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ORIGINAL

A dragonfly algorithm for solving the Fixed Charge Transportation Problem FCTP

Un algoritmo libélula para resolver el problema de transporte de carga fija FCTP

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ABSTRACT

The primary focus of this article is dedicated to a thorough investigation of the Fixed Load Transportation Problem (FCTP) and the proposition of an exceedingly efficient resolution method, with a specific emphasis on the achievement of optimal transportation plans within practical time constraints. The FCTP, recognized for its intricate nature, falls into the NP-complete category, notorious for its exponential growth in solution time as the problem's size escalates. Within the realm of combinatorial optimization, metaheuristic techniques like the Dragonfly algorithm and genetic algorithms have garnered substantial acclaim due to their remarkable capacity to deliver high-quality solutions to the challenging FCTP. These techniques demonstrate substantial potential in accelerating the resolution of this formidable problem. The central goal revolves around the exploration of groundbreaking solutions for the Fixed Load Transportation Problem, all while concurrently minimizing the time investment required to attain these optimal solutions. This undertaking necessitates the adept utilization of the Dragonfly algorithm, an algorithm inspired by natural processes, known for its adaptability and robustness in solving complex problems. The FCTP, functioning as an optimization problem, grapples with the multifaceted task of formulating distribution plans for products originating from multiple sources and destined for various endpoints. The overarching aspiration is to minimize overall transportation costs, a challenge that mandates meticulous considerations, including product availability at source locations and demand projections at destination points. The proposed methodology introduces an innovative approach tailored explicitly for addressing the Fixed Charge Transport Problem (FCTP) by harnessing the inherent capabilities of the Dragonfly algorithm. This adaptation of the algorithm's underlying processes is precisely engineered to handle large-scale FCTP instances, with the ultimate objective of unveiling solutions that have hitherto remained elusive. The numerical results stemming from our rigorous experiments unequivocally underscore the remarkable prowess of the Dragonfly algorithm in discovering novel and exceptionally efficient solutions. This demonstration unequivocally reaffirms its effectiveness in overcoming the inherent challenges posed by substantial FCTP instances. In summary, the research represents a significant leap forward in the domain of FCTP solution methodologies by seamlessly integrating the formidable capabilities of the Dragonfly algorithm into the problem-solving process. The insights and solutions presented in this article hold immense promise for significantly enhancing the efficiency and effectiveness of FCTP resolution, ultimately benefiting a broad spectrum of industries and logistics systems, and promising advancements in the optimization of transportation processes.

Keywords: Optimization; Dragonfly Algorithm; Fixed Charge Transportation Problem; NP-Hard Problem.

RESUMEN

El objetivo principal de este artículo es una investigación exhaustiva del Problema de Transporte de Carga Fija (FCTP) y la propuesta de un método de resolución extremadamente eficiente, con un énfasis específico en la consecución de planes de transporte óptimos dentro de limitaciones prácticas de tiempo. El FCTP,

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reconocido por su intrincada naturaleza, pertenece a la categoría NP-completo, notoria por su crecimiento exponencial en el tiempo de solución a medida que aumenta el tamaño del problema. En el ámbito de la en los puntos de destino. La metodología propuesta introduce un enfoque innovador adaptado explícitamente para abordar el Problema de Transporte de Carga Fija (FCTP) aprovechando las capacidades inherentes del algoritmo Dragonfly. Esta adaptación de los procesos subyacentes del algoritmo está diseñada con precisión para manejar instancias de FCTP a gran escala, con el objetivo último de desvelar soluciones que hasta ahora han permanecido esquivas. Los resultados numéricos de nuestros rigurosos experimentos ponen de manifiesto la extraordinaria capacidad del algoritmo Dragonfly para descubrir soluciones novedosas y excepcionalmente eficientes. Esta demostración reafirma inequívocamente su eficacia a la hora de superar los retos inherentes que plantean las instancias sustanciales del PTCP. En resumen, la investigación representa un importante salto adelante en el ámbito de las metodologías de solución de FCTP al integrar a la perfección las formidables capacidades del algoritmo Dragonfly en el proceso de resolución de problemas. Las ideas y soluciones presentadas en este artículo encierran la inmensa promesa de mejorar significativamente la eficiencia y eficacia de la resolución de FCTP, beneficiando en última instancia a un amplio espectro de industrias y sistemas logísticos, y prometiendo avances en la optimización de los procesos de transporte.

Palabras clave: Optimización; Algoritmo Libélula; Problema de Transporte de Carga Fija; Problema NP-Difícil.

INTRODUCTION

Transportation is a crucial aspect of modern society that involves the movement of people and goods from one location to another using various modes such as aviation, rail, road, and marine. The transportation sector is closely linked to daily life, economic, social, and service activities, making it one of the most important and exploitable industries. Its significance lies in enabling people to participate in human activities and facilitating the transportation of goods and passengers to meet the communication, production, export, and trade requirements of a growing population.[1] This research work aims to present a combinatorial optimization problem known as the fixed charge transportation problem (FCTP).[2]

The fixed charge transportation problem FCTP is a generalization of the classical transportation problem for which one seeks to send goods from m sources to n destinations. The goal is to meet the demand of all customers while minimizing the total cost of transport.[3] For the well-known classic transport problem, the sending of a product from a source to a destination is associated with a variable cost proportional to the flow sent. However, the FCTP problem also incorporates fixed costs in addition to variable costs associated with each arc used to transport flow, these fixed costs make the problem much more complex and difficult to solve. Many researchers have attempted to solve the FCTP, with Hirsch and Dantzig showing that it is an NP-Complete problem that admits an optimal solution at an extreme point.[4] Balainski converted the FCTP into a linear integer problem, which can be solved using linear transport methods, and found an optimal solution.[5] Aldakha proposed a heuristic algorithm for solving small FCTP problems, consisting of obtaining the best initial solution, improving it with techniques, and verifying its optimality.[6]

In addition, Klose deals with the complexity of the FCTP.[7] He showed that the resolution time in relation to the size of the problem increases exponentially for which it is regarded as NP-hard. Additionally, Klose proposed an approximate algorithm to address the problem. moreover, in the last twenty years, several heuristic and metaheuristic methods have been proposed by other researchers to solve FCTP.[8]

To solve the FCTP problem, several heuristic and metaheuristic methods have been proposed in recent years.[9,10] Like, Genetic Algorithms (GA),[11] Particle Swarm Optimization (PSO),[12] Ant Colony Method (ACO),[13] etc. most of these methods are inspired by nature. So, the Dragonfly Algorithm (DA) method is part of the metaheuristic class recently created and applied on some NP-Complete problems and which is inspired by the unique and superior swarming behavior of dragonflies, such as navigation, avoidance of dragonfly enemies and foraging. DA has been successfully evaluated and tested on several problems similar to our FCTP problem and real optimization problems like TSP problem, VRP problem, etc.[14,15] As well as it has obtained remarkable and very comparative results compared to other well-known methods in the literature.[16,17,18]

This paper is divided into four sections; In the first section we talked about the descriptive and mathematical model of FCTP problem. In the second section, the characteristics and processes of the proposed DBA method are described. Next, we presented the numerical results of the proposed method compared with the old results found by the other methods. Finally, we concluded with a concluding statement and some perspectives.

Problem description

The fixed cost transport problem FCTP is a case of the transport problem where an additional fixed cost is paid to send a stream from an origin to a destination. We have a group of sources i = 1, ..., m with limited capacities Si which provide several destinations j = 1, ..., n which also require specific quantities of product Dj. A variable transportation cost is charged for each product unit sent by the producers to the warehouses plus a fixed cost regardless of the quantity transported. The problem seeks to find the quantity of product to send from each source to the destination in order to minimize the total fixed and variable transport costs. While the fixed cost makes the problem difficult to solve by conventional algorithms. Moreover, it is better to consider the balanced problem, i.e. the availability equals the demands i.e. Si = Dj. Indeed, it is easy to find a solution for this type of problems. The mathematical formulation of the FCTP is as follows:

$$Min\ Z = \sum_{i=1}^{m}\sum_{j=1}^{n}(c_{ij}x_{ij} + f_{ij}y_{ij}) \qquad (1)$$

$$y_{ij} = \begin{cases} 1, & x_{ij} \geq 0 \\ 0, & x_{ij} = 0 \end{cases} \quad \sum_{j=1}^{n} x_{ij} \leq S_i \qquad i = 1,2,\ldots,m$$

$$\sum_{i=1}^{m} x_{ij} \geq D_j \qquad j = 1,2,\ldots,n$$

$$x_{ij} \geq 0$$

$$i = 1,2,\ldots,m\ ;\ j = 1,2,\ldots,n$$

c_{ij} : variable cost from centre *i* to point *j;*
x_{ij} : quantity send from centre *i* to point *j*;
f_{ij} : fixed cost from centre *i* to point *j* ;
y_{ij} : a binary variable that takes 0 or 1;
S_i : quantity available in center *i*;
D_j : quantity requested by point *j;*

Dragonfly algorithm

Man benefited in developing his life from his simulation of nature, and was inspired by many means of solving problems from it, such as the method of knowing the location of the bait for ants, and the dragonfly was one of the insects that fly with high efficiency in a group, and this insect has super intelligence that enables it to know the optimal path to reach the desired goal, especially problems in the form of networks.[19]

The Dragonfly algorithm (DA) is a Swarm Intelligence (SI) and population-based algorithm used for optimization.[20] Swarm Intelligence algorithms are a class of optimization algorithms that take inspiration from the collective behavior of social animals, such as ants, bees, and birds. Population-based algorithms, on the other hand, are a class of optimization algorithms that maintain a population of candidate solutions and use them to iteratively search for the optimal solution. Is a recent and interesting nature-inspired metaheuristic optimization algorithm used to solve a wide variety of optimization problems.[21] There are 3000 different species of dragonflies and their life cycle has two stages called nymph and adult. Dynamic (migratory) and static (feeding) swarms constitute respectively the exploitation and exploration phases of AD.[22,26,27] Where in the exploitation phase, large numbers of dragonflies cause swarms to migrate in one direction over long distances and distract enemies. And in the exploration phase, however, dragonflies form small groups and fly around a small area to search for food and attract flying prey.

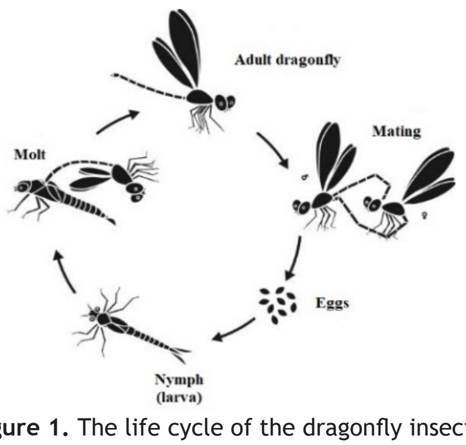

Figure 1. The life cycle of the dragonfly insect

To inspire the method of DA, one must know some information and characteristics about dragonflies.[23] They often live in a swarm either for food (hunting) or for mobility (migration). The first is called static behavior, while the other is called dynamical behavior. Migration and hunting behaviours inspired the idea of AD.[24] In addition, these behaviors correspond to the heuristic phases.

The static behavior is appropriate for the exploration phase and is required to ensure the preservation and expansion of the search area to reach the optimum in that vast area, while the exploitation phase is important because it focuses the search effort on the best existing solutions regardless of the order of access, by searching in the area adjacent to them.

- In dragonfly's algorithm, there are five main operations that are observed:
- Separation operation: this operation aims to prevent collisions among artificial dragonflies that are within close proximity to each other.
- Alignment operation: the purpose of this operation is to maintain compatibility of the speed between dragonflies that are in the same proximity.
- Cohesion operation: the cohesion operation is responsible for maintaining the cohesiveness of dragonflies by steering them towards the centre of their neighbourhood.
- Food attraction operation: this operation drives the movement of dragonflies towards a food source.
- Enemy distraction operation: enemy distraction consist of creating a false trail to mislead the enemy and lead them away from the intended destination.

The artificial dragonfly uses a set of five operations to ensure its survival through migration and hunting.

To compute the separation operation (SO), use the following equation:

$$S(r,p) = -\sum_{q=1}^{N} X(p,r) - X(q,r) \qquad (2)$$

X(p,r) : Situation of pth solution in rth iteration;
X(q,r) : Situation of qth neighboring solution in rth iteration;
N : Number of neighboring solutions;
S(p,r) : Separation between pth and neighborings in rth iteration.
The alignment operation (AO) is calculated using the following equation:

$$A(p,r) = \frac{\sum_{q=1}^{N} V(p,r)}{N} \qquad (3)$$

A(p,r) : Alignment for pth solution in rth iteration;
V(q,r) : Velocity for qth neighboring solution in rth iteration;
The calculation of the cohesion operation (CO) involves the application of the following equation:

$$C(p,r) = \frac{\sum_{q=1}^{N} X(q,r)}{N} - X(p,r) \quad (4)$$

C(p,r) : Cohesion for p^{th} solution in r^{th} iteration;
To determine the food attraction (FA), the following equation can be used:

$$F(p,r) = X^{+} - X(p,r) \qquad (5)$$

X^+ : Situation of the food in rth iteration;
F(p,r) : Food attraction for pth solution in rth iteration.
The food has been evaluated using the best available information from all previous attempts.
To compute The enemy distraction (ED), use the following equation:

$$E(p,r) = X^{-} + X(p,r) \qquad (6)$$

X^- : Location of the enemy in rth iteration;
E(p,r) : Enemy distraction for pth solution in rth iteration.

Integrating prior operations dynamically facilitates accurate updates to the artificial dragonfly's position. In each round, this position is modified using both the step vector (*ΔX(p,r)*) and the position vector (*X(p,r)*).

Remarkably, the step vector in the Dragonfly Algorithm (DA) aligns with the velocity vector in Particle Swarm Optimization (PSO). The process of adjusting the dragonflies' locations is guided by the PSO framework, with these vectors being mathematically represented in the following equations:

$$\Delta X(p,r+1) = sS(p,r) + aA(p,r) + cC(p,r) + fF(p,r) + eE(p,r) + w\Delta X(p,r) \quad (7)$$

Here, s, a, c, f, e, and w represent the respective weights for separation, alignment, cohesion, food attraction, enemy distraction, and inertia. We can compute the updated dragonfly positions as follows:

$$X(p,r+1) = X(p,r) + \Delta X(p,r) \quad (8)$$

Dragonfly algorithm based for fctp: the proposed approach

The objective of the FCTP problem is to minimize total transportation costs when distributing goods from multiple suppliers to multiple customers while considering various constraints. However, the original Dragonfly Algorithm (DA) was designed for continuous optimization problems, while the FCTP is a discrete optimization problem. In this research, we adapt the DA specifically for addressing the FCTP. The following steps outline the procedure used in our proposed approach.

Initialization

The initial step in implementing the DragonFly Algorithm involves utilizing the pb-DA (presumably a problem-specific variant of the Dragonfly Algorithm) to generate an initial population. This population is created from a set of p solutions, and the initialization process entails generating a random permutation of elements ranging from 1 to l = m + n for each solution. In this representation, there is no requirement for a correction algorithm. Each chromosome represents the source priorities and deposits for a transportation tree.

Evaluate fitness of initial population

Decoding and calculating the result of each solution of initial population.

Determinate the maximum number of iterations

The maximum number of iterations can vary between different methods and often necessitates experimentation and tuning to determine an appropriate value for a specific problem. Striking a balance is crucial, as it involves allowing the algorithm sufficient time to effectively explore the search space while avoiding excessive computation time. In our case, we have selected two maximum iteration limits (300 and 500 iterations) as per our requirements.

Distribute the solutions into neighborhoods

Determinate the Similarity between all solution in order the distribute the solutions into different neighborhoods.Two solutions are considered two-neighborhood if their percent similarity (number of similar items divided by total number of items in the solution) between them is greater than a predefined value. The similarity matrix contain the value 1 if the node in index i of S1 equal to node in index i of S2, if they not equal the matrix take the value 0.

S1	1	6	8	2	4	3	9	7	5
S2	9	6	2	8	4	3	1	7	5
Similarity Matrix	0	1	0	0	1	1	0	1	1

Figure 2. The solution representation

Determinate the food source and enemy

Determine the solutions that represent the food source X+ and enemy X- in the population based on their values of the objective function.

X+ : The best Solution in the Population. X- : The worst Solution in the population.

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Define the best solution in each neighborhood

In the Dragonfly Algorithm, the best solution in each neighborhood refers to the most optimal solution within a specific local region of candidate solutions.

Execute the DA operations

Separation operation

When the similarity percentage between two solutions (located in the same neighborhood) exceeds a predefined value, randomly select and exchange two nodes in the same element in both solutions.

Repeat this between the current solution and all other solutions in the same neighbor. Figure 3 shows the separation concept.

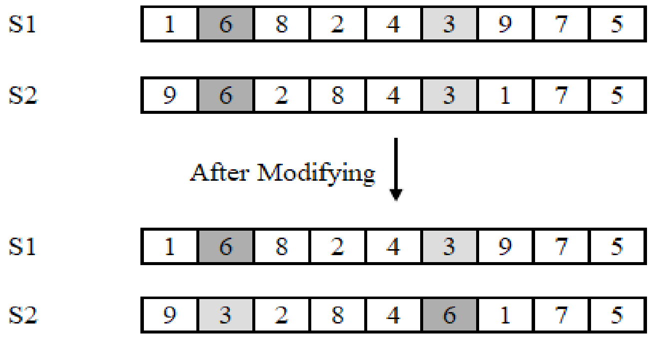

Figure 3. Separation operation in DA

Alignment operation

Round the current solution to the optimal solution within the neighborhood, as illustrated in figure 4., where S1 represents the optimal solution, and S2 represents the current solution within the current neighborhood.

Randomly choose two consecutive nodes, denoted as N1 and N2, from the best solution. If N1 and N2 are not in the same order in the current solution (S2), perform an alignment by swapping N2 with the next node after N1.

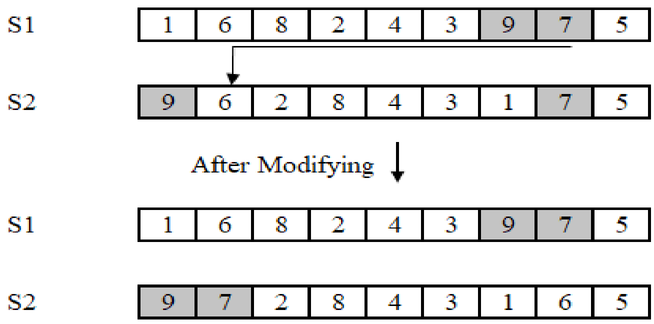

Figure 4. Alignment operation in DA

Cohesion operation

All solutions within the same neighborhood are rounded to maintain the mass of the neighborhood. The idea of this operator is similar to the alignment operator, except that the alignment operator is only performed between the current solution and the best solution in the current neighborhood.

Food attraction operation

In the food attraction operation, the current solution is rounded to the best solution in the population (representing the food source in DA).

Enemy distraction operation

This operation tries to find two consecutive nodes that exist in the same order in the current and the worst solution in the population (N1, N2). S1 and S2 represent the worst solution and the current solution, if N1, N2 are found, perform enemy diversion by exchanging N2 with a random Node in S2. Figure 5 illustrates the idea of this operation.

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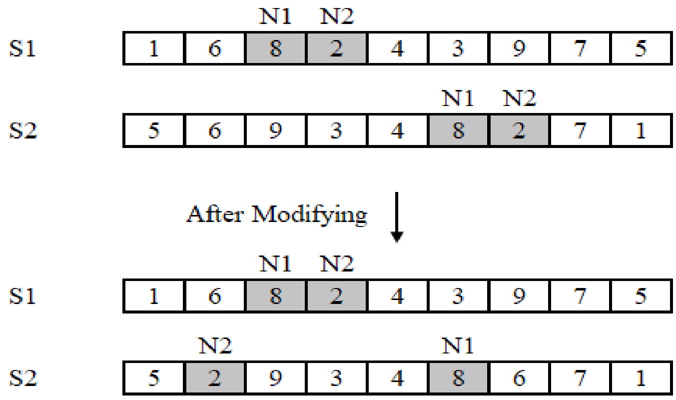

Figure 5. Enemy distraction operation in DA

Repeat the steps 4 to 8 until the maximum number of iterations is met

Continuously execute steps 4 through 8 until the specified maximum iteration count is reached. This ensures the process iterates a set number of times before concluding.

Return the optimum transportation Plan

Return the optimal solution found for the FCTP problem, specifically the transport plan with the lowest cost.

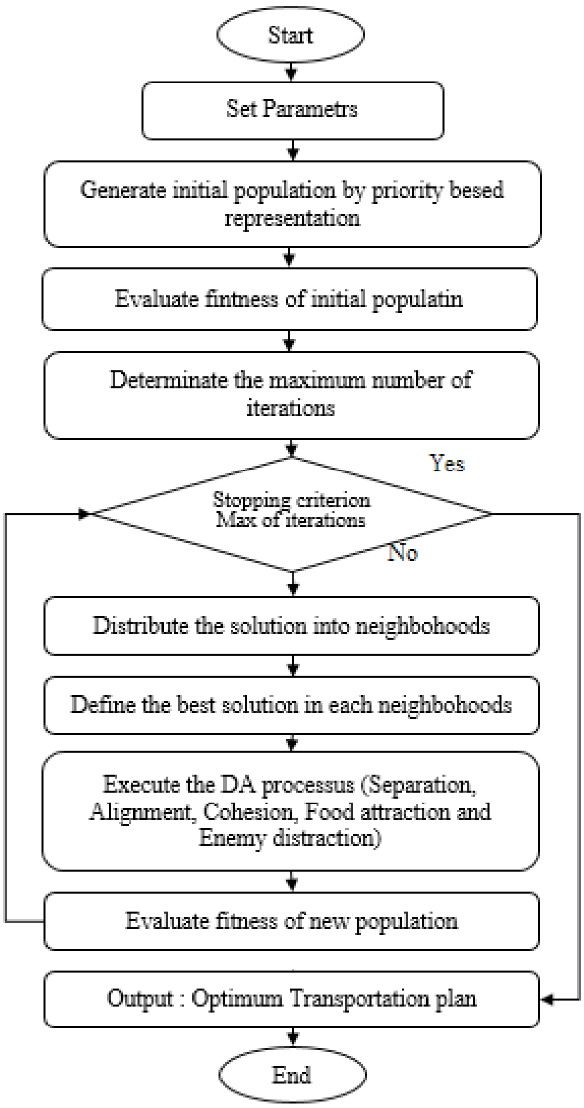

Figure 6. Process of the proposed DA for FCTP

RESULTS AND DISCUSSION

To comprehensively evaluate the efficacy of the Dragonfly algorithm in addressing the FCTP problem, a comprehensive set of systematic experiments was undertaken within the context of this research. These experiments constituted an essential means for gauging the algorithm's performance. Our proposed approach underwent meticulous assessment using a well-established dataset of six FCTP instances sourced from reference.[25] This dataset was thoughtfully curated to encompass varying problem dimensions, spanning small, medium, and large instances. This deliberate selection aimed to ensure a robust evaluation of the algorithm's proficiency across diverse problem complexities.

Practical implementation of our proposed approach was executed using Python, a versatile and widely-adopted programming language. Computational execution occurred on hardware equipped with an 11th generation Intel Core i7 processor with 8 GB of RAM. This hardware configuration was judiciously chosen to optimize the algorithm's performance throughout the experimentation process.

In pursuit of methodological rigor and equitable comparisons, the parameters governing our proposed approach were meticulously defined and standardized across all experimental runs, as meticulously documented in table 1. These critical parameters encompassed the maximum number of iterations, systematically investigated at two distinct values, specifically set to either 300 or 500 iterations. Additionally, we systematically scrutinized the impact of population size on algorithmic performance, considering two discrete values: 10 and 20. This exhaustive exploration of parameter space was instrumental in offering a comprehensive understanding of the algorithm's behavior under varying conditions, thereby enhancing the depth of our evaluation.

Table 1. Parameter Configuration

Parameter	Value
Separation weight	0,1
Alignment weight	0,1
Cohesion weight	0,7
Food Attraction weight	1,0
Enemy Distraction weight	1,0
Number of iteration	300 and 500
Population size	10 and 20

Table 2. The results by proposed approach DA and standard GA for FCTP problem

Problem size	Parameters		St-GA		Pg-GA		Proposed DA	
	Pop	Max-Gen	Best	Time(s)	Best	Time(s)	Best	Time(s)
4 x 5	10	300	9304	0,1315	9291	0,1284	9291	0,1266
	20	500	9291	0,1217	9291	0,1255	9291	0,1195
5 x 10	10	300	13384	0,3296	12718	0,3124	12718	0,2924
	20	500	12899	0,3372	12718	0,3051	12718	0,2772
10 x 10	10	300	15306	1,7125	13934	1,7123	14074	1,6771
	20	500	14844	1,7024	14065	1,6590	13934	1,6003
10 x 20	10	300	27316	3,1756	22258	3,1203	22150	3,0624
	20	500	26861	3,1312	22150	3,1012	22095	2,8089
20 x 30	10	300	44453	8,2365	32840	7,3625	32492	6,3251
	20	500	43963	7,9933	32492	6,2155	32471	5,2137
30 x 50	10	300	76789	20,1254	55611	19,1023	55143	17,1753
	20	500	76636	20,5143	55313	18,1623	54700	15,1700

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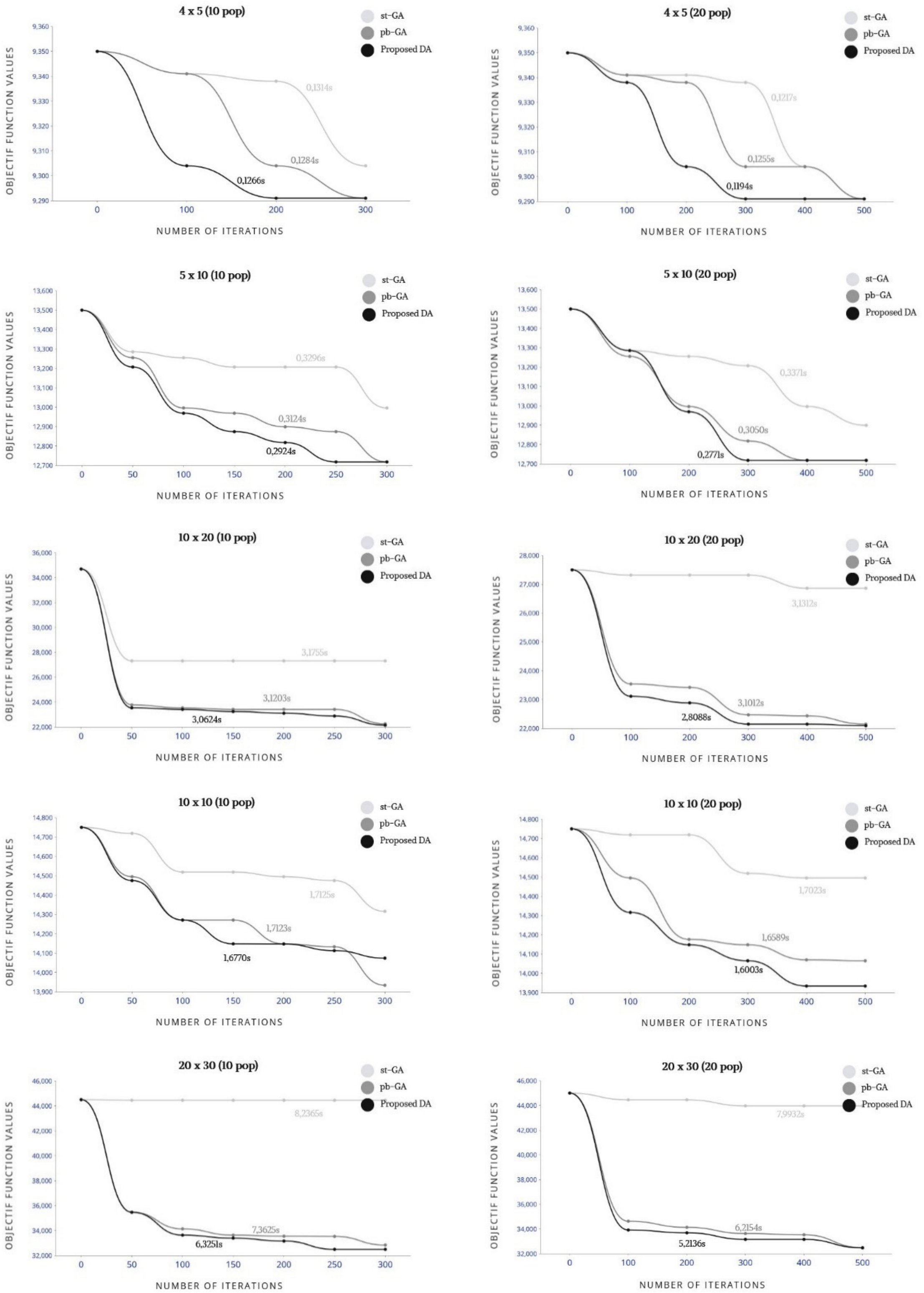

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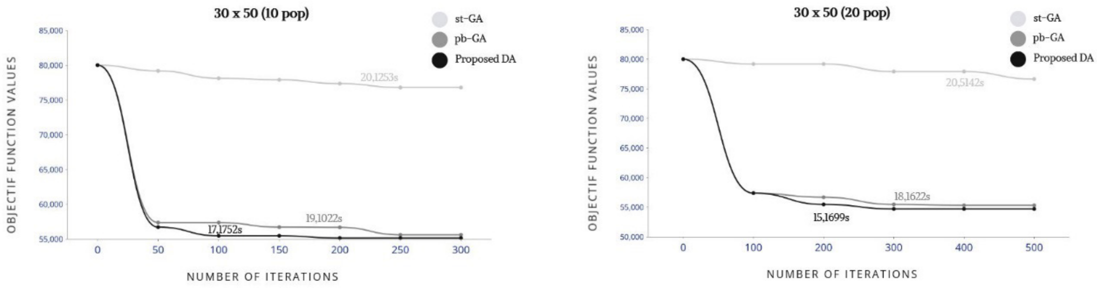

Figure 7. Convergence Comparison: Dragonfly Algorithm vs. st-GA and pb-GA for FCTP

To assess the effectiveness of our proposed Dragonfly Algorithm (DA) in solving the FCTP problem, we conducted a comparative analysis against well-established methods from the literature, namely st-GA[26] and pb-GA.[27,28,29,30] Table 2 provides an overview of the experimental outcomes, showcasing the optimal solutions achieved by each algorithm and their corresponding computation times in seconds. Remarkably, our DA outperforms the other methods, demonstrating superior efficiency in addressing the FCTP.

Figure 7 illustrates the results of our comparative analysis, highlighting the performance of DA in terms of iterations. Across various datasets, including 4x5, 5x10, 10x10, 10x20, 20x30, and 30x50 instances, DA consistently secured the top position, further substantiating its effectiveness in solving the problem.

CONCLUSIONS

In this research, we have employed the Dragonfly Algorithm (DA) to address the Fixed Charge Transportation Problem (FCTP). The DA, drawing inspiration from the natural behaviors of dragonflies, has showcased its prowess in resolving a wide array of optimization challenges, ranging from feature selection to power flow management and image segmentation. Nevertheless, when confronted with intricate combinatorial optimization problems (COP), it is often necessary to make modifications or hybridizations to effectively navigate the complex search space.

The FCTP, characterized by discrete variables and a set of stringent constraints, presents a formidable NP-hard problem in which the goal is to find the optimal transportation plan while considering fixed charges.

To assess the efficacy of our DA-based FCTP method, we have employed six FCTP instances from established sources. These datasets vary in the number of destinations and the distances between them. Our results have been benchmarked against four well-established methods, all evaluated using the same datasets.

In conclusion, our proposed DA-based approach for the FCTP has demonstrated competitive performance within the context of the benchmarked results. This study marks an initial step in tailoring DA for COP problems such as the FCTP, opening the door to further discoveries and advancements in the future.

The effective integration of DA into a traditional problem such as the FCTP, as demonstrated in this study, establishes a solid groundwork for its potential utilization in tackling similarly complex optimization issues, especially those commonly encountered in scheduling and planning contexts. Moreover, the prospect of combining DA with another algorithm for enhancing convergence characteristics and addressing an extended range of optimization challenges.

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