A hybrid firefly algorithm for the sales representative planning problem

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Article Info

Article history:

Received Jul 7, 2024
Revised Sep 5, 2024
Accepted Sep 29, 2024

Keywords:

A pharmaceutical sales
Firefly algorithm
Metaheuristics
Optimization
Orienteering problem
Representative

ABSTRACT

In the rapidly increasing pharmaceutical sector, sales representatives are employed by pharmaceutical manufacturers and distributors to inform and educate physicians. To convince providers to prescribe the medications to their patients, these representatives rely on their product expertise and people's abilities to close deals. Instead of making direct sales, pharmaceutical sales representatives help medical professionals get the medications, treatments, and information they need to give their patients the best care possible. Furthermore, they inform the public about novel and occasionally life-saving treatments and share interesting medical developments. This study presents a hybrid methodology that integrates the benefits of local search and the firefly algorithm (FA) to determine the optimal planning for a sales representative. The objective is to maximize the rewards while adhering to certain constraints. The objective is to maximize the rewards while adhering to certain limits. Utilizing local search, the hybrid algorithm enhances firefly's global search behaviour and produces the best possible sales presentation planning. The experimental findings demonstrate the superior performance of the suggested algorithm compared to the FA and other literature methods in the sense of enhancing the convergence rate and preventing local minima. Furthermore, it can enhance the best-known solution for most benchmark instances.

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1. INTRODUCTION

Pharmaceutical sales representatives are specialists in their company's product lines; they must understand not just about their employer's medicines but also about competing drugs. Pharmaceutical companies produce medicines and market comparable products, so their representatives must be well-versed in everything that's available on the market at any given time in order to explain product differences to providers and emphasize the advantages of the pharmaceuticals they represent [1]. Sales representatives have non-stop days, and they know how to work hard. But to increase their sales time and revenues, sales representatives need to take control of their days and carefully plan their activities. Sales representatives work long hours and are known for their hard work. However, to maximize their sales time and income, sales professionals must take charge of their days and meticulously plan and arrange their activities. A sales representative's daily plan allows them to be as productive as possible in meeting their objectives. The most productive sales representatives are extremely well-organized, goal-oriented, and focused. They plan their days in advance. They always set priorities, get rid of distractions, assign tasks, and put in place a well-organized time management system [2], [3]. Nowadays, the pharmaceutical business is facing severe competition in a challenging economic environment. To succeed, they need to either surpass their rivals in market share or keep an advantage over them through creative ideas or offerings. The field sales force's efficacy is crucial in every situation. That's why, they must precisely plan their operations to get new clients, improve sales per customer, and meet defined goals. Sales rounds are a key component of sales technique. Sales representatives face important challenges when it comes to preparation, planning, and optimization. To maximize potential sales, pharmaceutical sales reps must establish a daily planner outlining which healthcare providers to visit and in what order. Usually, the doctor provides a time window when she meets with representatives between other professional responsibilities (such as examining patients and filing documents). A representative must arrive at the office before the doctor's time window closes [3]. Several sales representatives go to the doctor and pharmacist on one or more days. It is impossible to take everything. In that case, the sales representatives select what they believe to be the most attractive points of interest (POI) (doctors, pharmacists).

This paper's objective is to identify optimal route planning for sales representatives or other field workers, including those in the retail food or pharmaceutical sectors, who are tasked with visiting their customers regularly at specific intervals to maximize the value gathered on a particular day while adhering to certain constraints (such as deadlines and total time). A route is a planned series of customer visits. That is, we attempt to create an optimal route based on maximizing the rewards of the sales representative, provided that the visits to doctors or pharmacists must be carried out within the specified period [2]. The sales representative planning problem is similar to an orienteering problem (OP). Each sales representative needs to tackle an OP variant [4]. One of the most important aspects of sales representative planning is creating routes for suitable sales representatives. Several methods for resolving the sales representative planning and OP are described in [1], [5]. There are various methods for tackling the sales representative planning problem; [3] solved the problem by applying a variable neighborhood search algorithm, which they modeled using the multi-period OP with multiple time windows (MuOPMTW). Zhang *et al.* [2] proposed using SOPTW to model the sales representative planning problem. The sales representative planning problem is equivalent to the OP variants. Many of the algorithms mentioned in the literature deal with OP with window time (OPTW) or (T) OPTW. The sales representative planning problem could also be solved using these algorithms. The most similar OP version to this problem is called the OPTW, in which a sales representative is scheduled to visit various doctors to collect rewards within a predetermined budget and window of time [1]. To solve OPTW, [6] developed an exact solution based on bidirectional dynamic programming. An extremely quick ILS approach to solving the TOPTW is proposed by Vansteenwegen *et al.* [7]. The ant colony system (ACS) method was created by [8]. A variety of different metaheuristics are also available in literature, such as a combination of a greedy randomized adaptive search procedure (GRASP) and an evolutionary local search (ELS), a granular variable neighborhood search (GVNS), and an artificial bee colony approach (ABC) [9]–[12]. In addition to tackling the route planning problem depicted by OPTW, [13] developed the GRASP-Tabu method, based on two approaches, a tabu search and GRASP, to solve the same problem. Yassen *et al.* [14] proposed a lion optimization algorithm for the team OP with a time window. The main contribution of this study can be summed up as follows: the sales representative planning problem is presented and formalized using a variation of the OP. To tackle the sales representative planning problem, we propose a method based on hybrid firefly and local search. The key component of the hybrid firefly algorithm (HFLS) is its ability to combine the advantages of its component methods. We empirically show the effectiveness of our proposed approach using benchmark instances from the literature. This can also improve the well-known solution in several benchmark datasets [15], [16].

We structure the remaining sections of the paper as follows: section 2 presents the formal specification of the sales representative planning problem. In section 3 provides a detailed explanation of our suggested hybrid firefly method. The final section contains the findings and provides recommendations for future research.

2. PROBLEM DESCRIPTION

The goal is to create a route allowing the sales representative to visit a customer (a doctor). We define the planning problem for sales representatives. Let us assume that a sales representative (a pharmaceutical representative) is assigned to a city or region where N potential consumers are available for visits. A set of attributes is assigned to each client i. These attributes include a profit, coordinates (x_i, y_i), service time (d_i), opening and closing times (O_i and C_i are a time window). Moreover, we assume that the traveling time t_{ij} between customers i and j is equal and given for every customer location. In general, not all clients can be visited along the route since the sales representative (pharmaceutical salesperson) route has a maximum time (T_{max}) that should not be exceeded. Each consumer is only allowed one visit. Customers' service starting times (s_i) fall inside a time window. Each representative must arrive within a specific time window. The goal of the sales representative planning problem is to determine the representative's route and enable her to maximize her overall incentive profit while taking into account any constraints that may occur

[13]. In general, the route's start and end times can vary. Furthermore, we assume that the starting and finishing locations for each route m are customers 1 and N, respectively. Typically, the initial and final locations in the pharmaceutical industry may be the same. Subsequently, we may model the sales representative planning problem as an integer programming problem using a decision variable, based on. Each route from 1 to N has a variable called x_{ij}, which we set to 1 if visit i is succeeded by visit j and 0 otherwise. Following the mathematical formulation suggested by [3], [13]. The objective function of the sales representative planning problem is defined in (1), where n represents the total number of customers, and r denotes the incentive associated with a specific client i. The goal function aims to identify m feasible routes that optimize the overall profit.

$$\text{Max} \sum_{i=2}^{N-1} \sum_{j=2}^{N} r_i x_{ij} \tag{1}$$

3. METHOD

3.1. Firefly algorithm

Yang [15] created the original firefly algorithm (FA) in [15], [16]. It imitates the primary traits of tropical fireflies' flashing behavior. Based on the idealized behavior of the flashing patterns and the communication style of tropical fireflies, the FA was created. FA constructs the algorithm's mathematical model using the following three idealized rules. Since all fireflies are unisex, they will all be drawn to one another regardless of gender. Their brightness directly relates to their attractiveness. As a result, the less brilliant firefly will travel toward the brighter one when there are two flashing fireflies. Both brightness and attractiveness diminish with increasing distance from one another in a proportionate manner.

The objective function's landscape influences or determines a firefly's luminosity. Since brightness is linked to the fitness function, it is assumed for simplicity's sake that the firefly's attraction is determined by its brightness. The difference in distance (rij) between fireflies i and j will determine their attractiveness (β). The firefly light intensity I(r) changes with the degree of absorption and decreases with increasing distance from the source as shown in Algorithm 1 [17], [18].

Algorithm 1. The standard firefly algorithm

```
Objective function f(x), x = (x1, x2,...,xd)^T
Initialize a population of fireflies xi (i = 1,2,...,n)
Calculate the light intensity Ii
Specify light absorption coefficient γ
while (t < Max_iteration) do
for i ← 1 to n (all n fireflies) do
   for j ← 1 to n (all n fireflies) do
         if (Ij > Ii) then
                  Move firefly i to the j in all d dimensions.
         end if
               Attractiveness depends on distance r via e^(-γr2)
               Assess novel solutions and adjust the amount of light intensity.
    end for
         end for
    Find the current best fireflies by ranking them
 end while
Sort the firefly and select the best one.
```

3.2. The proposed adaptive approach for the firefly algorithm

It is not possible to directly apply the FA to tackle discrete optimization problems since it was initially designed to solve continuous optimization problems. FA is modified to tackle the sales presentative planning problem by combining the move inversion mutation, which simulates firefly movement.

3.2.1. The representation of firefly

One of the most critical problems in creating a discrete FA is representing and initializing the solution. The permutation representation is a solution representation for the sales presentative planning. In this illustration, a consumer is represented by an array member, and the tour order is indicated by the index [19].

3.2.2. Initialization

The initial population is created at random. Including one greedy solution among the random solutions would undoubtedly contribute to improved exploitation.

3.2.3. Light intensity

The light intensity can determine a firefly's luminosity. This value is determined by the overall profit of the firefly's customers. Since sales presentation planning aims to identify the route with the maximum profit, a firefly with a more profitable route will have a brighter, more intense light. An intensity of light is obtained for a firefly x by using (1).

3.2.4. Distance

In Hamming distance, a firefly at y_i and a firefly at y_j are separated by a distance of $r_{i,j}$.

$$r_{i,j} = Hamming\_Distance(y_i , y_j) \tag{2}$$

The number of non-corresponding elements determines the Hamming distance between two permutations.

3.2.5. Attractiveness

A firefly's attractiveness is defined by its brightness, represented in its objective function. In (3) represents it.

$$\beta(r) = \beta_O e^{-\gamma r^2} \tag{3}$$

In this context, r represents the distance between two fireflies, β(r) is the attractiveness of a firefly at that distance, γ is a constant light absorption coefficient, and β_0 is the brightness of a more brilliant firefly. Next, we utilize (3) to determine the firefly j's attractiveness as seen by firefly i at a distance r. If firefly j's attraction is greater than firefly i's brightness, firefly i will get to firefly j; otherwise, firefly i will move randomly.

3.2.6. Light absorption

The light absorption coefficient (γ) describes how a firefly's attraction varies. Its value is crucial in establishing the convergence speed and the behaviour of the FA. In principle, γ ∈ [0, N], but in reality, γ depends on the problem's features that must be solved.

3.2.7. Movement

When one brighter firefly, j, attracts another, i, its movement is dictated by (4).

$$x_i = rand(2 , r_{i,j}) \tag{4}$$

Where the distance r_{ij} between fireflies i and j is, a firefly's movement length will be chosen randomly from 2 to r_{ij}. The solutions that a firefly has changed when it moves. We utilize inversion mutation to express movement, as the firefly representation is a permutation representation [20].

3.2.8. Inversion operator

An inversion operator is employed to generate new fireflies or possible solutions. In the beginning, choose one customer (C_1) at random from the route index. Next, choose the second customer (C_2) by adding the movement length to the first customer (C_1). An inversion operator can preserve the route that has already been established as shown in Figure 1 [20].

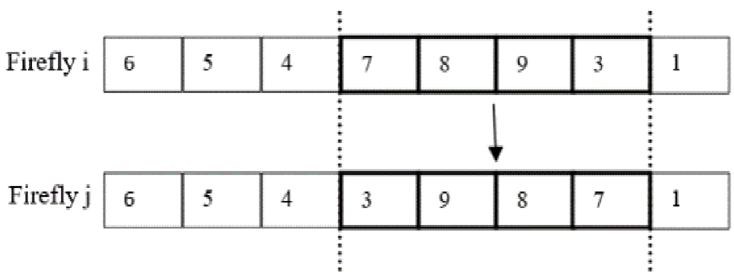


Figure 1. Inversion operator

3.2.9. General firefly algorithm method

In this method, a swarm of fireflies is initialized, and the intensity of the flashing lights is determined for each one. In each firefly, a random and greedy solution is generated. Because the flashing light may be defined in a way related to the objective function of the issues under consideration, optimization algorithms can be created to produce effective, optimum solutions.

Choose the firefly that is the brightest or most appealing during the pairwise comparison of the light intensity cycle. The less brilliant firefly will go in the direction of the brighter one if there is one, and it will move at random if there isn't. The attractiveness determines the movement distance [15].

The inversion mutation is used to generate new solutions each time a firefly moves randomly. In the next movement, the previous solution represented by the firefly is modified, and the novel firefly is assessed and adjusted for light intensity. The current solution is iteratively updated during the loop. The optimal solution thus far is finally provided as shown in Algorithm 2 [16].

Algorithm 2. The standard FA algorithm for sales representative planning

```
Input: Problem instance ()
Output: Optimal Route S* (C1, C2...Cn)
Initialize all the parameters (α;β;γ;n)
Define size population, number of iterations
Objective function f(x), x =(x1,x2,...,xd)^T
Create a population of fireflies xi (i = 1,2,...,n)
Compute the light intensity Ii
while (t < Max_iteration) do
for i ← 1 to n (all n fireflies) do
   for j ← 1 to n (all n fireflies) do
         if (Ij > Ii) then
                            Determine the Hamming distance between xi and xj.
          Move firefly xi towards xj, using inversion mutation
             Update the position of xi
               Check the Feasibility of the solution
          end if
       Attractiveness depends on distance r via e^(-γr2)
                   Assess novel solutions and adjust the amount of light intensity.
       end for
   end for
        Select the best fireflies by ranking.
end while
Sort the fireflies and select the best one
```

3.3. Local search

To improve the FA's fitness function, the paper suggests using local search methods. Iteratively searching four distinct neighborhoods, the local search technique alternates between shortening the entire search time and raising the overall score. The neighborhood is investigated for overall distance decrease using a typical 2-Opt technique that minimizes crossings.

A neighborhood swap is then used to exchange locations between routes to find the shortest route between selected customers. After that, the insert neighborhood uses the construct technique to see whether it may enhance the score of the existing solution. It then iteratively explores other neighborhoods until no improvement is provided. Lastly, replace attempts to swap out included sites with non-included locations that are part of the existing solution. To perform the move with the greatest score gain, the replace neighborhood is first examined in the best-improving manner possible.

At every iteration, a neighborhood solution Y is selected from N(X), and the results of its objective function is calculated. Y takes the place of X as the new current answer if it is not worse than X. Following a predetermined number of iterations, the algorithm is completed as shown in Algorithm 3 [21].

Algorithm 3. The local search algorithm

```
Input: Solution of firefly
Output: Best found solution
while termination criterion not reached do
    2-Opt;
     Swap;
    Replace;
   Insert;
end while
Return local optimum;
```

3.4. Proposed hybrid firefly and local search

In the realm of optimization, interest in hybrid metaheuristics has grown significantly in recent years. Hybrid algorithms provide the best solutions for a wide range of practical or traditional optimization issues [13]. To achieve greater results, these combinations increase the benefits of employing a single practice. In this study, we combine some of the benefits of both algorithms to present a novel hybrid algorithm based on local search and FA. We refer to the suggested approach as the HFLS, which combines the attraction strategy of FA with the integrating capabilities of local search to improve convergence speed and population diversity. Regarding the attraction technique, the firefly method can automatically split the entire population into subgroups based on variations in light intensity. Additionally, one of the FA forms can escape the local minima due to long-distance mobility via Lévy flight. Because of these benefits, FA performs well in both diversification and exploration [22]–[25]. While local search offers enhanced solutions. To help sales representatives (such as pharmaceutical industries) arrange their own routes, we offer a solution procedure [2], [3]. Using a firefly method for solution creation and local search as its local optimizer, the HFLS algorithm finds the best route for sales representatives by following this general scheme as shown in Algorithm 4.

Algorithm 4. Pseudo-code for hybrid firefly local search

```
Input: Problem instance ()
Output: Optimal Route R' (C_1, C_2...C_n)
F=-∞
R' = {};
while termination criterion not reached do
        R_0 ← Firely Method solution ();
        R ← local search (R_0);
    if (F(R) > F) then
        R' =R
        F=F(R)
    end if
end while
Return R'
```

4. RESULTS AND DISCUSSION

The sales representative planning problem has long been difficult in combinatorial optimization because of its complexity and the requirement for effective route planning. Traditional approaches frequently struggle with large-scale cases, resulting in unsatisfactory solutions. Recent studies have explored metaheuristic approaches, but there remains a gap in achieving high-quality solutions and computational efficiency. This work aims to close this gap by presenting a HFLS. This section presents experimental findings obtained after applying the HFLS to the sales representative planning Problem, including parameter sets, performance assessment, and a comparison study. The findings of each experiment are analysed, and explanations are provided. The proposed methods were programmed in Java and ran on a PC with an Intel Core i5, Windows 10 OS, and 8 GB RAM.

4.1. Benchmark instances

The following subsection describes the test set. The method is tested in numerous instances. Various simulations were carried out on test problems to evaluate the HFLS approach to optimization problems. Ten runs were conducted to test the HFLS. To ensure a fair comparison between various approaches, identical conditions were used for every experiment. The HFLS algorithm was evaluated on the available test problems and compared to various literature approaches, including GRASP-TB, iterated local search (ILS), the firefly method, and GRASP-TB method, ILS, ACS, slow simulated annealing (SSA), GVNS, and ABC approach [6]–[13]. Righini and Salani [6] proposed the test problems for the OPTW in literature, which are based on Solomon's instances. 48 of Solomon's instances have 100 series nodes (c100, r100, and rc100) [26].

4.2. Parameter settings

In this study, an initial test is conducted to identify the appropriate values for the parameters of the suggested approaches. The suggested methods are run 10 times during the initial test to examine their performance. The parameter settings used in this study are as follows: iteration number=100, population size=15, β_0=1, and γ=0.1.

4.3. Computational results
4.3.1. Comparison of HFLS with the literature methods

We compared our algorithm with the following algorithms to evaluate its performance. Figures 2 to 4 and Table 1 offer complete results of the HFLS performance and the literature methods. The HFLS approach introduced 40 new best-known solutions and enhanced the best-known solutions by 67.7%. This signifies that the algorithm performs well and can select the optimum route for sales representatives. Table 1 summarizes the findings of the HFLS, ILS, ACS, GVNS, SSA, ABC, and GRASP-TB. The table displays the average profit (Avg) for each instance. For all instances (from c100 to rc200), the average results achieved by the HFLS are better than those of other methods. The HFLS method outperforms other methods because the grand mean of Avg is 691.84, while those other methods are 669.17, 615.5, 628.06, 628.06, 613.04, and 625.58.

Table 1. Comparison of HFLS with the literature methods

Instance	Nombre	GRASP-TB Avg	HFLS Avg	ILS Avg	ACS Avg	SSA Avg	GVNS Avg	ABC Avg
c100	9	376.67	393.33	362.22	366.67	366.67	360	366.44
r100	12	291.67	297.25	276.92	281.88	281.58	271.33	279.33
rc100	8	254.57	268.71	253.43	260.71	260.71	246.71	260.51
c200	8	945	955	911.25	930.5	931.25	922.25	927.5
r200	11	1077.1	1118	963.9	983.98	979.5	958.84	977.86
rc200	8	1070	1118.75	925.25	944.61	948.63	919.1	941.84
Grand mean		669.17	691.84	615.5	628.06	628.06	613.04	625.58

Figure 2 presents the results of the HFLS method, ILS, GRASP-TB, ACS, SSA, GVNS, and ABC, for instance, dataset 1. As shown in Figure 2(a), for the majority of instances c100, r100, and rc100, the HFLS method outperforms other methods, except instances c104, R101, R104, and R108, where the HFLS is slightly worse than the others. Also, notably in Figure 2(b), for the instances c100, r100, and rc100, the HFLS outperforms other methods, except in some instances where the HFLS profit is less than the others.

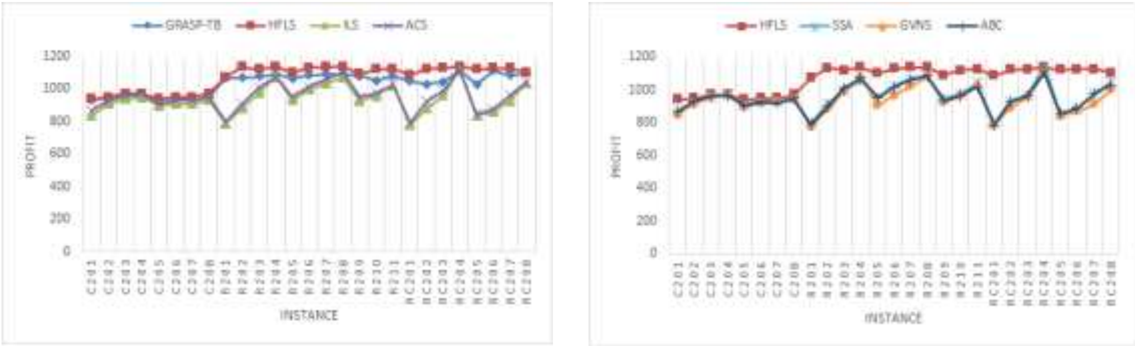
(a) (b)

Figure 2. Results of HFLS, (a) ILS, GRASP-TB, ACS and (b) SSA, GVNS, and ABC (instance set 1)

Figure 3 describes the results of the HFLS method, ILS, GRASP-TB, ACS, SSA, GVNS, and ABC, for instance, dataset 2. Specifically, as can be seen from Figure 3(a), the HFLS provides superior results than other algorithms, for instances of c200, r200, and rc200. Still, in instances, C202, C203, and C206, the performance of the HFLS is comparable to that of other algorithms. Also, as can clearly be observed from Figure 3(b), the HFLS can obtain good solutions for instances of c200, r200, and rc200, Unlike in some instances, the HFLS gives similar profit results to ILS, GRASP-TB, and ABC.

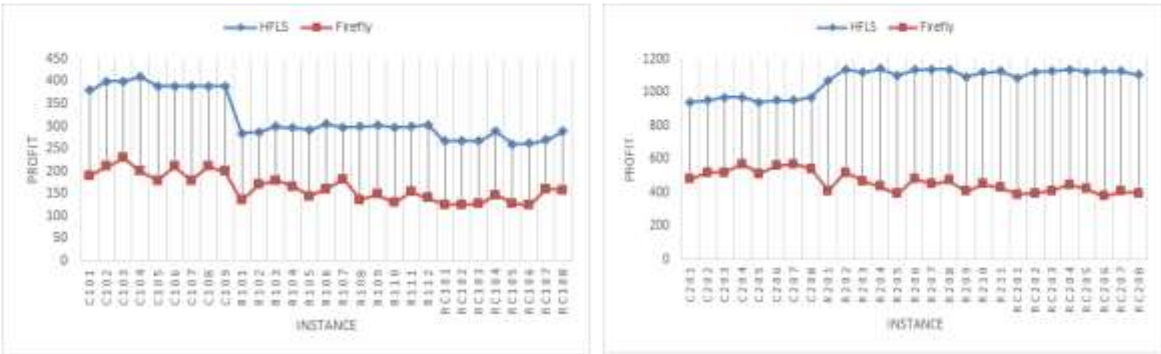
4.3.2. Comparison of HFLS with the firefly method

Figure 4 presents the results of the HFLS firefly method for Solomon's instances. As demonstrated in Figure 4(a), the performance of HFLS surpasses the firefly method in every instance of c100, r100, and rc100. As can be seen, using the HFLS approach produces higher-quality results. Also, the HFLS method performs better than the firefly method in all instances, as shown in Figure 4(b).



(a) (b)

Figure 3. Results of HFLS, (a) ILS, GRASP-TB, ACS and (b) SSA, GVNS, and ABC (instance set 2)



(a) (b)

Figure 4. Results of the HFLS method (a) for instance set 1 and (b) instance set 2

The above results mean that, in a practical system, this approach provides optimal route planning for sales representatives to maximize the gains obtained on a given day while maintaining specific constraints. According to computational results, combining local search and the FA is an effective approach to solving the sales presentation planning problem. Compared to other approaches found in literature and the firefly method, the HFLS method produces better results in every instance, as seen by the results above. This may be explained by indicating that this proposed approach is the HFLS, which integrates the attraction technique of FA with the combining capacity of location search, allowing for advances in the rate of convergence and the diversity of the population. Furthermore, taking into account, these results demonstrate that adding a heuristic to the firefly method enhances the quality of the algorithm and the score of solutions such as insert, and replace. Additionally, the 2-OPT and swap operators allow the algorithm to improve the overall quality of its solutions. Despite the improved benefits provided by the HFLS method, there are instances where the method does not give better results. However, these do not significantly affect the algorithm's overall efficiency.

5. CONCLUSION

The main goal of the current study was to propose a HFLS, to tackle the sales representative planning problem. The proposed method combines some of the benefits of the FA and local search. The advantage of HFLS is that it may provide strong exploration effectiveness, whereas local search is good at exploitation due to the neighborhood operator. The present study makes noteworthy contributions to the literature by offering an application of the HFLS method to a sales representative planning problem. The experimental findings show that the proposed algorithm can obtain very competitive results and is effective in most instances. In terms of results, this algorithm performs better than the methods found in literature. It introduced the best new solutions while enhancing the existing ones. As an extension to the work, it would be interesting to assess tests with real data sets and employ various novel-inspired metaheuristic approaches. In addition, it is recommended that further research to be undertaken in the following areas such as network routing, factory scheduling, crowdsourcing, and logistics planning.

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