm1084	0.495	0.011
tsp225	0.000	0.000	pcb1173	0.924	0.010
pr226	0.000	0.000	d1291	0.447	0.084
gr229	0.010	0.000	d1655	1.062	0.151
gil262	0.000	0.000	u1817	1.356	0.268
pr264	0.000	0.000	u2152	1.496	0.270
a280	0.000	0.000	pr2392	1.044	0.137

Table 12 shows the performance comparison between MCF-ABC and BCO [73]. MCF-ABC obtains better δ_{avg} than BCO for 33 instances, while BCO outperforms MCF-ABC in solving si535. MCF-ABC is able to consistently solve 39 out of 56 instances to the known optimum as compared with 22 out of 56 instances by BCO.

Table 13: Performance comparison between MCF-ABC and HDABC [89].

Instances	HDABC	MCF-ABC	Instances	HDABC	MCF-ABC
eil101	0.05	0.00	lin318	0.26	0.00
pr107	0.10	0.00	rd400	0.26	0.00
pr124	0.00	0.00	gr431	1.01	0.00
pr144	0.02	0.00	pr439	0.22	0.00
ch150	0.31	0.00	pcb442	0.15	0.00
kroA150	0.05	0.00	u574	0.37	0.00
pr152	0.00	0.00	rat575	0.75	0.02
rat195	0.61	0.00	u724	0.33	0.02
d198	0.27	0.00	rat783	0.91	0.00
kroA200	0.05	0.00	pr1002	0.71	0.01
kroB200	0.02	0.00	pcb1173	0.77	0.01
ts225	0.00	0.00	d1291	1.64	0.08
pr226	0.00	0.00	d1655	1.28	0.15
gr229	0.38	0.00	fnl4461	1.30	0.24
gil262	0.00	0.00	pla7397	1.47	0.27
pr264	0.00	0.00	pla85900	2.23	0.77
pr299	0.06	0.00			

Table 13 shows the performance comparison between MCF-ABC and HDABC [89]. MCF-ABC obtains better δ_{avg} than HDABC for 27 instances. For the other six instances, both MCF-ABC and HDABC obtain δ_{avg}=0.00. MCF-ABC is able to solve 23 out of 33 instances to the known optimum, as compared with 6 out of 33 instances by HDABC.

Table 14: Performance comparison between MCF-ABC and CLK [105].

Instances	CLK	MCF-ABC	Instances	CLK	MCF-ABC
pr1002	0.126	0.011	pr2392	0.283	0.137
si1032	0.005	0.000	fl3795	0.732	0.184
vm1084	0.038	0.011	fnl4461	0.145	0.239
pcb1173	0.041	0.010	rl5915	0.277	0.435
d1291	0.216	0.084	pla7397	0.275	0.273
d1655	0.170	0.151	rl11849	0.409	0.512
u1817	0.361	0.268	pla85900	0.698	0.774
u2152	0.546	0.270			

Table 14 shows the performance comparison between MCF-ABC and CLK [105]. MCF-ABC and CLK employ the same implementation of the LK local search strategy. Comparing with CLK, MCF-ABC obtains

better δ_{avg} in solving smaller-scale instances (*dim*≤3795). However, CLK outperforms MCF-ABC for larger-scale instances, i.e. fnl4461, pla7397, rl11849, and pla85900.

Table 15: Performance comparison between MCF-ABC and ESACO [60].

Instances	ESACO	MCF-ABC	Instances	ESACO	MCF-ABC
lin105	0.000	0.000	rat783	0.043	0.000
d198	0.000	0.000	pr1002	0.179	0.007
kroA200	0.000	0.000	fl3795	0.388	0.178
a280	0.004	0.000	fnl4461	0.482	0.215
lin318	0.059	0.000	rl5915	0.669	0.439
pcb442	0.050	0.000	pla7397	0.553	0.233
att532	0.055	0.004	rl11849	0.764	0.479

Table 15 shows the performance comparison between MCF-ABC and ESACO [60]. Both MCF-ABC and ESACO are able to solve lin105, d198 and kroA200 to the known optimum. However, for the TSP instances with *dim*>200, MCF-ABC outperforms ESACO. MCF-ABC is able to solve 7 out of 14 instances to the known optimum within 3000 neighbourhood search operations as compared with 3 out of 14 instances by ESACO.

Table 16: Performance comparison between MCF-ABC and QPSO [115].

Instances	QPSO	MCF-ABC	Instances	QPSO	MCF-ABC
swiss42	0.000	0.000	pr1002	0.000	0.000
gr229	0.010	0.000	pcb1173	0.002	0.000
pcb442	0.000	0.000	d1291	0.096	0.010
gr666	0.029	0.003	u1817	0.073	0.136
dsj1000	0.026	0.003	fl3795	0.025	0.022

Table 16 shows the performance comparison between MCF-ABC and QPSO [115]. Both MCF-ABC and QPSO employ an LK-based local search. MCF-ABC obtains better or equal δ_{avg} as compared with QPSO in solving all the ten instances except u1817. MCF-ABC is able to solve 5 out of 10 instances to the known optimum within 10000 neighbourhood search operations as compared with 3 out of 10 instances by QPSO.

Table 17: Performance comparison between MCF-ABC and HBMO [72].

Instances	HBMO	MCF-ABC	Instances	HBMO	MCF-ABC
eil101	0.000	0.000	pr439	0.000	0.000
lin105	0.000	0.000	pcb442	0.000	0.000
pr107	0.000	0.000	d493	0.000	0.000
pr124	0.000	0.000	rat575	0.000	0.007
bier127	0.000	0.000	p654	0.000	0.000
ch130	0.000	0.000	d657	0.000	0.002
pr136	0.000	0.000	rat783	0.000	0.000
pr144	0.000	0.000	dsj1000	0.012	0.004
ch150	0.000	0.000	pr1002	0.001	0.000
kroA150	0.000	0.000	vm1084	0.005	0.007
pr152	0.000	0.000	pcb1173	0.003	0.000
rat195	0.000	0.000	d1291	0.000	0.042
d198	0.000	0.000	d1655	0.122	0.008
kroA200	0.000	0.000	u1817	0.028	0.172
kroB200	0.000	0.000	u2152	0.390	0.140
ts225	0.000	0.000	pr2392	0.028	0.027
pr226	0.000	0.000	fl3795	0.370	0.041
gil262	0.000	0.000	fnl4461	0.350	0.121
pr264	0.000	0.000	rl5915	0.012	0.186
a280	0.000	0.000	pla7397	0.009	0.132
pr299	0.000	0.000	rl11849	0.098	0.273
rd400	0.000	0.000	pla85900	0.210	0.447
fl417	0.000	0.000			

Table 17 shows the performance comparison between MCF-ABC and HBMO [72]. The local search strategy employed by HBMO is known as ENS. ENS is similar to the LK local search because they both use multiple neighbourhood structures. For the instances with smaller dimensions (i.e. $dim<500$), both MCF-ABC and HBMO are able to yield the known optimum within 5000 neighbourhood search operations. MCF-ABC outperforms HBMO in solving several medium-scale instances, i.e. u2152, pr2392, fl3795, and fnl4461. However, for larger-scale instances, i.e. rl5915, pla7397, rl11849, and pla85900, HBMO yields better δ_{avg} as compared with MCF-ABC.

To statistically compare the overall performance of MCF-ABC and other algorithms, the Wilcoxon signed rank test with 95% confidence interval is employed. The results of the Wilcoxon signed ranks test are summarised in Table 18. Table 18 indicates that, based on the 95% confidence interval, the proposed MCF-ABC model significantly outperforms 15 algorithms, with $W \leq W_{Cri,N}$ and $R^+ > R^-$. Besides, it is comparable with CLK, QPSO and HBMO ($W > W_{Cri,N}$).

Table 18: The Wilcoxon signed ranked test for the comparison of MCF-ABC and state-of-the-art algorithms.

Comparisons (MCF-ABC vs …)	Citation	N	R^+	R^-	W	$W_{Cri,N}$	Significant Difference
ABC [RS]	[34]	9	45	0	0	5	yes
ABC [RSS]		8	36	0	0	3	yes
ABC [RI]		9	45	0	0	5	yes
ABC [RIS]		9	45	0	0	5	yes
ABC [RR]		9	45	0	0	5	yes
ABC [RRIS]		7	28	0	0	2	yes
ABC [RRSS]		7	28	0	0	2	yes
ABC [RS, RSS, RRSS]		8	36	0	0	3	yes
ABC [RI, RIS, RRIS]		7	28	0	0	2	yes
ACO-ABC	[70]	8	36	0	0	3	yes
2-opt ABC	[86]	8	36	0	0	3	yes
TSPoptBees	[9]	26	351	0	0	98	yes
BCO	[73]	34	587	8	8	182	yes
HDABC	[89]	27	378	0	0	107	yes
CLK	[105]	15	84	36	36	25	no
ESACO	[60]	11	66	0	0	10	yes
QPSO	[115]	7	22	6	6	2	no
HBMO	[72]	17	71	82	71	34	no

5. Conclusions

The Artificial Bee Colony (ABC) algorithm is a swarm-intelligence-based model for solving various optimisation problems. One of the crucial components of ABC is the neighbourhood search, which is performed by the employed and onlooker bees. When ABC is used to solve combinatorial discrete optimisation problems, single or multiple problem-specific perturbative heuristics are adopted as the neighbourhood search mechanism of the employed and onlooker bees. When there are multiple neighbourhood search heuristics, the selection of these heuristics has a significant impact on the performance of the ABC optimisation model. In this study, we have proposed the use of a hyper-heuristic method, namely Modified Choice Function (MCF), to guide the selection of the neighbourhood search heuristics in ABC. Ten low-level heuristics (LLHs) have been adopted in the proposed MCF-ABC model. Besides that, the Lin-Kernighan (LK) local search strategy is incorporated into MCF-ABC to further enhance its usefulness.

The proposed MCF-ABC model has been evaluated with 64 TSP instances. The experimental results show that MCF-ABC significantly outperforms MCF-ABC(4), which uses four LLHs with basic operations. This indicates that a variety of LLHs brings advantages to the search process. In addition, MCF-ABC statistically outperforms Random-ABC, which utilises a random LLH selection strategy. The comparison studies indicate that MCF-ABC is competitive among the state-of-the-art algorithms.

Acknowledgement

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