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THE MATHEURISTIC APPROACHES FOR HUB LOCATION OPTIMIZATION IN MULTIMODAL TRANSPORTATION NETWORKS

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ABSTRACT: This research addresses the integration of strategic, tactical, and operational planning within an intermodal hub distribution network. While previous studies have explored network problems with the aim of developing efficient solution methodologies, many rely on simplistic assumptions, often resulting in solutions based on limited variables that may not adequately reflect complexities. To bridge this gap, the study presents a comprehensive approach that incorporates realistic scenarios. Specifically, we formulate a multi-period, multi-allocation, and multi-capacity intermodal hub location problem using a mixed-integer nonlinear programming (MINLP) model with chance constraints. To effectively solve this complex model, a matheuristic algorithm—hybridizing metaheuristics (adaptive simulated annealing and tabu search) with nonlinear programming—is proposed. The algorithm demonstrates high efficiency, accurately solving small- to medium-sized problems while providing high-quality solutions for large-scale instances within limited computational time. Notably, the algorithm reduces average computational time by approximately 50% relative to the optimization approach. Empirical studies utilizing the algorithm examine the effects of variations in service quality and costs on the network structure and overall costs. The study reveals that reducing delivery frequency and increasing lead time influence costs and hub configurations, with economies of scale from diverse vehicle types lowering transportation expenses. However, expanding rail service often yields no benefits in this case, as factors like geography, costs, and operational constraints significantly impact the optimal logistics network design.

Keywords: Location problem, Multimodal transportation, Matheuristics, Adaptive simulated annealing, Tabu search

1. INTRODUCTION

The facility location problem is a critical component of strategic transportation network design, extensively studied across diverse fields to develop efficient solutions for real-world applications. Beyond transportation networks, this problem holds significance in humanitarian relief operations [1–3] and urban mobility planning [4].

In logistics and transportation, hubs enhance economies of scale within many-to-many distribution networks. Previous studies [5–8] show that hubs reduce operational costs, improve service frequency, and bolster resilience against demand variability. However, existing approaches often fail to capture operational complexities, despite the need for reliable long-term strategic decisions. Traditional literature frequently assumes economies of scale occur only on hub-to-hub arcs, represented by a constant discount factor applied to unit transportation costs [5, 9–10]. Serper and Alumur [11] extend this by introducing multiple vehicle types for inter-hub connections, yet this approach has not been comprehensively applied across the entire network.

Focusing on service-level, some researchers [12–13] incorporate service quality to guarantee specific levels, highlighting the importance of such factors in network design. Additionally, Raa [14] proposes inventory cyclic planning for supply chain networks to reduce variability and mitigate the bullwhip effect in uncertain environments. This methodology has been widely applied in production planning, inventory replenishment, vehicle routing, and scheduling, but rarely in hub location problems.

Several researchers have studied hub location problems from varied perspectives [7, 15–17], yet most consider elements such as multiple hub types, modal connectivity costs, service windows, vehicle capacities, delivery lead times, service levels, or demand uncertainty in isolation.

Integrating strategic, tactical, and operational decision-making is critical, as balancing long-, medium-, and short-term horizons is essential to meet demand in dynamic environments. However, this integration creates highly complex optimization problems, difficult to solve analytically. Limited research has explored heuristics and metaheuristics [18–20] for such integrated problems. These methods have shown effectiveness in location-inventory-routing problems, producing optimal or near-optimal solutions with reduced computational effort. Still, their application to hub location problems in multimodal transportation networks remains limited, leaving a research gap.

This study examines the hub location problem in a distribution network managed by a logistics provider. It considers multi-period, multi-allocation, and multi-capacity hub placements, incorporating multimodal transportation with road and rail. Warehouses serve as origins, retail outlets as destinations, and hubs are strategically located in high-potential areas. The network employs various vehicle and container types for different routes.

Key service quality issues include ensuring on-time delivery, managing delivery frequencies, and setting delivery lead times by distance. Cost components comprise hub costs, transportation expenses, inventory costs, and penalties for late deliveries.

The objectives of this research are threefold: first, to propose an efficient method for solving the multimodal hub location problem in distribution networks through a matheuristic algorithm. This hybrid combines adaptive simulated annealing (ASA) and tabu search (TS) with mathematical programming to solve complex, large-scale networks. Second, it investigates how service quality and operating cost variations affect network structure and total costs. Third, it examines the impact of vehicle-type differentiation in realizing economies of scale, moving beyond constant discount factor assumptions, and its influence on network design and costs.

The paper is organized as follows: Section 2 presents the modeling framework and introduces a mixed-integer nonlinear programming (MINLP) model with chance constraints. Section 3 describes the proposed matheuristic algorithm, Section 4 provides a computational study, Section 5 offers empirical analysis of the intermodal hub network, and Section 6 concludes with key insights and directions for future research.

2. RESEARCH SIGNIFICANCE

This study contributes originality by integrating strategic, tactical, and operational perspectives into a unified intermodal hub location model with chance constraints, formulated as a mixed-integer nonlinear program. Unlike previous research with simplifying assumptions, our approach addresses realistic complexities through a novel matheuristic that hybridizes adaptive simulated annealing, tabu search, and nonlinear programming. The framework advances both methodology and practice, delivering efficient, high-quality solutions for large-scale multimodal logistics networks.

3. MODELING FRAMEWORK

This study focuses on resolving a logistics challenge within a multimodal hub distribution network. The hub serves as a critical node for consolidating and dispersing goods from various origins destined for a specific region. The network, managed by a service provider responsible for warehousing and transportation, handles the flow of goods from initial dispatch from warehouses to deliver at retailers and grocery stores, as shown in Fig.1.

The hub's operation begins with receiving goods from origin nodes via trucks. These goods are sorted and consolidated with other items headed to the same destination. They are then transported to another hub within the region by road or multimodal means. Upon arrival at this secondary hub, the goods are segregated and distributed to final destinations using trucks, as shown in Fig.2.

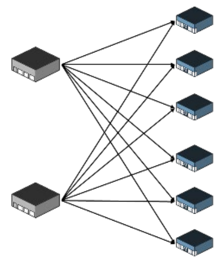

Fig.1 Delivery alternatives from an origin to a destination, an example of direct delivery route.

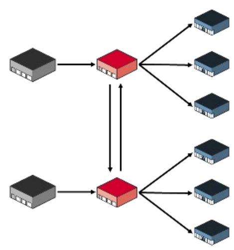

Fig.2 Delivery alternatives from an origin to a destination, an example of delivery route via hub(s).

Economies of scale are achieved in the initial and subsequent transport segments ($i-k$ and $k-l$) by consolidating goods into less-than-truckload (LTL) shipments. This approach optimizes transportation costs by using larger trucks or rail containers. For the final transport segment ($l-j$), full-truckload (FTL) shipments are dispatched using appropriate truck types. Depending on their location and rail freight service availability, hubs can function as either road or multimodal hubs.

This research incorporates multimodal connectivity costs linked to the transportation mode of each hub. Goods handling at multimodal hubs involve specialized equipment and expertise, leading to higher costs than truck-based operations. Delays in synchronizing goods at the hub incur inventory costs during waiting periods.

This study considers three delivery options (as shown in Fig.1 and Fig.2): Direct delivery from origin i to destination j, delivery through a single hub ($i-k-j$), and delivery through two hubs ($i-k-l-j$).

Delivery lead time, measured from the departure from origin i to arrival at destination j, is calculated based on the average travel time for each $i-j$ pair. Considering driver working hours (8 hours per day),

lead times are classified as same-day, next-day, next 2-days, or next 3-days, depending on the $i-j$ route length. Delays in final delivery result in goods being scheduled for the next period, incurring penalties for the service provider.

To ensure service within a specified lead time with a certain probability, chance-constrained programming or probabilistic constraints are employed. The confidence level $\boldsymbol{\alpha}$ indicates the likelihood of meeting customer demand within the designated time frame, defined as the probability of on-time delivery in this context.

3.1 Model Formulation

Consider a node set $\boldsymbol{N}=\boldsymbol{N_o}\cup\boldsymbol{N_c}\cup\boldsymbol{N_h}$, where $\boldsymbol{N_o}$, $\boldsymbol{N_c}$ and $\boldsymbol{N_h}$ denote the set of nodes that correspond to origins, destinations, and potential hubs, respectively. Apart from having different hub types (road hub and intermodal hub), we also consider multiple sizes of the hub: small, medium, and large, so let $\boldsymbol{S}$ be a capacity set of the hub. To reduce the number of parameters and variables indices that relate to different vehicle types and transportation modes, we merge the indices of vehicle types in each transportation mode into one index. Then let $\boldsymbol{V}=\boldsymbol{V_{ro}}\cup\boldsymbol{V_{ra}}$ be a set of vehicle types for both road and rail transportation, where $\boldsymbol{V_{ro}}$ and $\boldsymbol{V_{ra}}$ denote the set of road vehicle types and rail container types, respectively. Furthermore, we denote $\boldsymbol{T}$ as a set of a finite planning horizon. The mathematical formulation of the Mixed-Integer Nonlinear Programming (MINLP) model is established utilizing the provided notation and mathematical expressions to define the optimization problem and decision variables as follows.

Parameters:

ξ_{ijt}	Uncertain demand at node $j\in N_c$ that originated from node $i\in N_o$ in period $t\in T$.
f_s	Setup and operating costs of hub size $s\in S$.
m_s	Multimodal connectivity cost for multimodal hub size $s\in S$.
c_{ijv}	Transportation cost per shipment from warehouse $i\in N_o$ to customer $j\in N_c$ of vehicle $v\in V$.
h	Hub inventory cost per unit per period.
g	Tardiness penalty cost per unit per period.
q_s	Capacity of hub size $s\in S$.
κ_v	Capacity of vehicle type $v\in V$.
R_{kl}	Inter-hub route between hub k and hub l that operates rail freight service
γ_{iklj}	Total service time requirements for hub-based shipments from warehouse $i\in N_o$ to customer $j\in N_c$ through hub $k\in N_h$ and $l\in N_h$.
Γ_{ij}	Delivery lead time between warehouse $i\in N_o$ and customer $j\in N_c$.
α	Level of service (on-time delivery).
ρ	Delivery frequency (i.e., every day, five times a week, three times a week, or once a week).
M	A sufficiently large number.

Decision variables:

$z_{ks}=$	1 if a road hub size $s\in S$ opens at node $k\in N_h$; otherwise, 0.
$\hat{z}_{ks}=$	1 if the opened road hub size $s\in S$ is operated as a multimodal hub at node $k\in N_h$; otherwise, 0.
$r_{iklj}=$	1 if path $i-k-l-j$ can be operated ($z_{ks}=1$ and $\gamma_{iklj}\le\Gamma_{ij}$); otherwise, 0.
$p_{jt}=$	1 if customer $j\in N_c$ is scheduled to be delivered on period $t\in T$; otherwise, 0.
$d_{ijt}=$	Flow that delivered from warehouse $i\in N_o$ to customer $j\in N_c$ in period $t\in T$ within the given lead time.
$\delta_{ijt}=$	Late flow in previous periods that delivered to customer $j\in N_c$ in period $t\in T$.
$\omega_{ijt}=$	Total flow delivered between warehouse $i\in N_o$ and customer $j\in N_c$ in period $t\in T$.
$x_{ijvt}=$	An amount of flow delivered from warehouse $i\in N_o$ to customer $j\in N_c$, by vehicle $v\in V$, in period $t\in T$.
$y_{ijvt}=$	A number of shipments delivered from warehouse $i\in N_o$ to customer $j\in N_c$, by vehicle $v\in V$, in period $t\in T$.
$\boldsymbol{u_{kt}}=$	Inventory at hub $\boldsymbol{k}\in\boldsymbol{N_h}$ in period $\boldsymbol{t}\in\boldsymbol{T}$.

Objective function (Eq. 1) is to minimize the total logistics costs, including multiple cost components: fixed and variable costs associated with the establishment and operation of logistics hubs. Additional costs consist of intermodal connectivity when goods are transferred between different transportation modes. Transportation costs are incurred across several transport segments. Hub inventory costs involve storing goods at the hubs, while tardiness penalty costs are incurred for delayed deliveries.

Model formulation (MINLP):

minimize

$$\sum_{s\in S}\sum_{k\in N_h} f_s z_{ks} + \sum_{s\in S}\sum_{k\in N_h} m_s \hat{z}_{ks} + \sum_{t\in T}\sum_{v\in V_{ro}}\sum_{k\in N_h}\sum_{i\in N_o} c_{ikv} y_{ikvt} + \sum_{t\in T}\sum_{v\in V}\sum_{l,k\in N_h} c_{klv} y_{klvt} + \sum_{t\in T}\sum_{v\in V_{ro}}\sum_{j\in N_c}\sum_{l\in N_h} c_{ljv} y_{ljvt}$$
$$+\sum_{t\in T}\sum_{v\in V_{ro}}\sum_{j\in N_c}\sum_{i\in N_o} c_{ijv} y_{ijvt} + h\sum_{t\in T}\sum_{k\in N_h} u_{kt} + g\sum_{t\in T}\sum_{j\in N_c}\sum_{i\in N_o} \delta_{ijt} \quad (1)$$

subject to

$$\sum_{t\in T} p_{jt} = \rho \qquad \forall j\in N_c \quad (2)$$

$$Pr\left(d_{ijt} = \xi_{ijt} \qquad \forall t\in T, i\in N_o, j\in N_c\right) \geq \alpha \quad (3)$$

$$\delta_{ijt} = \left(\xi_{ijt} - d_{ijt}\right) + \delta_{ijt-1}\left(1-p_{jt}\right) \qquad \forall t\in T, j\in N_c, i\in N_o \quad (4)$$

$$\omega_{ijt} = \left(d_{ijt} + d_{ijt-1}(1-p_{jt-1})\right) p_{jt} + \delta_{ijt-1} p_{jt} \qquad \forall t\in T, j\in N_c, i\in N_o \quad (5)$$

- Flow conservation constraints

$$\sum_{v\in V_{ro}}\sum_{k\in N_h} x_{ikvt} + \sum_{v\in V_{ro}}\sum_{j\in N_c} x_{ijvt} = \sum_{j\in N_c} \xi_{ijt} \qquad \forall t\in T, i\in N_o \quad (6)$$

$$\sum_{v\in V_{ro}}\sum_{l\in N_h} x_{ljvt} + \sum_{v\in V_{ro}}\sum_{i\in N_o} x_{ijvt} = \sum_{i\in N_o} \omega_{ijt} \qquad \forall t\in T, j\in N_c \quad (7)$$

$$\sum_{v\in V_{ro}} x_{klvt} + R_{kl}\sum_{v\in V_{ra}} x_{klvt} = \sum_{v\in V} x_{klvl} \qquad \forall t\in T, k,l\in N_h, k\neq l \quad (8)$$

- Hub and delivery route constraints

$$\sum_{v\in V_{ro}}\sum_{i\in N_o} x_{ikvt} + u_{kt-1} \leq \sum_{s\in S} q_s z_{ks} \qquad \forall t\in T, k\in N_h \quad (9)$$

$$\sum_{v\in V}\sum_{k\in N_h} x_{klvt} + u_{lt-1} \leq \sum_{s\in S} q_s z_{ls} \qquad \forall t\in T, l\in N_h \quad (10)$$

$$\sum_{t\in T} x_{klvt} \leq M\sum_{s\in S} \hat{z}_{ks} \qquad \forall v\in V_{ra}, k,l\in N_h, k\neq l \quad (11)$$

$$\sum_{t\in T} x_{klvt} \leq M\sum_{s\in S} \hat{z}_{ls} \qquad \forall v\in V_{ra}, k,l\in N_h, k\neq l \quad (12)$$

$$\sum_{s\in S} z_{ks} \leq 1 \qquad \forall k\in N_h \quad (13)$$

$$\hat{z}_{ks} \leq z_{ks} \qquad \forall s\in S, k\in N_h \quad (14)$$

$$r_{iklj} \geq \sum_{s\in S} z_{ks} + \sum_{s\in S} z_{ls} - 1 \qquad \forall j\in N_c, k,l\in N_h, i\in N_o \quad (15)$$

$$r_{iklj}\gamma_{iklj} \leq \Gamma_{ij} \qquad \forall j\in N_c, k,l\in N_h, i\in N_o \quad (16)$$

- Vehicle related constraints

$$x_{ikvt} \leq \kappa_v y_{ikvt} \qquad \forall t\in T, v\in V_{ro}, i\in N_o, k\in N_h \quad (17)$$

$$x_{klvt} \leq \kappa_v y_{klvt} \qquad \forall t\in T, v\in V, k,l\in N_h \quad (18)$$

$$x_{ljvt} \leq \kappa_v y_{ljvt} \qquad \forall t\in T, v\in V_{ro}, l\in N_h, j\in N_c \quad (19)$$

$$x_{ijvt} \leq \kappa_v y_{ijvt} \qquad \forall t\in T, v\in V_{ro}, i\in N_o, j\in N_c \quad (20)$$

- Inventory related constraints

$$u_{kt} = u_{kt-1} + \sum_{v\in V_{ro}}\sum_{i\in N_o} x_{ikvt} - \sum_{v\in V}\sum_{l\in N_h} x_{klvt} \qquad \forall t\in T, k\in N_h \quad (21)$$

$$u_{lt} = u_{lt-1} + \sum_{v\in V}\sum_{k\in N_h} x_{klvt} - \sum_{v\in V_{ro}}\sum_{j\in N_c} x_{ljvt} \qquad \forall t\in T, l\in N_h \quad (22)$$

$$d_{ijt}, \delta_{jt}, \omega_{ijt}, x_{ijvt}, u_{kt} \geq 0 \qquad \forall t\in T, v\in V, j\in N_c, k,l\in N_h, i\in N_o \quad (23)$$

$$z_{ks}, \hat{z}_{ks}, r_{iklj}, p_{jt} \in \{0,1\} \qquad \forall t \in T, s \in S, j \in N_c, k,l \in N_h, i \in N_o \tag{24}$$

$$y_{ijvt} \in \mathbb{N} \qquad \forall t \in T, v \in V, j \in N_c, k,l \in N_h, i \in N_o \tag{25}$$

Objective function (Eq. 1) is to minimize the total logistics costs, including multiple cost components: fixed and variable costs associated with the establishment and operation of logistics hubs. Additional costs consist of intermodal connectivity when goods are transferred between different transportation modes. Transportation costs are incurred across several transport segments. Hub inventory costs involve storing goods at the hubs, while tardiness penalty costs are incurred for delayed deliveries.

Delivery frequency constraint (Eq. 2) ensures that the delivery schedule for each customer adheres to a predefined frequency and compliance with that schedule. Service level constraint (Eq. 3) ensures that the delivery service level meets a specified threshold (denoted by α), accommodating demand uncertainty. For example, a 95% service level means that 95% of deliveries must be on time. Late flow (Eq. 4) calculates the quantity of goods delayed for delivery within a given period. If there are delays, the late flow is incorporated into the subsequent period's delivery schedule. Total flow calculation (Eq. 5) determines the total flow of goods delivered to a customer within a specific period. It includes the current period's demand, undelivered goods from previous periods due to non-delivery days, and late flows from preceding periods. Flow conservation constraints (Eq. 6-8) ensure the accurate accounting of goods flow within the network. Eq. 6 ensures that the total goods leaving the origins match the total goods to be delivered. Eq. 7 ensures that each destination receives the correct quantity of goods from the origins. Eq. 8 stipulates that inter-hub shipments via rail occur only on routes with rail services.

Hub capacity constraints (Eq. 9-10) ensure that the total inbound flow and inventory at each hub do not exceed the hub's capacity at the start of each period. Intermodal hub constraints (Eq. 11-12**)** determine whether a hub operates as an intermodal hub based on its handling of rail shipments, ensuring that hubs with intermodal capabilities meet specific conditions. Hub selection and size constraints (Eq. 13-14) ensure that only one size of hub is selected at a given location and the hub can operate as a multimodal hub or not.

Delivery route validation (Eq. 15-16) ensures that the total service time for routes through hubs does not exceed permissible lead times, marking validated routes as usable. Vehicle capacity constraints (Eq. 17-20) ensure that the flow of goods along any route does not exceed the vehicle's capacity. Inventory holding constraints (Eq. 21-22) ensure consistency in inventory levels across planning periods.

Variable constraints (Eq. 23-25) define the binary and non-negativity conditions for specific variables, ensuring that elements such as the number of shipments or the status of routes and hubs comply with required conditions.

To solve the model, we first reformulate the stochastic MINLP model as a stochastic mixed-integer programming (MIP) model because Eq. (4) and Eq. (5) contain the products of binary and continuous variables. Furthermore, the demand $\boldsymbol{\xi_{ijt}}$ is unpredictable, which is a normal distributed random variable with mean $\boldsymbol{\mu_{ijt}}$ and standard deviation $\boldsymbol{\sigma_{ijt}}$. The deterministic form of the chance constraints, Eq. (3), can be rewritten by applying the cumulative distribution function (CDF) of $\boldsymbol{\xi_{ijt}}$ as follows:

$$d_{ijt} = \mu_{ijt} + z_{(1-\alpha)}\sigma_{ijt} \quad \forall t \in T, i \in N_o, j \in N_c \tag{26}$$

where $\boldsymbol{z_{(1-\alpha)}}$ is a critical value of the standard normal distribution at the confidence level $\boldsymbol{\alpha}$.

This process involves finding a critical value $\boldsymbol{z_{(1-\alpha)}}$, which is a standard normal variable corresponding to a confidence level $\boldsymbol{\alpha}$. The value $\boldsymbol{z_{(1-\alpha)}}$ represents the threshold such that the probability of falling below this value is $\boldsymbol{\alpha}$. By leveraging the inverse of the standard normal CDF, we determine $\boldsymbol{z_{(1-\alpha)}}$ (for example, $\boldsymbol{z_{(0.95)}}$ approx. 1.645 for 95% confidence). Incorporating this, the chance constraint can be rewritten as a deterministic constraint that ensures, with probability $\boldsymbol{\alpha}$, the demand does not violate the model's conditions. This approach effectively converts the stochastic constraint into a more manageable form, facilitating subsequent optimization.

Therefore, the problem can be solved by using the following MIP formulation with service-level constraints:

Minimize Eq. (1),
subject to Eq. (2), (4) - (26).

4. MATHEURISTIC

The proposed solution approach involves a matheuristic algorithm amalgamating adaptive simulated annealing (ASA), tabu search (TS) metaheuristics, and a nonlinear programming (NLP) model (ASATS&NLP). ASATS metaheuristics serve as the master stage, including the exploration process within defined neighborhood boundaries, while the NLP is the slave stage, fine-tuning solutions provided by the master. Binary variables are initially optimized at the master level before feeding into the slave level. The algorithm iteratively refines solutions by communicating between the master and slave stages until termination criteria are met, optimizing the overall algorithmic process.

4.1 Master Stage - Adaptive Simulated Annealing and Tabu Search (ASATS)

The proposed matheuristic algorithm, ASATS, addresses the multimodal hub network problem through a strategic integration of ASA and TS. The algorithm dynamically adjusts temperature based on cost function variations and employs Tabu Search to enhance solution diversity. To ensure scalability and robustness in handling large-scale scenarios, key termination parameters, including maxVisit, maxNonImp, and maxRound, are introduced for algorithmic flexibility and preventing local optima entrapment. The algorithm's sequential execution involves initializing delivery schedules and hub selections, validating hub-based routes, calling the slave algorithm with fixed parameters, adjusting delivery flows based on NLP solutions, recalculating costs, and iterative evaluation until termination criteria are met. If the termination conditions are not satisfied, the algorithm regenerates an initial solution and applies to a neighborhood search operator. This iterative process continues until the termination criteria are met, optimizing the multimodal hub network solution.

Neighborhood search mechanism

Six distinct neighborhood search operators are introduced to enhance optimization efficiency in the study. These operators, such as "Swap," "Add," "Remove," "ImHub," "Size," and "SwapDay," target hub locations, sizes, multimodal operations, and delivery schedules. By iteratively applying these operators and updating the tabu list, diverse solutions are generated, enabling thorough exploration of the multimodal hub network.

4.2 Slave Stage – Nonlinear Programming Model

The NLP model, derived from the MINLP model, differs in removing hub-related constraints (Eq. 13-16) and vehicle capacity constraints (Eq. 17-20), focusing on flow-unit transport costs for initial flow calculations.

Model formulation (NLP):

Minimize

$$\sum_{k\in N_h}\sum_{s\in S} f_s z'_{ks} + \sum_{k\in N_h}\sum_{s\in S} m_s \hat{z}'_{ks} + \sum_{t\in T}\sum_{v\in V_{ro}}\sum_{i\in N_o}\sum_{k\in N_h}\frac{c_{ikv}}{\kappa_v}x'_{ikvt}$$
$$+\sum_{t\in T}\sum_{v\in V}\sum_{k,l\in N_h}\frac{c_{klv}}{\kappa_v}x'_{klvt} + \sum_{t\in T}\sum_{v\in V_{ro}}\sum_{l\in N_h}\sum_{j\in N_c}\frac{c_{ljv}}{\kappa_v}x'_{ljvt}$$
$$+\sum_{t\in T}\sum_{v\in V_{ro}}\sum_{i\in N_o}\sum_{j\in N_c}\frac{c_{ijv}}{\kappa_v}x'_{ijvt} + h\sum_{t\in T}\sum_{k\in N_h}u_{kt} + g\sum_{t\in T}\sum_{i\in N_o}\sum_{j\in N_c}\delta_{ijt} \quad (27)$$

subject to Eq. (2), (4) – (12), (21) – (23), (26).

Then, all solutions that were determined during this phase are returned to the master phase.

5. COMPUTATIONAL STUDY

The computational study assesses the proposed matheuristic algorithm against optimal solutions, measuring optimality gap and computational time. Five datasets representing varying distribution network sizes are created, incorporating different origin-destination pairs, candidate hubs, truck types, and container varieties, over a seven-period planning horizon. Each dataset comprises nine problem instances with varied service levels and delivery frequencies, totaling 45 instances for evaluation. Origin-destination flows follow a uniform distribution, while costs related to hub setup, operations, and transportation are obtained from a logistics provider, including multimodal connectivity costs equivalent to 15% of total hub expenses.

5.1 Computational Results

The data sets for computational study are provided in Table 1. The computational study utilized Intel Xeon E5-2620 v3 2.60 GHz CPUs to compare MINLP solutions obtained using Xpress within a 24-hour timeframe to those derived from the proposed matheuristics (ASATS&NLP).

Table 1. Data sets for computational study

Data set	Number of origin nodes ($\boldsymbol{i}$)	Number of destination nodes ($\boldsymbol{j}$)	Number of potential hubs ($\boldsymbol{k}$)
1	2	20	5
2	3	40	10
3	4	60	15
4	5	80	20
5	6	100	25

While Xpress achieved feasible or near-optimal solutions for 38 of 45 instances, producing a 6.44% average gap with lower bounds, ASATS&NLP yielded no optimal solutions but achieved comparative optimality with an average gap of

5.24%. Notably, ASATS&NLP significantly reduced computational times, completing tasks within approximately 8 hours on average, contrasting with Xpress's 16-hour average for solvable instances within the specified timeframe. Fig.3 and Fig.4 show the proposed algorithm's efficiency enhancements in terms of solution optimality and computational time compared to Xpress across various instances, respectively.

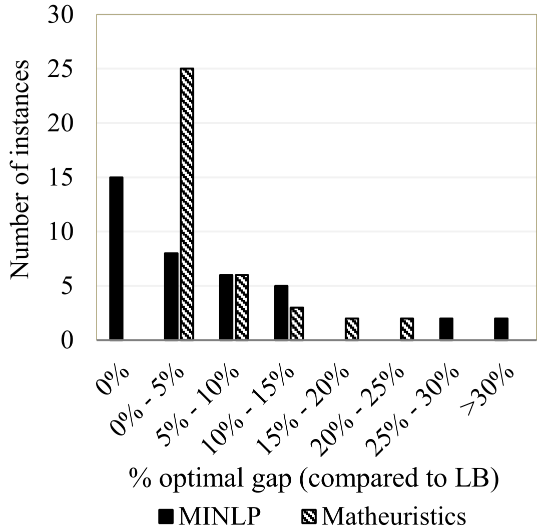

Fig.3 Percent optimal gap of MINLP's and Matheuristic (ASATS&NLP)'s solution values compared to LB.

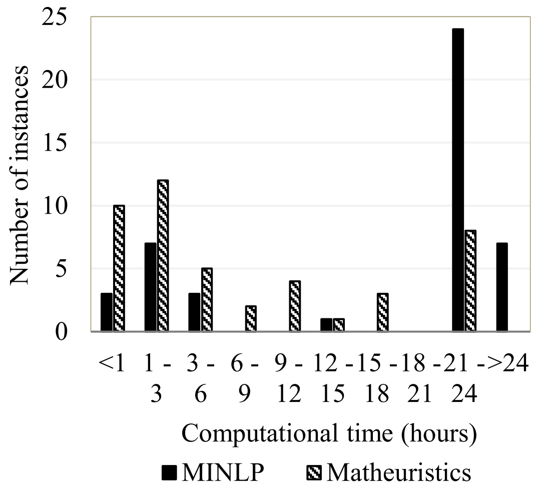

Fig.4 Computational time compared between MINLP and Matheuristic (ASATS&NLP).

6. EMPIRICAL STUDY

This section aims to investigate the impacts of variations in service quality, costs, and vehicle types on the network structure and total costs through generated logistics data based on Thailand's rail freight services. This dataset concerns two warehouses that distribute products to 96 demand nodes nationwide, one warehouse located in the West and the other in the East.

Twenty potential hub locations were identified based on areas with high potential and high demand density: four locations in Bangkok and vicinity, five locations in central area, one location in eastern, three locations in north-eastern, three locations in northern, and four locations in southern. Four truck types for road transportation and three container types for rail transportation were utilized. Each vehicle type differs in capacity, loading/unloading times, and speeds, as specified by the company. Due to the limitations of rail freight services in Thailand, only available rail freight routes were considered.

6.1 Experimental Design

This study investigates the effects of various factors on intermodal hub networks, specifically focusing on service level (α), delivery frequency (ρ), delivery lead time (Γ), and intermodal connectivity cost (m_s). Of these, the first three factors pertain to service parameters, while the last relates to cost. The service level is evaluated at four probabilities of on-time delivery: 100%, 97%, 95%, and 90%. Delivery frequency is analyzed across four intervals: daily, five times per week, three times per week, and once per week. Service lead time is categorized into three levels: normal delivery, extended delivery, and immediate delivery (no lead time).

Table 2. Factors

Factors		Levels
Service quality	Service level (α)	{100%, 97%, 95%, 90%}
	Delivery frequency (ρ)	{7, 5, 3, 1}
	Delivery lead time (Γ)	{Normal, Extended, None}
Cost	Multimodal connectivity cost (m_s)	{15%, 10%, 5%, 0% }
Transportation	Variation of vehicle type	{1T, 2T1C, 3T2C, 4T3C }

To determine the impact of intermodal connectivity cost on network structure, four levels of intermodal costs are considered, set at 15%, 10%, 5%, and 0% of the hub setup and operating costs. In addition to service and cost factors, economies of scale are examined through different transport fleet configurations rather than varying constant discount factors. The fleet variations include: a single truck type for all routes (1T), two truck types and one container type (2T1C), three truck types and two container types (3T2C), and four truck types and three container types (4T3C). All the factors studied are outlined in Table 2.

6.2 Results and Discussions

The first investigation examines how the probability of on-time delivery impacts on total costs. As shown in Fig.5, higher service levels lead to increased total costs, particularly with daily deliveries or deliveries of five times per week, due to higher tardiness penalty costs. Conversely, for lower delivery frequencies, total costs decrease as service levels fall. This decrease is because consolidating deliveries to fewer days significantly lowers transportation costs, which outweigh the increased penalty costs due to economies of scale. However, total costs may rise if customers impose higher penalty fees.

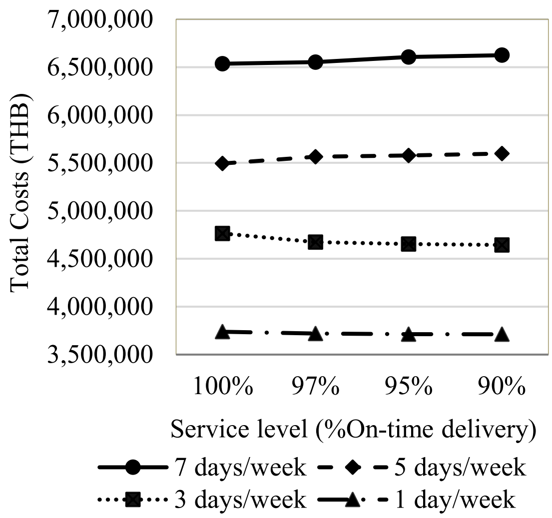

Fig.5 Effects of different service quality on total costs.

The second factor analyzed is the impact of delivery frequency on total costs, as shown in Fig. 5. Reduced delivery frequency lowers total costs due to economies of scale achieved through flow consolidation. Although hub inventory costs rise, the savings in transportation costs are substantially greater. In the scenario with 100% on-time delivery, reducing delivery frequency shifts some commodities from direct delivery $(i - j)$ to being routed through the hub network. Transportation costs are the dominant factor in this hub distribution network, and the economies of scale associated with fewer deliveries allow for using larger vehicle types, thus significantly reducing total transportation costs.

This analysis highlights the trade-off between service quality and total costs within the hub network. Regarding hub locations, the study found that only one small hub is established in all scenarios. Changes in on-time probabilities do not affect hub locations, whereas changes in delivery frequency do.

This section analyzes the impact of delivery lead time on the hub network. The study considers three service lead time scenarios: normal, extended, and no lead time restrictions. As indicated in Table 3, delivery lead time significantly affects both total costs and the hub network configuration under conditions of 100% on-time delivery and daily delivery schedules. Total costs slightly decrease as delivery lead times become more flexible. Notably, extending the delivery lead time does not influence the use of two-hub routes, suggesting that intermodal transportation usage remains consistent. However, with extended delivery times, the frequency of single hub usage and the number of hubs established both increases.

Table 3. Total costs and percentage of delivered flow at different delivery lead-time.

	Delivery lead time		
	Normal lead time	Extended lead time	No lead time
Total costs (THB)	6,535,632	6,321,505	6,256,277
% Flow delivery			
Direct route	87.42%	84.21%	83.80%
Single-hub route	12.58%	15.79%	16.20%
Two-hub route	0.00%	0.00%	0.00%

The study explored four levels of intermodal connectivity cost: 15%, 10%, 5%, and 0% of the hub setup and operating costs. Reducing intermodal connectivity costs does not affect total costs or the hub network structure. This suggests that most deliveries are made via direct or single hub routes.

The study then explores the economies of scale by differentiating between vehicle types instead of using traditional constant discount factors. Four-fleet variations are examined. As illustrated in Fig.6, using multiple vehicle sizes significantly reduces total costs.

Table 4 shows that when only one truck type or a combination of two truck types with one container type is used, deliveries are made directly from origin to destination. However, a notable observation arises when three truck types and two container types are employed: in this scenario, a two-hub route is utilized, with 100% of inter-hub transportation conducted via intermodal means.

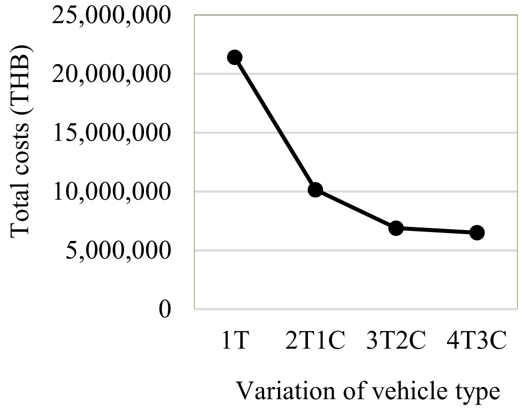

Fig. 6 Total costs at different variation of vehicle type.

Table 4. Percentage of delivered flow at different variations of vehicle type

Delivery routes	Number of vehicle types			
	1T	2T1C	3T2C	4T3C
Direct route	100%	100%	56.11%	87.42%
Single-hub route	0.00%	0.00%	0.41%	12.58%
Two-hub route	0.00%	0.00%	43.48%	0.00%

7. CONCLUSIONS

This study makes several significant contributions beyond the development of a computationally efficient algorithm for large-scale logistics network optimization. First, it introduces a novel matheuristic algorithm that synergistically integrates adaptive simulated annealing (ASA) and tabu search (TS) within a nonlinear programming (NLP) framework. While prior research [21-22] has demonstrated the effectiveness of individual metaheuristics such as SA and TS in solving combinatorial problems, this approach advances the methodological frontier by combining these techniques into a cohesive, scalable framework capable of effectively managing complex logistics networks. This integration results in substantial reductions in computational time, enabling the attainment of near-optimal solutions within practical timeframes—an essential requirement in real-world logistics applications.

Second, the research contributes to the understanding of how advanced metaheuristic algorithms can be effectively applied within operational contexts characterized by large problem sizes and complex constraints. Unlike existing approaches that primarily emphasize algorithmic efficiency in abstract models using theoretical or limited datasets [23-24], this study demonstrates tangible improvements in solution quality and computational speed. Empirical results reveal that the proposed algorithm reduces the solution gap by over 17% and terminates the search process in nearly half the time required by traditional mixed-integer nonlinear programming (MINLP) methods. Such reductions in optimality gaps translate into enhanced cost-efficiency in logistics operations by minimizing waste stemming from suboptimal decision-making. This underscores the inherent trade-off between solution optimality and computational efficiency, a consideration discussed in the literature [17].

Third, aligned with the suggestions of previous research [16, 24], this research provides a comprehensive empirical analysis of the influence of various operational factors—such as delivery frequency, lead times, vehicle heterogeneity, and infrastructure investments—on network configurations and total costs. Grounded in a case study based on logistics data from Thailand, these insights demonstrate how strategic decisions, and external variables impact the logistics network structure and overall cost efficiency. The findings indicate that changes in delivery frequency substantially affect total costs, while variations in lead times significantly influence hub network configurations. Moreover, employing multiple vehicle types across the entire network—rather than relying solely on constant discount factors on inter-hub arcs—yields economies of scale that dramatically reduce transportation costs. Notably, the case study shows that operating an intermodal hub network can sometimes be more costly than a road-only network. Additionally, expanding rail freight services across the network does not invariably produce expected cost savings, emphasizing the importance of contextual factors such as geographical constraints and demand patterns. These insights offer practical guidance for logistics planning and policymaking.

Finally, the study underscores the practical significance and scalability of the proposed framework, establishing it as a valuable tool for optimizing large and complex multimodal networks under real operational constraints. While this research primarily targets road and rail transportation, the framework provides a foundation for future development into dynamic, multimodal, and environmentally sustainable logistics models. Incorporating emerging technologies, such as machine learning and advanced data analytics, promises to further expand the contribution, addressing contemporary challenges related to efficiency, sustainability, and resilience in logistics operations.

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