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Minimizing Transportation Cost in Supply Chain Logistics Problem Using Optimization Techniques

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Abstract

Supply chain logistics transportation involves planning, coordination and movement of products between warehouses to customers via distribution networks while managing freight costs, warehouse handling costs and operational limitations in order to deliver products in timely and cost-effective manner. In recent years, the COVID-19 pandemic has exerted a significant impact on global supply chains in terms of increased transportation costs and more complicated operational limitations, thereby rendering the minimization of costs a major concern of logistics decision-making. This study deals with the optimization problem of a supply chain logistics data which includes 8,361 customer orders, warehouses, freight costs, warehouse costs and product-warehouse eligibility limits. The main objective of the study is to reduce the total transportation cost while satisfying operational and business restrictions. In order to reach this goal, three optimization methods are applied which are the Vogel's Approximation Method followed by Modified Distribution Method (VAM-MODI), Integer Linear Programming (ILP) and Pre-emptive Goal Programming (GP). The findings explain that both the ILP and Pre-emptive GP models are able to allocate all orders and achieve a total transportation cost reduction from $13,341,913.03 to $13,172,055.04 which indicates a total of 1.27% reduction in the cost in comparison to historical allocations. The Pre-emptive GP model also enhances good delivery performance while retaining the optimum level of cost. In contrast, VAM-MODI only give minimal cost reduction and can only be deployed in a portion of the orders because of the structural and feasibility constraints. The results show that precise and multi-objective optimization techniques give better and more realistic operationally accurate solutions to complex allocation of supply chain logistics problems. Future research may extend this study by incorporating uncertainty, sustainability-related objectives and dynamic demand conditions into the optimization framework.

1. Introduction

A supply chain refers to a connected network of organizations, individuals, activities and technologies involved in the creation and delivery of a product from its origin to the final consumer [1]. All the stages involved in obtaining a completed product or service to the customer are included in a supply chain, beginning with producers of raw materials, followed by production, warehousing, distribution, retail and final delivery to end customers. The components of a supply chain consist of producers, vendors, warehouses, transportation companies, distribution centers and retailers. Meanwhile, supply chain logistics is a subset of the supply chain that focuses on transportation, warehousing and inventory activities, involving the handling, movement and coordination of goods throughout the supply chain, covering both inbound and outbound logistics [2]. Inbound logistics refers to the procurement and transportation of materials to production facilities, while outbound logistics concerns the delivery of finished goods to retailers or end users. Logistics management includes essential activities such as inventory management, warehousing, transportation, distribution, customer service and returns management, which help organizations reduce operating costs, optimize inventory levels, streamline transportation processes and improve responsiveness to customer needs [2].

Supply chain management plays an important role in minimizing overall operational costs while ensuring an efficient production cycle and maintaining profitability. An effective supply chain allows organizations to collaborate closely with suppliers and employees to develop the right product, ensure timely delivery, meet financial goals and continuously improve performance, which in turn increases customer satisfaction [3].

A number of previous studies have applied various optimization techniques to solve supply chain logistics problems in real world. For example, Vogel's Approximation Method and the Modified Distribution Method (VAM-MODI) have been used to minimize transportation costs in the Turkish iron and steel industry, as well as in factory transportation scheduling, demonstrating that the method is effective in industrial logistics systems [4], [5]. In addition, Integer Linear Programming (ILP) has been widely applied to assign delivery tasks and also optimize routing in logistics services, which lead to improved utilization of resources and cost efficiency [6], [7]. Furthermore, Goal Programming has been used in humanitarian logistics to enhance warehouse and inventory planning during disaster relief operations [8]. However, many existing studies focus on specific applications or relatively simplified scenarios, which highlights the need for further studies that integrates multiple optimization approaches with large-scale real-world data and complex operational constraints.

Over the past few years, global supply chains have faced significant disruptions following the COVID-19 pandemic. Many industries experienced severe operational challenges, including transportation delays, rising fuel costs, material shortages and unpredictable demand patterns [9]. Customer expectations for faster delivery and lower shipping costs have increased, placing additional pressure on logistics systems to remain efficient while controlling costs [10]. Rising operational expenses, inflation and regulatory requirements have further intensified cost management challenges. In Malaysia, logistics operations face similar issues, including limited coordination in logistics regulations, lack of expertise in advanced supply chain strategies, inventory forecasting difficulties and increasing operational costs, especially among small and medium-sized enterprises [11], [12].

Transportation cost remains one of the most significant contributors to total logistics expenses. Efficient transportation planning is therefore essential to ensure cost-effective logistics operations while satisfying operational constraints [13]. Despite its practical relevance, many existing logistics allocation approaches lack the ability to incorporate complex operational constraints simultaneously and provide cost-optimal solutions based on real-world data. Motivated by this issue, optimization techniques provide structured and systematic approaches to solving transportation and allocation problems under defined constraints. Thus, this study applies several optimization techniques to address transportation cost minimization in a supply chain logistics problem using real-world logistics data.

2. Materials and Methods

2.1 Data Description and Data Preparation

The dataset used in this study is the Supply Chain Logistics Problem Dataset obtained from Brunel University London [14]. It represents a real-world logistics environment and consists of 8,361 customer orders that require assignment to feasible warehouses for fulfilment. This dataset consists of seven tables. The information of the dataset of supply chain logistics problem is shown in Table 1. Based on Table 1, OrderList is the primary data which records the historical customer orders, while the other six additional tables define the problem and restrictions that indicate the operational constraints and rules of the supply chain logistics network.

Table 1 Information of supply chain logistics problem dataset

Table	Description
OrderList	Contains information about historical customer orders including product ID, quantity, weight, origin port and destination port
FreightRates	Provides freight costs and delivery time per lane, weight bracket
WhCosts	List storage cost per unit at each warehouse
WhCapacities	Specifies daily order capacity of each warehouse

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ProductsPerPlant	Indicates which products are available at each warehouse
VmiCustomers	Lists customers who are restricted to specific warehouses
PlantPorts	Defines allowed links between warehouses and their associated shipping ports

The data of supply chain logistics problem is prepared and the feasible cost structure for the data is created. The analysis is based on supply chain logistics data which consists of 8,361 orders and several plant-port locations. Python is used in the Jupyter Notebook integrated development environment (IDE) to clean and pre-process the data. Several operational constraints such as product-warehouse compatibility, VMI constraints and freight lane availability are used to filter the infeasible warehouse-order combinations and build a feasible cost matrix reflecting the true operating conditions. All optimization models are based on the resulting feasible cost matrix.

2.2 Key Cost Factors

There are two main cost factors considered in this study which are freight cost and warehouse cost, while the total transportation cost for each feasible warehouse-order assignment is computed as the sum of freight cost and warehouse cost. This total cost serves as the core input for all optimization techniques applied in the study. The calculation for freight cost, warehouse cost and total cost is expressed in (1), (2) and (3), based on the dataset [14].

$$\text{Freight cost}, C_r = max\,(mincost_r, rate_r \times w_j) \tag{1}$$

$$\text{Warehouse cost}, C_i = h_i \times q_j \tag{2}$$

$$\text{Total cost}, C_{ij} = \text{Warehouse cost } C_i + \text{Freight cost } C_r \tag{3}$$

where:
mincost_r = minimum freight charge for freight rate row r
rate_r = Freight rate for freight rate row r
w_j = Weight for order j
h_i = Handling cost per unit at warehouse i
q_j = Order quantity (units) for order j

2.3 Feasibility Constraints

To construct a realistic optimization model, operational feasibility constraints are applied. These include product-warehouse compatibility constraints, VMI customer restrictions, valid warehouse-port connections, and available freight lanes. Only warehouse-order pairs that satisfy all feasibility conditions are included in the optimization models, and this is to ensure that the resulting solutions reflect real-world logistics rules.

The feasibility conditions are represented mathematically through the feasibility indicator defined in (8), the feasibility constraint in (9) and the composite feasibility formulation in (10).

2.4 Transportation Problem Formulation

The transportation problem aims to determine the most cost-effective assignment of orders to warehouses while satisfying feasibility constraints [15]. A cost matrix is constructed in which rows represent warehouses, columns represent orders, and each cell contains the total transportation cost for a feasible assignment. Infeasible assignments are excluded from the matrix.

The mathematical formulation of the transportation problem is expressed by the objective function in (6), which minimizes the total transportation cost, subject to the assignment constraint in (7) and the feasibility constraint in (9).

2.5 Optimization Techniques

2.5.1 Vogel's Approximation Method and Modified Distribution Method

Vogel's Approximation Method (VAM) is applied to generate an initial basic feasible solution for the transportation problem. The method uses penalty costs, calculated as the difference between the lowest and second-lowest costs in each row and column, to guide allocation decisions [16]. VAM is selected because it typically produces initial solutions closer to the optimum compared to simpler methods such as the North-West Corner Method or Least Cost Method [17].

The Modified Distribution Method (MODI) is then applied to improve the initial solution generated by VAM. MODI evaluates opportunity costs for unoccupied cells and iteratively adjusts allocations until no further cost reduction is possible [17]. The opportunity cost k_{ij} for each unoccupied cell is calculated by using the formula in (4).

$$k_{ij} = c_{ij} - (u_i + v_j) \tag{4}$$

where u_i and v_j are dual variables associated with the row and column constraints respectively, while c_{ij} is unit transportation cost from source i to destination j.

The VAM-MODI combination is used to solve a balanced transportation problem for a subset of orders that satisfy classical transportation model assumptions.

2.5.2 Integer Linear Programming

Integer Linear Programming (ILP) is employed to model the full logistics problem across all feasible warehouse-order assignments. A binary decision variable is defined to indicate whether an order is assigned to a particular warehouse. The objective function minimizes total transportation cost subject to assignment constraints and feasibility conditions [18].

Each order must be assigned to exactly one feasible warehouse, and assignments are restricted by product eligibility, VMI rules, freight lane availability, and warehouse capacity limits. The ILP model is solved using an exact optimization algorithm based on the branch-and-cut method, which combines branch-and-bound and cutting-plane techniques to obtain a globally optimal solution [18].

The formulation of ILP model is presented as follows. The decision variable for the ILP model formulation is defined as (5).

$$x_{ij} = \begin{cases} 1, & \text{if order } j \text{ is assigned to warehouse } i \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The binary decision variable x_{ij} denotes the assignment of order j to warehouse i, where $x_{ij} = 1$ if the assignment is selected and $x_{ij} = 0$ otherwise.

The objective function in (6) aims to minimize total transportation cost across all assigned orders.

$$\text{Min } Z = \sum_{i \in P} \sum_{j \in O} c_{ij} x_{ij} \tag{6}$$

where:
$i \in P$ = Set of feasible warehouses
$j \in O$ = Set of orders
c_{ij} = Total transportation cost

The objective function is subject to the following constraints. Order assignment constraint which means that each order must be assigned to exactly one feasible warehouse is displayed in (7).

$$\sum_{i \in P_j} x_{ij} = 1 \quad \forall j \in O \tag{7}$$

Meanwhile, feasibility indicator that involves product-warehouse compatibility, VMI customer rules and freight lane validity is defined as (8).

$$\text{feas}_{ij} = \begin{cases} 1, & \text{if warehouse } i \text{ is allowed and able to serve order } j \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

Feasibility constraint:

$$x_{ij} \leq \text{feas}_{ij} \quad \forall i \in P, \forall j \in O \tag{9}$$

where:

$$\text{feas}_{ij} = prodOK_{i,prod_j} \times vmiOK_{i,cust_j} \times laneOK_{port_i,dest_j} \tag{10}$$

where:
$prodOK_{i,prod_j}$ = Product-warehouse compatibility
$vmiOK_{i,cust_j}$ = VMI customer rules
$laneOK_{port_i,dest_j}$ = Freight lane validity

Thus, if any of these conditions is violated, then $\text{feas}_{ij} = 0$ which force the assignment to be prohibited. If all are satisfied, $\text{feas}_{ij} = 1$ which the assignment of the orders is allowed. The feasibility constraint in (9) ensure that the ILP is evaluated on a valid cost matrix structure.

Furthermore, the warehouse capacity constraint is formulated as (11).

$$\sum_{j \in O} x_{ij} \leq Cap_i \quad \forall i \in P \tag{11}$$

where Cap_i denotes the maximum number of orders that warehouse i can process.

Due to strict feasibility restrictions, a soft capacity constraint is introduced by incorporating a slack variable s_i as shown in (12).

$$\sum_{j\in O} x_{ij} \leq Cap_i + s_i \quad \forall i\epsilon P \tag{12}$$

where $s_i \geq 0$ represents the excess number of orders assigned to warehouse i.

2.5.3 Goal Programming

Goal Programming (GP) is applied as an extension of the ILP model to address multiple logistics objectives. A pre-emptive goal programming approach is used, where minimizing transportation cost is assigned the highest priority, followed by minimizing delivery time [19].

In this study, Pre-emptive Goal Programming (GP) is to be applied to prioritize cost minimization first, then followed by minimization of delivery time. This reflects real-world business priorities where the company must minimize cost but also seeks to improve shipping timeliness. The Pre-emptive GP model is solved sequentially in two stages.

The formulation for the first stage GP method is exactly the same as ILP formulation to minimize total transportation cost as shown in (6), and subject to assignment, feasibility and capacity constraints in (7), (9) and (12) respectively. After solving this stage, the optimal cost $Z_1{}^*$ becomes the cost target for the next stage.

For the second stage, the objective function is to minimize total transport delivery time while maintaining optimal transportation cost, as displayed in (13).

$$\text{Min } Z_2 = \sum_{i\in P}\sum_{j\in O} t_{ij}x_{ij} \tag{13}$$

where t_{ij} is transportation time (TPT) for assigning order j

The objective function of (13) is subject to constraints in (7), (9) and (12) once again, and a cost-fixing constraint obtained from the first stage as shown in (14).

$$\sum_{i\in P}\sum_{j\in O} c_{ij}x_{ij} = Z_1{}^* \tag{14}$$

The cost-fixing constraint ensures that the optimal transportation cost obtained in the first stage is preserved during second stage. This ensures that TPT is minimized without sacrificing cost optimality.

2.6 Calculation of Cost Reduction and Performance Improvement

To evaluate the effectiveness of the optimization techniques applied in this study, both the absolute and percentage of reductions in transportation cost are calculated by comparing the optimized solutions with historical allocations. The historical cost represents the total transportation cost incurred under the original warehouse-order assignments recorded in the dataset. This cost is computed using the same freight rate structure and formulation of warehouse cost applied to the optimized solutions to ensure a consistent and fair comparison. Meanwhile, the optimized cost is obtained from the allocation results produced by each optimization method. The calculation of cost reduction is shown in (15) and (16).

$$\text{Cost Reduction} = \text{C}_{\text{historical}} - \text{C}_{\text{optimized}} \tag{15}$$

$$\text{Percentage Reduction (\%)} = \frac{\text{C}_{\text{historical}} - \text{C}_{\text{optimized}}}{\text{C}_{\text{historical}}} \times 100\% \tag{16}$$

where $\text{C}_{\text{historical}}$ is the total historical transportation cost and $\text{C}_{\text{optimized}}$ is the total cost obtained from the optimization model.

2.7 Network Graph Visualization of Optimized Logistics Flows

To support the interpretation of optimization results, this study uses network graph visualization to illustrate the structure of optimized logistics flows generated by different optimization methods.

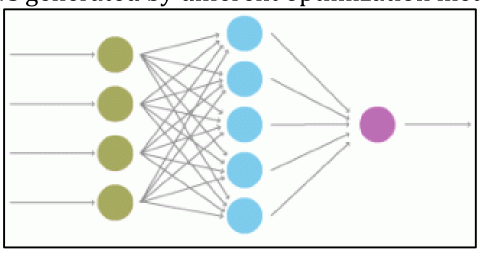


Fig. 1 Illustrative example of a network graph visualization

Fig. 1 illustrates the conceptual structure of the network graph used in this study to visualize optimized supply chain logistics flows. The left layer represents warehouses which serve as supply nodes where products are dispatched. The middle layer corresponds to origin ports associated with each warehouse. The right layer represents destination ports serving customer demand locations. Directed edges indicate feasible transportation links that satisfy product-warehouse compatibility, VMI customer restrictions, and available freight lanes. This visualization framework is applied to the optimized allocation outputs generated by the VAM-MODI, ILP and Pre-emptive GP models to illustrate the distribution and concentration of shipment flows across the logistics network.

3. Results and Discussion

The optimization results demonstrate the effectiveness of applying structured optimization techniques to a real-world supply chain logistics problem.

3.1 Feasible Cost Structure Result

The result of feasible cost matrix constructed is shown in Fig. 2.

```
# Build cost matrix (m x n) where INF for infeasible
INF = 1e12
m = len(plants); n = len(order_ids)
cost_matrix = np.full((m,n), INF, dtype=float)
for i,p in enumerate(plants):
    sub = cost_df[cost_df['plant']==p].set_index('order_id')
    for j, oid in enumerate(order_ids):
        if oid in sub.index:
            cost_matrix[i,j] = float(sub.loc[oid,'total_cost'])

# Save a copy for debugging
pd.DataFrame(cost_matrix, index=plants, columns=order_ids).to_csv(OUTDIR/"debug_cost_matrix.csv")
print('Built cost_matrix with shape', cost_matrix.shape)

Excel file: C:\Users\User\Downloads\FYP1\Supply chain logisitcs problem FYP.xlsx
Loaded data. Orders: 8361 Plants(ports): 19
Finished building feasible cost_df. Rows: 18764 orders with NO feasible plant: 0
Built cost_matrix with shape (15, 8361)
```

Fig. 2 Result for construction of feasible cost structure

Fig. 2 shows that a feasible matrix with 18,764 unique warehouse-order cost combinations, was obtained following a thorough selection and filtering process. This implies that on average, there are more than two warehouses that could serve each order after all technical constraints mentioned above were applied. No order was left without at least one feasible warehouse and this proved the existence of the complete and operationally sensible dataset. Finally, a cost matrix of dimension 15 x 8,361 was constructed which consists of 15 possible warehouses and 8,361 destination orders. This high-dimensional array represents the input of all the future modelling through optimization techniques.

3.2 Vogel's Approximation Method and Modified Distribution Method (VAM-MODI) Results

Fig, 3 displays outputs of the allocation of the feasible orders in the supply chain logistics problem dataset using VAM-MODI method.

```
final_vam = merged[output_cols].copy().rename(columns={'plant':'plant_code_optimized'})
final_vam['Total_cost_optimized'] = pd.to_numeric(final_vam['Total_cost_optimized'], errors='coerce')
final_vam['total_cost_historical'] = pd.to_numeric(final_vam['total_cost_historical'], errors='coerce')
final_vam['delta'] = final_vam['Total_cost_optimized'] - final_vam['total_cost_historical']

outpath = OUTDIR/"final_allocation_with_orderinfo_VAM_MODI.csv"
final_vam.to_csv(outpath, index=False)
print('Saved final file:', outpath)
print('Sum historical:', final_vam['total_cost_historical'].sum(skipna=True), 'Sum optimized:', final_vam['Total_cost_optimized'].sum(skipna=True))

VAM initial assignments saved, rows: 8361
No loop found; stopping MODI
Saved VAM-MODI final allocation, rows: 3583
Saved final file: fyp_outputs_VAMMODI\final_allocation_with_orderinfo_VAM_MODI.csv
Sum historical: 11314637.477540582 Sum optimized: 11192580.04340433
```

Fig. 3 Result for VAM-MODI method

Based on Fig. 3, 8,361 orders were initially considered. After applying all feasibility filters, 3,583 orders remained with at least one feasible warehouse-port combination. These feasible combinations were the cost matrix used in the VAM-MODI algorithm. Then VAM process generated an initial feasible allocation of all feasible orders. Subsequently, the MODI method evaluated improvement opportunities by computing dual potentials (u and v) and opportunity costs. From Fig. 3, the algorithm reached convergence after 0 iterations, which suggests that there were no additional improving loops to be made, and the VAM solution in the MODI model was already locally optimum.

From the total historical cost calculated based on original route and optimized cost using VAM-MODI method, reduction of cost can be calculated as shown in (17) and (18).

$$\begin{aligned}\text{Value of cost reduction} &= 11314637.48 - 11192580.04 \\ &= \$122057.44\end{aligned} \tag{17}$$

$$\begin{aligned}\text{Percentage of cost reduction} &= \frac{122057.44}{111314637.48} \times 100\% \\ &= 1.08\%\end{aligned} \tag{18}$$

The calculation for the value and percentage of cost reduction in (17) and (18) represent a cost reduction of $122,057.44, accounts for 1.08% by applying VAM-MODI method to assign the orders.

There are only 3,583 orders were assigned feasible tasks by the VAM-MODI output, which is about 43 percent of the overall set of data. This is not due to limitations of the computation, but reflects the reality of operational constraints within the supply chain. Many orders were excluded because of violation of the feasibility criteria such as product-warehouse incompatibility, VMI restrictions, unavailability of valid freight lanes and warehouse-port constraints that make some warehouses inaccessible to the required destination ports. As a result, more than half of the orders cannot be reallocated from their historical warehouses, which inherently limits the potential magnitude of cost reductions achievable through VAM-MODI.

Furthermore, the classical VAM-MODI method is structurally limited because it can only optimize transportation cost within the feasible cost matrix and does not consider transit time or multi-objective trade-offs. The MODI phase converged instantly without requiring improvement iterations, indicating that the initial VAM solution was already optimal within a very limited feasible region. Although VAM-MODI provides a valid baseline cost minimization model and generates minor yet meaningful cost savings, its performance is severely constrained by real-world feasibility restrictions and model simplicity, which justifies the application of more advanced optimization techniques such as Integer Linear Programming and Goal Programming in complex supply chain logistics environments.

3.3 Integer Linear Programming (ILP) Optimization Results

Fig. 4 presents outputs of the allocation of the feasible orders in the supply chain logistics problem dataset using ILP method.

```
outpath = OUTDIR/"final_allocation_with_orderinfo_ILP.csv"
final_df.to_csv(outpath, index=False)

# Diagnostics & prints
assigned_count = final_df['plant_code_optimized'].notna().sum()
unassigned_count = final_df['plant_code_optimized'].isna().sum()
print("Final saved:", outpath)
print("Assigned orders:", int(assigned_count))
print("Unassigned orders:", int(unassigned_count))
print("Sum historical cost (sum of available):", final_df['total_cost_historical'].sum(skipna=True))
print("Sum optimized cost (for assigned):", final_df['Total_cost_optimized'].sum(skipna=True))
print("Done.")
```

```
Running ILP (USE_CAPACITY = True ) ...
ILP did not find feasible/optimal solution. Status code: 2
Retrying ILP with capacity constraints removed (fallback)...
Fallback ILP (no capacity) solved. Status: OPTIMAL
Assignments extracted (count): 8361
Final saved: fyp_outputs_ILP\final_allocation_with_orderinfo_ILP.csv
Assigned orders: 8361
Unassigned orders: 0
Sum historical cost (sum of available): 13341913.028516047
Sum optimized cost (for assigned): 13172055.043414628
Done.
```

Fig. 4 Outputs of feasible assigned route for the orders using ILP method

The results of Fig. 4 indicate that ILP solver able to determine a globally optimal solution to all 8,361 orders in terms of the set of assignments. The total cost was optimized to be $13,172,055.04 and the historical total cost is $13,341,913.03. The calculation for the value and percentage of cost reduction is displayed in (19) and (20).

$$\begin{aligned}\text{Value of cost reduction} &= 13341913.03 - 13172055.04 \\ &= \$169857.99 \\ &\approx \$169858\end{aligned} \tag{19}$$

$$\begin{aligned}\text{Percentage of cost reduction} &= \frac{169858}{13341913.03} \times 100\% \\ &= 1.27\%\end{aligned} \tag{20}$$

According to the calculation in (19) and (20), this represents a cost reduction of approximately $169,858 or 1.27%. Although the percentage of improvement appears modest, it represents a substantial absolute cost saving in large-scale logistics operations.

The original ILP model with warehouse capacity constraints failed to obtain a feasible solution, indicating that aggregate demand implied by order-level assignments could not be satisfied simultaneously within the strict feasibility constraints imposed by product-warehouse compatibility, VMI customer restrictions, and freight lane availability. The combination of limited alternative warehouses for certain products and customers with relatively tight capacity bounds resulted in a very narrow feasible solution space, such that no assignment could satisfy all constraints at the same time.

Thus, capacity constraints were relaxed to ensure feasibility, allowing the ILP solver to obtain a globally optimal solution that allocates all orders while fully satisfying feasibility constraints related to products, customers and freight lanes. The resulting solution represents the lowest possible transportation cost under the current operational arrangement without capacity limitations.

The ILP results are considered operationally appropriate because the model incorporates all critical business constraints, evaluates all feasible warehouse-order combinations simultaneously using an exact optimization algorithm, and allocates all orders without violating feasibility, thereby producing solutions that are not only mathematically optimal but also strategically meaningful for real-world supply chain decision-making.

3.4 Pre-emptive Goal Programming (GP) Results

Fig. 5 shows the output of allocation of the feasible orders including total delivery time in the supply chain logistics problem dataset using Pre-emptive GP method.

```
outpath = OUTDIR/"final_allocation_with_orderinfo_preemptive_gp_.csv"
final_df.to_csv(outpath, index=False)

print("Done. Method used:", method_used)
print("Final CSV:", outpath)
print("Assigned orders:", int(final_df['plant_code_optimized'].notna().sum()))
print("Unassigned orders:", int(final_df['plant_code_optimized'].isna().sum()))
print("Sum historical cost:", final_df['total_cost_historical'].sum(skipna=True))
print("Sum optimized cost:", final_df['Total_cost_optimized'].sum(skipna=True))
print("Done.")
```

```
Stage 1: Minimizing total cost...
Stage 1 solved. Optimal total cost: 13172055.043414602
Stage 2: Minimize total TPT subject to total cost == Stage1 optimal cost ...
Stage 2 solved. Total TPT: 37511.0
Raw assignments saved (count): 8361
Done. Method used: Preemptive (Stage1 cost + Stage2 tpt)
Final CSV: fyp_outputs_preemptive GP\final_allocation_with_orderinfo_preemptive_gp_.csv
Assigned orders: 8361
Unassigned orders: 0
Sum historical cost: 13341913.028516047
Sum optimized cost: 13172055.043414628
Done.
```

Fig. 5 Outputs of feasible assigned route for the orders using Pre-emptive GP method

According to Fig. 5, the model minimized total cost under the same feasibility constraints as the ILP model in the first stage. The optimal cost obtained in the Stage 1 was equal to the optimal cost of the ILP which is $13,172,055.04, which confirms the fact that the goal programming process was properly aligned with the primary objective.

In the second stage, the model minimizes total delivery time subject to a hard constraint that the total cost must not exceed the optimal cost achieved in Stage 1. Such pre-emptive structure implies realistic managerial priorities, and cost minimization is addressed as the primary objective, and delivery time is optimised only when it does not interfere with cost efficiency. Stage 2 optimization gave a minimum total delivery time of 37,511 aggregated days with a total of all 8,361 orders being allocated to feasible warehouses. Notably, the overall cost was the same in the Stage 1 optimum, which serves to prove that the secondary goal did not interfere with the primary cost-minimization objective.

The findings illustrate the usefulness of the pre-emptive GP approach in integrating the operational performance issues beyond price. The GP solution provides a multi-objective solution that is balanced and is aligning closely with business requirements that maximize both the economic efficiency and the delivery performance. It is of great use especially in logistics where minimizing delivery time can enhance customer satisfaction, compliance and competitiveness of the service level, even when transportation costs remain unchanged.

3.5 Visualization of Warehouse-Port Assignment Patterns Across Optimization Methods

Network visualization offers a familiar way of understanding how all the optimization methods place warehouse, origin ports and destination ports in the data.

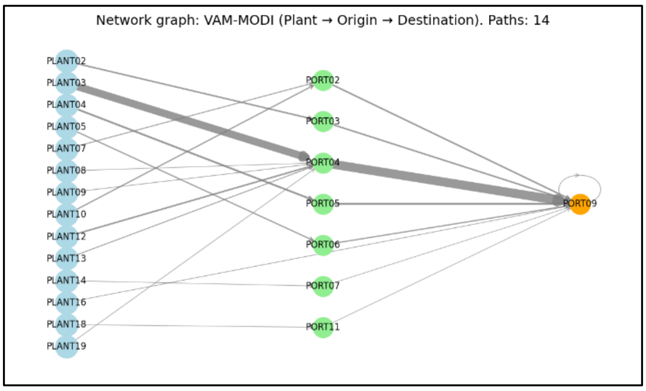
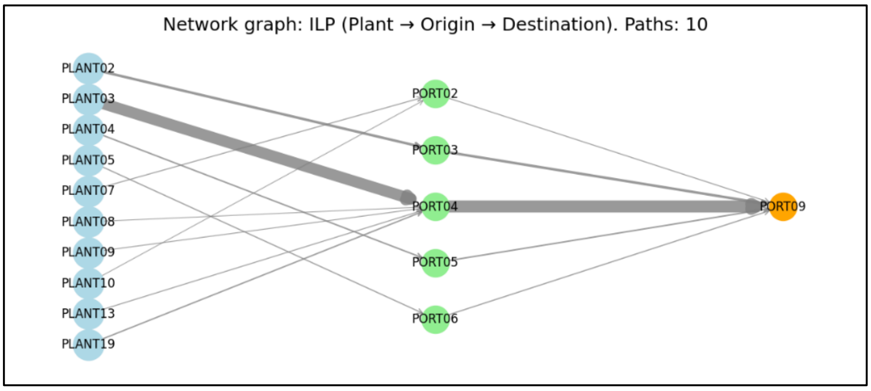
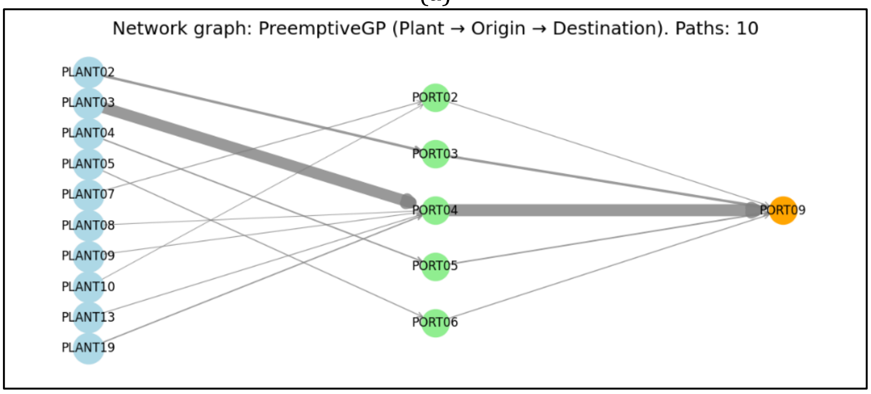


Fig. 6 Network Graph of VAM-MODI Assignments

Fig. 6 shows a VAM-MODI network graph, indicating that there is a pattern of assignment dependent on costs determined by feasibility constraints, product-warehouse restrictions, freight lane availability, and VMI constraints. According to the visualization, a large proportion of feasible assignments are concentrated on the PORT04-PORT09 path that is denoted by the thickest edges in the diagram. This is an indication that VAM-MODI prefers the cheapest origin-destination routes out of the existing routes. In the meantime, most orders have limited routing choices, which leads to natural concentration over strong feasible lanes. The fact that there are relatively large 14 paths evidences that there are many possibilities of warehouses-ports combinations considered by VAM-MODI. The flow distribution is however not even and this indicates limited flexibility in terms of reallocation. This visual pattern is consistent with previous analytical findings that indicate that the set of orders that could be optimized were only 3,583 and that the set of orders converged instantly because of the narrow solution space.



(a)



(b)

Fig. 7 Network Graph Assignments (a) ILP; (b) Pre-emptive GP

The network structure in Fig. 7 represented by the ILP and Pre-emptive GP models is more selective and focused on routing than the VAM-MODI method. Since ILP will minimize the total transportation cost within these feasible combinations of warehouse-order combinations, its result will automatically tend to favour the most globally inexpensive origin destinations paths. This is why ILP network resembles Pre-emptive GP Stage 1 result, and there is a high concentration of flow using the powerful lanes such as PLANT03-PORT04-PORT09 path. The ILP assignment is effective in defining the optimal cost base on which the Pre-emptive GP model is later build.

Pre-emptive GP graph that is visually similar to the ILP result reflects two stage design of the algorithm. At the first stage, the GP model optimizes the minimum possible transportation cost that was obtained using the ILP model; and at the second stage, it optimizes the total delivery time (TPT) without violating this cost optimum. Pre-emptive GP removes high-TPT routes or slightly less efficient one with flexibility, and some lower-priority paths are removed off the network. Consequently, the Pre-emptive GP network becomes concentrated to fast and low-cost routes, and PLANT03-PORT04-PORT09 is the dominating flow of both models.

In general, the consistency of the cost structure is confirmed by the fact that the ILP and Pre-emptive GP graph are similar. The structure of the shipping routes is overall focused, operationally realistic and aligned with the goals of cost minimization and delivery time.

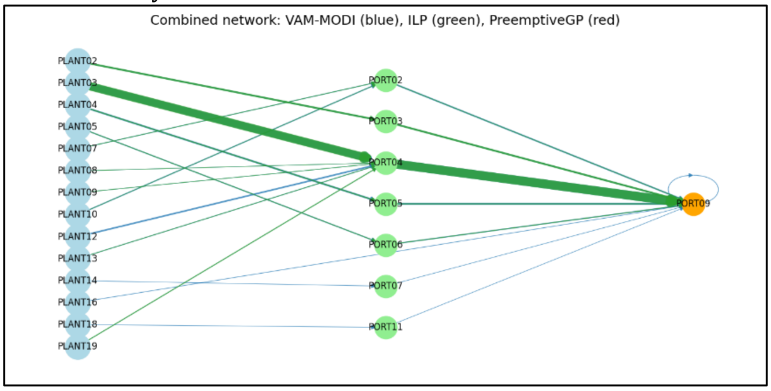


Fig. 8 Combined Network Graph Across All Methods

The combined graph in Fig. 8, which overlays the results of VAM-MODI (blue), ILP (green), and Pre-emptive GP (red), reveals how the three methods align and diverge in their routing structures. The visualization proves that most of the high-volume routes are common to methods, in particular, the PLANT03-PORT04-PORT09 route that is the most prominent in all colour layers. This supports previous numerical results that ILP and Pre-emptive GP have the same cost-optimal solution, and VAM-MODI finds a similar dominating path when running under cost-minimization logic although using a smaller feasible dataset. It can also be observed in the colour overlap that there was a lot of agreement in the results of ILP and Pre-emptive GP. Conversely, the blue VAM-MODI tracks represent rather wider range of paths as there is no multi-objective optimization and capacity modelling, but at lesser levels of intensity. In general, the combined visualization underlines the structural consistency of optimal paths in between algorithms.

4. Conclusion

This study investigated a supply chain logistics problem with the objective of minimizing transportation cost using optimization techniques. Real-world logistics data involving customer orders, warehouses, freight rates and operational constraints were used to formulate and solve the problem.

The findings demonstrate that optimization techniques are practical and effective tools for supporting logistics decision-making under realistic constraints. Based on the results, both Integer Linear Programming (ILP) and the Pre-emptive Goal Programming (GP) approach produced better performance compared to the VAM–MODI method, as they able to allocate all customer orders while satisfying the defined feasibility constraints. The optimization models in this study can be adapted to similar logistics planning problems in manufacturing, retail and distribution sectors. This study does not consider the uncertainty, environmental objectives or dynamic demand conditions. Therefore, future research may extend this work by incorporating these conditions.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Goh Hui Yee, Wan Nor Munirah Ariffin;* ***data collection:*** *Goh Hui Yee;* ***analysis and interpretation of results:*** *Goh Hui Yee, Wan Nor Munirah Ariffin;* ***draft manuscript preparation:*** *Goh Hui Yee, Wan Nor Munirah Ariffin. All authors reviewed the results and approved the final version of the manuscript.*

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