

Optimization of Cement Distribution Route Based on Hybrid Genetic-Firefly Algorithm (GAFA)

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ABSTRACT

This study focuses on optimizing the cement distribution route to improve efficiency, reduce costs, and minimize environmental impacts. A hybrid Genetic-Firefly Algorithm (GAFA) approach, integrating the Genetic Algorithm (GA) and the Firefly Algorithm (FA), is developed to solve the complex problem of determining the optimal distribution route to ensure timely, efficient, and sustainable delivery. The Data from PT Semen Baturaja includes three factory locations and 128 distributor points. Various parameter configurations are tested, including population size, mutation probability, total execution time, average execution time, standard deviation of execution time, best factory, and best distance to provide their impact on algorithm performance. The empirical results show that the optimal configuration produces the lowest total distance of 205.14 kilometers and high execution-time efficiency. The best route covers 128 strategic distribution points in the Sumatra region. These results prove the effectiveness of the hybrid GAFA algorithm in optimizing cement distribution routes, contributing significantly to operational efficiency and transportation cost savings. Thus, this approach offers a practical, efficient solution for optimizing cement distribution routes in the manufacturing industry.

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1. INTRODUCTION

Distribution of goods in industry is a routine activity that ensures the smooth flow of goods from the factory to the distributor. [1]. This process plays an essential role in supporting logistics efficiency with transportation as a key element in the delivery of goods. However, transportation is often a major contributor to total operating costs, compared to other activities. [2]. Therefore, determining the optimal distribution route by considering distances and delivery times to various locations is a crucial factor for optimizing efficiency and reducing costs. [3].

One of the main challenges in cement distribution in the manufacturing industry is ensuring timely delivery. At the same time, optimizing distance and cost efficiency contributes to achieving environmental sustainability. [4], [5]. In addition, by integrating the cement distribution route principle into the distribution process, the industry not only supports efforts to reduce greenhouse gas emissions but can also improve the company's image as an industrial player that cares about sustainability and gains a competitive advantage [6], [7].

Each vehicle in the cement distribution not only delivers products to demand points, such as distribution centers or customers, but also collects products or materials for recycling or returning to the manufacturer. For this reason, it is necessary to support the creation of a more efficient and environmentally friendly distribution network [8]. One of them is in the manufacturing industry at PT Semen Baturaja, where goods are shipped daily to different, distant locations. In the distribution network analyzed in this study, cement

is supplied by three factories that operate as independent distribution sources with different production capacities. The Palembang Factory and the Lampung Factory each have a production capacity of approximately 1,200 tons per day, whereas the Baturaja Factory operates on a much larger scale with a capacity of up to 10,000 tons per day. Although production capacity is not the primary focus of this study, these differences provide important operational context as they may influence distribution load allocation and highlight the complexity of multi-source distribution. Including this information helps ensure that the hybrid GAFA model reflects real-world distribution conditions while supporting a more balanced planning framework across multiple supply sources. So, the importance of the cement distribution route approach will be the leading solution in choosing the optimal transportation route. Determining the best route is a strategy that can help companies reduce transportation costs and ultimately increase the company's profitability [9], [10]. Long-distance and local transportation need to be considered to minimize the distance and delivery time to the destination. Therefore, it is necessary to determine the optimal transportation route, taking into account the factory's location relative to the distributor's (warehouse's) location [11].

Research on cement distribution route optimization has been widely conducted across various fields of the manufacturing industry to address complex optimization problems. In optimal path search, there is no single algorithm that is considered optimal for every case, because each algorithm's performance can vary depending on the situation. Traditional optimization methods, such as gradient-based techniques or exact solution approaches, are often inefficient for high-dimensional, non-convex search spaces because they require substantial computational time. On the other hand, stochastic exploration through metaheuristics can overcome the common limitations of classical methods, such as getting stuck in local minima, thus avoiding premature convergence [12]. In addition, processing with Genetic Algorithm (GA) and Firefly Algorithm (FA). Many algorithms are used in route optimization [10].

Several previous studies have shown that GA, which searches for optimal solutions in large problem spaces with efficient computational time, exploits the principle of natural selection through selection, crossover, and mutation. [13], [14]. The Firefly algorithm uses an optimal solution search based on the attraction between fireflies, determined by the light intensity (or optimality level) of each individual [15], [16]. These two algorithms have complementary characteristics; GA is strong in global exploration [17], [18]. Since FA excels at local exploitation, however, it often suffers from limitations in global search, as it tends to focus on solutions within certain regions that are more appealing [19]. Further research on hybrid algorithms demonstrated that combining GA and FA produces a hybrid GAFA that leverages the strengths of both to improve convergence speed and solution quality, enabling it to provide an optimal solution for determining the cement distribution route in the manufacturing industry.

To improve the accuracy of green transportation route-optimization simulation, this study evaluates parameter configurations. [20], including variations in population size, mutation probability, and number of generations [21], to spread its impact on the performance of the hybrid GAFA algorithm. The proposed algorithm leverages GA exploration through FA selection, crossover, handling, and intensification to find optimal solutions around the local optimum. With the correct parameters, this algorithm can optimize operational costs, such as travel time and fuel, and provide adaptive solutions in real-time scenarios, such as facing changing conditions, such as traffic or weather. This combination improves distribution efficiency by enabling routes that save time and resources, making it ideal for real-world applications. This is expected to yield more efficient and accurate solutions for the optimal cement distribution route [22].

The application of the hybrid GAFA algorithm in this context aims to leverage the strengths of each algorithm while overcoming the weaknesses that arise when used separately. The results of this study represent an essential contribution to the application of hybrid optimization algorithms to real-world logistics problems, especially in the cement distribution sector.

2. RELATED WORK

This study combines the Genetic Algorithm (GA) with the Firefly Algorithm (FA) to form GAFA. This hybrid GAFA can solve various optimization problems, especially by efficiently finding globally optimal solutions. Research on hybrid GA and FA achieves high solution quality and can find the global optimal solution by exploring a series of search points [19], [23]. It saves time by quickly reaching the optimal or near-optimal solution in early iterations while maintaining low computational cost through efficient function evaluation. It can also avoid local optima and accelerate the search for the optimal solution.

Research on combining GA and FA concepts enables the formation of individuals in a new generation not only through the GA process but also through the FA mechanism, which is designed to prevent local optima and increase solution diversity while balancing exploration and exploitation [24]. Genetic Algorithms (GA) have been widely recognized as one of the most effective metaheuristics for solving complex Vehicle Routing Problems (VRP), and GA is able to avoid stagnation and remain stable when applied to large-scale logistics networks [25]. FA contributes strong local-search refinement through its adaptive attractiveness mechanism,

enabling efficient convergence while maintaining population diversity [26]. According to the researcher in [27], ACO is able to construct feasible routes but is highly sensitive to pheromone initialization, often reinforcing early suboptimal paths that lead to imbalanced route structures and longer travel distances. PSO performs even worse due to low positional diversity and rapid stagnation, resulting in the poorest overall distance among all tested algorithms. These limitations show that both ACO and PSO struggle with the non-linear, multimodal, and constraint-rich nature of the routing problem, thereby reinforcing the need for more robust hybrid approaches such as GAFA.

The hybrid GA-FA approach has been proven to design optimal query execution plans with fewer generations, thereby speeding up the process and improving the efficiency of big data processing [28]. This method is not only fast but also produces high-accuracy solutions, making it very practical for a wide range of fields that require efficient, stable solutions to large-scale problems.

A combination of multi-objective algorithms, including the Firefly and Genetic algorithms, is used to optimize the objective function. The results show that increasing the weight coefficient makes the effect of costs on the objective function increasingly significant, leading to lower production costs. This shows that the greater the weight coefficient, the lower the production emissions in the objective function, even as the number of emissions increases [22].

In this study, the GAFA hybrid algorithm is shown to be effective in optimizing cement distribution at PT Semen Baturaja, resulting in the shortest travel distance and a relatively efficient execution time. These results can be compared with several similar studies that use optimization algorithms, such as GA, FA, and other hybrids, to highlight the advantages and disadvantages of each in solving distribution and logistics problems, as shown in Table 1.

Table 1. Comparison of similar research

Researcher	Method	Case Study	Optimized Parameters	Advantage	Weakness
Authors of this paper	Hybrid GAFA (Genetic Algorithm - Firefly Algorithm)	Cement distribution, PT Semen Baturaja	Population size, mutation probability, number of generations, total execution time (s), average execution time (s), std dev of execution time (s), best factory, best distance	Combining GA and FA produces optimal solutions in terms of distance, best factory, and best distance.	Algorithm convergence is influenced by crossover and mutation parameters.
Oliveira, et al. (2020) [26]	Hybrid Genetic-Firefly Algorithm	Optical transport network	Execution time (s), cost, configuration	Combining GA and FA can yield an optimized path	Lower computing time
Dashtdar, et al. (2022) [29]	FA-GA hybrid	Economical dispatch of power plants	A new setting of the α and β parameter values, mutation (pm), and crossover (pc) based on the sigmoid function, local search	Optimizing the objective function can reduce fuel costs and pollution emissions.	Concentrates on substantial parameters and is tested on more complex Bus systems.
Bade, et al. (2024) [30]	Generic Algorithm (GA)-Particle Swarm Optimization (PSO)	Wind-solar-biomass system with battery and hydrogen storage	Configuration assessment, economic analysis, technical analysis, social-political analysis, and environmental analysis	Performance is superior due to fast convergence, the lowest final fitness value, and a stable optimization process	Limitations such as premature convergence (in PSO) or overexploration (in GA).
Xiao, et al (2024) [31]	Hybrid genetic grey wolf	Minimize radiation dose, provide a safe route	Road section, distance (KM), radiation dose (MSV)	Integrating the radiation environment and road network to plan emergency response plans	Limitations on shortest paths in static networks
Palomino-Pérez, et al. (2024) [32]	Mixed-integer linear programming model, Genetic algorithm	Designing a reverse logistics network for medical waste management	Optimal Cost, time (s)	Determining routes for two-destination locations, with multiple depots, time windows, capacity constraints, and varying waste types, across a multi-period horizon.	Uncertainty in parameters such as demand, capacity, or costs.

Researcher	Method	Case Study	Optimized Parameters	Advantage	Weakness
Sun & Wang (2023) [33]	NSGA-II algorithm-MOPSO algorithm	Multi-objective two-echelon vehicle routing determination with simultaneous pick-up and delivery	Desirability weight, transportation cost per product, distance between nodes, the amount of greenhouse gas emissions per kilometer, product transfer time, amount of time, the time the vehicle arrives, the amount of accumulated perishability time, the maximum capacity, the accumulated load, the total travel time	Designing optimal routes and their sequences to minimize transportation costs	Uncertainty in some problem parameters and intermediate warehouse transfers
Komijani & Sajadieh (2024) [34]	Particle Swarm Optimization (PSO) and Simulated Annealing (SA)	Routing under uncertainty in perishable goods supply chains	Suppliers, retailers, products, the main products, the secondary products, raw materials, vehicles, time periods, scenario	Optimization under uncertainty and enhancing decision-making within the perishable goods supply chain	Implementation of more complex algorithms
Forghani, et al. (2023) [35]	Genetic Algorithm	Determination of the hydrogen delivery pipeline route between production and distribution sites in Oman with GA	Distance, transportation costs, and available infrastructure.	Suitable for VRP problems in logistics	Susceptible to local optimum
Trachanatzi, et al. (2020) [36]	VRP, E-PCVRP FA	Route determination to minimize distance and cost	Solution vector 1 and 2, coordinate x, coordinate y, parameters of comparison algorithms	Can optimize distance and cost	Costs may be related to financial costs
Li, et al. (2023) [37]	Mixed integer nonlinear programming (MINLP)- Grey Wolf Optimizer (GWO)	Designing a multimodal transport network with a hub-and-spoke structure to transport food and masks	Supply, hub capacity, and demand	Efficiency of transportation time and transportation costs of the hub-and-spoke structure transportation network for transporting food and masks	The role of the government regarding transportation companies in designing effective transportation networks
Xu, et al (2025) [38]	An adaptive Genetic hyper-heuristic algorithm (AGA-HH)	Two-echelon vehicle routing problem with dual customer satisfaction	Minimize the total costs, maximize time window satisfaction, and maximize freshness satisfaction	Improvements in distribution cost reduction, time window compliance, and product freshness preservation.	Challenges in collecting real-world data sets from community group purchasing companies due to confidentiality agreements and commercial sensitivities.
Ali & Kumar (2022) [39]	Hybrid multi-objective evolutionary programming-Firefly Algorithm (MOEPFA)	A hybrid multi-objective evolutionary programming-Firefly Algorithm for different types of distributed generation in the distribution system	Scenario 1 for the base case or without DG, scenario 2 for DG with active power injected, scenario 3 for DG injected with reactive power only, and scenario 4 for DG injected with both active and reactive power.	MOEPFA solves multi-objective power system problems that minimize total active and reactive power losses and improve voltage profiles, while accounting for the cost of energy losses.	The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.
Wu, et al (2021) [40]	Genetic Algorithm, Gradient	Location-inventory routing determination	Vehicle	The optimal location of distribution centers, replenishment	Constraints of route length and vehicle load,

Researcher	Method	Case Study	Optimized Parameters	Advantage	Weakness
	Descent Algorithm (GD)		parameters, parameters, parameters	plans for both distribution centers and retailers, and a vehicle-routing scheme for each period.	which in turn will increase fuel consumption costs.
Babaeinesa mi, et al (2021) [41]	Genetic algorithm	Genetic algorithm approach to perform a supply chain model	Distance traveled, costs	GA is effective in global exploration	High computation time on large datasets
Rigakis, et al. (2021) [15]	Firefly Algorithm	Creating a travel itinerary for a group	Travel plan design, prize-collecting vehicle routing problem	The FA approach can provide efficient and satisfying travel for heterogeneous groups.	It is necessary to route vehicles that combine clustered nodes.
Yuan, et al. (2024) [42]	Firefly Algorithm	Planning a hybrid system of wind turbine units, photovoltaic panels, and battery storage	Presents stochastic modeling for planning island systems and takes into account uncertainties in load and renewable energy power.	Low planning costs, renewable resources. batteries provide flexibility, improving the planning costs of remote systems	Parameters have uncertainties, and different values may be obtained in each scenario.

Based on comparisons with previous studies, this study's hybrid GAFA algorithm provides an optimal balance between exploration and exploitation capabilities and computational efficiency. The comparison shows that combining GA and FA can potentially improve the quality of solutions to complex distribution and logistics problems. While other studies have shown promising results with various methods, the hybrid GAFA provides an effective alternative with simpler parameter tuning complexity compared to other hybrids, such as Genetic Algorithm-Ant Colony Optimization (GA-ACO) or Genetic Algorithm-Particle Swarm Optimization (GA-PSO), which are more sensitive to parameter variations.

3. METHOD

This study uses a structured approach to optimize cement distribution routes in the manufacturing industry, leveraging a hybrid GAFA. The research methodology comprises several stages: problem identification, data collection, model development, algorithm implementation, and performance evaluation.

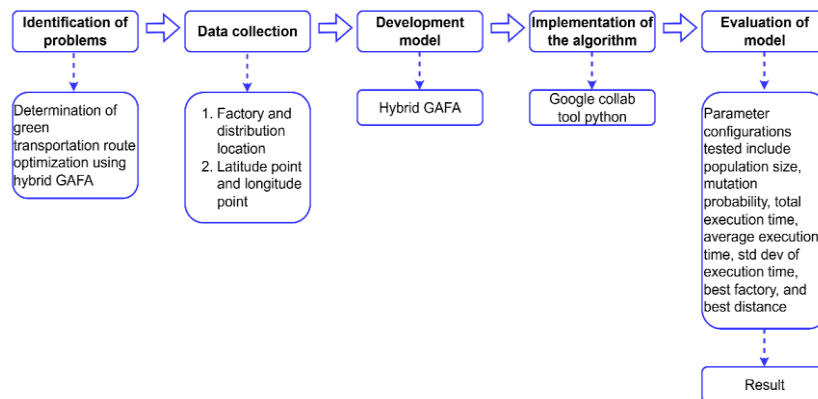


Figure 1. Cement distribution route optimization framework

3.1 Identification of Problem

This research begins by identifying the primary issues in the cement distribution process, particularly the inefficiencies in selecting optimal routes between factories and distributors. The use of non-optimal routes may lead to excessive fuel consumption, increased operational costs, longer travel times, and higher carbon emissions, all of which hinder sustainability efforts. This problem is especially significant for PT Semen Baturaja, which conducts daily distribution activities across wide and geographically diverse service areas. Moreover, delivery timeliness is a critical factor, as delays in distribution can disrupt the progress of customers' construction projects.

Based on these challenges, an optimization mechanism is required to generate distribution routes that are efficient, stable, and adaptive to operational conditions. The hybrid GAFA approach is selected due to

its capability to handle complex search spaces by integrating the global exploration ability of the Genetic Algorithm (GA) with the local exploitation capability of the Firefly Algorithm (FA). The combination of these two algorithms is expected to produce higher-quality routing solutions and enhance the determination of optimal routes within PT Semen Baturaja's operational environment.

3.2 Data Collection

The data required in this study include the locations of factories and distribution points, along with their geographical coordinates (latitude and longitude), which are essential for constructing the cement distribution route. This information is used to identify potential obstacles that may affect delivery efficiency, such as long travel distances, isolated nodes, or uneven distributor distribution. By obtaining accurate and validated spatial data, the study can build a distribution network representation that reflects actual operational conditions.

In addition to collecting coordinate data, a verification process is carried out to ensure consistency and alignment between the actual locations and the data used in the modeling process. The collected data are then processed and organized into a structured format to serve as input for the GAFA algorithm. The availability of comprehensive and well organized data enables the optimization model to respond more adaptively to changing field conditions, resulting in more accurate, efficient, and implementable distribution routes within the operational context of PT Semen Baturaja.

3.3 Development Model

At this stage, the optimization model is developed by combining the Genetic Algorithm (GA) and Firefly Algorithm (FA), referred to as the hybrid GAFA. The main objective of this model is to obtain the most optimal distribution route. The model is built using a dataset and implemented in Google Colab with the Python 3.7 programming language.

The process begins with the initialization of the population using GA and FA. GA is employed for global solution exploration through steps such as chromosome initialization, fitness calculation, crossover, and mutation. After mutation, the solution is passed to FA for further exploitation. FA operates by initializing parameters, evaluating the fitness of fireflies, updating light intensity, ranking fireflies, and moving them toward better solutions. This process repeats until the maximum number of iterations is reached, producing the optimal distribution solution. The proposed hybrid GAFA operates in two stages: GA first explores the global search space to produce high-quality initial routes, and FA subsequently refines these routes through localized search. The overall workflow of GAFA is illustrated in Algorithm Z, while the detailed GA and FA procedures are presented in Algorithm X and Algorithm Y, respectively.

The optimization process begins with GA, which generates the initial population through chromosome initialization, fitness evaluation, crossover, and mutation to maintain diversity. Once GA identifies promising route solutions, these candidates are refined by FA through the computation of firefly brightness, light-intensity updates, ranking, and movement toward more optimal positions. This iterative interaction between GA's global exploration and FA's local exploitation continues until the maximum number of iterations is reached. Through this integrated approach, the hybrid GAFA produces more stable and efficient route solutions that align with PT Semen Baturaja's distribution objectives, demonstrating improved convergence and optimization performance compared with the standalone algorithms.

Algorithm X. Genetic Algorithm (GA) for Route Optimization

```

1: Input:
2: Factory coordinate f, distributor coordinates D,
   population_size, generations, mutation_rate.
3: Output:
   Best route R*, best distance Dist*.
4: Initialize population P with random permutations of distributors.
5: For each generation do
6:   For each individual ind in P do
7:     Compute total_distance(ind, f, D).
8:     Compute fitness(ind) = 1/total_distance.
9:   End for
10:  Select individuals based on fitness (roulette wheel selection).
11:  Apply crossover to selected parents to generate offspring.
12:  Apply mutation (swap two positions) to maintain diversity.
13:  Update population P with new offspring.
14: End for
15: Identify best individual R* with minimum total_distance.
16: Dist* ← total_distance(R*, f, D).
17: Return R*, Dist*.

```

To provide a more structured explanation of the execution steps within the GA, FA, and hybrid GAFA frameworks, the following pseudocode is presented as an illustration of the computational processes involved in the distribution optimization stage., the following pseudocode presents the Genetic Algorithm (GA) used to generate initial candidate routes in the distribution optimization stage.

The following pseudocode outlines the Firefly Algorithm (FA), which performs localized refinement of candidate routes obtained from GA:

Algorithm Y. Firefly Algorithm (FA) for Route Optimization

```

1: Input:
   Factory coordinate f, distributor coordinates D,
   population_size, generations,  $\beta_{\min}$ ,  $\alpha$ ,  $\gamma$ .
2: Output:
   Best route R*, best distance Dist*.
3: Initialize population P with population_size random permutations of distributors.
4: For each generation do
5:   For each firefly ind in P do
6:     Compute total_distance(ind, f, D).
7:     Compute brightness(ind) =  $1 / (1 + \text{total\_distance})$ .
8:   End for
9:   Set new_population  $\leftarrow$  P.
10:  For each firefly i in P do
11:    For each firefly j in P do
12:      If brightness(i) < brightness(j) then
13:        Compute distance r between i and j in solution space.
14:        Compute  $\beta = \beta_{\min} + (1 - \beta_{\min}) \cdot \exp(-\gamma \cdot r^2)$ .
15:        Update position of firefly i toward j:  $i_{\text{new}} = i + \beta \cdot (j - i) + \alpha \cdot (\text{rand} - 0.5)$ .
16:        Discretize  $i_{\text{new}}$  to a valid route (integer indices in  $[0, |D|-1]$ ).
17:        Replace firefly i in new_population with  $i_{\text{new}}$ .
18:      End if
19:    End for
20:  End for
21:  P  $\leftarrow$  new_population.
22: End for
23: Select best firefly R* in P with minimum total_distance.
24: Dist*  $\leftarrow$  total_distance(R*, f, D).
25: Return R*, Dist*.

```

Building upon the outputs of Algorithm X (GA) and Algorithm Y (FA), the following pseudocode presents the hybrid GAFA mechanism that integrates both processes:

Algorithm Z. Hybrid GAFA for Cement Distribution Route Optimization

```

1: Input:
   Factory coordinates F, distributor coordinates D,
   GA parameters (population_size_GA, generations_GA, mutation_rate),
   FA parameters (population_size_FA, generations_FA,  $\beta_{\min}$ ,  $\alpha$ ,  $\gamma$ ).
2: Output:
   Hybrid best routes R*, hybrid best distances Dist* for each factory.
3: For each factory f in F do
   // --- Stage 1: GA-based global exploration
4:   Run Genetic Algorithm (Algorithm X) with:
5:     - factory coordinate = f
6:     - distributor coordinates = D
7:   Obtain GA_best_route(f) and GA_best_distance(f).
   // --- Prepare initial firefly population for FA
8:   Initialize firefly population P_FA with:
9:     - One firefly set to GA_best_route(f),
10:    - Remaining fireflies generated as random perturbations
      (e.g., slight permutations) of GA_best_route(f).
   // --- Stage 2: FA-based local refinement
11:  Run Firefly Algorithm (Algorithm Y) with:
12:    - factory coordinate = f
13:    - distributor coordinates = D
14:    - initial population = P_FA
15:  Obtain refined best route R*_f and Dist*_f.
   // --- Store hybrid GAFA result for factory f
16:  R*[f]  $\leftarrow$  R*_f
17:  Dist*[f]  $\leftarrow$  Dist*_f
18: End for
19: Return R*, Dist*.

```

3.4 Algorithm Implementation

The algorithm implementation follows a two-stage optimization process in which the Genetic Algorithm (GA) serves as the global exploration mechanism. In the first stage, GA initializes and evolves a population of route candidates through chromosome initialization, fitness evaluation, crossover, and mutation to maintain population diversity. These operations enable GA to explore the solution space broadly and identify high-potential route structures. The selection mechanism ensures that fitter individuals are more likely to be retained in subsequent iterations, thereby improving the quality of the initial solutions that will be refined in the next stage.

In the second stage, the Firefly Algorithm (FA) performs localized refinement on the candidate routes generated by GA. FA computes the brightness of each firefly based on route fitness, updates light intensity, and applies attractiveness rules to guide fireflies toward more optimal positions within their local neighborhood. Randomization is incorporated to prevent stagnation and preserve exploratory capability. Through the integration of GA's global search and FA's local intensification, the hybrid GAFA achieves balanced exploration and exploitation, resulting in more stable convergence and higher-quality distribution routes. This structured implementation demonstrates superior optimization performance compared with applying GA or FA individually.

3.5 Evolution of Performance

The evaluation stage aims to measure the performance of the hybrid GAFA algorithm in determining the optimal distribution route from the factory to the distributor. The evaluation is conducted by configuring several parameters, including population size, mutation probability, total execution time, average execution time, the standard deviation of execution time, best-performing factory, and best-generation distance. These parameters are analyzed to understand their influence on solution quality, computational efficiency, and convergence stability. The findings from this evaluation support the identification of effective parameter settings and provide insights into the algorithm's behavior under various operational conditions.

To enhance methodological clarity and reproducibility, the evaluation process is aligned with the pseudocode and algorithm tables presented in the preceding section. This alignment ensures that each performance indicator corresponds directly to the operational steps of GA and FA within the hybrid workflow. By referencing these structured algorithmic descriptions, the analysis demonstrates how the interaction between GA's global exploration and FA's local refinement influences execution dynamics and contributes to the robustness of the GAFA-based distribution route optimization.

4. RESULTS AND DISCUSSION

This study focuses on optimizing cement distribution at PT Semen Baturaja. The data obtained from PT Semen Baturaja included location names and latitude and longitude coordinates covering three cement factories and 128 Distributors. Optimization of cement distribution routes from factories to distributors was based on the distance between each factory and each distributor. To obtain coordinate points, researchers used Google Maps (www.maps.google.com). The process begins with data collection: location names and coordinates are obtained from addresses, and then factory and distributor coordinate points are searched for. Table 2 and Table 3 present examples of factory and distributor data.

Table 2. Data on factory location names and coordinates

No	Location name	Coordinates (Latitude)	Coordinates (Longitude)
1	Baturaja factory	-4.114961	104.162709
2	Palembang factory	-3.024565	104.744624
3	Panjang factory	-5.459095	105.316238

Table 3. Example data of distributor name and coordinates

No	Location name	Coordinates (latitude)	Coordinates (longitude)
1	APM distributor - Karya Jaya	-3.063110	104.743670
2	APM distributor - Km 12	-2.914126	104.678448
3	APM distributor - Perintis	-2.975330	104.777550
4	APM distributor - Plg star	-2.914030	104.714550
5	APM distributor - Sako	-2.919840	104.775680
...	...	...	...
128	Wika beton yagaloka/bakauheni	-5.838543	105.769922

By determining coordinates from the factories' and distributors' addresses, the locations' geographic positions can be identified. These coordinate points are then visualized on a map to show the distribution of factory and distributor locations. This visualization, as shown in Figure 2, provides a clear representation of the geographical distribution of all locations. Through this distribution, distribution patterns and potential proximity between locations can be more easily understood, thereby supporting a deeper analysis of supply chain efficiency and distribution strategies in the region.

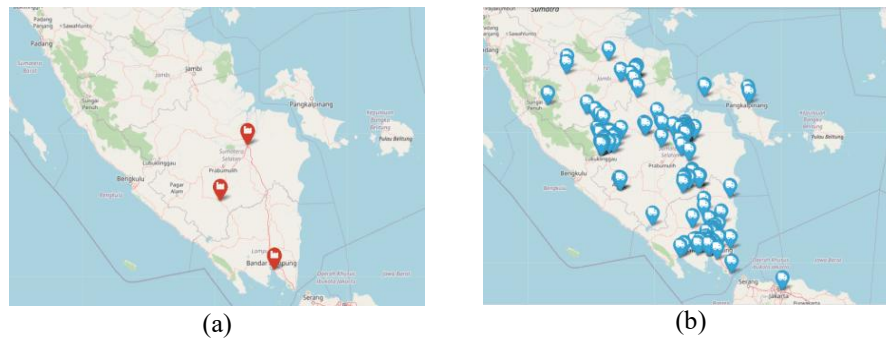


Figure 2. Geographical distribution location (a) factory and (b) distributor

The next step is to test the GAFA algorithm across various parameter configurations to evaluate its performance. The architecture of the GAFA algorithm is shown in Figure 3.

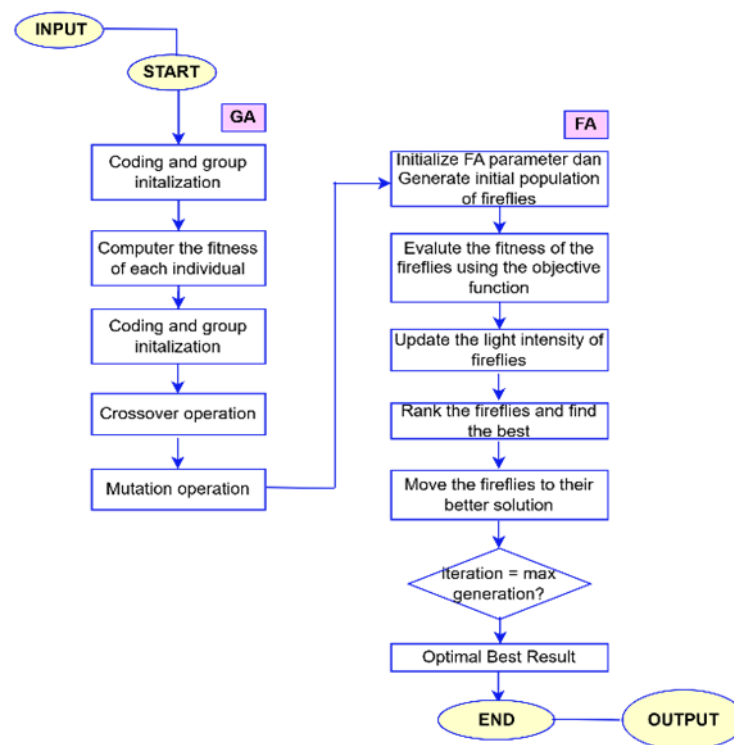


Figure 3. Flowchart for GAFA hybrid

Figure 3 shows the workflow of the hybrid GAFA (Genetic Algorithm-Firefly Algorithm) algorithm to determine the best route in optimization. The algorithm begins by inputting the best route data for the GAFA process. Furthermore, the GAFA process comprises two main parts: the GA (Genetic Algorithm) and the FA (Firefly Algorithm). The GA part begins with the initialization of coding and population grouping. Then, everyone is evaluated to calculate their fitness value. This algorithm includes crossover and mutation operations to produce a new population. After that, the algorithm searches for the best individual from the entire population and evaluates whether the stopping criteria have been achieved. If not, the process will be repeated until the desired criteria are met, namely, the maximum iterations. Once completed, the best results from GA will be used as input for the FA part.

In the FA section, the FA parameters are initialized, and a population of fireflies is generated. Each firefly is evaluated based on the objective function, followed by an update of its light intensity. The fireflies

are sorted, and their best positions are moved to better solutions. After all iterations are completed, the algorithm will produce the optimal optimization result.

Testing was done by varying the population size, crossover probability, mutation probability, and number of generations. The population size was tested at 10, 50, 100, and 150 individuals to assess how these values affect the algorithm's performance. The crossover probability was kept constant at 0.8, while the mutation probability was tested at 0.05 and 0.1 to evaluate its effect on solution diversity and convergence potential. The number of generations was set to three levels (30, 50, and 100) to determine the number of iterations required for the algorithm to reach the optimal solution. The combination of all these parameters yielded 20 configurations, enabling a more in-depth analysis of the impact of each parameter on the final optimization result. The test results are shown in Table 4.

Table 4. Parameter combination of the hybrid GAFA algorithm for optimization experiments

No	Population size	Mutation probability	Number of generations	Total execution time (s)	Average execution time (s)	Std Dev of execution time (s)	Best factory	Best distance
1	10	0.05	30	6.25	2.08	0.23	Panjang factory	234.75
2	50	0.05	30	26.96	8.99	1.26	Panjang factory	220.65
3	100	0.05	30	34.31	11.44	2.03	Baturaja factory	219.43
4	150	0.05	30	59.3	19.77	2.16	Baturaja factory	217.39
5	10	0.05	50	12.76	4.25	0.69	Panjang factory	230.27
6	50	0.05	50	37.42	12.47	3.29	Palembang factory	224.15
7	100	0.05	50	53.29	17.76	3.78	Panjang factory	205.14
8	150	0.05	50	64.31	21.44	3.19	Baturaja factory	209.63
9	10	0.05	100	13.37	4.46	0.81	Panjang factory	243.27
10	50	0.05	100	34.09	11.36	0.51	Panjang factory	219.9
11	100	0.05	100	66.82	22.27	1.85	Palembang factory	216.5
12	150	0.05	100	97.6	32.53	1.99	Baturaja factory	208.26
13	10	0.1	30	5.53	1.84	0.46	Baturaja factory	241.96
14	50	0.1	30	19.26	6.42	2.12	Palembang factory	217.03
15	100	0.1	30	29.19	9.73	0.83	Palembang factory	209.22
16	150	0.1	30	47.54	15.85	2.63	Panjang factory	222.5
17	10	0.1	50	11.75	3.92	0.66	Panjang factory	241.47
18	50	0.1	50	36.95	12.32	1.45	Palembang factory	214.17
19	100	0.1	50	61.74	20.58	1.13	Panjang factory	214.57
20	150	0.1	50	100.7	33.57	4.43	Palembang factory	213.73

From Table 4, with 20 conducted experiments, the influence of parameter variations on the hybrid GAFA algorithm has been identified. Experiment #7 shows the lowest Best Distance of 205.14, indicating that the parameter configuration in this experiment is the most effective in finding the optimal route. In addition, experiment #13 recorded the lowest average execution time of 1.84 seconds and the lowest total execution time of 5.53 seconds, indicating that the combination of population size, mutation probability, and number of generations in this experiment allows the algorithm to run very efficiently. Experiment #10 also stands out with the lowest execution-time standard deviation of 0.51 seconds, indicating high consistency in the algorithm's performance in this configuration. Overall, these results show that variations in population size, mutation probability, and the number of generations significantly affect the GAFA algorithm's performance in determining the best route. The configuration that produces the lowest Best Distance and the highest execution-time efficiency strikes an optimal balance between solution quality and processing speed, which is essential

for applying this algorithm in the context of cement distribution, where efficiency and reliability are required. A visualization of the performance matrix comparison based on experiments is shown in Figure 4.

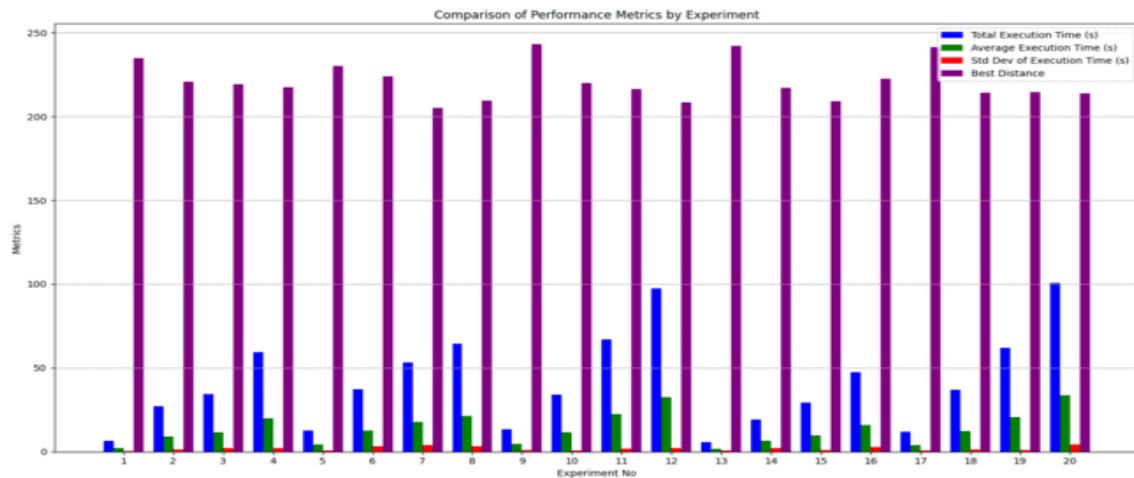


Figure 4. Comparison of performance metrics of the experiments

In the 7th experiment, the factory that became the distribution center was the Panjang factory. The optimization results using the hybrid GAFA algorithm produced the best route covering several widely spread cement distribution points, namely from Gudang Map - Alang-Alang to H. Tiwa. The total distribution points include 118 strategic locations, such as the warehouses of CV Setia Raya - Ki Merogan, PT Roberto Saut Jaya, Inti Beton Pegayut, and Wika Beton Yogaloka/Bakauheni, as well as various essential points in the Sumatra region. The total distance for this optimal route is 205.143 kilometers, which is the best result for achieving cement distribution efficiency in this study. The lowest best distance with the route from the Panjang factory is shown in Table 5.

Table 5. Factory to distributor

Factory	Distributor
Panjang Factory	(54, 'gudang map - alang-alang'), (49, 'gudang cv. Setia raya - ki. Merogan'), (95, 'paal merah'), (109, 'sumber niaga delsia'), (103, 'pt.bima sakti bakti persada'), (27, 'bp rindang lematang'), (56, 'gudang mwp - belitang'), (111, 'talang gulo 1, 2, & 3'), (98, 'plta kerinci merangin hidro'), (87, 'map candimas'), (105, 'radja mix'), (64, 'gudang rajawali - bk 16'), (15, 'bkj sekampung udik'), (20, 'bmu metro'), (57, 'gudang mwp - mesuji oki'), (59, 'gudang mwp bersaudara - sekayu'), (36, 'gudang apm - karya jaya'), (90, 'merlung'), (102, 'pt roberto saut jaya'), (83, 'inti beton pegayut'), (116, 'terawas jaya'), (39, 'gudang apm - plg star'), (86, 'karya makmur'), (8, 'bbp pesawaran'), (82, 'inti beton indralaya'), (48, 'gudang cv arjuna - betung'), (19, 'bmu kotabumi'), (24, 'bmu tuba rawajitu'), (88, 'map tubaba'), (22, 'bmu rumbia'), (125, 'wbp sta 80/81'), (47, 'gudang citra mandiri'), (14, 'bkj pekalongan'), (42, 'gudang arjuna - belitang'), (79, 'hastera jaya'), (81, 'indo bangunan'), (66, 'gudang samajaya sa - seka'), (23, 'bmu tanggamus'), (119, 'tsb bernung'), (7, 'bbp korpri'), (100, 'proyek zak batching plant cv. Belal'), (97, 'pemb. Taman kuliner lawang agung'), (69, 'gudang sepakat buana jaya'), (32, 'cv demang bersaudara'), (12, 'bintara bangunan'), (65, 'gudang samajaya sa - poly'), (52, 'gudang lie otto - soak palembang'), (75, 'gudang vinayaka - karya jaya'), (108, 'sinar baru'), (35, 'gemilang'), (2, 'bangka tengah'), (58, 'gudang mwp bersaudara - betung'), (63, 'gudang putra balkom - belitang iii'), (60, 'gudang mwp lempuing tugumulyo'), (61, 'gudang ogan ilir - samudra panca'), (17, 'bkj sukadana'), (25, 'bmu tubaba'), (124, 'wbp sta 60'), (80, 'indah jaya'), (34, 'eco rahmat'), (92, 'muaro bungo 1'), (93, 'muaro bungo 2'), (107, 'simpang ahok 1 & 2'), (55, 'gudang map - bayung lencir'), (11, 'bintang dunia'), (62, 'gudang pt. Lie otto pratama'), (26, 'bp infratekno sarana jaya metro'), (68, 'gudang samudra panca - bk 16'), (94, 'ogan jaya'), (5, 'batching plant pt. Lie otto pratama'), (18, 'bmu kalirejo'), (71, 'gudang serasan sm - plg s'), (99, 'proyek rs pratama'), (13, 'bkj batanghari'), (122, 'tsb tj. Karang'), (6, 'bbp garuntang'), (41, 'gudang apm duren ijo'), (51, 'gudang lie otto - bayung lencir'), (101, 'pt golden blossom sumatera'), (76, 'gudang vinayaka - pusri'), (3, 'barokah'), (121, 'tsb pringsewu'), (123, 'tsb tj. Senang'), (30, 'citra mulia'), (104, 'remban sungai beraes'), (78, 'harapan jaya'), (114, 'tb.nabila'), (91, 'muara bulian'), (53, 'gudang lie otto bayung lencir'), (16, 'bkj sribawono'), (120, 'tsb kedondong'), (29, 'bendungan batangasai sarolangun'), (84, 'inti beton tanjung api2'), (67, 'gudang samudra panca'), (110, 'sumber niaga trijaya'), (21, 'bmu pringsewu'), (118, 'tsb bakung'), (31, 'cp simpang mandala'), (117, 'tj. Lumut/ ling. Timur 1 & 2'), (28, 'bp tcp tegineneng'), (43, 'gudang arjuna tani'), (0, 'agil'), (38, 'gudang apm - perintis'), (50, 'gudang hub bukit - lie otto'), (4, 'batching plant cv. Duta garuda adid'), (89, 'mentok, bangka'), (10, 'bintang aneka jaya'), (45, 'gudang baturaja multi usaha - pali'), (96, 'pangkal balam, pangkal pinang'), (40, 'gudang apm - sako'), (113, 'tb.makmur'), (1, 'an3'), (74, 'gudang sungai lilin'), (112, 'tb yuda'), (9, 'bbp pringsewu'), (106, 'sbii tanggamus'), (85, 'jogja keramik'), (37, 'gudang apm - km 12'), (44, 'gudang arjuna tani pasar suryadi'), (127, 'wika beton yogaloka/bakauheni'), (46, 'gudang bmu - lonsum'), (70, 'gudang serasan - kenten'), (73, 'gudang spj pasar suryadi'), (126, 'wika beton tengineneng'), (72, 'gudang sinar adiguna - belitang'), (115, 'tempino 1 & 2'), (33, 'cv kusuma wardana'), (77, 'h.tiwa')

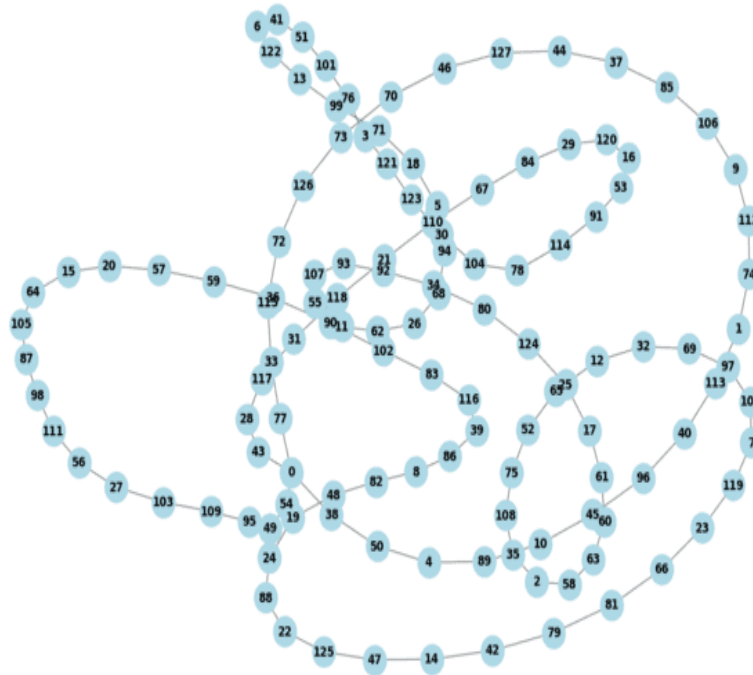


Figure 5. Route from Panjang factory to the distributor

Figure 5 shows the route from the Panjang factory with point 0 to the nearest distributor, which is the MAP Distributor - Alang-alang with point 54, and then to point 49 → 24 → ... → 77 and back to point zero based on the results of the GAFA hybrid algorithm.

5. CONCLUSION

This study has successfully proven that the hybrid Genetic Algorithm-Firefly (GAFA) is effective in optimizing cement distribution routes at PT Semen Baturaja. By combining GA's capabilities for global exploration with FA's for local exploitation, this algorithm can produce optimal solutions with minimal total distance travel. Experiments with 20 parameter configurations showed significant effects of variations in population size, mutation probability, and the number of generations on algorithm performance. The 7th experiment, with the shortest distance (Best Distance) of 205.14 km, yielded the optimal parameter configuration for determining the best route. In addition, several other configurations provided optimal results in terms of execution time efficiency, such as the 13th experiment, with the lowest average execution time of 1.84 seconds, and the 10th experiment, with the lowest standard deviation in execution time of 0.51 seconds, demonstrating consistent performance. The optimal route from the factory in Panjang to various cement distribution points in the Sumatra region covers 128 locations and totals 205,143 kilometers. These results confirm that the GAFA algorithm achieves high distribution efficiency, which is essential in the logistics context of PT Semen Baturaja. In conclusion, this study provides an essential contribution to the application of the hybrid GAFA algorithm for cement distribution route optimization. It demonstrates that it can achieve an optimal balance between solution quality and execution time efficiency. The application of hybrid GAFA to distribution route optimization enables PT Semen Baturaja to improve operational efficiency and significantly reduce transportation costs. Future enhancements of the GAFA framework will focus on strengthening its methodological robustness and practical applicability. Several research directions are proposed: (1) expanding parameter optimization through additional experimental scenarios to improve convergence stability, (2) integrating real-time GPS or telematics data to enable dynamic route adjustments under changing traffic or operational conditions, (3) conducting scalability testing on larger and more complex distribution networks, (4) exploring hybridization with other metaheuristics such as ACO or PSO and incorporating deep learning approaches to further enhance search efficiency, and (5) developing an alternative-route information module that incorporates detailed road-network attributes, including intersections, curve sharpness, bridge conditions, and segment-specific risk levels. Incorporating these operational factors into the weighting functions of distance or travel time will allow GAFA to produce solutions that are not only mathematically optimal but also safer, more efficient, and more representative of real-world logistics conditions.

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