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RESEARCH ARTICLE

Maximizing the Supply Chain Profit in Multimodal Transportation Problem with Transfer Part using Two-Echelon Genetic Algorithm

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Abstract Multimodal transportation is a highly effective method for optimizing deadlines and reducing inventory costs, both of which are crucial in a supply chain environment. This study employs a mathematical programming model to optimize the supply chain profit for multimodal transportation distribution within a specified time window. The model considers five factors, such as production cost, transportation cost, transport time, penalty cost, and sales price. Additionally, a Two-Echelon Genetic Algorithm (TEGA) is proposed to solve the optimization problem, and a numerical example is provided to validate the model and algorithm. The study compares the performance of the proposed algorithm with the exact solution from a previous study, presents implementation details and numerical experiment results, and analyses the findings. The results demonstrate the efficiency and robustness of the algorithm, making it a significant contribution to transportation planning for freight transportation and supply chain management.

Keywords: Multimodal Transportation, Two-echelon Genetic Algorithm, Supply Chain Profit.

Introduction

Supply chain and logistics management in modern industries is a critical feature of operations management as customers tend to have quick and efficient exposure to varied and reliable products. In current logistic networks, logistic costs are 35% to 50% of the total transportation costs [1]. Reducing logistic costs will save a lot of money for businesses thus making products more affordable on the market. Applying multimodal transport into a logistic network will increase transportation efficiency, reduce inventory backlog and improve customer service levels while minimizing overall costs [2-6]. Multimodal transportation is described as combining two or more transportation modes such as road, rail, sea or air to move goods efficiently under a single contract.

In general, multimodal transport involves two parts which are transportation and transfer parts, taking into account both transfer time and costs as stated in Tang and Huo [1]. The difference between multimodal and single transport modes is just the transfer parts. The transfer part occurs because the delivery process from the factory to the market cannot be carried out directly. This is due to some geographical location factors where the delivery can be accomplished using the appropriate transportation mode. The transfer component of multimodal transport incurs both costs and transfer time. While many multimodal studies primarily focus on reducing overall costs, often neglecting specific transportation expenses such as transfer costs [7-8], this study seeks to fill that gap and provide a comprehensive analysis.

This paper implements a mathematical programming model based on the previous study for distribution network design with a time window in the form of Mixed-Integer Nonlinear Programming (MINLP) model.

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Further analysis of the proposed method is explained in this paper. The cost optimization of the supply chain with multimodal transportation considered three stages of supply chain manufacturer, distribution hub and market. This study will focus on maximizing the supply chain profit by using a TEGA. This model may be useful as decision support for supply chain management.

Literature Review

Multimodal Transportation Problem

Multimodal transport is becoming more popular and rapidly developed due to the pattern of globalization. A survey regarding optimization in the multimodal transportation problem can be found in [9-10]. The key objective of multimodal transport is to fully exploit the benefits of various transportation modes in order to increase economic performance [11-14]. According to Chen *et al.* [15], multimodal transport study focuses primarily on two issues: one is transport network and another is performance management.

Firstly, the transport network structure involves the selection of transport mode and model of a multimodal transport network. Floden *et al.* [16] discovered that multimodal transportation modes were selected specifically based on costs, yet the transport efficiency standards were guaranteed. Winebrake and Green [17] studied travel costs in the United States for the medium and heavy vehicles and examined that the range of vehicles would be influenced by emerging technology and policies. The choices of multimodal modes of transport are also highly dependent on transport and operational conditions, for example, demand and inventory [16-21].

Second, the issue that the logistic department often addressed, is the optimum efficiency management in multimodal transportation. A multi-product and multi-factory maximizing profit model are suggested by Jolayemi and Olarunniwo [22]. The technique of minimizing the model size was developed and the outcomes were similar to the theoretical model in consideration of costs of manufacturing, transport, inventory and placement in warehouses. Beresford *et al.* [23] studied multimodal transport by focusing on a case study. The authors developed a cost model as a framework in terms of heavy bulk freight shipments.

However, it is also very crucial to consider transport and transfer time in the multimodal transportation system, Ziliaskopoulos and Wardell [24] has created a number of optimum routing methods that improve the time to handle these issues. Galvez *et al.* [25] present the Transfer Graph method for multimodal time-dependent transport networks to optimize multiple transport systems in Europe. Nevertheless, the study mentioned only focuses on the transportation problem but not the supply chain network.

A few methods have been used to solve this multimodal transportation problem. Zheng *et al.* [26] proposed an improved particle swarm optimization algorithm to solve multimodal transport path for cold chain logistics. Ko *et al.* [27] suggested a multi-objective stochastic model to improve bioenergy production with multimodal transportation. The results show that multimodal transportation costs, especially for long-distance delivery.

Authors in Galvez *et al.* [28] proposed a unique integration technique that combines a heuristic algorithm and exact solution optimization for multimodal petroleum supply chain design. Yao and Liu [29] developed an ant colony algorithm to minimize the total transportation cost involving multimodal transportation path. The results obtained show that the algorithm was able to solve the multimodal path optimization well.

Tang and Huo [1] explored the cost optimization of multimodal transport in the supply chain. The authors include both transport and transfer parts in their optimization model. However, they did not explain how the transfer part operates from the factory to the distribution hub and then to the market. Therefore, this study focuses on getting more insight into the transfer part. They also solve the model by using LINGO software that gives an exact solution which usually takes a longer time to execute and the larger the problem, the more complex the solution space. Therefore, a heuristic approach is proposed to solve the optimization problem.

Genetic Algorithm for Multimodal Transport

The genetic algorithm (GA) is a heuristic search technique inspired by an evolutionary biological model. In computation, it is used to find exact or approximate solutions to search problems and hard optimization. It provides an efficient, effective technique for optimization and machine learning applications. Wang and Wang [30] explore the application of the genetic algorithm for the multimodal transportation network. The authors presented an improved GA to minimize the total transportation cost. However, they did not consider the transfer part in their model. Zhang *et al*. [31] compared GA with other heuristic methods and concluded that GA produces better solutions and is efficient for multimodal network design problems.

Jiang [32] proposed GA in a multimodal transportation route optimization model to minimize the total transport cost. The algorithm can successfully avoid trapping in the local optimal solution and achieve the result faster, proving the algorithm's practicality in determining transportation plans involving multimodal transport. Zou *et al.* [33] combined clustering algorithm and GA in their study for multimodal optimization scheduling problems. The results are compared with the other three different algorithms and prove that the proposed algorithm gave better optimal solutions. Liu *et al.* [34] employed genetic algorithms to leverage the advantages of multimodal transportation. They introduced a calculation model and theoretical algorithm aimed at optimizing small regional logistics transportation networks.

GA's efficiency in searching for the globally optimum solution will produce a better solution than others for the model. The previous findings validate that GA can achieve an almost optimal solution and produce more profits through the optimization process. In this study, an improved two-echelon GA (TEGA) is proposed to solve multimodal transport with a transferring part.

Mathematical Model

Problem Description

This paper implemented a mathematical programming model based on Tang and Huo [1] which aims to maximize supply chain profits by taking account of the costs of manufacturing, distribution hub rentals, purchasing price and the penalty costs as it involves time window. Multi-factories, over one distribution hub and multi-market supply chains are part of the distribution network. During the transit, three types of transportation modes are utilized, with the transfer taking place only at the distribution hub. Figure 1 shows the distributed supply chain network diagram for multimodal transport.

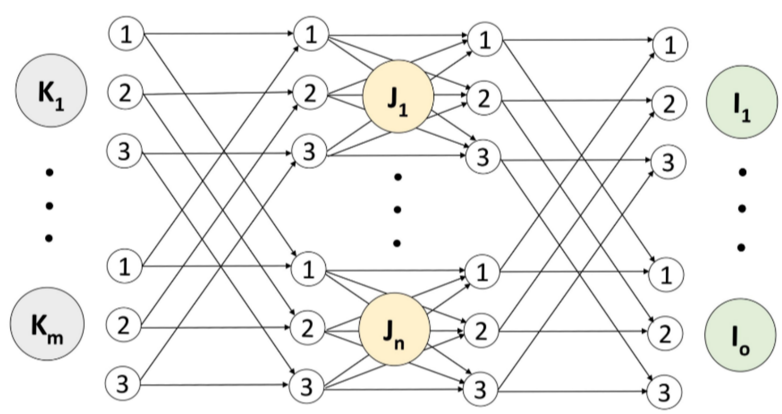

Figure 1. Multimodal transport for distribution supply chain network diagram

The model considers three distinct methods of travel: land, air and sea. Hence, the transport costs and delays can vary by transport mode. Even for a similar product, the processing costs and time, freight costs, transport time and other considerations are also varied due to geographical location variations between the distribution hub and manufacturing lines. As it is a distribution network design with a time window, the transport time is very sensitive. Due to a lack of demand, there are penalties for late arrivals and storage costs for early arrivals.

Model Assumption

Considering the complexity of the model, the assumptions are defined as follows:

- The sales price for each product is known.
- Transfer only happens at the distribution center and just once.
- Demand is fixed for each market.

- The market delivery period is the same for a similar product.
- Single operating costs rate.

The Sets and Settings

I	:	The set of market, $i \in I$;
J	:	The set of distribution hub, $j \in J$;
K	:	The set of production factory, $k \in K$;
M	:	The set of transport modes, $m \in M$;
h_i	:	The selling price of market i;
Q_i	:	Market i demand for the commodity;
t_i	:	The arrival time to market i;
w_j	:	The capacity of distribution hub j;
f_j	:	The rental cost of distribution hub j;
G_k	:	The maximum production capacity of factory k;
v_k	:	The manufacturing costs of factory k;
$d_j^{m,m'}$	:	Transfer time in distribution hub j from transportation mode m to m';
$l_j^{m,m'}$	:	Transfer costs in distribution hub j from transportation mode m to m';
b_{jk}^{m}	:	Unit transportation costs from factory k to distribution hub j by transportation mode m;
$c_{ij}^{m'}$	:	Unit transportation costs from distribution hub j to market i by transportation mode m';
$\bar{b}_{jk}^{m}$	:	Transportation time of mode m from factory k to distribution hub j;
$\bar{c}_{ij}^{m'}$	:	Transportation time of mode m' from distribution hub j to market i;
a_i	:	Minimum hour for the market i delivery;
b_i	:	Maximum hour for the market i delivery;
S	:	Penalty rate of an early arrival (cost per hour);
S'	:	Earliness penalty costs;
θ	:	Tardiness penalty rate (cost per hour);
θ'	:	Tardiness penalty costs;

The Decision Variables

$$\mu_j = \begin{cases} 1, & \text{if distribution hub } j \text{ capacity can meet the demand,} \\ 0, & \text{otherwise.} \end{cases}$$

$$\alpha_{jk}^{m} = \begin{cases} 1, & \text{if transportation mode } m \text{ is used from factory } k \text{ to distribution hub } j, \\ 0, & \text{otherwise.} \end{cases}$$

$$\beta_{ij}^{m'} = \begin{cases} 1, & \text{if transportation mode } m' \text{ is used from distribution hub } j \text{ to market } i, \\ 0, & \text{otherwise.} \end{cases}$$

$$\gamma_{jk}^{m,m'} = \begin{cases} 1, & \text{if transport mode change in distribution hub } j \text{ from factory } k, \\ 0, & \text{otherwise.} \end{cases}$$

x_{jk}^{m} : Delivery quantity from factory k to distribution hub j by transportation mode m

$y_{ij}^{m'}$: Supply of market i from distribution hub j by transportation mode m'

The Model Formulation

The mathematical model below was taken from [1] to solve the optimization problem involving multimodal transportation.

Max

$$Z = \sum_{i=1}^{I} h_i Q_i - \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\left(v_k + b_{jk}^{m}\right)\alpha_{jk}^{m} x_{jk}^{m} - \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{m'=1}^{M}\gamma_{jk}^{m,m'} l_j^{m,m'} \alpha_{jk}^{m} x_{jk}^{m} - \sum_{j=1}^{J} f_j \mu_j - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m'=1}^{M} c_{ij}^{m'} \beta_{ij}^{m'} y_{ij}^{m'} - S' - \theta' \tag{1}$$

Subject to:

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\alpha_{jk}^{m} x_{jk}^{m} \le G_k, \quad k \in K \tag{2}$$

$$\sum_{k=1}^{K}\sum_{m=1}^{M}\alpha_{jk}^{m} x_{jk}^{m} \le w_j \mu_j, \quad j \in J \tag{3}$$

$$\sum_{k=1}^{K}\sum_{m=1}^{M}\alpha_{jk}^{m} x_{jk}^{m} = \sum_{i=1}^{I}\sum_{m'=1}^{M}\beta_{ij}^{m'} y_{ij}^{m'}, \quad j \in J \tag{4}$$

$$\sum_{i=1}^{I}\sum_{m'=1}^{M}\beta_{ij}^{m'} y_{ij}^{m'} = Q_i, \quad i \in I \tag{5}$$

$$\sum_{m=1}^{M}\sum_{m'=1}^{M}\left(\alpha_{jk}^{m}\bar{b}_{jk}^{m} + \gamma_{jk}^{m,m'} d_j^{m,m'} + \beta_{ij}^{m'}\bar{c}_{ij}^{m'}\right) = t_i, \quad k \in K, i \in I, j \in J \tag{6}$$

$$S' = \begin{cases} (a - t_i)s, & t_i < a, \quad i \in I \\ 0, & t_i \ge a, \quad i \in I \end{cases} \tag{7}$$

$$\theta' = \begin{cases} 0, & t_i \le b, \quad i \in I \\ (t_i - b)\theta, & t_i > b, \quad i \in I \end{cases} \tag{8}$$

$$\sum_{m=1}^{M}\alpha_{jk}^{m} \le 1, \quad k \in K, \ j \in J \tag{9}$$

$$\sum_{m'=1}^{M}\beta_{ij}^{m'} \le 1, \quad j \in J, \ i \in I \tag{10}$$

$$\sum_{m=1}^{M}\sum_{m'=1}^{M}\gamma_{jk}^{m,m'} \le 1, \qquad k \in K, \quad j \in J \tag{11}$$

$$x_{jk}^{m},\ y_{ij}^{m'} \ge 0, \quad x, y \in Z, \quad k \in K, \quad j \in J, \quad m, m' \in M \tag{12}$$

The equations described in the model formulation can be summarized as follows. Equation (1) expresses the objective function that seeks to maximize the total profits of the supply chain. In this study, profit, Z is determined by subtracting the total revenue, $\sum_{i=1}^{I} h_i Q_i$ with all costs consisting of production cost and delivery cost from the factory to distribution hub, $\left(v_k + b_{jk}^{m}\right)\alpha_{jk}^{m}\, x_{jk}^{m}$, transfer cost, $\gamma_{jk}^{m,m'}\, l_{j}^{m,m'}\, \alpha_{jk}^{m}\, x_{jk}^{m}$, holding cost at distribution hub, $f_j \mu_j$, delivery cost from distribution hubs to market, $c_{ij}^{m'}\, \beta_{ij}^{m'}\, y_{ij}^{m'}$ and the penalty cost, $S' - \theta'$. Constraint (2) and (3) are the factory capacity demand and distribution hubs storage capacity respectively. The product flow conservation is represented by equations (4) and (5). Equation (6) indicates the sum of transportation time and transfer time. Constraints (7) and (8) demonstrate the penalty costs for earliness and tardiness. If it is zero, it means that the products arrive within the required delivery time. Equations (9) and (10) denote whether transportation mode is used or not for the product flow. Equation (11) indicates that transfer only happens once from factory k to distribution hubs j. Constraint (12) denotes the decision variables range.

Genetic Algorithm (GA)

GA mimics the natural biological mechanisms based on Darwin's theory of evolution. There are five phases that GA generally follows which are initial population, fitness evaluation, selection, crossover and mutation as shown in Figure 2 below:

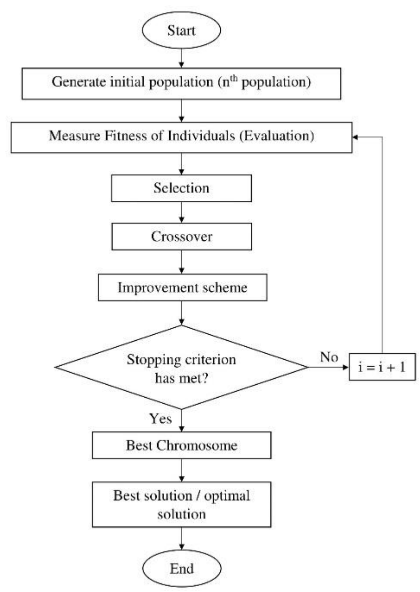

Figure 2. Flow chart of general GA

Since this study is a distribution network, it involves a two-echelon transportation problem in which Part A is transportation from the factory to the distribution hub and Part B is transportation from the distribution hub to the market. Therefore, a two-echelon genetic algorithm from [35] is applied to solve the multimodal distribution network design. Figure 3 shows the general procedure of two-echelon genetic algorithm (TEGA) employed in this study.

Step 1:	Generate solutions or chromosomes to initialize the population based on the data sets with population size of 100.
Step 2:	Evaluate all the chromosomes by using fitness function and choose the best 50 chromosomes.
Step 3:	Select 2 chromosomes as parent using the roulette wheel selection based on fitness value of the chromosomes.
Step 4:	Perform the crossover and mutation operation for Part B.
Step 5:	Apply the Shipment Allocation on the sub-chromosomes.
Step 6:	Then, perform the crossover and mutation operation for Part A based on the results obtained from Part B.
Step 7:	Calculate the transfer and penalty cost from the overall product flow from factory to the market. Then, evaluate it by using fitness function.
Step 8:	If offspring is better than previous generation, replace the old generation then proceed to the next step. If offspring is worse than old generation, skip this step and proceed to the next step.
Step 9:	Repeat the above steps until the stopping criteria is met.

Figure 3. Procedure of TEGA.

The initial population is generated randomly from the data sets available according to the parameters that have been decided. In the permutation representation, every chromosome (or solution) is assessed in relation to its total supply chain profit for the crossover process. The chance of chromosome selection will be determined by the fitness value of each chromosome. The parents (chromosomes) are chosen using roulette-wheel selection for crossover according to the fitness function below with N denotes population size:

$$F_p = \frac{1}{Z_p} \text{ where } p = 1, 2, \ldots, N.$$

The crossover procedure is based on the idea that the child generated will outperform the parents. Hence, it is intended to keep more gene traits from the primary parent (base chromosome) than from the second parent (donor chromosome). A random number r between [0,1] is assigned to each gene in the base chromosome. The associated gene will be transmitted from the base chromosome into the child if $r \leq 0.90$. Then, the unfilled genes in the offspring are filled from the second parent according to the order-based crossover operator.

According to [35], the crossover operator acquires 90% of gene features from the base parent chromosome and the remaining 10% from the donor chromosome, hence the mutation operation is not used in TEGA. They concluded that these qualities contributed to the TEGA's efficiency. Finally, every chromosome is enhanced by an improvement process that allocates the maximum allowable freight quantities to each path for a better solution. The process repeats until the stopping criteria are met which is the maximum generation number.

Results and Analysis

In this section, all the computational results will be analysed and discussed. All of the computation calculations are carried out using a laptop with an Intel(R) Core(TM) i7-1065G7 CPU @ 1.30GHz, 16.00 GB, Windows 10, 64-bit operating system and Microsoft Visual C++ Studio 2022. Data sets from [1] are used to generate sets of initial solutions. The analysis will focus on various genetic parameter settings in order to determine the most optimized genetic parameters for maximizing the total supply chain profits. The performance of GA in this study will then be concluded at the end of this paper.

Identify the Best Generation Number under Constant Population Size

Four different simulations at constant generation numbers of 100, 1,000, 5,000 and 10,000 at various population sizes are carried out in this section to identify the best population size by comparing the maximum values of the objective function. In this section, the best population size and the computing time will be summarized. In conclusion, the ideal population size of GA is determined by the number of generations. Table 1 illustrates the best population size obtained by varying the maximum generation number.

Table 1. The Best and Minimum Generation Number in GA

Population Size	Average Profit	The Best Generation Number	Minimum Generation Number in GA
100	52,722.40	6,503	7,000
500	52,683.00	738	800
1000	52,707.60	179	200
2000	52,760.80	225	300
4000	52,756.60	110	200

Since the most significant generation number is 6,503 among the five computation experiments, a minimum generation number of 7,000 must be set in the algorithm. All the experiments above will be able to reach a better solution provided the minimum generation number is 7,000 regardless of the population size. From this simulation, the best generation number is 225 with the maximum supply chain profit is 52,760.80. However, an appropriate population size can increase the efficiency of GA as the outcome might be a poor solution when the population is too large. Hence, a few experiments have been carried out to identify the best population size in the following section.

Identify the Best Population Size under Constant Generation Number

Four different simulations at constant generation numbers of 100, 1,000, 5,000 and 10,000 at various population sizes are carried out in this section to identify the best population size by comparing the maximum values of the objective function. In this section, the best population size and the computing time will be summarized.

In conclusion, the ideal population size of GA is determined by the number of generations. Table 2 illustrates the best population size obtained by varying the maximum generation number.

Table 2. Summary of Results at 100, 1000, 5000 and 10,000 times of Generation

Generation Number	Average Profit	The Best Population Size	Computing Time (seconds)
100	52,721.33	2,000	348
1000	52,728.33	1000	1,755
5000	52,817.00	100	1,536
10000	52,832.00	500	9,557

For 100 and 1000 generations, the experiments returned a maximum profit at a population number of 2,000 and 1,000 respectively. Hence, a higher population number which is greater than 2,000 will lead the search to a poor outcome. Whereas in 5,000 generations, there is a possibility of getting a poor solution if the population number is higher than 100.

Finally, for 10,000 generations, the best population number cannot be too small or too large because a poor solution will be obtained if the population size is too small and the solutions will keep repeated when the population is too large. Therefore, in conclusion, the population size has to be large when the generation number is too small and the population size should not be too large for a moderate generation number. Lastly, for a very large generation number, a moderate population is sufficient to obtain a good solution.

Conclusions

The study focuses on maximizing supply chain profits using the principle of time value of money. The experiments conducted using a genetic algorithm (GA) showed that the ideal population size of GA is determined by the number of generations. For 100 and 1000 generations, the experiments returned a maximum profit at a population number of 2,000 and 1,000 respectively. In 5,000 generations, a population number higher than 100 may lead to a poor solution. For 10,000 generations, the best population number should not be too small or too large.

As a further experiment for validating the performance of our GA algorithm, comparisons have been made with the previous method approach by Tang and Huo [1]. Based on the values of maximum profit obtained from the different parameters' experiments, the best profit is 52,832. The result shows a higher value compared to the existing solution which is 52,026.

The GA proposed has demonstrated superior performance in optimizing the overall supply chain profit for multimodal distribution network design compared to alternative methods. This showcase emphasizes GA's efficiency as a heuristic approach for resolving multimodal transportation issues, as explored in prior research [30, 31, 35]. The presented cost optimization model and its computational results can be incorporated into transportation planning, providing valuable insights to the methodology for tackling extensive challenges in multimodal distribution networks. As a result, proficient supply chain management becomes crucial for ensuring the sustainability of businesses, especially during demanding periods like the COVID-19 pandemic.

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