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A NOVEL APPROACH AND HYBRID PARALLEL ALGORITHMS FOR SOLVING THE FIXED CHARGE TRANSPORTATION PROBLEM

This article is dedicated *to the efficient resolution of the fixed charge transport problem (FCTP) with the goal of identifying optimal solutions within reduced timeframes. FCTP is a combinatorial and NP-complete problem known for its exponential time complexity relative to problem size. Metaheuristic methods, including genetic algorithms, represent effective techniques for obtaining high-quality FCTP solutions. Consequently, the integration of parallel algorithms emerges as a strategy for expediting problem-solving.* ***The proposed approach****, referred to as the parallel genetic algorithm (PGA), entails the application of a genetic algorithm across multiple parallel architectures to tackle the FCTP problem. The primary aim is to explore fresh solutions for the fixed charge transportation problem using genetic algorithms while concurrently optimizing the time required to achieve these solutions through parallelism. The FCTP problem is fundamentally a linear programming challenge, revolving around the determination of optimal shipment quantities from numerous source locations to multiple destinations with the overarching objective of minimizing overall transportation costs. This necessitates consideration of constraints tied to product availability at the sources and demand dynamics at the destinations.* ***In this study,*** *a pioneering approach to addressing the Fixed Charge Transportation Problem (FCTP) using parallel genetic algorithms (PGA) is unveiled. The research introduces two distinct parallel algorithms: The Master-Slave Approach (MS-GA) and the Coarse-Grained Approach (CG-GA). Additionally, investigation into the hybridization of these approaches has led to the development of the NMS-CG-GA approach.* ***The numerical results*** *reveal that our parallelism-based approaches significantly improve the performance of genetic algorithms. Specifically, the Master-Slave (MS-GA) approach demonstrates its advantages in solving smaller instances of the FCTP problem, while the Coarse-Grained (CG-GA) approach exhibits greater effectiveness for larger problem instances.* ***The conclusion reached is*** *that the novel hybrid parallel genetic algorithm approach (NMS-CG-GA) outperforms its predecessors, yielding outstanding results, particularly across diverse FCTP problem instances.*

Keywords: *Parallel Genetic Algorithm (PGA); Fixed Charge Transportation Problem (FCTP); Master-Slave Approach; Coarse-Grained Approach; Hybrid parallel genetic algorithm Approach.*

1. Introduction

Combinatorial optimization problems seek to optimize an objective function subject to constraints by finding the best solution from a finite set of possible solutions that are characterized by a combinatorial structure, such as a graph, network, or set of objects. They have wide-ranging applications in various domains, including computer science, operations research, physics, economics, and biology. One primary motivation for studying combinatorial problems is their relevance to real-world problems. For example, in operation research, combinatorial problems are used to optimize resource allocation, scheduling, and logistics.

1.1. Problematic

The fixed charge transportation problem (FCTP) is a well-known combinatorial optimization problem that belongs to the class of NP-hard problems [1]. It is an extension of the liner transportation problem, which involves minimizing the cost of shipping goods from a set of suppliers to a set of customer's subject to supply and demand constraints. The objective is to minimize the total cost of shipping goods from a set of suppliers to a set of customers, subject to supply and demand constraints. In a real problem, the fixed costs may include costs such as handling and setup costs, which are incurred regardless of the amount of goods being shipped.

The computational complexity of FCTP depends on several factors, including the number of sources and destinations. The complexity is bounded by the size of the problem instance, which generally increases as the problem size increases, making it more difficult to solve. Therefore, more efficient tools and methods are needed to solve larger instances of the problem.

1.2. Objective and approach

We seek to solve the FCTP problem in a more efficient way. To achieve this, we have opted for the utilization of parallel genetic algorithms (PGA) [2 – 4]. The main objective of PGAs is to increase the effectiveness of genetic algorithms by leveraging the power of parallel computing. To find new optimal solutions to the FCTP problem in a reasonable and fast time. This approach offers several benefits, including the effectiveness of genetic algorithms and the strength of parallel architectures. The effectiveness of genetic algorithms comes from their ability to adapt and evolve solutions over time, while the strength of parallel architectures lies in their ability to process large amounts of data in parallel. By combining these two strengths, we hope to find solutions to the FCTP problem that are both high-quality and generated quickly.

1.3. Paper outline

To achieve this objective, the work was divided into the following order: first, we provide a general overview of the FCTP problem and its mathematical model. The following section discusses related works that deal with the FCTP problem. Next, we present a general overview of standard genetic algorithms, including their main processes and genetic operators, such as selection, crossover, and mutation. The proposed parallel genetic algorithm for FCTP problem explores three different models of parallelism. The first model, "The Master-Slave approach," is a commonly used parallel algorithm design pattern in parallel computing. The second parallel genetic algorithm model, called "Coarse-Grained Approach," divides the initial population into small subpopulations, which are then processed by different processors in parallel. The third model combines the advantages of both Master-Slave and Coarse-Grained approaches to find better solutions to the FCTP problem. The proposed approaches based on genetic algorithms and parallelism architectures are tested on several instances of the FCTP problem. The results are then compared to the standard genetic algorithm SGAs in the numerical results section. Finally, the paper concludes with a summary of the findings and potential future directions for research or perspectives.

2. Related work

There are several methods to solve FCTP problem. Here are some of the most commonly used methods with their logical links; First, we find the Integer Linear Programming (ILP). It is an exact optimization method that solves the FCTP by expressing the problem as a set of linear equations and constraints [8]. The logical link between ILP and FCTP is that the problem can be mathematically represented and solved using a set of linear equations and constraints, where the objective is to minimize the total cost of shipping goods while considering the fixed costs [9]. Second, there is the Heuristic Algorithm; they are approximate optimization methods that quickly find near-optimal solutions to the FCTP. The logical link between heuristic algorithms and FCTP is that they use a set of heuristics to find good solutions, without guaranteeing that the solution is optimal [10]. Third, we discover the Metaheuristic Algorithms: Metaheuristics are optimization methods that are designed to explore the search space more efficiently than heuristic algorithms [11, 12]. The most widely known Meta-heuristic algorithms are Genetic algorithm (GA) [13]. Lastly, we come across the Hybrid Approaches; these approaches combine different optimization techniques, such as ILP formulations, heuristic and metaheuristic algorithms, to find good solutions to the FCTP. The logical link between hybrid approaches and FCTP is that they leverage the strengths of each optimization technique to find high-quality solutions more efficiently [14]. Recently, we embarked on a novel approach by harnessing parallelism for the first time to address the FCTP problem, yielding remarkable results when compared to alternative methods [15]. In summary, the methods for solving the FCTP vary in terms of their approach and level of optimization. By choosing the most appropriate method for a given problem instance.

3. Problem description and mathematical model

The Fixed Charge Transport Problem (FCTP) is a combinatorial optimization problem. It was formulated by Hirsch and Dantzig [4]. Balinski modified the FCTP to make the problem as a linear integer problem [6]. Adlakha proposed a simple heuristic algorithm to solve the FCTP at a small size [7]. We have a destination group $j = 1, ..., n$ served by a group of production centers $i = 1, ..., m$ while each producer has a given production capacity S_i and each destination has a demand to satisfy D_j. 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 is to determine the amount of product to be sent from each production location for each warehouse to minimize the total fixed and variable costs to serve all destinations. Thus, the problem contains two costs; variable cost $c_{ij}\ x_{ij}$ proportional to the quantity shipped and a fixed cost $f_{ij}y_{ij}$ regardless of the quantity transported. Moreover, it is better to consider the balanced problem $S_i = D_j$. Indeed, it is easy to find a solution for this type of problems. The mathematical formulation of the FCTP is as follows:

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

$$y_{ij} = \begin{cases} 1, & \text{if } x_{ij} > 0, \\ 0, & \text{if } x_{ij} = 0, \end{cases}$$

$$\text{s.t} \qquad \sum_{j=1}^{n} x_{ij} \le S_i, \quad i = 1,2,\ldots,m;$$

$$\sum_{i=1}^{m} x_{ij} \ge D_j, \quad j = 1,2,\ldots,n;$$

$$x_{ij} \ge 0,$$

where c_{ij} : variable cost from source i to destination j;
x_{ij} : quantity transported on the route (i,j);
f_{ij} : fixed cost associated with route (i,j);
y_{ij} : a binary variable $y_{ij} = 1$ if $x_{ij} > 0$ and 0 if $x_{ij} = 0$;
S_i : amount of supply at source i;
D_j : amount of demand at destination j;

4. Methodology and implementation

In this study, we employed two distinct approaches to solve the FCTP problem. The first approach used a standard genetic algorithm with its standard processes (SGA). For the second approach, we proposed and implemented a parallel genetic algorithm (PGA) that incorporates a parallel mechanism into the genetic algorithm processes. Subsequently, we compared the two methods to demonstrate the superiority of the second method (PGA) in terms of efficiency, which can refer to either discovering new solutions to the FCTP problem or obtaining existing solutions within a shorter period. Since solving combinatorial problems involves finding ultimate solutions, we also place a significant emphasis on the time it takes to find them. Hence, time plays a crucial role in solving these problems.

4.1. Genetic algorithm for FCTP

The standard genetic algorithm (SGA) operates on a population of candidate solutions, each represented as a set of parameters, often called a chromosome. The algorithm begins by randomly generating an initial population of solutions. Then, it iteratively selects pairs of parent solutions from the current population, based on their fitness, and combines them to create new child solutions. next generation solutions are created by applying genetic operators such as crossover and mutation. The new child solutions are then evaluated for their fitness, and the best ones are selected to become part of the next generation. This process of selection, reproduction, and evaluation is repeated for a fixed number of generations or until a satisfactory solution is found. The hope is that by applying these genetic operators, the population will converge to the optimal solution [16].

4.1.1 Priority based encoding

There are several encoding methods adapted to FCTP problem; like the matrix encoding [17], the prüfer number encoding [18]. However, the priority-based encoding is a more suitable coding for our FCTP problem [19]. In this case, the solution is represented by an entire string of length equal to the number of sources (m) plus the number of customers (n). Fig. 1. represents an example of this encoding.

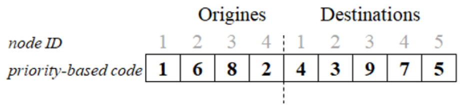

Fig. 1. Chromosome by priority based-encoding

4.1.2 SWAP mutation

Mutation is a genetic operator that consists of exchanging the positions of some genes within the same chromosome with probability. There are typically numerous mutations that are suitable for the FCTP. Besides, we are interested in the SWAP, he works on the permutation of the gene values of two randomly chosen positions [20], the principle of which is shown below (Fig. 2).

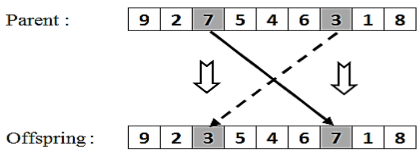

Fig. 2. Example of SWAP crossover

4.1.3 IPX crossover operator

The crossover is the most important operator in GA, it allows to create new solution spaces at each iteration of the algorithm. For the FCTP problem, several operators are applied. So, we have already developed a new crossover operator that we called Inversion Position-based crossover IPX [21] (Fig. 3).

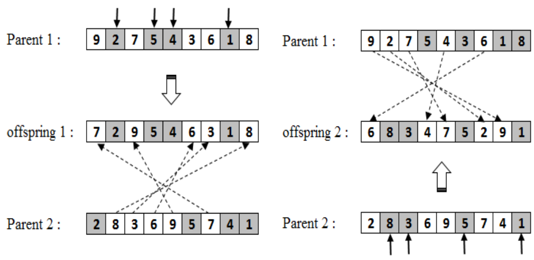

Fig. 3. Example of the IPX crossover

4.1.4 Elitism selection

Selection is a genetic process that selects chromosomes from the current generation which will be used to create new populations. It is formulated to ensure that the best members of the population persist. We used the method of selection by elitism which consists of copying the best chromosome to pass to the next generation [22] (Fig. 4).

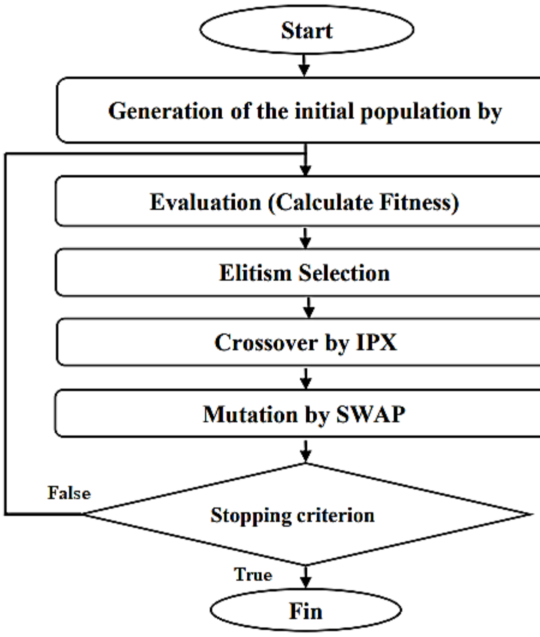

Fig. 4. Standard genetic algorithm diagram

Note that the diagram above is a simplified representation of a genetic algorithm, and there are many variations and additional steps that can be included depending on the specific problem being solved.

4.2. A proposed parallel algorithm for FCTP problem

Parallel genetic algorithms (PGAs) are particularly useful for problems that require a large amount of computational resources to solve because they can distribute the workload across multiple processors or computing nodes. Additionally, PGAs can help overcome the limitations of standard genetic algorithms (GAs), such as premature convergence or difficulty in finding a global optimum. Normally, after a certain number of iterations, the standard genetic algorithm finds the best solution. However, to save more time and optimize the objective function; the parallelism will introduce diversity in the population and give more dynamism to explore and exploit new probable solutions, in order to obtain a better solution for the FCTP problem compared to that obtained by the standard genetic algorithm (SGA). There are several parallel genetic architectures. In this study, we used three models that we have presented below.

4.2.1 Master-Slave approach

The Master-Slave approach (MS-GA) is based on distributed evolutionary algorithms. In practice, with each evolution, the population is divided into subsets that are the subject of genetic operations (crossing and mutation) in parallel on several threads. Then, we combine the subsets of the population so that it moves on to the next evolution. For this case, the population is shared between the different threads and each one starts the processes (crossover and mutation) individually, as illustrated in Fig. 5. In practice, each thread launches the genetic processes and finds new individuals to select the better [23]. Algorithm 2 represents the evolution algorithm in which a transmitted population is divided into subsets according to equation (2) below:

$$\mathrm{Size}\left(\mathrm{subpopulation}\right)=\frac{\mathrm{Size(Population)}}{\mathrm{number\ of\ threads}}. \qquad (2)$$

For each thread, their population is passed to Algorithm 1 after the genetic operations. The join() function ensures that the main thread waits for all other threads to complete. Finally, all returned subpopulations are combined to form a new population. In general, the master processor acts as a central controller and manages the flow of data between the slaves. The slaves, on the other hand, perform the actual computations and communicate with the master only when they have completed their task.

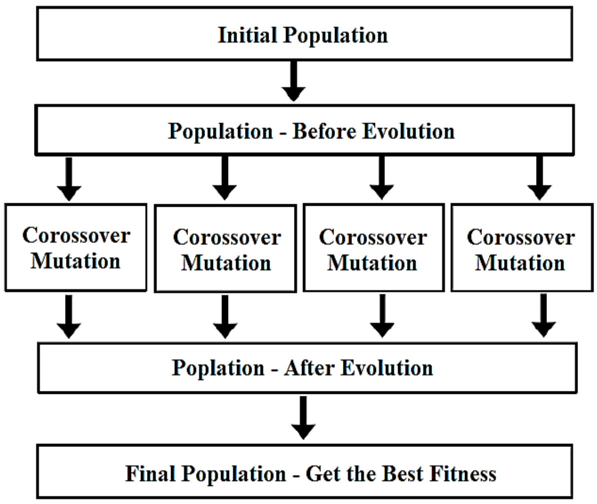

Fig. 5. Illustrative depiction of the Master-Slave model

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Algorithm 1 : For each thread (Master-Slave Approach)

Begin
Get the size for old population
Create a new population with the same size to store result
For counter j from 0 to size do
    Perform evolution on the population passed in
    Choose two parents from old population
    Perform crossover on the two parents
    Add child Tour to new population
End for
For each Tour in the new population do
    Perform mutation on the Tour to add more genetic material
End for
End

Algorithm 2 : Parallel genetic algorithm (Master-Slave Approach)

Begin
Create two lists with size 4 to store Population
Create 4 threads
Get the size for each sub-population = pop/thread-size (4)
Split the population into sub-populations
For** number of threads **do
    Create sub population
    Create threads and start
End for
Wait for all threads to finish using join ()
Store evolved populations in an array
Create a new population of the original size
***For** number of threads **do** (Combine sub-sets into one)*
    Add the new tour list to the new population
***End** for*
Return the new population
End

4.2.2 Coarse-Grained approach MS-GA

The Coarse-Grained approach consists of partitioning the population into subsets before performing the genetic evolution processes, such that each subpopulation performs the genetic evolution processes on its own and returns the best fitness of its population. After all subpopulations have completed operations, Coarse-Grained must manually choose the most optimal chromosome within the subpopulations. So, we divide the population into four sets of subsets of the population. Thus, in this case, each initialized subpopulation consists of 25 chromosomes as long as the initial population and the maximum number of iterations is 100 times. This is shown in Figure 6.

The Coarse-Grained approach is based on separating the population on the different threads before performing the genetic evolution operators, so that the threads only need to send their new generation to the algorithm common general genetics [24]. Indeed, after an iteration of the parallel general algorithm, we can know the best chromosome according to their fitness function. In this scenario, the operation was performed 100 times. Algorithm 3 represents the pseudo-code of the Coarse-Grained Approach.

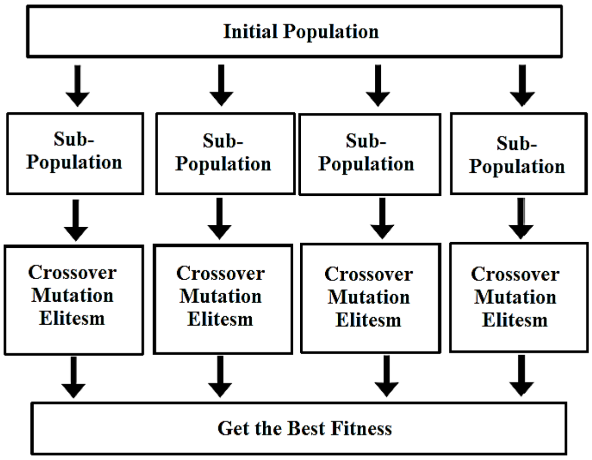

Fig. 6. Representative scheme of Coarse-Grained model

Algorithm 3 : For each thread (Master-Slave Approach)

Begin
For counter j from 0 to 100 do
    Perform evolution on the population passed in
End for
End

In Algorithm 3, we present the Coarse-Grained model approach. In this model, the population is divided by the number of threads to ensure that the workloads of each thread are equivalent to optimize the capacity of the processors. After each genetic evolution, we evaluate the fitness of populations returned by different threads to obtain the best solution during the next generations. On the other hand, the main thread must wait until all the threads have finished their processes before performing the comparison and choosing the best fitness.

4.2.3 New hybrid approach NMSCG-GA

The performance improvement of the master-slave approach decreases when the size of the instances increases on the other hand and the performance of the Coarse-Grained approach is not efficient for small instances. Therefore, it largely takes time to configure the threads; therefore, we propose a hybridization approach NMSCG of two previous approaches (Master-Slave and Coarse-Grained in order to find new solutions for the FCTP problem [25]. To address FCTP and optimize objective functions more efficiently, especially for large instances that demand substantial solving time, we introduce a hybrid approach in Algorithm 4. This approach is adaptable, contingent on the instance size.

For instances with a small size (less than 10*20), the algorithm attempts to implement the Master-Slave parallel approach, while for larger instances, it utilizes the parallel Coarse-Grained approach. You can find the detailed description of the proposed approach in Algorithm 4 below.

Algorithm 4 : NMSCG-GA

Begin
*If the size is smaller than (10*20) then*
    Choose the Master-Slave Approach
Else
    Choose the Coarse-Grained Approach
End if
End

5. Experimental results and discussion

After the results obtained for other similar combinatorial problems such as the traveling salesman problem TSP, an extension of the genetic approach with the principle of parallelism in the case of FCTP is carried out. so, we applied this approach to solve several instances of the standard FCTP problem already cited in previous articles with different sizes using the priority-based representation. This experimental study is treated the linear version of the FCTP problem. Thus, to see the effectiveness of the proposed approaches, we compared them with the standard genetic algorithm using four randomly generated test problems with different FCTP problem sizes and different difficulty levels.

As the size and complexity of search problems increase in the application of GAs, it becomes imperative to develop faster algorithms that can still yield satisfactory solutions. The work conducted has showcased various instances where parallel GAs have effectively combined speed and efficiency. This means we're getting better at using parallel GAs effectively in the future.

In this section of the numerical experiments, we conducted a comparative analysis between the standard genetic algorithm (GA) and two parallel genetic algorithm models (MS-GA and CG-GA) [15]. Additionally, we introduced a new parallel genetic algorithm, NMSCG-GA, which seamlessly integrates both genetic algorithm and parallelism mechanisms. These methods were put to the test in solving five instances of the Fixed Charge Transportation Problem (FCTP) with varying sizes: 4x5, 5x10, 10x10, 10x20, 20x30, 30x50, and 50x100. The objective was to deduce the optimal solutions obtained by each method, particularly focusing on the NMSCG-GA model. Table 1 showcases a comprehensive comparison of the results achieved using these different approaches.

Table 1

Best results by proposed approach and standard GA for FCTP problem

Problem size	SGA	MS-GA	CG-GA	NMSCG-GA
4 x 5	9291	9291	9291	9291
5 x 10	12718	12718	12718	12718
10 x 10	13987	13934	13987	13934
10 x 20	22258	22150	22095	22095
20 x 30	32936	32683	32526	32471
30 x 50	55450	55269	55007	**54700**
50x100	85235	**84312**	**84312**	**83963**

Above is the table of the best solutions found by the different models of the proposed approach in comparison with the standard genetic algorithm mentioned in Section 2. The results obtained by the models of the parallel genetic algorithm are more optimal than those of the standard genetic algorithm, especially for large instances (10x20, 20x30, and 30x50). For example, the solution found by the NMSCG-GA model for the 30x50 instance is 54700, while it is 55450 for the SGA, 55269 for the MG-GA and 55007 for CG-GA. To evaluate the performance of the numerical results found, we used the standard instances of the FCTP problem that are already mentioned in the reference articles.

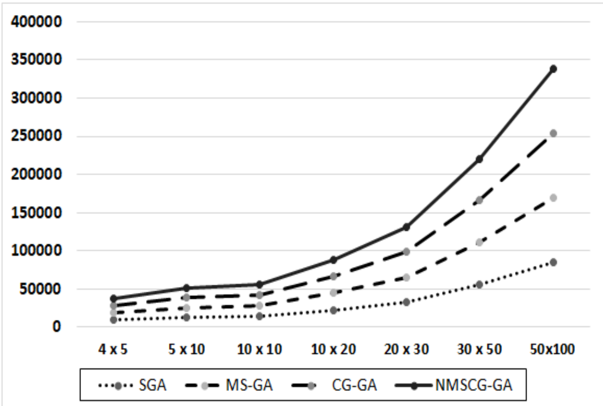

Fig. 7. Best Cost Comparison of NMSCG-GA Hybrid Approach and Other Methods for Seven Different FCTP Problem instances

The obtained results demonstrate that the novel approach, which leverages parallelism (NMSCG-GA), significantly enhances the performance of the genetic algorithm (GA). Specifically, the Master-Slave (MS-GA) approach proves to be advantageous for smaller instances (5 x 10 and 10 x 10), whereas the Coarse-Grained (CG-GA) approach exhibits greater effectiveness for larger instances. However, the most remarkable finding is that new hybrid approach (NMSCG-GA) combines the strengths of both MS-GA and CG-GA, making it more efficient and outperforming the other methods across all types of problem instances.

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Conclusions

In this study, the integration of parallelism into the genetic algorithm successfully enhanced the solving performance of the Fixed Charge Transportation Problem (FCTP). A comparison was made between the standard genetic algorithm and three distinct architectures: Master-Slave (MS-GA), Coarse-Grained (CG-GA), and the novel Hybrid Approach (NMSCG-GA). All three approaches showcased the effectiveness of employing genetic algorithms in conjunction with parallelism. However, the recently proposed Hybrid Approach (NMSCG-GA) surpassed the others by introducing diversity and dynamism into the population, resulting in significant time savings and optimization of the objective function. Leveraging parallelism, NMSCG-GA demonstrated superior performance in effectively addressing the FCTP problem with enhanced efficiency and effectiveness. These findings underscore the potential of this approach as a promising solution for complex optimization challenges.

As the size and complexity of search problems increase in the application of GAs, it becomes imperative to develop faster algorithms that can still yield satisfactory solutions. The work conducted has showcased various instances where parallel GAs have effectively combined speed and efficiency. This study enables us to observe the impact of parallelism on both the results and the time required to solve the FCTP problem. Furthermore, since genetic algorithms have successfully implemented parallelism to solve the combinatorial optimization problem of FCTP, it encourages us to consider using parallelism in conjunction with other methods, such as exact methods, approximate methods, or artificial intelligence, to discover new solutions for FCTP [25]. Finally, all combinatorial problems have been resolved.

Contribution of authors

Implementation of the proposed approach, definition of the problematic, determine of the method, analysis of the literature, redaction of the paper – **Ahmed Lahjouji El Idrissi**; approach programming, Collect of the data, redaction of the paper – **Ismail Ezzerrifi Amrani**; research methodology and presentation of results, revision of the document – **Adil Ben-Hdech**; setting and substantiation of the purpose and objectives of the study, analysis of the literature, review and analysis of references – **Ahmad EL Allaoui**.

All authors have read and agreed to the published version of this manuscript.

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НОВИЙ ПІДХІД І ГІБРИДНІ ПАРАЛЕЛЬНІ АЛГОРИТМИ ДЛЯ РОЗВ'ЯЗАННЯ ЗАДАЧІ З ТРАНСПОРТУВАННЯМ ФІКСОВАНОГО ЗАРЯДУ

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У статті основна увага приділяється ефективному розв'язанню задачі перенесення фіксованого заряду (FCTP) шляхом пошуку оптимальних рішень за коротший проміжок часу. Завдання FCTP – це комбінаторна та NP-повна задача, для вирішення якої потрібен експонентний час по відношенню до розміру завдання. Метаевристичні методи, такі як генетичні алгоритми, це методи, які можуть забезпечити високоякісні рішення проблеми FCTP. Отже, використання паралельних алгоритмів може допомогти скоротити час, необхідний вирішення завдання. Пропонований метод, який називається паралельним генетичним алгоритмом (PGA), передбачає застосування генетичного алгоритму з використанням декількох паралельних архітектур для вирішення проблеми FCTP. Мета полягає в тому, щоб досліджувати нові рішення для фіксованого завдання перенесення заряду з використанням генетичного алгоритму, одночасно оптимізуючи час, необхідний

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досягнення цих рішень, використовуючи паралелізм. Завдання FCTP – це завдання лінійного програмування, що включає визначення оптимальної кількості продуктів, які необхідно транспортувати з декількох пунктів відправлення в кілька пунктів призначення, з метою мінімізації загальної вартості транспортування. Це має бути зроблено з урахуванням обмежень щодо наявності продуктів у пунктах відправлення та попиту на продукти у пунктах призначення. Ми пропонуємо генетичний алгоритм із трьома архітектурами паралелізму на вирішення завдання перенесення фіксованого заряду. Перший підхід – це підхід «провідний-підлеглий», другий – це «великозернистий» підхід, а третій поєднує в собі обидва підходи, щоб скористатися їхніми відповідними перевагами. Численні результати показують, що наші підходи, що базуються на паралелізмі, покращують продуктивність генетичних алгоритмів. Зокрема, для вирішення проблеми FCTP підхід «провідний-підлеглий» (MS-GA) виявився кращим для невеликих екземплярів, в той час як підхід Coarse-Grained більш ефективний для більших екземплярів тієї ж проблеми. Ми укладаємо, що запропоновані підходи до вирішення фіксованого завдання перенесення заряду є чудовим прикладом того, як ці алгоритми можуть бути використані для вирішення інших комбінаторних завдань та підвищення ефективності існуючих рішень.

Ключові слова: паралельний генетичний алгоритм (PGA); завдання перенесення фіксованих зарядів (FCTP); підхід «провідний-підлеглий»; «великозернистий» підхід; підхід гібридного паралельного генетичного алгоритму.

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