

## OPTIMIZING PALM OIL BIOMASS COLLECTION: GENETIC ALGORITHM APPROACHES IN SOLVING LOCATION-ROUTING PROBLEM

(Mengoptimumkan Pengumpulan Biojisim Minyak Sawit: Pendekatan Algoritma Genetik dalam Menyelesaikan Masalah Penghalaan-Lokasi)

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### ABSTRACT

The transition from traditional fossil fuels to renewable energy sources, such as biofuels derived from palm oil biomass, represents a promising avenue in sustainable energy development. However, managing biomass supply chain (BSC) can be challenging, with biomass collection being particularly complex. Hence, this research delves into the intricacy of a location-routing problem (LRP) within the context of palm oil biomass collection. The study aims to enhance the efficiency of palm oil biomass collection by identifying optimal locations for collection facilities and devising vehicle routing strategies at minimum costs. To achieve these objectives, the research employs genetic algorithm (GA) approaches, incorporating innovative strategies, namely automated mutation operator selection (AMOS) and elite child population (ECP). Three GA variations are proposed to inspect the impacts of strategies in GA solution methods. These approaches are evaluated through computational experiments to measure optimisation quality in solving the LRP within the palm oil BSC. The findings underscore the effectiveness of the proposed methods in addressing the LRP. The proposed solution methods could establish a framework for decision-making processes within the biomass energy industry, particularly concerning facility siting and vehicle routing.

**Keywords:** location-routing problem; genetic algorithm; palm oil biomass; biomass supply chain

### ABSTRAK

Peralihan daripada bahan api fosil tradisional kepada sumber tenaga diperbaharui, seperti *bio-fuel* yang diperoleh daripada biojisim minyak sawit, merupakan satu jalan penyelesaian yang menjanjikan dalam pembangunan tenaga mampan. Walau bagaimanapun, mengurus rangkaian bekalan biojisim (BSC) boleh jadi mencabar, dengan proses pengumpulan biojisim yang sangat kompleks. Oleh itu, kajian ini menyelidik masalah penghalaan lokasi (LRP) dalam konteks pengumpulan biojisim minyak sawit. Kajian ini bertujuan untuk meningkatkan kecekapan pengumpulan biojisim minyak sawit dengan mengenal pasti lokasi optimum dan merangka strategi penghalaan kenderaan pada kos minimum. Untuk mencapai objektif ini, penyelidikan menggunakan pendekatan algoritma genetik (GA), menggabungkan strategi inovatif, iaitu pemilihan pengendali mutasi automatik (AMOS) dan populasi anak elit (ECP). Tiga variasi GA dicadangkan untuk memeriksa impak strategi dalam kaedah penyelesaian GA. Kaedah-kaedah GA ini dinilai melalui eksperimen pengiraan untuk mengukur kualiti pengoptimuman dalam menyelesaikan LRP dalam BSC minyak sawit. Penemuan menunjukkan keberkesanan kaedah yang dicadangkan dalam menangani LRP. Kaedah penyelesaian yang dicadangkan boleh mewujudkan rangka kerja untuk proses membuat keputusan dalam industri tenaga biojisim, terutamanya mengenai penempatan fasiliti dan penghalaan kenderaan.

**Kata kunci:** masalah penghalaan lokasi; algoritma genetik, biojisim minyak sawit; rangkaian bekalan biojisim

## 1. Introduction

In Malaysia, a significant amount of palm oil waste is generated, making this biomass an excellent feedstock for biofuel. This study focuses on optimising a biomass supply chain (BSC) network consisting of mills and collection facilities. Mills serve as resource sites for palm oil biomass, while collection facilities function as centralized points for gathering and processing the biomass. The placement of these facilities plays a crucial role in determining the overall efficiency of the BSC by affecting travel distances and associated costs. Additionally, operational efficiency and costs are influenced by the routing decisions for biomass collection. Many BSC studies address facility location problems (FLP) and vehicle routing problems (VRP) separately, which can lead to suboptimal solutions (Cao *et al.* 2021b). Solving these problems in isolation may overlook interactions between facility placement and transportation efficiency, resulting in higher costs or inefficiencies. Therefore, this research aims to optimize the locations of collection facilities and routing decisions simultaneously, framing the BSC problem as a location-routing problem (LRP).

Most BSC models are formulated as mixed-integer programming (MIP) problems and solved using commercial solvers like General Algebraic Modeling System (GAMS), which employ exact algorithms such as branch and bound. While these methods ensure optimality, they become impractical for large-scale problems due to long computation times (Atashbar *et al.* 2018). To address this, researchers are increasingly turning to heuristics and metaheuristics, which, may effectively generate near-optimal solutions for large-scale scenarios but do not ensure global optimality.

This research proposes a genetic algorithm (GA) as the solution method for the LRP. GA is a powerful optimization technique known for its robustness and versatility in solving complex search and optimization problems. Its robust global search capabilities are a result of mutation operators that maintain variety during the search process (Deep *et al.* 2009) and population-based search strategies (Katoch *et al.* 2021). This study develops genetic algorithm (GA) solutions that integrate innovative strategies, including Automated Mutation Operator Selection (AMOS) and Elite Child Population (ECP), to enhance the optimisation of LRP. Three GA variations are proposed to inspect the impacts of strategies in GA solution methods. The originality and novel innovations of proposed GA also include a realistic chromosome construction for limited vehicle fleets, the AMOS strategy for adaptive mutation, and the ECP strategy for guiding searches towards optimal solutions. These advancements enhance GA theory and can be adapted to various LRP and VRP.

The article is structured into six sections. Section 2 reviews relevant literature. Section 3 outlines the problem definition and assumptions. Section 4 details the GA solution methods. Section 5 discusses the results, encompassing GA variation testing and parameter sensitivity analysis. The final section concludes with summaries and limitations.

## 2. Literature Review

A significant amount of study has been conducted in the last few years to examine the structures of the BSC network. The BSC research has concentrated on several facets of decision-making, including allocation problems (AP) (Wang *et al.* 2021), facility location problems (FLP) (Zhao & Li 2016), location-allocation problems (LAP) (Soha *et al.* 2021), VRP (Vahdanjoo *et al.* 2021), and LRP (Habibi *et al.* 2018). A detailed review of BSC research related to these problems is available in our earlier work (Foo *et al.* 2024).

Mixed-integer linear programming (Chugh *et al.* 2016; Tagliabue *et al.* 2021) and stochastic programming (Xie & Huang 2018; Saghaei *et al.* 2020) are preferred methods, with many studies using commercial solvers with exact algorithms (Woo *et al.* 2018; Salleh *et al.* 2019). However, exact algorithms are typically suitable only for small-scale problems (Atashbar *et al.* 2018). Some researchers employed heuristics (Mayerle & Neiva de Figueiredo 2016) or metaheuristics (Vahdanjoo *et al.* 2021) for optimisation. Among the metaheuristics, Genetic

Algorithm (GA) is one of the most popular methods (Mirkouei *et al.* 2017; Salimi & Vahdani 2018). Table 1 summarises the LRP in BSC research, including the characteristics of network and solution methods. It shows all researchers used heuristics or metaheuristics, with population-based algorithms (e.g., GA) and single-solution methods (e.g., Tabu Search (TS)). The literature indicates that GA is highly effective for tackling large-scale BSC problems and has demonstrated its capability in solving the LRP.

Table 1: Articles related to LRP in BSC research

| Article                             | Model Formulation and Solution Method                                       | Characteristics                                                                    |
|-------------------------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------------------|
| Habibi <i>et al.</i> (2018)         | Modified Simulated Annealing (SA), GA, and firefly algorithm                | Two-echelon LRP; Single recipient; First echelon routing decisions.                |
| Asadi <i>et al.</i> (2018)          | Non-Dominated Sorting GA II and multi-objective particle swarm optimisation | Two-echelon LRP; Single recipient; First echelon routing decisions.                |
| Cao <i>et al.</i> (2021b)           | TS and variable neighborhood search                                         | Two-echelon LRP; Multiple recipients; First echelon routing decisions              |
| Morales Chavez <i>et al.</i> (2021) | Two-phase heuristic method, SA                                              | Three-echelon LRP; Multiple recipient; First echelon routing decisions.            |
| Li <i>et al.</i> (2019)             | Hybrid GA with TS and local search                                          | Two-echelon split delivery LRP; Single recipient; First echelon routing decisions. |
| Cao <i>et al.</i> (2021a)           | Hierarchical TS                                                             | Two-echelon LRP; Multiple recipients; Routing decisions for both echelons.         |

A gap analysis shows that existing GA methods for LRP are primarily suited for two-echelon networks with a single recipient, making them unsuitable for single-echelon scenarios with multiple facilities. To address this limitation, this research introduces new GA strategies for single-objective single-echelon LRP with multiple facilities. This study builds upon our previous work (Foo *et al.* 2024), which addressed a multi-objective single-echelon location-routing problem for the same BSC network structure. That research aimed to determine the optimal locations for collection facilities and plan biomass collection routes from the mills. The problem was formulated as a mathematical model using mixed-integer linear programming (MILP) and solved with the GAMS optimizer, utilizing its built-in exact algorithm. While the previous study primarily tackled the multi-objective LRP, it also examined single-objective optimization scenarios. To evaluate the effectiveness of the proposed GA solution methods, the GAMS solutions from our previous research will serve as a benchmark. A comparative analysis will be conducted between GAMS and GA solutions, focusing on optimizing the total cost objective function.

The proposed GA build on Yu *et al.* (2022)'s work for waste management, which finds initial solutions with GA and refines them with SA. Their GA assume unlimited vehicles and assigning routes based on shortest distance, which may lead to excess capacity and higher costs. Our three proposed GA methods offer several advancements by introducing the elitism strategy, incorporating a limited vehicle fleet, using the AMOS strategy for adaptive mutation selection, and applying the ECP strategy to guide the search toward higher-quality solutions.

### 3. Problem Definition and Assumption

This paper develops GA approaches for a BSC network involving mills and collection facilities (Figure 1). Determining optimal facility locations and truck routes is crucial to minimising total costs. Thus, this BSC investigation aligns with the single-objective location-routing problem. The assumptions for GA are:

- (a) Only one truck visits each mill, the truck may visit more than one mill provided that the total load stays within the truck's capacity.

- (b) Trucks start and end their routes at the same open collection facility, with no inter-facility flow.
- (c) Facility locations, capacities, and vehicle capacities are predefined.

It is noteworthy that this article focuses solely on the proposed GA solution methods, while the mathematical model related to the research problem can be found in our previous research article (Foo *et al.* 2024).

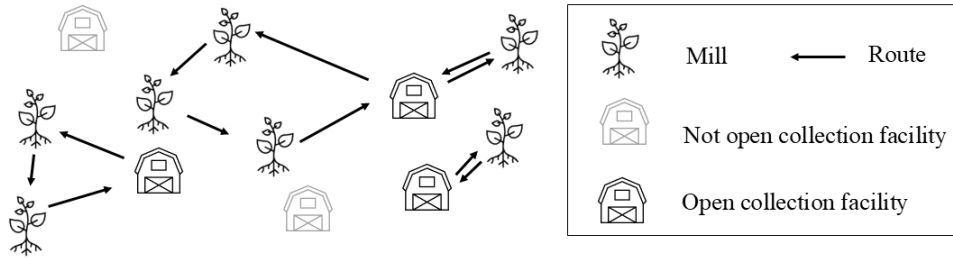


Figure 1: The investigated LRP network

## 4. Genetic Algorithm Solution Methods

### 4.1. Genetic algorithm variations

Three GA variations are proposed, namely, GA variation with No AMOS strategy and No NECP strategy (NAMOS\_NECP), GA variation with AMOS strategy and No NECP strategy (AMOS\_NECP), and GA variation with AMOS strategy and ECP strategy (AMOS\_ECP). The GA variation NAMOS\_NECP is shown in Figure 2. It begins with random permutations, encoded onto chromosomes as detailed in Section 4.2. These chromosomes are decoded into feasible solutions. The search ends when a maximum number of generations (*MaxGen*) is reached. Selection is based on fitness, with parents chosen via roulette wheel and crossed over using the order crossover operator at a rate (CR). Offspring are mutated at a rate (MR) using random operators. Each generation produces normal child chromosomes (*NChild[i]*) and combines with elite chromosomes (*EChrom[i]*) to form the next generation. This process continues until the termination criteria are satisfied.

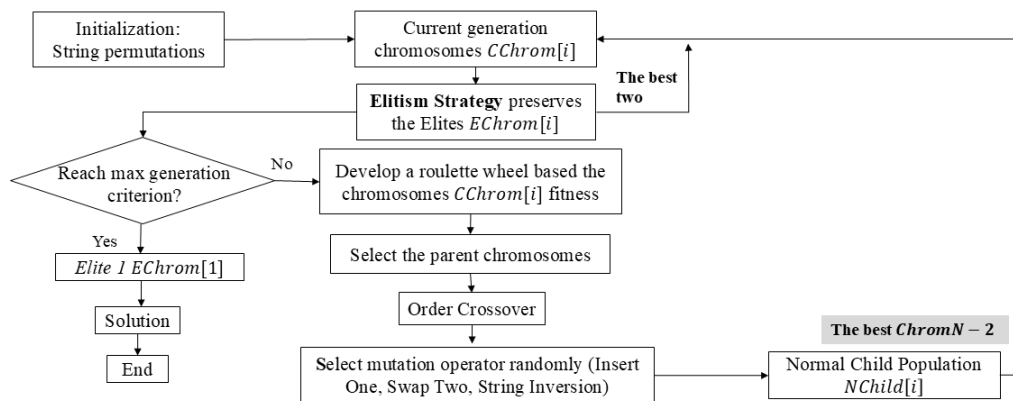


Figure 2: NAMOS\_NECP mechanism (GA variant 1)

Figure 3 shows the AMOS\_NECP mechanism, which resembles NAMOS\_NECP but differs in the mutation phase. It uses the Automated Mutation Operator Selection (AMOS) strategy to adaptively choose mutation operators based on generation count (Details in Section 4.3). Figure 4 illustrates the

AMOS\_ECP mechanism, which builds on AMOS\_NECP by adding the Elite Child Population (ECP) strategy. This strategy uses the best chromosome (*Elite [1]*) as the elite parent to generate elite child population 1, which consists of four elite offspring. Similarly, the second-best chromosome (*Elite [2]*) serves as the parent to produce elite child population 2, also comprises of four elite offspring. The top offspring from each elite child population is then selected and combined with the elite chromosomes and normal child chromosomes to form the next generation. The details of the ECP strategy executed on the elite parent can be found in Section 4.4.

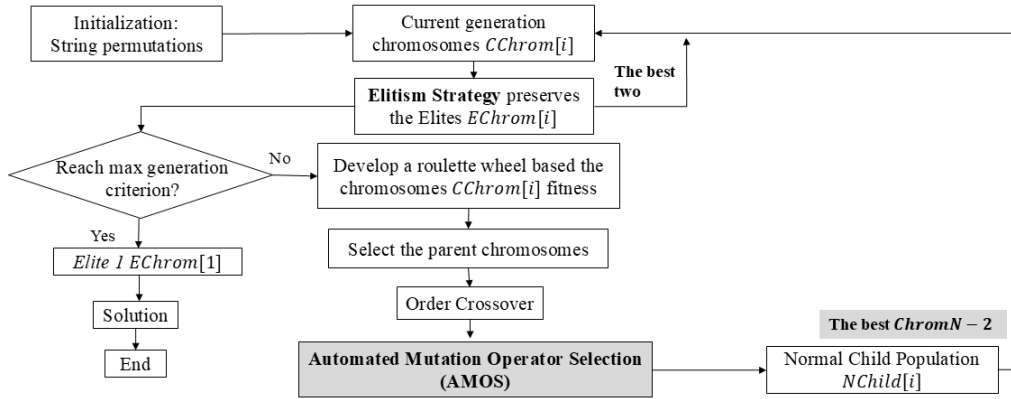


Figure 3: AMOS\_NECP mechanism (GA variant 2)

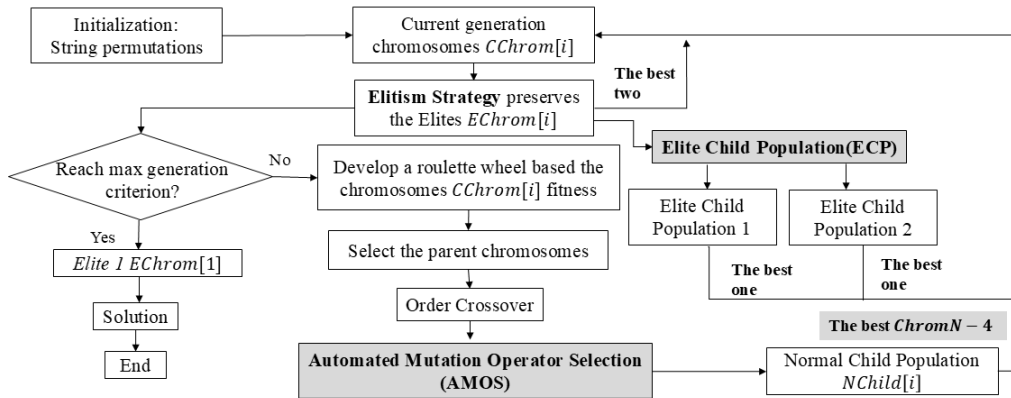


Figure 4: AMOS\_ECP mechanism (GA variant 3)

## 4.2. Chromosome construction

The proposed chromosome construction improves upon the reference GA method by accounting for vehicle availability and randomizing facility openings and route assignments. The proposed method reflects real-world conditions and explores a broader solution space. Figure 5 illustrates the chromosome construction process, starting with string permutations of mill ( $F$ ) and facility ( $C$ ) nodes and concluding with the assignment of trucks ( $H$ ) as well as mill and facility assignment details. The mill string contains information about the biomass quantity available ( $q^F$ ) at each mill, while the facility string contains about information of facility capacities ( $t^C$ ). Mill string is divided into fragments based on a random  $FCutN$  (Eq. 1) Each segment must fit within the capacity of truck ( $c_h^H = 25 \text{ tons}$ ), or it is further sliced. The slicing process ensures that each fragment fits within the truck's capacity. When a node causes the total load to exceed the truck's capacity, it and the subsequent nodes will be assigned to a new truck. For

instance, the second fragment is divided into  $\{F3, F8, F4\}$  and  $\{F2, F6, F7\}$ . In  $\{F3, F8, F4\}$ , the total biomass to be collected is 18.8697 tons. Including F2 in this fragment would increase the total to 26.9567 tons, exceeding the truck's capacity, so F2 is assigned to a different fragment (belong to another truck).

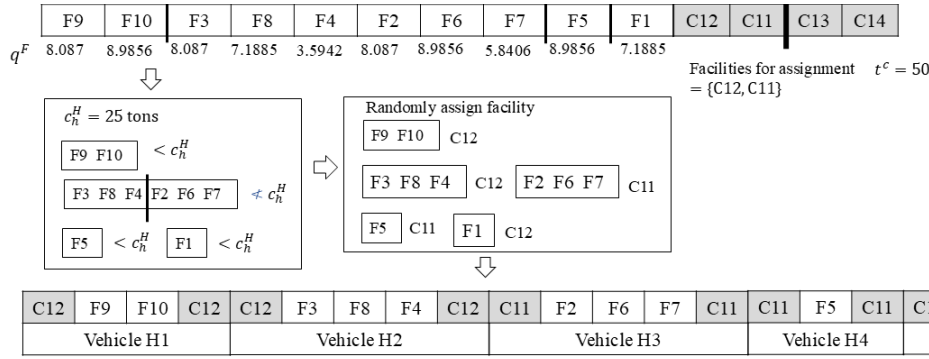


Figure 5: A chromosome construction example

$$\begin{aligned}
 FCutN &= [MinFCut, MaxFCut], \\
 MinFCut &= \text{ceil} \left( \frac{TAqF}{c_h^H} \right) - 1, \\
 MaxFCut &= \begin{cases} nH - 1, & \text{if } nH < FarmN, \\ FarmN - 1, & \text{otherwise,} \end{cases}
 \end{aligned} \tag{1}$$

where

$FarmN$  = total mill nodes,  
 $TAqF$  = total biomass available in BSC,  
 $c_h^H$  = capacity of truck h,  
 $n^H$  = number of trucks.

Facility nodes are assigned based on a random *OpenCN* (Eq. 2), determining how many facilities to open. Mill fragments and facility assignments are made randomly. While this random approach might not ensure balanced assignments, it prioritizes ensuring that the total biomass collected from the assigned mills fits within the facility capacity. If this requirement is not met, the construction process restarts from the beginning. The final chromosome integrates vehicle routes with their assigned facilities. Although the assignments in the final chromosome may not always be balanced, the objective function's total cost acts as a controlling mechanism in GA evolution, eventually eliminating chromosomes with unnecessary facility or truck usage that result in high total costs.

$$\begin{aligned}
 OpenCN &= [MinCoFa, MaxCoFa], \\
 MinCoFa &= \text{ceil} \left( \frac{TAqF}{t^c} \right), \\
 MaxCoFa &= CoFaN,
 \end{aligned} \tag{2}$$

where

$OpenCN$  = number of collection facilities to be opened,

$t^c$  = capacity of the facility,

$CoFaN$  = number of collection facilities available,

$MinCoFa$  = minimum number of collection facilities that must be opened  
to handle the total biomass available in BSC,

$MaxCoFa$  = maximum number of collection facilities allowable to be opened  
to handle the total biomass available in BSC.

#### 4.3. Automated Mutation Operator Selection (AMOS) strategy

Instead of randomly selecting mutation operators, the AMOS strategy uses a predefined preference order. With  $MaxGen$  as the maximum generations, the boundary points are  $GenBY1 = \lceil \frac{1}{3}MaxGen \rceil$ ,  $GenBY2 = \lceil \frac{2}{3}MaxGen \rceil$ . Three mutation operators are employed, Insert One, Swap Two, and String Inverse. These can be illustrated using a simple example of a mill string containing five nodes: {F1, F2, F3, F4, F5}. If the Insert One operator is applied, it randomly selects a node (e.g., F4) and inserts it into a new position, resulting in {F1, F4, F2, F3, F5}. If the Swap Two operator is selected, it randomly picks two nodes (e.g., F2 and F5) and swaps their positions, producing {F1, F5, F3, F4, F2}. Lastly, the String Inverse operator selects a random sub-segment (e.g., {F2, F3, F4}) and reverses it, generating {F1, F4, F3, F2, F5}. Initially, in domain  $[1, GenBY1]$ , the Insert One operator is used for minimal changes. In domain  $(GenBY1, GenBY2]$ , the Swap Two operator aids exploration, while the String Inverse operator is used in  $(GenBY2, MaxGen]$  to enhance diversity and avoid local optima.

#### 4.4. Elite Child Population (ECP) strategy

This research introduces the Elite Child Population (ECP) strategy to improve the chances of finding an optimal solution. ECP creates a new population from current elites, preserving beneficial gene sequences. New chromosomes are generated by applying new random cuts to elite permutations without genetic operators, offering additional potential solutions for the LRP.

As illustrated in Figure 4, the elitism strategy remains integrated within the AMOS.ECP mechanism. Elite chromosomes, *Elite [1]* and *Elite [2]*, are directly carried over to the next generation, ensuring their preservation. The execution of the ECP strategy does not eliminate the elite chromosomes. Instead, it operates on these elites to generate two distinct groups of elite offspring, which are elite child population 1 and elite child population 2.

*Elite [1]* serves as the elite parent, with the ECP strategy applied to generate four elite offspring. Figure 6 illustrates the application of the ECP strategy to *Elite [1]*. The elite parent, with an value of 6, undergoes duplication to form four strings. New random cuts are generated for each string to slice the mill string at random positions. For example, *EChildA[1][1]* and *EChildA[1][3]* both have  $FCutN = 3$ , but their cuts are positioned differently.

Since the mill string is divided into fragments based on  $FCutN$  and must fit within the truck capacity, any fragment exceeding this capacity is further sliced. The fragments are then randomly assigned to the open facilities. This process results in varied chromosome structures and decoding outcomes, such as different vehicle routes and facility assignments (see Section 4.2 for details). These four elite offspring form elite child population 1, and the best offspring from this population is selected to advance to the next generation. The same process is applied to *Elite [2]*, producing elite child population 2, from which the best offspring is also carried forward to the next generation.

### 5. Result Discussion

This section presents the computational results of the proposed GA variations (NAMOS, NECP, AMOS, NECP, and AMOS.ECP) and their parameter sensitivity analysis. Computational experiments were con-

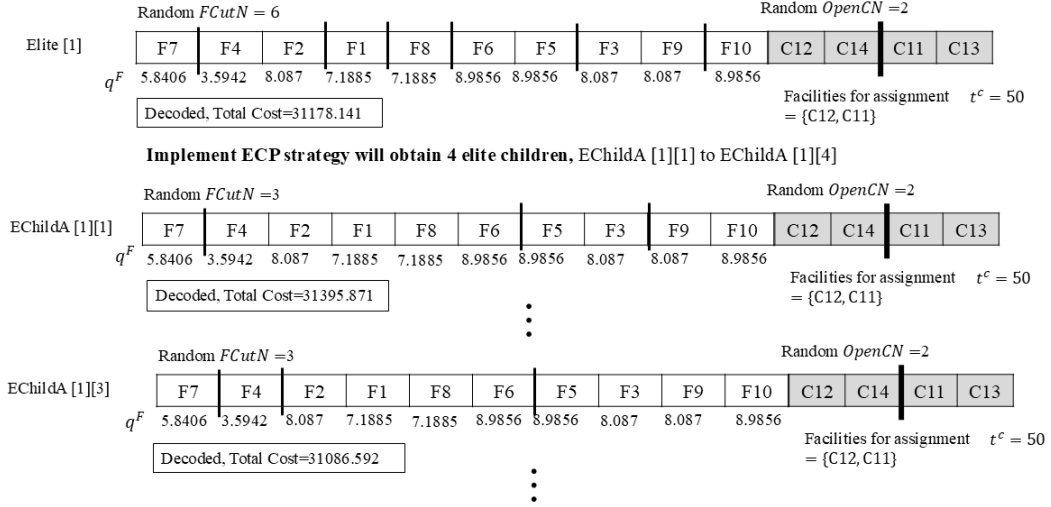


Figure 6: A chromosome construction example

ducted to evaluate the impacts of the proposed AMOS and ECP strategies on solution quality. NAMOS\_NECP, AMOS\_NECP, and AMOS\_ECP represent the proposed GA mechanism with no strategies, one strategy, and two strategies, respectively. Experiments used a test instance with tens mills and four candidate facility locations, as described in our previous work (Foo *et al.* 2024). In that study (Foo *et al.* 2024), the test instance was solved using a mathematical model implemented in GAMS. The objective function value obtained from GAMS (RM30610.524) will serve as the benchmark for comparison. In this section, the results obtained from the proposed GA variations will be compared and evaluated against this GAMS benchmark solution.

### 5.1. Genetic algorithm variation testing

This section presents the results for the proposed GA variations. The parameter circumstances are population size  $ChomN = 20$ , normal child population size  $ChildN = 40$ ,  $CR = 0.8$ ,  $MR = 0.1$ , and  $MaxGen = [100, 400]$  with and increments of 100. Each GA variation was tested in 10 trials.

Figure 7 shows the average results from ten trials for each circumstance, compared to the total cost objective function value obtained from GAMS (RM30,610.524). The results indicate that GA can produce near-optimal solutions, particularly when configured with higher settings. A detailed comparison of GA performance and GAMS is analyzed through the mean percentage error (MPE) and best trial percentage error (PE), which will be discussed later in the analysis of Table 2. Among all variations and scenarios, AMOS\_NECP and AMOS\_ECP outperform NAMOS\_NECP. AMOS\_ECP generally provides better average values than AMOS\_NECP, except at  $MaxGen = 400$ . Nevertheless, AMOS\_ECP still performs slightly better than NAMOS\_NECP overall. This exception at  $MaxGen = 400$  highlights that the inherent randomness (stochastic nature) of GA remains in the algorithm, even though the proposed strategies have improved GA performance in other  $MaxGen$  settings.

Figure 8 presents the best trial results from ten trials under each scenario. Comparing the best trial results across  $MaxGen$  settings, the AMOS\_ECP variation outperformed the other two at  $MaxGen = 100$  and 300, while NAMOS\_NECP achieved the best performance at  $MaxGen = 200$ . At  $MaxGen = 400$ , all variations produced similarly close best trial results. These findings suggest that each GA variation has the potential to achieve the best trial performance under different settings.

Table 2 presents the MPE and best trial PE from the computational experiments. These percentage errors measure the deviation of GA results from the optimal solution obtained from GAMS. An analysis of the MPE results shows that AMOS\_NECP and AMOS\_ECP had lower average errors compared to NAMOS\_NECP. Specifically, AMOS\_ECP achieved MPEs of 0.5055%, 0.3864%, and 0.3511% for

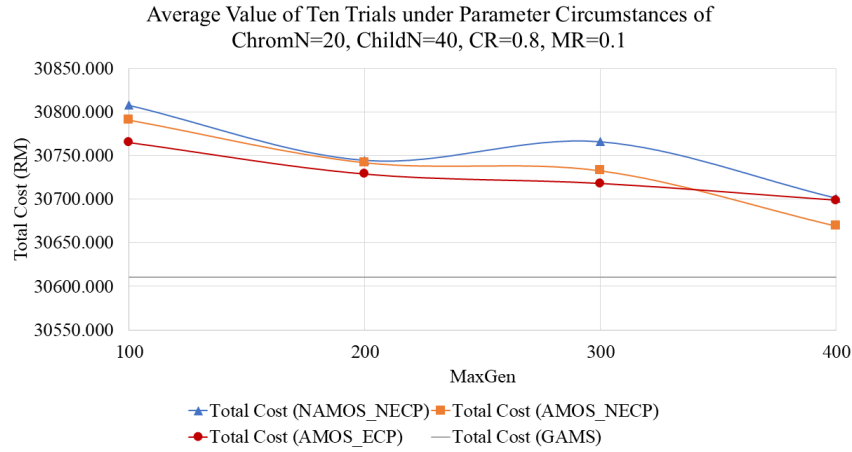


Figure 7: Average trial value using GA variations

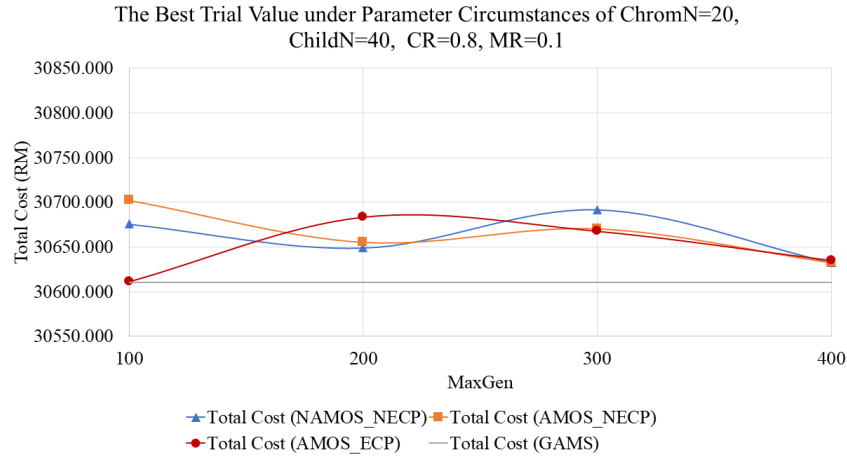


Figure 8: The best trial value using GA variations

*MaxGen* values of 100, 200, and 300, respectively, while AMOS\_NECP had the lowest MPE of 0.1924% at *MaxGen* = 400.

Table 2: Mean and best trial percentage errors for GA Variations

| Generation | Mean Percentage Error (MPE) of Trial Values (%) |               |               |                | Percentage Error (PE) of Best Trial Value(%) |               |               |               |
|------------|-------------------------------------------------|---------------|---------------|----------------|----------------------------------------------|---------------|---------------|---------------|
|            | 100                                             | 200           | 300           | 400            | 100                                          | 200           | 300           | 400           |
| NAMOS_NECP | 0.6445                                          | 0.4380        | 0.5079        | 0.2963         | 0.2125                                       | <b>0.1252</b> | 0.2651        | <b>0.0713</b> |
| AMOS_NECP  | 0.5893                                          | 0.4298        | 0.3995        | <b>*0.1924</b> | 0.2995                                       | 0.1462        | 0.1955        | <b>0.0713</b> |
| AMOS_ECP   | <b>0.5055</b>                                   | <b>0.3864</b> | <b>0.3511</b> | 0.2878         | <b>*0.0025</b>                               | 0.2381        | <b>0.1868</b> | 0.0801        |

\*The least value among all results

In terms of PE for the best trial value (Table 2), AMOS\_ECP excelled at *MaxGen* settings of 100 and 300, with PE values of 0.025% and 0.1868%, respectively. The PE of 0.025% at *MaxGen* = 100 is the lowest recorded. At *MaxGen* = 200, NAMOS\_NECP achieved the best PE of 0.1252%. For *MaxGen* = 400, both NAMOS\_NECP and AMOS\_ECP had a PE of 0.0713%.

## 5.2. Genetic algorithm parameter sensitivity analysis

This section examines the sensitivity of GA parameters for AMOS.ECP methods. The CR was varied from 0.7 to 0.9 with increments of 0.1, and MR from 0.05 to 0.2 with increment of 0.05, with ten trials for each CR-MR pair. Table 3 shows that GA performance was most stable with  $CR = 0.7$ .  $CR = 0.8$  outperformed  $CR = 0.9$ , except at  $MR = 0.15$ . The  $CR = 0.9$  and  $MR = 0.15$  had the smallest MPE of 0.2783% from the GAMS solution. Table 3 also shows the best trial results, the GA with  $CR = 0.8$  out-performed  $CR = 0.9$  with  $MR = \{0.05, 0.1, 0.2\}$ , except at  $MR = 0.15$ . The GA with  $CR = 0.8$  and  $MR = 0.1$  had the smallest deviation from the GAMS solution, at PE = 0.0801%.

Table 3: Mean and best trial percentage errors for AMOS.ECP with varying CR and MR

| MR       | Mean Percentage Error (MPE) of Trial Values (%) |        |                |        | Percentage Error (PE) of Best Trial Value(%) |                |        |        |
|----------|-------------------------------------------------|--------|----------------|--------|----------------------------------------------|----------------|--------|--------|
|          | 0.05                                            | 0.1    | 0.15           | 0.2    | 0.05                                         | 0.1            | 0.15   | 0.2    |
| CR = 0.7 | 0.4538                                          | 0.4144 | 0.3729         | 0.4452 | 0.1206                                       | 0.1549         | 0.1039 | 0.1745 |
| CR = 0.8 | 0.4158                                          | 0.2878 | 0.4377         | 0.4053 | 0.1181                                       | <b>*0.0801</b> | 0.1951 | 0.1829 |
| CR = 0.9 | 0.4889                                          | 0.4409 | <b>*0.2783</b> | 0.4140 | 0.2471                                       | 0.1277         | 0.0958 | 0.2112 |

\*The least value among all results

## 6. Conclusion

The results show that all GA variations can achieve near-optimal solutions, especially with *MaxGen* set to 400 generations. On average, AMOS.NECP and AMOS.ECP have the smallest deviations from the optimal solution. This suggests that incorporating AMOS and ECP strategies effectively guided the search process towards better outcomes. Despite the inherent randomness of GA, sensitivity analysis indicates  $CR = 0.9$  and  $MR = 0.15$  has a lowest MPE, suggesting a higher chances of near-optimal solutions and is recommended for cost optimisation. Though, the best trial near-optimal solution is found in  $CR = 0.8$  and  $MR = 0.1$  with lowest PE.

In real-world scenarios, these BSC problems are often large-scale, making the conventional MIP formulation and exact algorithms impractical. Therefore, the proposed GA solution offers a viable alternative for solving palm oil BSC location-routing problems. With its robustness and versatility in handling complex optimization and search problems, GA can efficiently generate feasible solutions, providing a fast approximation even if it does not always guarantee optimality.

In the future work, this research will be expanded by including multi-objective single-echelon and two-echelon LRP scenarios. Additionally, we are enhancing the AMOS strategy and extending it to incorporate other termination criteria.

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