Bio-Inspired Ant Lion Optimizer for a Constrained Petroleum Product Scheduling

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ABSTRACT Real-world optimization problems demand sophisticated algorithms. Over the years bio-inspired approach, a subset of computational intelligence has demonstrated remarkable success in real-world use cases, especially where exact or deterministic algorithms are ineffective. Petroleum product scheduling is a complex optimization task belonging to the combinatorial problem category. The problem size and the constraints compound the complexity of the petroleum product scheduling problem. However, conventional optimization methods such as the exact or deterministic algorithm produced a poor solution quality to the petroleum products scheduling problem. Therefore, this study leverages the potency of a bio-inspired approach, Ant Lion Optimizer (ALO) in its basic state to enhance the solution quality. This is in line with She-Shin Yang’s proposition, father of bio-inspired algorithms who advocated for the application of existing bio-inspired algorithms to tackle real-world problems rather than developing new algorithms. Bio-inspired is a computational paradigm that models the characteristics of natural biological entities to solve complex problems. We also used the Chaotic Particle Swarm Optimization (CPSO) algorithm for the same problem to unveil the efficacy of the roulette wheel function in ALO. The results show a 24.8% and 23.9% reduction in the original cost of distribution on ALO and CPSO respectively. Also, 99.5% of the constraints are met. Thus, problems of scarcity, minimum allocation and product availability are solved using the penalty constraint handling method. The exact algorithm showed a 14% reduction in the original cost. However, despite the effectiveness, further work on constraint handling methods and other bio-inspired computation approaches such as Genetic algorithms and their variants could be possible in the future scope. Moreover, other real-world problem domains such as power distribution in the power, sector could be a possible application of the ALO.

INDEX TERMS Optimization, bio-inspired algorithms, ant lion optimizer, particle swarm optimizer, petroleum product scheduling, chaotic functions, penalty constraint handling method.

I. INTRODUCTION

Optimization is an all-domain-centric subject. It involves searching for the best alternative given an objective function subject to constrained or unconstrained variables [1]. Amidst several options, finding the best solution could be complex or nearly impossible. Optimization need arises when there are unlimited resources. To this end, every organization strives to strategically plan and design their system to maximize profit amidst scarce resources [2]. Conventional optimization techniques may not give optimum solutions to some problems as demonstrated in this study [3]. The problem complexity suggests the need for a more sophisticated optimization technique. The problem size and the constraints are the major characteristics of a complex problem, and many real-world problems belong to this category. Typically, scheduling is a combinatorial optimization problem. Combinatorial optimization is finding an optimal solution to perform a collection
of tasks by several agents at minimal cost, time and resources. It either minimizes cost or maximizes profit based on defined constraints. The complexity lies in a large number of decision variables and constraints. The efficacy of the algorithm applied determines the solution quality. Many conventional algorithms are not effective in finding optimal solutions [4], [5], [6].

Bio-inspired computation models the principle found in biological beings or activities to solve complex real-world problems. Different authors classify the algorithm based on certain defined criteria. For example, evolutionary and swarm intelligence are classified based on the operation mode of the organisms [7]. The evolutionary-based algorithm is inspired by the theory of evolution. The principle is the survival of the fittest [8]. Swarm intelligence on the hand, involves the cooperation of the individual organisms to solve a problem. Evolutionary is competitive while swarm intelligence is cooperative when searching for an optimal solution, [9]. Another classification, based on search mechanisms is Heuristics and Metaheuristics. In recent times, [10] presented a more comprehensive categorization. The nine groups are based on Evolutionary algorithms [11], chemical processes [12], social activities [13], physics [14], sporting activities [15], musical compositions [16], plant characteristics [17], mathematics [18], and Swarm-based. ALO could be classified as an Evolutionary Algorithm. It is a metaheuristic algorithm that operates by the survival of the fittest (see the subsequent section for a more comprehensive description). ALO and its variant have demonstrated significant performance in medical applications, engineering controls, and wireless networks, amongst others [15]. Despite its wide application, there is a need to extend it to solve petroleum product scheduling problems.

Petroleum product scheduling is a combinatorial optimization problem. It consists of a variety of products such diesel, kerosene, paraffin, petrol etc. These refined products are transported from the production centres to various distribution centres [19]. Usually, the distribution centres are based on demand and allocation policies which could result in scarcity or surplus if not strictly ahead. The oil and gas sector faces numerous challenges in Nigeria. Typically, transporting crude oil and refined products to and from the upstream and downstream respectively results in overhead costs [3]. More so, customers’ satisfaction and the company’s profit must be balanced. Therefore, an optimum scheduling solution is critical to realizing this goal. The proposed study attempts to proffer a solution by reducing the distribution cost of twelve (12) petroleum products using data from Pipeline Petroleum Marketing Company (PPMC) as a case study. PPMC is a subsidiary of Nigeria National Petroleum Cooperation [20]. The petroleum product distribution matrix of PPMC is a typical constrained optimization problem.

Optimization problems could be constrained or non-constrained. However, many real-world problems are constrained. Typically, engineering design optimization problems, energy management in a microgrid, and wireless sensor networks [21], [22], [23]. A variety of constrained handling methods is integrated into the algorithm to obtain an optimum or near optimum solution. Such constrain handling methods like the penalty method, separatist approach, feasibility preserving technique [24], and Lagrange multiplier [25]. Petroleum product optimization is a complex task; thus, it belongs to the class of combinatorial problems [26]. From the preceding, it could be deduced that gradient-based algorithms are used in the petroleum optimization model evaluation. Studies have shown that the gradient-based optimization method is not effective in solving some real-world problems [27]. Among the limitations of the conventional gradient-based methods are poor solution quality, high computation cost, and implementation complexity [28]. Bio-inspired algorithms have shown better alternatives to conventional methods [29], [30], [31], [32]. Upon this premise, therefore, the study models and evaluates petroleum product scheduling optimization using a subsection of a public refinery in Nigeria. The bio-inspired algorithm approach would be employed to implement the model and compare the result using the existing conventional method in the literature.

The remaining parts of the paper are structured as follows: Section II discusses the related concepts and works; Section III presents the study methodology while Section IV presents the results. The study’s final remark and future scope are presented in Section V.

II. RELATED WORKS
The study considers related work on ALO applications, chaotic optimization, constraint handling techniques, and petroleum scheduling. TABLE 1 presents the summary.

A. ANTLION OPTIMIZER (ALO) APPLICATIONS
ALO has shown significant performance in both constrained and unconstrained optimization problems. In an unconstrained engineering problem like gear train design, ALO has been utilized to optimize the parameter tuning [33]. ALO has shown effectiveness in handling the Integrated Maintenance Scheduling problem [34]; optimal design in engineering problems [35]; optimized the turning parameter in PID controller [36]. A hybrid ALO and genetic operators have demonstrated efficiency in data mining and big data analytics [33], [37]. A hybrid ALO and Wavelet Support Vector Machine were proposed for the accuracy of feature selection in hyperspectral image processing [38]. The multi-Layer neural network problem has also been addressed with ALO [39]. It has also demonstrated effectiveness in image processing [40]. Also, energy and resource distribution optimization in the power sector has experienced a significant impact on ALO [41], [42].

B. CHAOTIC-IMPROVED BIO-INSPIRED ALGORITHMS
Chaotic functions have demonstrated significan results in handling premature convergence in many bio-inspired algorithms including the Chaotic bee colony algorithm [43], and the Chaotic harmony search algorithm [44]. Contemporary
studies have also shown a wide range of chaotic improved optimization. For example, Varol Altay & Atalas integrated chaotic function variants into the birds’ swarm algorithm to address the local optima entrapment problem. The authors applied the modified variant of the birds swarm algorithm to benchmark functions and real-world engineering design optimization problems [45]. According to the authors, the improved version outperformed the basic counterpart [45]. Again, League Champion Algorithm (LCA) has been modified with various chaotic functions including logistic, circle, and sinusoidal maps to balance exploitation and exploration in the basic LCA [46]. The study showed that the Chaotic LCA is superior to the basic version when tested with popular benchmark optimization problems according to the authors [46]. A chaotic system has also demonstrated significant enhancement in Optic inspired optimization algorithms as presented in the article, titled “Chaos-based optics-inspired optimization algorithms as global solution search approach” [47]. Similarly, Chaos has been used to handle the local optima problem in Particle Swarm Optimizer (PSO). The same has shown improved performance in various optimization spaces such as data clustering [48], reactive power optimization [49], electric load forecasting [50], and many more. Chaotic PSO would also be extended to the petroleum product schedule in the proposed study to measure its effectiveness.

C. CONSTRAINT HANDLING TECHNIQUES

Not all solutions of the variable space are viable in many real-world optimization tasks. There are usually restrictions referred to as constraints. These constraints intensify the difficulty of the optimization procedure. Finding optimum or near optimum solutions that satisfy all the constraints is usually challenging. Several constraints handling techniques are available in the literature [24]. The popular methods are the penalty function, separatist method, feasibility preserving method, and hybrid approaches [24]. Penalty constrained handling method converts the constraint to unconstraint by incorporating a term called penalty to the objective function. The solution consequently decreases the objective value [51].

$$\gamma(\vec{u}) = f(\vec{u}) + \left[ \sum_{i=1}^{d} q_i h_i + \sum_{j=s+1}^{e} p_j k_j \right]$$  \hspace{1cm} (1)

where $\gamma(\vec{u})$ and $f(\vec{u})$ represent the modified and original objective functions respectively, $h_i$ and $k_j$ denotes the inequality and equality constraints respectively, while $q_i$ and $p_j$ are the penalty parameters [21], [51]. The penalty method is broadly divided into two categories, interior and exterior penalty methods. The exterior penalty approach requires the knowledge of the feasible solution and it is not suitable for many real-world problems. In the exterior penalty method, on the contrary, the knowledge of the feasible solution is not a prerequisite [24]. The exterior penalty paradigm has demonstrated effectiveness when integrated with the Genetic Algorithm (GA) [24].

D. PETROLEUM PRODUCT SCHEDULING

Various transportation means exist for shipping petroleum products, including roads, vessels, railways, and pipelines. Although the pipeline is the most economical, it is capital intensive and less efficient [52]. The benefits of optimization in refinery operations cannot be underestimated. Implicitly, it determines the business is sustained amidst highly competitive and unstable environmental challenges. Enhancing the planning and services of petroleum products is a paramount management concern in the oil and gas industry [53]. In a highly constrained and competitive environment, management and stakeholders need an efficient optimization model to maximize profit [54]. Although some commercial tools
TABLE 2. Petroleum product demand matrix source [20].

| Products | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | Availability |
|----------|----|----|----|----|----|----|----|----|--------------|
| Fuel oil | 3700 | 2010 | 444 | 48 | 228 | 11174 | 744 | 1104 | 16470 |
| Lubricating oil | 15272 | 10526 | 19520 | 4112 | 9254 | 10512 | 12040 | 9838 | 43088 |
| Kerosene | 15024 | 970 | 350 | 2988 | 2258 | 11416 | 8168 | 4674 | 37234 |
| Gasoline | 16580 | 326 | 1406 | 22 | 192 | 696 | 1668 | 838 | 13216 |
| Wax | 1920 | 180 | 722 | 692 | 400 | 772 | 1996 | 820 | 12480 |
| Bitumen | 1560 | 550 | 1510 | 556 | 204 | 822 | 156 | 696 | 11130 |
| Others | 2304 | 456 | 1978 | 274 | 574 | 862 | 1316 | 622 | 3192 |
| Total | 10260 | 4592 | 3682 | 2874 | 4308 | 7610 | 5750 | 5130 | 17086 |
| Total cost | 4310 | 4120 | 5150 | 1030 | 1694 | 3214 | 1926 | 3384 | 15008 |
| Total cost | 8508 | 56 | 82 | 746 | 1250 | 7416 | 4030 | 616 | 16424 |
| Total cost | 1068 | 480 | 528 | 92 | 156 | 960 | 240 | 152 | 3072 |
| Total cost | 70 | 16 | 32 | 6 | 20 | 96 | 18 | 18 | 2016 |
| Policy | 0.2 | 0.2 | 0.4 | 0.4 | 0.6 | 0.8 | 0.4 | 0.8 | 0 |

Some production scheduling models are available in the literature; including the nonlinear planning model [53]. It is a three-phased planning model that involves raw material supply optimization, processing, and commercialization. The study proposed a nonlinear mixed integer programming (MIP) to maximise oil refinery production using a gradient-based algorithm. Although the study obtained a satisfactory result, according to the authors [53], they also recommended an enhanced approach to optimize the operation cost. [54] proposed an in-line certification (ILC) approach to optimize petroleum product scheduling. [26] proposed a hybrid model for schedule lube oil production. The lube oil plant is a subsection of a petroleum refinery. The “flow network optimization (FNO)” was integrated with a binary integer linear programming (BILP)” to form the hybrid model. The study analysed the six sections and products of the lube oil plant using an Indian-based petroleum oil refinery. The four constraints including reservoir capacity, change over time, flow and yield rate and slop occurrence were considered in the proposed hybrid model [26]. The model was evaluated with a software tool, LINDO to be exact. The authors claimed that optimal solutions were obtained based on certain assumptions. [20] developed a multi-objective multi-constrained linear programming model for the petroleum product supply chain. The study outlined the various products and their distribution centres of a subunit of a public refinery in Nigeria. The proposed model was evaluated with TORA (an operation research software package). About a 14% reduction of the initial distribution cost was obtained [20].

A. PETROLEUM PRODUCT PROBLEM DEFINITION

TABLE 2 describes the petroleum product distribution matrix. It consists of twelve products (fuel oil, lubricating oil, kerosene, gasoline, wax, bitumen, and others) and eight distribution centres. Also, the unit transportation cost of each product from the source to the depot is given in the unit cost row, while the total quantity of each product available is presented in the availability column. The company operates on certain policies. First, the distribution policy (policy row) that states that a certain percentage of the product must be sent to a depot to sustain customers’ satisfaction and avoid scarcity. Then the demand policy states that not more than the requested amount of product should be shipped to a depot. TABLE 3 is an illustration of the quantity of each product shipped to the eight depots. The zero quantity is highlighted in red colour indicating that nothing was shipped to those depots. By implication, the company policy is violated and it could result in scarcity of those products at their corresponding location. Aside from policy violations, the total shipping cost is relatively high. The present research attempts to satisfy the constraints at reduced shipping costs.
TABLE 3. Quantity of products supplied to the depots [20].

|    | D1   | D2   | D3   | D4   | D5   | D6   | D7   | D8   |
|----|------|------|------|------|------|------|------|------|
| 1  | 1690 | 2010 | 44   | 4    | 288  | 10554| 744  | 994  |
| 2  | 4746 | 10526| 1952 | 822  | 2776 | 4204 | 8428 | 8582 |
| 3  | 14054| 970  | 36   | 568  | 2258 | 6846 | 8168 | 4206 |
| 4  | 11210| 326  | 140  | 4    | 58   | 278  | 1168 | 0    |
| 5  | 750  | 180  | 96   | 692  | 120  | 308  | 0    | 820  |
| 6  | 232  | 350  | 152  | 200  | 62   | 240  | 0    | 110  |
| 7  | 1000 | 456  | 498  | 54   | 172  | 344  | 0    | 622  |
| 8  | 2730 | 4592 | 368  | 574  | 1292 | 3644 | 4026 | 0    |
| 9  | 190  | 4210 | 516  | 206  | 1694 | 2898 | 1926 | 3046 |
| 10 | 8452 | 56   | 8    | 150  | 376  | 2966 | 3856 | 554  |
| 11 | 0    | 480  | 290  | 18   | 46   | 384  | 168  | 0    |
| 12 | 8    | 16   | 4    | 2    | 6    | 38   | 12   | 0    |

The total cost of distribution N2,353,050

TABLE 4. Problem definition and data description.

| Notation | Description                     | Data Type     | Boundary        | Unit  |
|----------|---------------------------------|---------------|-----------------|-------|
| p        | Product index                   | Integer       | u<p>0           | -     |
| q        | Depot index                     | Integer       | v<q>0           | -     |
| Dpq      | The quantity, p demanded from depot, q | Decision Variable | 19520< Dpq<22 | Barrel|
| Apq      | Quantity of product, p available at source | Decision Variable | 43088<Apq>3072 | Barrel|
| u        | Number of products available for shipping | Integer       | 12<u>0         | -     |
| v        | Number of depots                | Integer       | 8<v>0           | -     |
| spq      | Product p shipping cost from source to depot q | Currency | - | Naira |
| G        | Summation of shipping cost      | Currency      | -               | Naira |
| Kpq      | Quantity of product, p supplied at depot, q | Integer values | 14054< Kpq>0   | -     |
| Rq       | Minimum quantity to be shipped to depot q | Integer values | 0               | -     |

B. OBJECTIVE FUNCTION DEFINITION FOR PETROLEUM PRODUCT DISTRIBUTION

From TABLE 2, the petroleum product demand matrix displays 12 petroleum products and 8 depots or distribution centres, resulting in 96 decision variables. Also, there are three major constraints namely, availability, demand, and policy constraints, resulting in 208 constraints. The availability constraint states that the total quantity of product to be allocated to various depots must not exceed the quantity available. Also, the demand constraint states that the quantity of product to be shipped to a depot must not exceed the quantity requested by that depot. While the policy constraint states that the quantity to be shipped to a depot must not be less than the designated percentage of the quantity requested by the depot. TABLE 3 shows the quantity of each product supplied to various depots according to PPMC. However, according to [20], there is no specific method for data generation in TABLE 3. TABLE 4 presents the problem definition and data description of the petroleum product matrix. Although the maximum product index, p is 12. However, it could be extended according to the problem space. The same applies to the depot index, q. The ALO uses an inbuilt linear scaling normalization technique to confine the search process within the designated search space as shown in Eq. (9). The objective function is shown in Eq. (2) and the notations are defined in TABLE 4.

Minimize:

$$G = \sum_{p}^{v} \sum_{q}^{u} G_p D_{pq}$$

(2)

Subject to:

$$\sum_{p=1}^{v} D_{pq} \leq A_p \forall p = 1, 2, 3, \ldots, 12 \quad \text{(Availability constraint)}$$

$$D_{pq} \leq K_{pq} \forall p = 1, 2, 3, \ldots, 12; q = 1, 2, 3, \ldots, 8 \quad \text{(Demand constraint)}$$

$$D_{pq} \geq R_q K_{pq} \forall p = 1, 2, 3, \ldots, 12; q = 1, 2, 3, \ldots, 8 \quad \text{(Policy constraint)}$$

$$D_{pq} \geq 0 \forall p = 1, 2, 3, \ldots, 12; q = 1, 2, 3, \ldots, 8 \quad \text{(Non-negativity constraint)}$$
We incorporate the penalty constraint handling method to ensure that the constraints are satisfied. Therefore, a new objective function is shown in Eq. (3)

\[
\psi_r (G) = f (G) + \Omega_r \sum h(D_{pq} (G))
\]  

(3)

where \( h(D_{pq} (G)) = \max(0, D_{pq} (G))^2 \).

\( h(D_{pq} (G)) \) is the exterior penalty function and \( \Omega_r \) is the penalty coefficient. The penalty coefficient simultaneously increases at every iteration \( r \) by a factor of 10, thereby generating an initial solution of an unconstrained problem for subsequent iterations. It results in the convergence of the progressive unconstrained problem towards the initial feasible location of the constrained problem.

C. STANDARD PSO AND CPSO

The PSO algorithm is a population-based algorithm that models a swarm of fish or birds during their foraging activities [57], [58], [59]. The swarm cooperate by comparing the individual (personal) best and cooperate (global) best location to find the food source (feasible solution to an optimization problem). Two equations control the kernel of the PSO algorithm, Eq. (4) and Eq. (5). An algorithm kernel is defined by the equations that control the search process of the algorithm [60].

\[
\bar{V}_i(t+1) = \omega \bar{V}_i(t) + m_1 \cdot \text{rand1}(.) \cdot (p_i - x_i) + m_2 \cdot \text{rand2}(.) \cdot (g - x_i),
\]

(4)

\[
\bar{x}_i(t+1) = x_i(t) + \bar{V}_i(t + 1),
\]

(5)

where, \( \bar{V}_i = (v_{i1}, v_{i2}, v_{i3}, \ldots, v_{in}) \) referred to the particle velocity, it is the distance to be covered by the particle from its current location; \( x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \) represents the local best position; \( x = (x_1, x_2, x_3, \ldots, x_N) \) is the global best position; \( \text{rand1}() \) and \( \text{rand2}() \) are simple randomization parameters; \( m_1 \) and \( m_2 \) are the acceleration constant; while \( \omega \) is the inertial weight. Comprehensive details about the PSO algorithm are available in the literature [57]. However, studies have shown that the standard PSO gets trapped in local optima [58], [59]. We consider the chaotic improved PSO variant CPSO to find an optimum or near optimum solution for the petroleum product distribution network, although the standard PSO solution would also be presented to demonstrate and compare the effect of chaos on the problem in question. Specifically, the logistic map is used to improve the randomization process. The chaotic map has shown significant performance in handling local optima entrapment problems in stochastic optimization algorithms [59], [60], [61]. This research considers the logistic map which has shown good results in stochastic optimization [60]. The logistic map function is shown in Eq. (6).

\[
c_{t+1} = \psi m_p (1 - c_t)
\]

(6)

where \( m_p \in (1, 0) \) and \( \psi \) is the parameter at (0,4) intervals. Hence, Eq. (7) represents the chaotic PSO (CPSO).

\[
\begin{align*}
\tilde{V}_i(t + 1) &= \omega \bar{V}_i(t) + m_1 \cdot c_t (.) \cdot (p_i - x_i) \\
&\quad + m_2 \cdot c_t (.) \cdot (g - x_i),
\end{align*}
\]

(7)

where \( c_t \) is the chaotic function. The concept is to generate initial values with the chaotic function using the property of sensitivity to initial conditions [58], [60], [62].

D. THE ALO ALGORITHM

The antlion optimizer (ALO) was developed by Mirjalili in 2015. Its inspiration came from the hunting lifestyle of the antlion [29]. The algorithm models the predator-prey relationship between the antlion and the ants in the trap. Readers are referred to [29] for the assumption that precedes the ALO. The algorithm concept consists of six stages: the ants’ random motion stage, antlion trapping pits, trap construction, descending of the ants towards the antlion, capturing prey and pit reconstruction, and last, leader selection stage [29]. The kernel of the algorithm is controlled using the following equations. The random motion is represented by Eq. (8):

\[
D_u = [0, \text{cums}\sum (2r (u_1) - 1), \text{cums}\sum (2r (u_2) - 1), \ldots, \text{cums}\sum (2r (u_k) - 1)]
\]

(8)

where \( \text{cums}\sum \) stands for the cumulative sum; \( u \) is the maximum iteration, and \( k \) represents the random movement step; \( r \) is a random number generator between zero and one. The random motion is further normalized using Eq. (9). The normalization enables the search to be confined within the designated search space.

\[
D^u_i = \frac{(D^u_i - y_i) \times (m_i - n^u_i)}{(g^u_i - y_i)} + n_i,
\]

(9)

where \( y_i \) represents the \( i \)-th variable minimum random motion; \( m_i \) is the \( i \)-th variable maximum random motion; while \( g^u_i \) is the maximum \( i \)-th variable at \( u \)-th iteration. The descending and towards the antlion is represented by Eq. (10).

\[
h^u = \frac{h^u}{F}, \quad g^u = \frac{g^u}{F}.
\]

(10)

where \( F \) is a factor given by \( f = 10^p \frac{\#}{u} \) where \( u \) is the current iteration and \( p \) is the maximum iteration, \( \# \) is a constant and it varies according to the maximum iteration [22]. Readers could refer to (Mirjalili, 2015a) for more details about the varying \( p \)-value. The last updating function is the Leadership selection process based on the roulette wheel given by Eq. 11.

\[
A^u_i = \frac{W^u_A + W^u_L}{2},
\]

(11)

where \( A^u_i \) is the \( i \)-th position of the ant at iteration \( u \)-th; \( W^u_A \) is the random motion within antlion based on the roulette wheel; and \( W^u_L \) represents the random motion around the leader at the \( u \)-th iteration.
The roulette wheel function is represented by eq.12:

\[ S_i = \frac{G_i}{\sum_{k=1}^{N} G_k} \tag{12} \]

where, \( S_i \) is the probability of being selected; \( G_i \) represents the individual, its fitness. \( K \) and \( N \) are the start and end paths respectively.

### IV. RESULTS AND DISCUSSIONS

#### A. ALO-BASED PETROLEUM PRODUCT SCHEDULING

The petroleum product scheduling matrix result using ALO is shown in TABLE 5. A population size of 2000 with 20 iterations is used in the experiments. The ALO demonstrated an efficient balance between exploitation and exploration by minimizing the shipping cost by 24.8% of the original cost. The convergence curve of the ALO algorithm is shown in Fig. 3. Also, 99.5% of the constraints are satisfied; only one is violated. The scheduling of the matrix shows that there is no zero product, in contrast to the original (PPMC) supply matrix in TABLE 3. It implies that the minimum quantity supply policy is satisfied, consequently solving the petroleum of possible scarcity. TABLE 5 also shows that no depot
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FIGURE 2. The ALO Algorithm flowchart.

received more quantity than it requested; thereby satisfying the demand policy.

B. OPTIMUM PETROLEUM PRODUCT SCHEDULING USING CPSO

TABLE 6 presents the petroleum product scheduling matrix result based on the CPSO algorithm. The convergence plot comparing the PSO CPSO, and ALO algorithm is also shown in Fig. 2. The PSO is presented to reveal the effect of the chaos in petroleum product scheduling. The chaos significantly improved the PSO search capability. Five thousand (5000) particles (search agents) at 30 iterations gave a near-optimum scheduling solution. In contrast to the original supply chain matrix shown in TABLE 3: distribution centres 7, 8, and 11 did not receive certain products denoted as “0” as indicated in TABLE 3; thereby violating the policy constraint. Most importantly the total shipping cost is reduced by 23.9% of the initial cost.

C. COMPARATIVE PERFORMANCE OF BIO-INSPIRED AND EXACT/DETERMINISTIC ALGORITHMS

TABLE 7 presents the petroleum product scheduling matrix using the exact algorithm, (TORA) [20]. As presented in TABLE 8, the result shows only a 14% reduction of the original cost. Contrarily, the bio-inspired alternatives, ALO and CPSO gave a significantly better cost reduction of 24.8% and 23.9% of the original cost respectively. Although the ALO outperformed the CPSO and the exact algorithm, it increases the high computation resources.

The experimental results of the proposed methodologies were obtained in the same environmental conditions. Specifically, in Intel® Pentium® CPU N3510 @ 1.99 GHz processor; 4.00 GB RAM; and windows 10 64 × 64 bit operating system.

D. ADVANTAGE OF THE PROPOSED METHOD

ALO is considered cost-effective since it converges with less computational power to reduce the original total distribution cost by 24.8%. TABLE 8 shows that 2000 search agents found the near-optimum solution within 20 iterations. CPSO on the hand utilizes more computational power by using 5000 search agents at 30 iterations to obtain a 23.9% cost reduction as shown in TABLE 8. The performance of ALO and CPSO is relatively better than that of the Exact or deterministic algorithm (14.0%) as shown in TABLE 8.

E. LIMITATIONS OF THE PROPOSED METHOD

Typically, there are two limitations in the proposed study. First, one of the constraints was relaxed to obtain the results. Therefore, more robust constraint handling methods could be a suggestion for further study. Secondly, although the proposed stochastic ALO and CPSO algorithm could handle more problem sizes than the available data, however, the data...
provided by PPMC in this proposed study is not sufficient to determine the exact estimation.

V. CONCLUSION

The performance of a bio-inspired algorithm does not only depend on the behaviour of the inspiration source, but also on the appropriate representation of the characteristics. For example, the PSO algorithm is a population-based algorithm that operates by cooperation, while ALO operates by competition i.e., survival of the fittest. Both algorithms initialize with simple random number distribution, however, subsequent steps of the ALO are controlled by the Roulette wheel function as shown in step 9 of our proposed algorithm in section 3E. The Roulette wheel function enables the ALO to avoid local optima entrapment. Unlike many algorithms including PSO, ABO, etc which use the simple random

TABLE 6. Quantity of products supplied to the depots using CPSO algorithm.

|    | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 |
|----|----|----|----|----|----|----|----|----|
| P1 | 740| 402| 178| 19 | 228| 8939| 744| 1104|
| P2 | 3054| 2105| 7808| 1645| 5552| 8410| 4816| 7870|
| P3 | 3005| 194| 350| 1195| 1345| 9133| 3267| 3739|
| P4 | 3316| 326| 1406| 9 | 192| 696| 667| 838|
| P5 | 384| 180| 289| 277| 240| 772| 1996| 656|
| P6 | 312| 110| 604| 556| 122| 658| 156| 557|
| P7 | 2304| 91| 791| 274| 574| 862| 1316| 498|
| P8 | 2052| 918| 1473| 1150| 2585| 6088| 2300| 4104|
| P9 | 862| 824| 2060| 412| 1016| 2571| 1926| 2707|
| P10| 1702| 11| 82| 298| 750| 5953| 1612| 616|
| P11| 1065| 480| 528| 96| 91| 960| 96| 152|
| P12| 70| 16| 13| 2| 20| 96| 18| 18|

Total cost of distribution N1,787,152

TABLE 7. Quantity of products supplied to the depots using exact algorithm [20].

|    | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 |
|----|----|----|----|----|----|----|----|----|
| P1 | 3700| 202| 44| 4 | 288| 10554| 744| 994|
| P2 | 15000| 1052| 1952| 822| 2776| 4204| 8428| 8854|
| P3 | 15024| 98| 36| 598| 2258| 6846| 8168| 4206|
| P4 | 10782| 32| 140| 4| 58| 278| 1168| 754|
| P5 | 1920| 180| 722| 692| 400| 772| 1996| 820|
| P6 | 1560| 550| 1510| 556| 204| 822| 156| 696|
| P7 | 896| 46| 198| 54| 172| 344| 922| 560|
| P8 | 2704| 460| 368| 574| 1292| 3044| 4026| 4618|
| P9 | 4310| 412| 516| 206| 1694| 2898| 1926| 3046|
| P10| 8508| 6| 8| 150| 376| 2966| 3856| 554|
| P11| 1068| 480| 528| 92| 156| 960| 240| 152|
| P12| 70| 16| 32| 6| 20| 96| 18| 18|

Total cost of distribution N2,025,200

TABLE 8. Comparative performance of CPSO, ALO, and exact algorithm.

| Algorithm       | Number of Iterations | Population Size | Computation time (sec.) | Relative performance to the original cost |
|-----------------|----------------------|-----------------|--------------------------|------------------------------------------|
| CPSO            | 30                   | 5000            | 23.6                     | 23.9%                                    |
| ALO             | 20                   | 2000            | 623.1                    | 24.8%                                    |
| Exact Algorithm | N/A                  | N/A             | N/A                      | 14.0%                                    |
number generation in the basic phase. Such algorithms usually get trapped in local optima despite the fast computation speed. This study applied two bio-inspired algorithms—one standard and the other improved variant to optimize petroleum product scheduling. It also compares the result of the two bio-inspired algorithms with the exact algorithm in the literature [20]. We also illustrate that the kernel representation of a BIA significantly affects its efficiency, especially in a real-world problem. The results show that ALO and CPSO reduced the distribution cost by 24.8% and 23.9%, respectively, while the exact algorithm minimized the total shipping cost by only 14%. The distribution matrix for CPSO and ALO showed that 99.5% of constraints are satisfied. The ALO algorithm produced better solution quality even at its basic state, although its convergence is significantly slow. Basic PSO on the other hand is ineffective in the petroleum product scheduling network. The chaotic function shows significant improvement in the PSO search performance in a real-world optimization problem. The chaotic function enhances algorithm performance.

In all, the proposed algorithms are robust and could handle many more products and depots, but the exact algorithm (TORA) cannot handle more than 100 decision variables. The study could also be extended to other domains such as power distribution, and resource allocation, among others. Besides other constraint handling methods like language multiplier could be a possible extension in the future study. In addition, other bio-inspired algorithms including Genetic algorithm and their variants are further suggestions for future work. Furthermore, other variants of ALO could be applied to the petroleum product scheduling to compare their result with the basic ALO.

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VOLUME 10, 2022