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Optimization of Delivery Allocation for Enhanced Fleet Utilization and Trip Minimization: A Case Study from an Indonesian Manufacturing Company †

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Abstract

Logistics efficiency is critical to operational success in manufacturing, especially for corrugated carton manufacturers. The challenges of this type of manufacturing include optimizing truck utilization, without which high costs, resource waste, and customer dissatisfaction can occur. Transportation consolidation can reduce trips, increase vehicle capacity, and lower carbon emissions. This study proposes a delivery optimization model using genetic algorithms within the Multi-Objective Evolutionary Algorithm (MOEA) framework. The results show that the model significantly improves fleet utilization from 75% to 100% and reduces delivery delays by adhering to predefined time windows, thereby improving cost efficiency and customer satisfaction.

Keywords: freight utilization; genetic algorithm; heterogeneous fleet; intelligent transportation systems; multi objective evolutionary algorithm

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1. Introduction

Logistics efficiency plays a crucial role in the operational success of a company, especially in a highly competitive industry such as manufacturing [1]. In this sector, timely and cost-effective delivery processes are vital for maintaining a steady supply chain and ensuring customer satisfaction. One of the major challenges in manufacturing logistics is managing deliveries efficiently to reduce operational costs, maximize fleet utilization, and meet customer demands in a timely manner [2]. Inefficient fleet allocation can lead to increased transportation costs, underutilized vehicle capacity, and delivery delays, all of which negatively impact companies' overall performance. Therefore, optimizing delivery allocation through advanced methodologies, such as mathematical modeling and heuristic algorithms, is essential to achieving a balance between cost reduction, timely deliveries, and optimal fleet usage.

In an increasingly competitive business world, manufacturing companies in the field of corrugated cardboard packaging production that fulfill consumer orders using a Make-to-Order production system often face challenges in meeting customer-specific product

specifications, such as paper thickness and dimensions. In addition, these diverse requests are allocated to trucks that are also diverse. This relatively high level of diversity makes it challenging for companies to deliver to different locations, often resulting in increased delivery times. One of the transportation problems that arises is the suboptimal use of trucks, which increases operational costs, wastes resources, and causes delivery delays due to limited truck availability. This has a negative impact on customer satisfaction levels [3]. In addition, investigations show that how trucks are used affects warehouse use, because if a substantial amount of product is delivery late it can cause the accumulation of goods in the warehouse, disrupting the procurement process [4].

One strategic approach that can be applied to improve logistics efficiency is transportation consolidation, which combines shipments from various points into one trip [5]. In the context of manufacturing, transportation consolidation allows for a reduction in the number of trips, the increased efficiency of vehicle capacity utilization, and reduced carbon emissions [6]. However, how this consolidation is applied is complex, with each vehicle having a different load capacity, each customer having different requirements, and numerous shipments needing to be made within a certain period. These conditions create complex optimization problems that require sophisticated approaches to solve them.

The problem of dispatch optimization in manufacturing is often categorized as an NP-hard problem [7], where the optimal solution is difficult to find in a reasonable timeframe using conventional methods. Genetic algorithms may be an effective approach to overcoming this challenge. As an evolutionary computation-based method, genetic algorithms use the principle of natural selection to find optimal solutions through an iteration process [8]. In the manufacturing industry, genetic algorithms can help design the best delivery routes by considering heterogeneous vehicle capacities, efficiently fulfilling customer demands, and ensuring compliance with predetermined time constraints.

Many studies have been proposed to solve problems with capacity considerations, including [9–12]. However, not all transportation models can be used in every depot condition. Therefore, the application of genetic algorithms in manufacturing logistics optimization allows companies to significantly improve operational efficiency through the concept of transportation consolidation. By integrating data related to vehicle capacity, the number of requests, and time constraints, genetic algorithms can produce close-to-optimal solutions in shorter computation times than traditional methods. This advantage is particularly relevant in the manufacturing industry, where efficiency and timeliness greatly affect the sustainability of production and distribution.

This study aims to develop a delivery optimization model that can be applied in the manufacturing industry, with a focus on increasing fleet utilization, reducing the number of trips, and meeting specific time window constraints for deliveries. By incorporating genetic algorithms, this study is expected to provide solutions that are not only operationally effective but also support environmental sustainability. This study is anticipated to offer practical guidance for manufacturing companies in managing logistics more efficiently, ensuring customer satisfaction by adhering to time windows, and mitigating the environmental impacts resulting from transportation activities.

2. Methodology

This research adopts the Operations Research (OR) framework [13] to address distribution challenges in the manufacturing industry using a metaheuristic approach. The problem is solved through a genetic algorithm (GA). The OR framework involves several stages: defining the problem, formulating the problem, developing a solution model using the GA, implementing and validating the model through case studies in findings section, and incorporating a time variable into the model to enhance route efficiency and further

optimize the distribution process. This research aims to develop a transportation system that is able to minimize travel distance and maximize vehicle fleet utilization while meeting logistical needs within specific customer time windows. This system is designed to handle operational complexity involving variations in vehicle capacity, differences in the specifications of products being transported, and wide-ranging customer delivery requirements. To achieve this goal, logistics operations managers must ensure that each customer is served by only one vehicle to avoid delivery redundancy. In addition, vehicle capacity utilization needs to be optimized so that the number of trips can be minimized. The vehicle load must also be maintained so that it does not exceed the vehicle's carrying capacity. Combining deliveries to several customers into a single route is an important strategy to reduce travel distances; however, the available vehicle capacity and adherence to specified time windows need to be considered.

2.1. Problem Definition

In the current logistics operations of the Indonesian manufacturing company studied, inefficiencies in fleet allocation have led to delivery delays and suboptimal vehicle utilization. The company relies on a manual scheduling system to allocate trucks for daily deliveries, grouping nearby customers while considering vehicle capacity constraints. However, historical data indicate that this approach resulted in an average delivery delay rate of 16.04% in 2023, with this figure reaching 24.55% in certain months. Additionally, fleet utilization is not optimal, as some trucks remain idle while others are overloaded, leading to inconsistencies in distribution efficiency. The imbalance in truck usage not only disrupts delivery schedules but also increases operational costs due to unnecessary additional trips and underutilized capacity.

The core issue in this problem arises from the lack of an optimized allocation model that effectively considers heterogeneous fleet capacities, varying product specifications, and diverse delivery zones. In the absence of a structured optimization approach, the company struggles to determine the optimal number of vehicles required while minimizing the delivery time and reducing fleet redundancy. Furthermore, the inconsistent scheduling of vehicle availability often leads to delays that affect warehouse management due to stock accumulation. This results in inefficiencies across the entire supply chain, impacting production flow and customer satisfaction. To address these challenges, a mathematical optimization model incorporating time-based constraints and fleet utilization strategies is necessary to streamline delivery allocation, enhance scheduling accuracy, and ensure cost-effective logistics operations. Table 1 provides a mathematical model formulation that has been designed according to company needs.

Table 1. Model notation.

Indices	
$i = 1, 2, 3 \ldots, I$	Customer locations, where I is the number departure node
$j = 1, 2, 3 \ldots, J$	Customer locations, where J is the number destination node
$k \in K$	Set of available vehicles in the fleet
d	Depot (starting and ending location of each vehicle)
Decision Variables	
X_{ijk}	Binary variable, 1 if vehicle k travels from location i to j, 0 otherwise
S_i	Arrival time of a vehicle at customer i
Y_{ik}	Binary variable, 1 if customer i is assigned to vehicle k, 0 otherwise

Table 1. *Cont.*

Parameters	
T_{ijk}	Travel time between locations i and j using vehicle k
A_i, B_i	Lower and upper bounds of the time window for customer i
t_i	Service time required at customer i
C_k	Capacity of vehicle k
D_i	Demand (shipment size) of customer i
T_{max}	Maximum allowed operational time for each vehicle
V	Set of all vehicles available for delivery

Assumptions

1. Each vehicle starts and ends its route at the central depot.
2. The fleet consists of heterogeneous vehicles with varying capacities.
3. Each customer is visited exactly once by one vehicle.
4. The total demand assigned to a vehicle cannot exceed its capacity.
5. Vehicles must complete their deliveries within a predefined maximum operational time.
6. Each customer has a specific time window in which they must be served.
7. Travel times between locations are known and deterministic.
8. Loading and unloading times at each customer location are fixed and included in the service time.
9. The optimization objective is to minimize the total delivery time while ensuring efficient fleet utilization and trip minimization.

2.2. Problem Formulation

To achieve this objective, the problem is formulated as a time-constrained Capacitated Vehicle Routing Problem (CVRP) with a heterogeneous fleet. The optimization function aims to minimize the total delivery time across all routes while taking into account vehicle constraints, service times, and customer time windows. The constraints enforce compliance with operational time limits, precedence relationships, and efficient scheduling to avoid unnecessary idle time. By integrating these constraints with an evolutionary optimization approach, such as a genetic algorithm (GA), the proposed model ensures that deliveries are scheduled in a way that reduces total travel time while maintaining high fleet utilization and minimizing the number of trips.

$$\min z = \sum_{k \epsilon K}^{p} \sum_{i \epsilon N}^{n} \sum_{j \epsilon N}^{n} T_{ijk} X_{ijk} \tag{1}$$

where

1. Time window constraint

Each customer must be served within their predefined time window:

$$A_i \leq S_i \leq B_i, \ \ \forall i \in N \tag{2}$$

2. Service time constraint

The departure time from a location must consider the service time

$$S_j \geq S_i + T_{ijk} + t_i, \ \ \forall (i,j) \in N, \ \forall k \in K \tag{3}$$

3. Fleet Return Time Constraint

All vehicles must return to the depot before the maximum allowed operational time:

$$S_{depot} + \sum_{(i,j)\in N} T_{ijk} X_{ijk} \leq T_{max}, \ \ \forall k \in K \tag{4}$$

where T_{max} is maximum allowed operational time for each vehicle

4. Precedence Constraint

If a customer is visited before another, the sequence must be respected:

$$S_j \geq S_i + T_{ijk}, \ \ \forall (i,j) \in N, \ \forall k \in K, \ if \ X_{ijk} = 1 \tag{5}$$

5. Capacity Constraint

The total demand assigned to a vehicle cannot exceed its capacity:

$$\sum_{i\in N} D_i Y_{ik} \leq C_k, \ \ \forall k \in K \tag{6}$$

where D_i is demand of customer i, C_k is capacity of vehicle k, and Y_{ik} is a binary variable (1 if customer i is assigned to vehicle k, 0 otherwise)

6. Non-Negativity and Binary Constraints

$$S_i \geq 0, \ \ \forall i \in N \tag{7}$$

$$X_{ijk} \in \{0,1\}, \ \ \forall i,j \in N, \ \forall k \in K$$

$$Y_{ik} \in \{0,1\}, \ \ \forall i \in N, \ \forall k \in K$$

2.3. Model Solution Based on Genetic Algorithm

The steps in the genetic algorithm are as follows [14]:

- Chromosome Initialization

The components, called genes in this problem, are binary numbers that represent customer notation from 1 to 35 customers, while 0 is called the starting point (depot). Therefore x_{011}, x_{021}, x_{031}, ..., x_{ijk} are the genes of the problem solutions, as illustrated in Figure 1.

1	0	1	1	0	...	0
X011	X021	X031	X041	X051	...	XIJK

Figure 1. Chromosome initialization.

The basis for using chromosome initialization as an initial step toward finding an optimum solution using the Traveling Salesperson Problem (TSP) approach is to obtain a route that minimizes the distance from n-customers, where each customer is visited exactly once before returning to the starting point. Data processing is performed by entering the distance matrix and the number of requests for each customer. The initial algorithm processing begins from the depot to the customer and/or other customers who are closest to them and meet the available truck capacity. The search for the solution is carried out until it meets the constraints formed in Equations (2)–(7).

- Definition of fitness function

The fitness function is defined as the objective function; in this formulation, the objective function is to find a solution to the distribution problem, namely minimizing the distance traveled with Equation (1).

To implement the mathematical model, it is necessary to design a function that represents the model in the source code, where d_{ij} is the distance traveled from point i to point j. x_{ijk} has a binary value according to the TSP approach; it has a value of 1 if point i to j is passed using vehicle k. However, if it is not, then the variable has a value of 0.

- Generating the population in each generation

The population is a collection of chromosomes, while a generation refers to the chromosomes that have evolved in each iteration. Each chromosome can produce a minimum value for the distance minimization solution, so the chromosome that survives in the next generation is the one with the minimum value. Figure 2 is the result of the generated population.

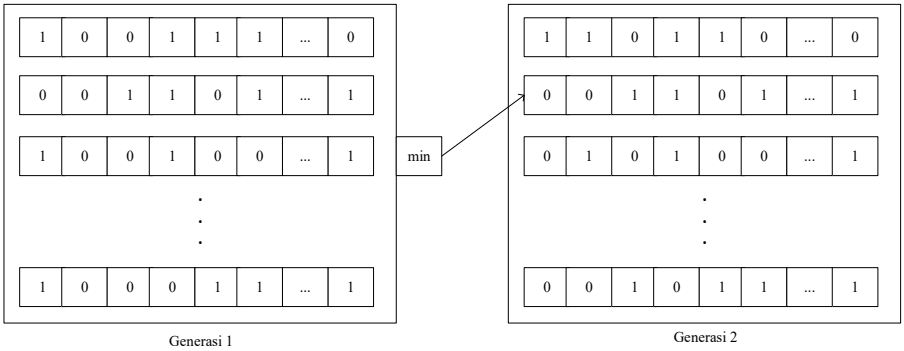


Figure 2. Population in generations.

- Plot to Pareto Front

After the value of each chromosome is obtained, the value is then plotted to the Pareto front. The goal is to display the optimum solution set to be applied.

- Mutation

Mutation is defined as the process of changing one or more gene values in a chromosome with the aim of achieving a better individual value. Each chromosome has a mutation probability value. The aim is to prevent premature convergence to a local solution by ensuring diversity in the population. The mutation probability is used to determine which chromosomes will survive to the next generation. Chromosomes with high mutation probability values will be selected in the selection.

- Crossover

Crossover is the process of changing one or more gene values in two chromosomes. Each chromosome also has a probability of crossover, which serves the same function and purpose as the probability of mutation.

- Selection

In determining which chromosomes will be retained for the next generation, a process called selection is carried out. The chromosome selection process is associated with the principle of Darwin's theory of evolution, where chromosomes with higher fitness levels will have a greater chance of being selected in the next generation. In addition to chromosomes with high fitness values, there are chromosomes that will be mutated and crossed over according to their mutation and crossover probabilities in the next generation. Therefore, in one population, the achieved fitness, mutation, and crossover values will be selected for the next generation, whereas unselected values will be rearranged randomly.

Figure 3 provides an overview of the flow of the genetic algorithm.

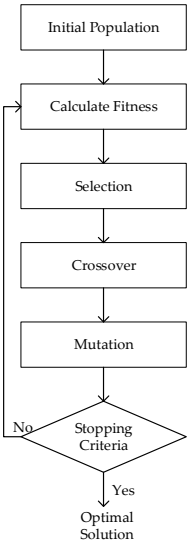


Figure 3. Overview of the flow of the genetic algorithm.

3. Findings

In logistics and transportation optimization, minimizing delivery time while maximizing fleet utilization is a crucial challenge, particularly in industries where timely deliveries directly impact customer satisfaction and operational efficiency. In the context of an Indonesian manufacturing company, inefficient delivery allocation can lead to excessive trip durations, underutilized fleet capacity, and increased operational costs. This study aimed to develop an optimized delivery allocation model that reduces total travel time while ensuring vehicles operate at maximum efficiency. By formulating a mathematical model incorporating time-based constraints, the study ensures that deliveries adhere to predefined time windows, minimizing delays and improving overall fleet productivity. The proposed model is tested using real data from a corrugated cardboard distribution company, PT XYZ, with the objective of optimizing fleet utilization and reducing travel time while fulfilling all customer demands.

The test, using a scenario that had 35 client locations with a total demand of 217,316 kg spread across 81 delivery routes, was conducted using real-world delivery data. To find the most effective route while considering fleet capacity and time constraints, a genetic algorithm (GA) was used with a Multi-Objective Evolutionary Algorithm (MOEA) framework. Three different types of trucks were used to fulfill the demand: eleven units of Truck A, which has a capacity of 1500 kg; fifty-one units of Truck B, which has a capacity of 2500 kg; and nineteen units of Truck C, which has a capacity of 4000 kg. The results show how the optimized model efficiently groups geographically proximate delivery locations, reducing unnecessary travel time and improving vehicle allocation.

The delivery time window analysis revealed a notable increase in scheduling precision. Prior to optimization, about 16.04% of deliveries were delayed, with certain months seeing a delay rate of 24.55%. Following the adoption of the suggested methodology, all deliveries were planned within their allotted time slots, guaranteeing that customer requests were met on time. Vehicles were kept within their maximum permitted operating hours by the system's successful adherence to operational time limitations. Furthermore, fewer trips were made overall, which further decreased fuel expenses and vehicle wear. These findings demonstrate that including time window limitations in the model improves the dependability and efficiency of delivery operations.

The suggested optimization approach demonstrated notable advantages over the company's prior manual scheduling technique. Prior to optimization, fleet utilization was around 75%, with 41 vehicles travelling an average of 950.7 km. Fleet utilization rose to 100% following the model's use, indicating a 25% improvement. Two scenarios emerged from the optimization of the overall journey distance: one involving 46 vehicles travelling 550 km and another involving 20 vehicles covering 1089 km. Additionally, the percentage of delivery requests that were met rose dramatically from 40% to 100%, indicating that the model can guarantee successfully on-time delivery while enhancing fleet efficiency and lowering operating expenses.

The results of this research emphasize the benefits of applying a metaheuristic method, particularly the genetic algorithm, in solving complicated vehicle routing issues that involve diverse fleet limitations. The suggested model's capability to improve both delivery times and fleet usage indicates that comparable approaches may be utilized in other sectors facing distribution issues. Future studies might investigate other metaheuristic methods, including Particle Swarm Optimization (PSO) or hybrid genetic algorithm (GA) strategies, to improve computational efficiency and scalability. The effective application of this model at PT XYZ shows that it could be relevant in different supply chain networks, highlighting its importance as a resource for enhancing delivery processes in the manufacturing industry.

4. Conclusions

The delivery allocation model proposed here, enhanced through the genetic algorithm method and executed with a Multi-Objective Evolutionary Algorithm (MOEA), has proven its capability in aiding logistics management by determining the most effective distribution routes. The model considers the diverse nature of vehicle fleets and the various product types being delivered and includes a time factor to improve operational efficiency. Its execution necessitates additional investigation into the incorporation of programming languages developed with advanced technologies in order to facilitate dynamic planning based on real-time information and establish a cohesive and well-integrated system. The main goal is to enhance the use of the fleet and reduce the number of trips, thus improving the entire distribution process. A primary benefit of this model is its capacity to greatly improve fleet usage (from 75% to 100%) and minimize delivery delays by following set timeframes. Furthermore, the model reduces travel distances and the use of fuel, resulting in cost savings. However, the model also has some limitations, including its reliance on accurate input data and the computational complexity involved in solving large-scale optimization problems, which may require substantial processing power. Future research could focus on integrating real-time data analytics, such as IoT and AI-driven forecasting, to further enhance route adaptability. Additionally, exploring hybrid optimization approaches, such as combining genetic algorithms with Machine Learning techniques or Particle Swarm Optimization (PSO), could improve the model's efficiency and scalability for broader applications across different industries.

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