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Optimization of Vehicle Routing Problem with Time Windows (VRPTW) with Hybrid Dragonfly Algorithm Approach on Delivery Routes

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ABSTRACT

Efficient product distribution is a critical component of supply chain management, especially for small-scale business that operate under limited vehicle capacity and strict delivery time constraints. This research focused on solving the Vehicle Routing Problem with Time Windows (VRPTW) by applying a hybrid optimization strategy that integrates the Nearest Neighbor (NN) method and Dragonfly Algorithm (DA) to reduce total travel distance while ensuring compliance with capacity and time windows requirements. In that proposed approach, the Nearest Neighbor method is utilized to construct an initial feasible route based on proximity considerations, whereas the Dragonfly Algorithm is employed to enhance the route configuration through balanced exploration and exploitation processes. The effectiveness of the hybrid method is evaluated using real contribution data obtained from HoneyBee Bakery & Cake, a small-cake bakery enterprise located in Palembang, Indonesia. The experimental results indicate that the Nearest Neighbor method generates an initial route with a total distance of 72.54 km. After applying the hybrid NN–DA optimization, the total travel distance is reduced to 62.65 km, achieving a reduction of 9.89 km or an efficiency improvement of 13.64%, without increasing the number of vehicles used. Furthermore, the parameter sensitivity analysis reveals that variations in the number of dragonflies and iterations have a considerable impact on solution quality and convergence behavior. Overall, the findings confirm that the proposed hybrid method offers an effective and practical solution for VRPTW in real-world distribution contexts. Additionally, a web-based application is developed to support route optimization and data processing, enabling easier adoption by non-technical users in small-scale distribution environments.

I. INTRODUCTION

Product distribution is a vital component of business operations, as it directly affects customer satisfaction and overall operational performance [1]. In small-scale enterprises, distribution activities are often constrained by limited vehicle capacity and strict delivery schedules. HoneyBee Bakery & Cake, a bakery business operating in Palembang City, encounters similar challenges in managing daily deliveries to multiple customer locations [2]. Inefficient route planning and delivery delays may result in product quality degradation, increased operational expenses, and a decline in customer trust.

Distribution route planning problems can be formulated as the *Vehicle Routing Problem with Time Windows* (VRPTW), which extends the classical *Vehicle Routing Problem* by incorporating service time constraints and vehicle capacity limitations [3]. VRPTW is recognized as a complex combinatorial optimization problem, where the size of the solution space grows rapidly with the number of customers, making exact optimization methods impractical for real-world applications [4]. Consequently, heuristic and metaheuristic approaches are widely adopted to obtain near-optimal solutions within acceptable computational time.

Among various metaheuristic techniques, the *Dragonfly Algorithm* (DA) has gained attention due to its swarm intelligence–based mechanism that effectively balances exploration and exploitation [5]. This algorithm is capable of searching large solution spaces and avoiding premature convergence. However, the performance of DA is strongly dependent on the quality of the initial solution. Poor initialization may lead to slow convergence and unstable optimization outcomes.

To mitigate this issue, the *Nearest Neighbor* (NN) method can be employed to construct an initial feasible solution based on the shortest-distance heuristic between customer locations [6]. Although NN alone does not guarantee optimal solutions, it provides a structured and feasible starting point that helps reduce the search space during subsequent optimization. Therefore, integrating NN with DA is expected to improve convergence stability and enhance solution quality in solving the VRPTW.

Based on these considerations, this study proposes a hybrid approach that combines the *Nearest Neighbor* method and the *Dragonfly Algorithm* to optimize distribution routes for HoneyBee Bakery & Cake. The proposed approach aims to minimize total travel distance while satisfying vehicle capacity and time window constraints. In addition, a web-based system is developed to support route optimization and data processing, enabling practical adoption by non-technical users. The findings of this study are expected to contribute to improved operational efficiency, reduced distribution costs, and more reliable delivery schedules for small-scale distribution operations.

II. Literature Study

A. Product Distribution & Delivery Delay

Product distribution refers to the process of delivering products from producers to consumers through an organized distribution system. According to [7], distribution is part of marketing activities that create value by ensuring product availability in terms of place and time. In operational contexts, distribution activities require effective route planning to ensure timely deliveries while minimizing operational costs.

Delivery delays occur when distribution activities exceed the predetermined time schedule. Such delays can negatively affect companies both internally and externally. Internally, delivery delays may increase the risk of product spoilage, particularly for products with limited shelf life. Externally, delays can result in customer complaints, reduced satisfaction and loyalty, and potential loss of sales [8]. Therefore, ensuring timely distribution is a critical aspect of operational performance.

Several factors influence the effectiveness of the distribution process, including facilities, transportation, and product availability [9]. Adequate facilities support smooth operational activities, while reliable transportation directly affects delivery timeliness. In addition, maintaining product availability is essential to prevent order mismatches and stock shortages. These factors highlight the importance of efficient route planning and scheduling in distribution systems, particularly when strict delivery time constraints must be satisfied.

B. Vehicle Routing Problem (VRP)

Vehicle Routing Problem (VRP) is an optimization problem that focuses on determining optimal routes for a fleet of vehicles to serve multiple customers at minimum operational cost. Since its introduction by Dantzig and Ramser in 1959, VRP has become a fundamental problem in logistics and distribution management [10]. The main objective of VRP is to minimize total distance, travel time, or transportation cost while ensuring that customer demands are satisfied efficiently.

Several VRP variants have been developed to address different operational constraints. Among them, the Capacitated Vehicle Routing Problem (CVRP) considers vehicle capacity limitations, while the Vehicle Routing Problem with Time Windows (VRPTW) incorporates service time constraints for each customer [4]. VRPTW is particularly relevant for distribution systems that require strict delivery schedules.

C. Vehicle Routing Problem with Time Windows (VRPTW)

Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the Vehicle Routing Problem (VRP) that focuses on determining efficient delivery routes while ensuring that each customer is served within a specified time window. Besides minimizing total travel distance, VRPTW incorporates vehicle capacity limitations and requires that each customer is visited only once within the assigned service time. These features make VRPTW more suitable for modelling real-world distribution systems than the classical VRP.

The implementation of VRPTW offers several operational advantages, such as reducing transportation costs, improving delivery efficiency, and increasing customer satisfaction through timely service [11]. Nevertheless, the inclusion of time window constraints increases the computational complexity of the routing process, making the problem difficult to solve using exact optimization methods. Therefore, metaheuristic algorithms are commonly employed to generate near-optimal solutions within a reasonable computation time.

D. Metaheuristics

Metaheuristic algorithms are widely used to solve complex optimization problems, including the Vehicle Routing Problem with Time Windows (VRPTW), where classical optimization methods become impractical due to high computational complexity. These algorithms are designed to balance exploration and exploitation in large search spaces, enabling them to handle non-linear and non-differentiable problems effectively. By combining stochastic mechanisms with local search strategies, metaheuristics are able to escape local optima and generate near-optimal solutions within reasonable computation time. Among various metaheuristic approaches, swarm intelligence–based algorithms have shown strong potential in addressing multi-constraint routing problems, making them suitable for VRPTW applications.

E. Dragonfly Algorithm (DA)

The Dragonfly Algorithm (DA) was introduced by Mirjalili in 2016 and is inspired by the static and dynamic swarming behaviors observed in dragonflies [12]. These two swarming patterns represent different movement strategies that enable dragonflies to effectively search for food and migrate over long distances. In optimization, these behaviors are analogous to exploitation and exploration processes.

In a static swarm, dragonflies move within a limited area while interacting closely with neighboring individuals, which reflects a local search behavior focused on intensifying the search around promising solutions. Conversely, dynamic swarming occurs when dragonflies migrate over long distances in a coordinated manner, representing a global search process that enhances exploration of the solution space [14]. The ability to balance these two behaviors allows DA to avoid premature convergence while maintaining search efficiency.

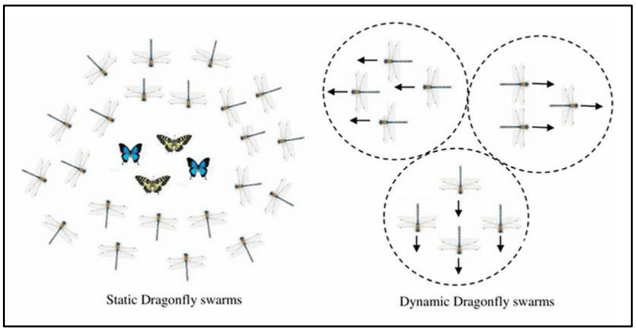

Figure 1. The static and dynamic swarming behaviors of dragonflies

To simulate dragonfly movements, DA incorporates interaction principles such as separation, alignment, cohesion, attraction toward food sources, and distraction from enemies. These principles collectively guide the movement of artificial dragonflies within the search space, enabling adaptive search behavior. When neighboring solutions are sparse, DA employs random movement mechanisms to maintain population diversity and improve global exploration capability.

Due to its flexible balance between exploration and exploitation, the Dragonfly Algorithm has been successfully applied to various complex optimization problems, including routing and scheduling problems with multiple constraints. These characteristics make DA suitable for solving the Vehicle Routing Problem with Time Windows (VRPTW), where both global route exploration and local solution refinement are required.

F. Nearest Neighbor (NN)

The Nearest Neighbor (NN) method is a simple heuristic approach commonly used to construct an initial feasible solution for routing problems. The basic principle of NN is to sequentially select the closet unvisited customer from the current location, thereby forming a route based on minimum local distance. Due to its simplicity, NN can be implemented efficiently and produces a valid initial route in a short computation time.

Although the Nearest Neighbor method does not guarantee an optimal solution and may lead to suboptimal routing when applied independently, it is widely used as an initialization strategy in metaheuristic-based optimization. A well-structured initial solution generated by NN can reduce the search space and improve convergence stability of subsequent optimization algorithms. Therefore, NN is often combined with metaheuristic approaches to enhance overall solution quality.

In this study, the Nearest Neighbor method is utilized to generate an initial solution for the Dragonfly Algorithm. By providing a feasible starting point that considers customer proximity, NN supports the Dragonfly Algorithm in refining distribution routes while satisfying vehicle capacity and time window constraints in the VRPTW.

III. METHODOLOGY

A. Research Workflow

The research process consists of several sequential stages, including data collection, data processing, problem formulation, algorithm implementation, and result analysis. At the initial stage, distribution data were obtained from HoneyBee Bakery & Cake, such as customer locations, demand quantities, vehicle capacity and delivery time windows. These data were then preprocessed to ensure their consistency and suitability for the optimization process.

After the processing stage, the distribution problem was formulated as a Vehicle Routing Problem with Time Windows (VRPTW), where objective is to determine efficient delivery routes while satisfying vehicle capacity limitations and customer time windows constraints. To address this problem, a hybrid optimization approach the Nearest Neighbor (NN) method and Dragonfly Algorithm (DA) was applied.

In this approach, the Nearest Neighbor method is first utilized to construct an initial feasible route by sequentially selecting the nearest unvisited customer from the current location. The resulting route is then used as the initial solution for the Dragonfly Algorithm. Subsequently, the Dragonfly

Algorithm improves the solution through swarm intelligence mechanisms in order to minimize the overall travel distance while maintaining the feasibility of capacity and time window constraints.

The overall research procedure of the proposed optimization approach is illustrated in Figure 2.

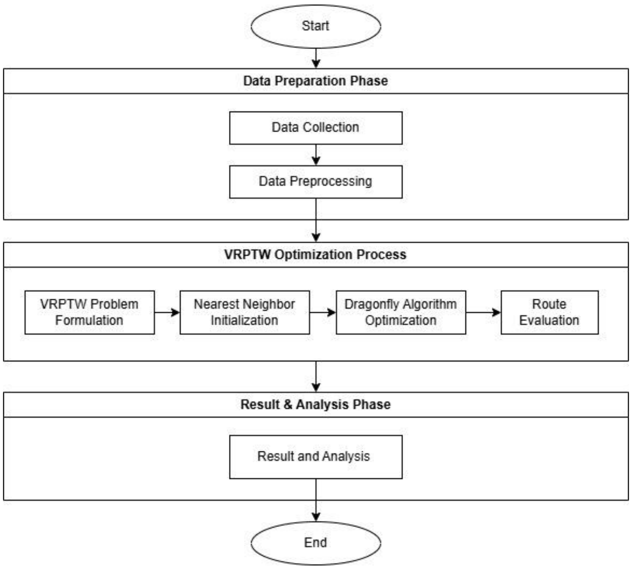

Figure 2. Research Workflow of the proposed hybrid Nearest Neighbor and Dragonfly Algorithm approach for solving the VRPTW

During the implementation stage, the algorithm was developed using Python along with supporting libraries for numerical computation and optimization. Finally, the performance of the proposed method was evaluated by comparing the total travel distance obtained from the initial route and the optimized route to assess the effectiveness of the hybrid optimization approach.

B. Data Collection

This study was conducted at HoneyBee Bakery & Cake, a bakery product distribution company located in Palembang, Indonesia. The company distributes bakery products daily to multiple customer locations with varying demand quantities and predefined delivery time windows. These operational characteristics make the distribution process suitable to be modeled as a Vehicle Routing Problem with Time Windows (VRPTW). The data collected in this study consist of:

1. Customer locations, represented by geographical coordinates (latitude and longitude).
2. Customer demand quantities, expressed in product units.
3. Vehicle capacity, representing the maximum load that can be carried in single route.
4. Delivery time windows, defining the allowable service time interval for each customer.
5. Inter-location distances, representing the travel distance between the depot and customers as well as between customer locations.

To accurately represent real-world travel distances, the distance between locations was calculated using the Haversine formula, which computes the great-circle distance based on geographical coordinates. The collected data serve as the primary input for formulating the VRPTW model and for generating feasible initial and optimized distribution routes using the proposed hybrid Nearest Neighbor–Dragonfly Algorithm (NN–DA) approach.

C. Problem Formulation (VRPTW)

The distribution routing problem addressed in this study is formulated as a Vehicle Routing Problem with Time Windows (VRPTW). In this problem, a set of customers must be served by a limited number of vehicles departing from and returning to a single depot. Each customer has a known demand and must be visited exactly once within a predefined service time window. Each vehicle has a fixed capacity that must not be exceeded.

Let the distribution network consist of one depot (indexed as 0) and Mcustomers (indexed as $i = 1,2, \dots, M$), served by a fleet of K identical vehicles. The travel cost or distance between location i and j is denoted as c_{ij}. The decision variable x_{ij}^k equals 1 if vehicle k travels directly from location $i$to j, and 0 otherwise. Another decision variable y_i^k indicates whether customer i is served by vehicle k.

Generally, VRPTW has two hierarchical objectives. The primary objective is to minimize the number of vehicles used, while the secondary objective is to minimize the total travel distance given the same number of routes. These objectives can be expressed as follows:

$$\min N V = K \tag{1}$$

$$\min T D = \sum_{i=0}^{M} \sum_{j=0}^{M} \sum_{k=1}^{K} c_{ij} \cdot x_{ij}^k \tag{2}$$

Subject to the following constraints:

1. Service assignment constraint, ensuring that each customer is served by exactly one vehicle:
$$\sum_{k=1}^{K} y_i^k = 1 \quad \forall i = 1, \dots, M$$
2. Flow conservation constraint, ensuring route continuity for each vehicle:
$$\sum_{j=0}^{M} x_{ij}^k = y_i^k \quad \forall i = 1, \dots, M; \forall k = 1, \dots, K$$
3. Vehicle capacity constraint, ensuring that total demand served by each vehicle does not exceed its capacity Q:
$$\sum_{i=1}^{M} y_i^k \cdot q_i \le Q \quad \forall k = 1, \dots, K$$
4. Depot constraint, ensuring that route start from the depot.
5. Time window constraint, ensuring that each customer is served within its allowable time interval. Let t_i denote the

arrival time at customer i, s_i the service time, and w_i the waiting time if the vehicle arrives early. The arrival time at the next customer must satisfy the time feasibility condition based on travel time and service duration.

The complete mathematical formulation of the VRPTW, including detailed flow balance and time feasibility constraints, follows the model proposed by [11]. Based on this formulation, a hybrid Nearest Neighbor–Dragonfly Algorithm (NN–DA) is applied to generate feasible initial solutions and further optimize the distribution routes while satisfying capacity and time window constraints.

D. Hybrid NN-DA Approach

To address the VRPTW formulated in the previous subsection, this study applied a hybrid optimization framework that integrates the Nearest Neighbor method (NN) with the Dragonfly Algorithm (DA). The Nearest Neighbor method is first utilized to construct an initial feasible routing solution. Subsequently, the Dragonfly Algorithm is employed to refine and optimize the generated routes, aiming to improve solution quality in terms of total travel distance and vehicle utilization while ensuring that vehicle capacity and time windows constrains are satisfied.

1) *Nearest Neighbor Initialization*

The Nearest Neighbor (NN) method is employed as an initialization technique to generate a feasible set of initial routes for the VRPTW. The procedure begins at the depot and sequentially selects the nearest unvisited customer according to the shortest level distance, while ensuring that vehicle capacity and time windows constraints are satisfied. If no additional customer can be feasibly inserted into the current route, the vehicle returns to depot, and a new route is created if are still customers that not have been served.

The result of Nearest Neighbor is a collection of feasible routes where each customer is visited exactly once. There routes are subsequently used to initialize the population of the Dragonfly Algorithm. By generating a structured and feasible initial solution, the Nearest Neighbor method reduces the search space and enhances the convergence stability of the following metaheuristic optimization process.

2) *Dragonfly Algorithm Optimization*

The Dragonfly Algorithm (DA) is a swarm intelligence-based metaheuristic that mimics the swarming behavior of dragonflies observed in nature. In optimization problems, that static swarming behavior represents the exploitation process, while the dynamic swarming behavior reflects the exploration process within the search space. In this study, each dragonfly represents a candidate solution corresponding to a potential set of distribution routes.

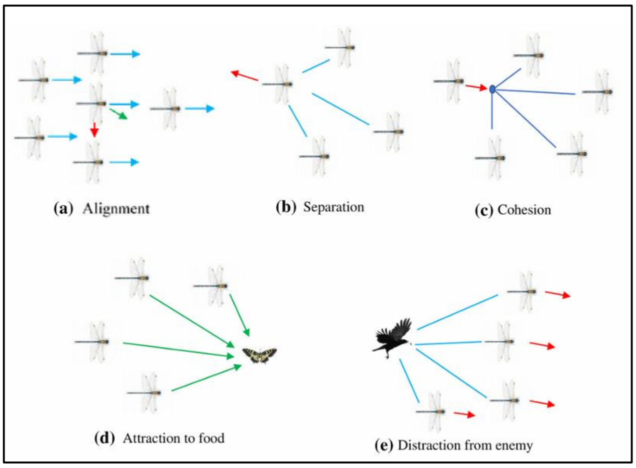

Figure 3. Primitive corrective patterns between dragonflies in a swarm (different steps of artificial dragonfly algorithm)

To simulate the movements of dragonflies. Five behavorial components are considered, namely separation, alignment, cohesion, attraction toward food sources, and distraction from enemies. These behavior collectively influence the update of the step vector for each dragonfly according to:

$$\Delta X_{t+1} = sS_i + aA_i + cC_i + fF_i + eE_i + \omega\Delta X_t$$

Where S_i, A_i, C_i, F_i, and E_i denote separation, alignment, cohesion, attraction, and distraction from enemies, respectively. The parameters s, a, c, f, and e represents weighting coefficients that regulate the contribution of each behavorial component, while w denotes the inertia weight.

The position of each dragonfly in the search space is updated using the following equation:

$$X_{t+1} = X_t + \Delta X_{t+1}$$

If no neighboring solution are detected within the defined neighborhood radius, a Levy Flight mechanism is applied to mainin diversity in the population and enhance global exploration capability. During the optimization process, each solution is evaluated based on VRPTW objective functions and constraint feasibility.

In this research, the initial population of the Dragonfly Algorithm is generated from the routes constructed using the Nearest Neighbor method. Through iterative updates and evaluation of candidate solution, the Dragonfly Algorithm progressively improves the distribution routes to obtain more optimal routing configuration.

E. System Flowchart

This subsection presents the system flowchart that illustrates the detailed of proposed distribution route optimization process. The flowchart describes the sequence of computational steps for the hybrid Nearest Neighbor and Dragonfly Algorithm used to optimize distribution routes in the VRPTW problem.

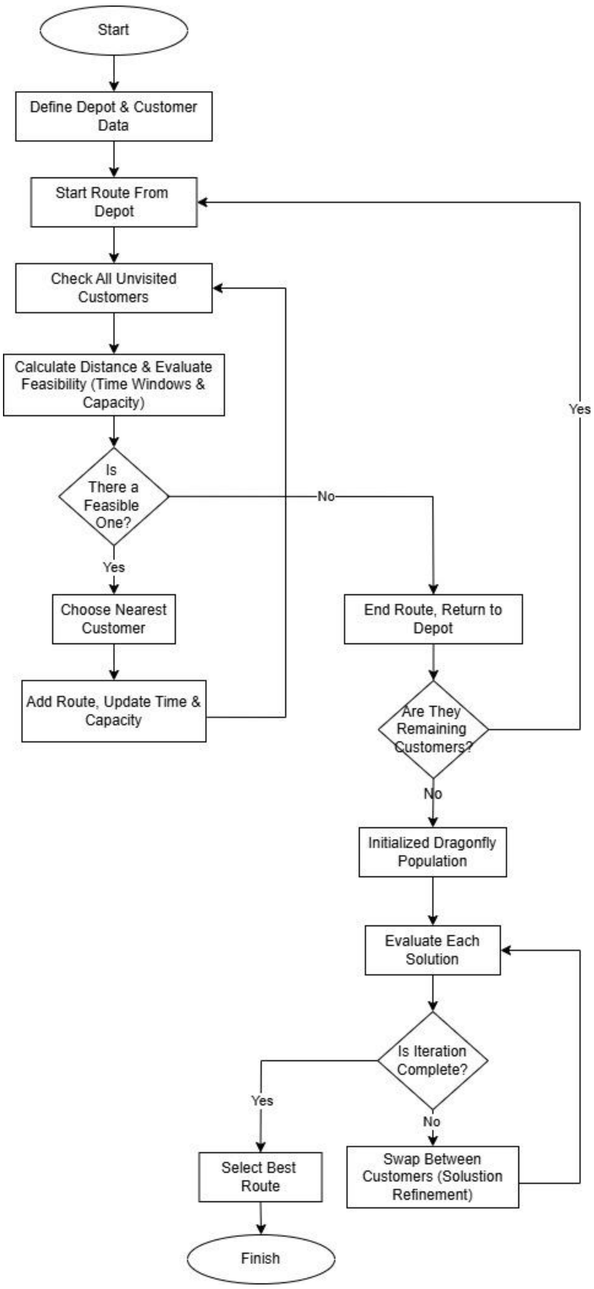

Figure 4. System flowchart of proposed hybrid Nearest Neighbor-Dragonfly Algorithm for VRPTW optimization.

In the initial routing phase, the algorithm starts from the depot and evaluates all unvisited customers by calculating the travel distance while considering feasibility constraints such as vehicle capacity and customer time windows. The nearest feasible customer is then selected and added to the route. This process continues iteratively until no additional feasible customers can be served, after which the vehicle returns to the depot.

After the initial routes are generated, the Dragonfly Algorithm is applied to further optimize the routing solution. The algorithm initializes a population of candidate solutions and evaluates each solution based on the objective function. Through iterative refinement processes, such as solution updates and customer swapping operations, the algorithm searches for improved routing configurations until the stopping criterion is satisfied.

IV. Result And Discussion

A. *System Overview and Testing Setup*

The developed system is a web-based application designed to support the optimization of distribution routes for the VRPTW problem. The system enables users to upload customer datasets, configure algorithm parameters, and generate optimized delivery routes based on the selected optimization method.

The user interface provides several main functionalities, including dataset upload, vehicle capacity configuration, parameters adjustment for the Dragonfly Algorithm, and route generation.

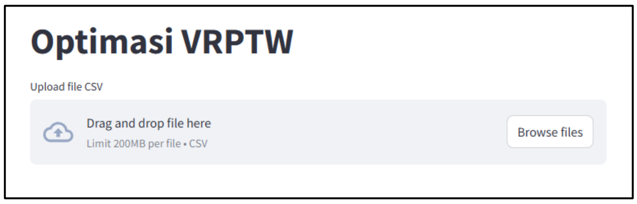

Figure 5. Dataset upload interface of the VRPTW optimization system.

Figure 5 shows the initial interface of system where user upload the dataset in CSV format. This interface serves as the entry point for loading customer data required for the optimization process.

Figure 6. Parameter configuration interface for the Dragonfly Algorithm.

Figure 6 present the parameters configuration interface where users can define vehicle capacity, select the optimization method, and adjust Dragonfly Algorithm parameters before generating the delivery routes.

After the optimization process is executed, the system generates the routing solution and provides visual output the distribution paths.

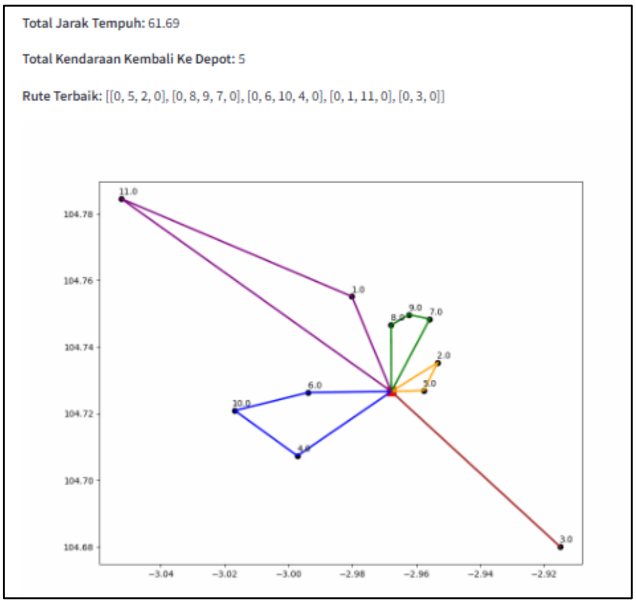

Figure 7. Visualization of optimized distribution routes.

Figure 7 illustrates the output interface displaying the optimization results, including the total travel distance, the number of vehicles returning to the depot, the best routes, and a graphical visualization of the delivery routes.

The system was tested using real customer data obtained from HoneyBee Bakery & Cake, including geographic coordinates, demand quantities, and service time windows constraints. The Dragonfly Algorithm parameters were configured based on experimental testing on obtain stable and effective optimization performance.

B. Customer Distribution and Location Map

The customer dataset used in this research was obtained from HoneyBee Bakery & Cake. The dataset contains important information required for the VRPTW optimization process, including geographic coordinates (latitude and longitude), customer demand quantities, and service time windows constrains for each delivery location.

TABLE I
CUSTOMER DATA USED IN THE VRPTW OPTIMIZATION PROCESS

ID	Coordinate	Demand	Ready Time	Due Time
1	-2.980148, 104.755182	112 Box	4:00	6:00
2	-2.95332, 104.73506	70 Box	4:00	5:00
3	-2.915004, 104.680069	40 Box	3:00	5:00
4	-2.997204, 104.707332	90 Box	5:00	6:00
5	-2.957643, 104.726935	60 Box	6:00	7:00
6	-2.993812, 104.726361	30 Box	6:00	7:00
7	-2.95579, 104.74841	30 Box	6:00	7:00
8	-3.016815, 104.720934	25 Box	5:00	6:00
9	-3.052264, 104.784511	20 Box	5:00	6:00
10	-2.967871, 104.746621	25 Box	6:00	8:00
11	-2962252, 104.749706	25 Box	6:00	8:00

Table 1 summarizes the customer information used in this study, including the location coordinates, product demand in boxes, and corresponding service time windows for each customer. To better understand the spatial distribution of delivery locations, the customer coordinates were visualized on geographic map. This visualization helps illustrate the relative position of customers and the depot within the distribution area

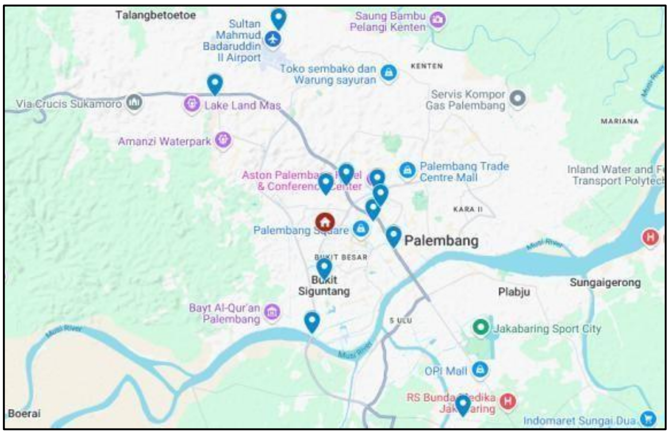

Figure 8. Customer location map.

Figure 8 presents the geographic distribution of customer location in Palembang. The map provides a visual overview of the delivery area, which is used as the basis for constructing and optimizing distribution routes in the VRPTW model.

C. Parameter Configuration of Dragonfly Algorithm

To evaluate the influence of algorithm parameters on the optimization performance, a series of parameter testing experiments were conducted using different number of dragonflies and iteration limits in the Dragonfly Algorithm. The objective of this testing stage was to identify a parameter configuration that produces stable and efficient routing solutions for the VRPTW problem.

TABLE II
PARAMETER TESTING WITH 10 DRAGONFLIES

Test	Number of Dragonflies	Max Iterations	Total Distance	Vehicle Returning to Depot
1	10	1000	63.17 km	5 times
2	10	2000	62.65 km	5 times
3	10	3000	62.65 km	5 times
4	10	4000	62.65 km	5 times
5	10	5000	62.65 km	5 times

TABLE III
PARAMETER TESTING WITH 20 DRAGONFLIES

Test	Number of Dragonflies	Max Iterations	Total Distance	Vehicle Returning to Depot
1	20	1000	62.65 km	5 times
2	20	2000	64.33 km	5 times
3	20	3000	62.65 km	5 times
4	20	4000	62.79 km	5 times
5	20	5000	62.65 km	5 times

TABLE IV
PARAMETER TESTING WITH 50 DRAGONFLIES

Test	Number of Dragonflies	Max Iterations	Total Distance	Vehicle Returning to Depot
1	50	1000	64.33 km	5 times
2	50	2000	64.33 km	5 times
3	50	3000	64.33 km	5 times
4	50	4000	64.33 km	5 times
5	50	5000	64.33 km	5 times

Based on experimental result, it can be observed that increasing the number of iterations gradually reduces the total travel distance until the solution stabilizes at 62.65 km, while the number of vehicles returning to the depot remains constant at 5 trips. These findings indicate that proper parameter configuration plays an important role in improving the efficiency of distribution route optimization.

D. Route Optimization Results

This study evaluates two approaches for solving the VRPTW problem: the original Dragonfly Algorithm (DA) with random initialization and a hybrid combining the Nearest Neighbor method with the Dragonfly Algorithm (NN-DA). The objective of this comparison is to analyze the impact of different initial solution strategies on the route optimization results.

The original Dragonfly Algorithm generated an initial route with a total travel distance of 85.20 km, while the Nearest Neighbor-Dragonfly Algorithm approach produced a shorter initial route of 72.54 km.

After the optimization process, the original Dragonfly Algorithm achieved a final travel distance of 58.58 km, whereas the Nearest Neighbor-Dragonfly Algorithm approach produced a final distance of 62.65 km.

TABLE V
COMPARISON RESULT

Method	Initial Distance	Optimized Distance	Vehicle Returning to Depot
Original Dragonfly Algorithm	85.20 km	58.58 km	4 times
Nearest Neighbor + Dragonfly Algorithm	72.54 km	62.65 km	5 times

Based on the results shown in Table V, the original Dragonfly Algorithm approach reduced the travel distance by 26.62 km (31.24%), while the Nearest Neighbor-Dragonfly Algorithm approach reduced the distance by 9.89 km (13.63%). In addition, the original Dragonfly Algorithm required only 4 vehicle returns to the depot, whereas the Nearest Neighbor-Dragonfly Algorithm approach required 5 returns.

These results indicate that the original Dragonfly Algorithm provides higher solution diversity, allowing the algorithm to explore a wider search space and discover more optimal routing solutions. The increased diversity helps the algorithm avoid the premature convergence and improves its ability to identify shorter delivery routes.

However, the main drawback of original Dragonfly Algorithm is the lack of stability, since different runs may produce different initial solutions, making the results less consistent across repeated experiments.

On the other hand, the Nearest Neighbor-Dragonfly Algorithm generates a more structured and repeatable initial solution because it consistently selects the closet customer during route construction. This results in a stable and predictable starting route. Nevertheless, the heuristic nature of Nearest Neighbor method limits the variation of route explored, which may lead to less optimal final solution after optimization.

Overall, the findings indicate that the original Dragonfly Algorithm provides better exploration capability, while the Nearest Neighbor-Dragonfly Algorithm offers higher stability and consistency in the initial solution. Therefore, the choice of initialization strategy should be adjusted according to the optimization objectives.

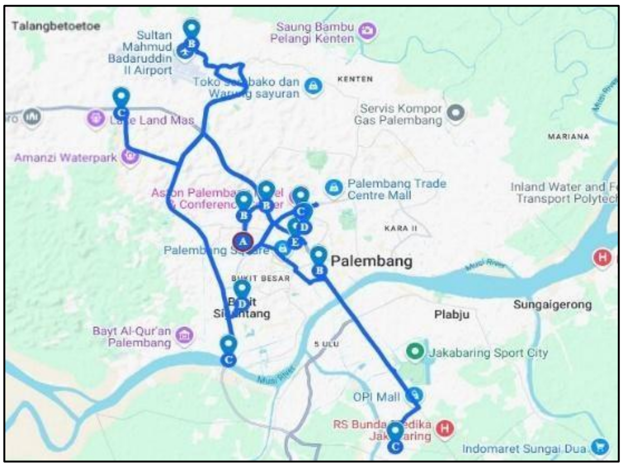

Figure 9. Customer route with original Dragonfly Algorithm

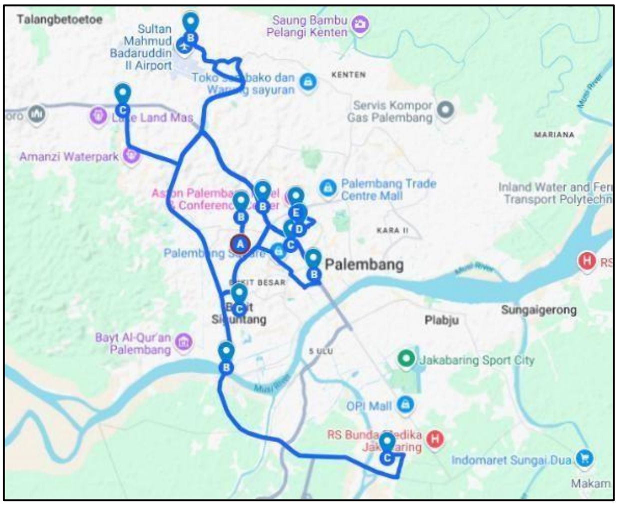

Figure 10. Customer route with Nearest Neighbor-Dragonfly Algorithm

The visual comparison of the generated routes shows that both approaches produce feasible delivery paths that satisfy the distribution constraints. However, differences in route structures can be observed, which contribute to the variations in the final travel distances obtained by each method.

E. Comparative Analysis and Efficiency Evaluation

Efficiency in route planning is an important indicator to evaluate the effectiveness of optimization algorithms. Efficient route planning aims to minimize travel distance, reduce operational costs, and maximize vehicle utilization within a coordinated delivery system [13]. In distribution optimization problems, efficiency is commonly measured by comparing the total travel distance before and after the optimization process and expressing the reduction as a percentage.

The efficiency of route optimization can be calculated using the following equation:

$$\text{Efficiency} = \frac{\text{Distance initial} - \text{Distance Optimized}}{\text{Distance initial}} \times 100$$

Where distance initial represents the total travel distance before optimization and distance optimized represents the total the travel distance after the optimization process.

$$\text{Efficiency} = \left(\frac{72{,}54 - 62{,}65}{72{,}54}\right) \times 100\% = 13{,}63\%$$

Based on experimental results, the Nearest Neighbor method produced an initial total travel distance of 72.54 km. After applying the Nearest Neighbor-Dragonfly Algorithm optimization, the total travel distance was reduced 62.65 km, resulting in reduction of 9.89 km.

Using the efficiency formula, the optimization process achieved an efficiency improvement of 13.64%. This reduction in travel distance directly contributes to improved distribution efficiency by reducing operational costs such as fuel consumption, vehicle usage, and travel time, while also supporting more timely product delivery.

$$\text{Efficiency} = \left(\frac{85{,}20 - 58{,}58}{85{,}20}\right) \times 100\% = 31{,}24\%$$

In addition, the original Dragonfly Algorithm achieved a lower final distance of 58.58 km. Although this result indicates better route optimization performance in terms of total distance, the method exhibits higher variability in the results due to the use of random initialization. Consequently, the solution generated by the original Dragonfly Algorithm tend to be less consistent across multiple runs compared to the hybrid Nearest Neighbor-Dragonfly Algorithm approach.

Based on efficiency calculation, the original Dragonfly Algorithm reduced the travel distance by 26.62 km, resulting efficiency improvement 31.24% compared to the initial route distance of 85.20 km.

TABLE VI
ROUTE OPTIMIZATION EFFICIENCY COMPARISON

Method	Initial Distance	Optimized Distance	Efficiency
Original Dragonfly Algorithm	85.20 km	58.58 km	31.24%
Nearest Neighbor + Dragonfly Algorithm	72.54 km	62.65 km	13.26%

Overall, the comparative analysis demonstrates that the Nearest Neighbor-Dragonfly Algorithm provides more stable and repeatable results, while the original Dragonfly Algorithm offers stronger exploration capability that may lead to shorter routes but with lower consistency. Therefore, the selection of the optimization approach should the trade-off solution capability and exploration capability depending on the objectives of the distribution optimization problem.

V. Conclusion

Based on research conducted, the developed system improves delivery efficiency and support service punctuality in the distribution process of HoneyBee Bakery & Cake. The web-based distribution route planning system developed in this study is capable of optimizing delivery route using a hybrid approach that combines Nearest Neighbor method with the Dragonfly Algorithm. The route optimization using the Nearest Neighbor method produced an initial total travel distance of 72.54 km. After applying the hybrid Nearest Neighbor-Dragonfly Algorithm approach, the travel distance was reduced to 62.65 km, resulting in a distance reduction of 9.89 km with an efficiency of 13.63%. The Dragonfly Algorithm with random initialization (Original Dragonfly Algorithm) achieved the best optimization result with a final travel distance of 58.58 km, corresponding to an efficiency improvement of 31.24%. However, this method shows higher variability in the results compared to the hybrid approach. The number of vehicles returning to the depot remained relatively consistent during the optimization process, indicating that the proposed method improves route efficiency without increasing fleet requirements.

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