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An efficient environmentally friendly transportation network design via dry ports: a bi-level programming approach

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Abstract

This paper addresses the problem of deciding the locations of dry ports by providing an intermodal rail-road p-hub median model, adopting a bi-level programming approach. In the proposed model, direct transportation and shipment between nodes are allowed instead of transportation merely through the hubs. In the bi-level programming approach, at the top level, the government/authority will decide the locations of the dry ports to increase the utilization of railways and minimize the construction and maintenance costs of dry ports as one of the important transportation infrastructures. Freight forwarders who are considered at the lower level aim to minimize the shipping costs by deciding the optimal shipping routes. A matheuristic approach based on the Genetic Algorithm (GA) is proposed to solve the given problem. Numerical analysis confirms that the proposed algorithm can provide satisfactory solutions for large instances where commercial solvers are not capable of finding the near optimal solutions in a reasonable computational time. Finally, the experimental results show that using the proposed transportation network model can decrease the total transportation costs along with significantly reduction of air pollution.

Keywords: Dry ports; Bi-level programming; Air pollution; Direct connection; Matheuristic algorithm.

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1. Introduction

The maritime transportation system plays a prominent role in international business. With the lower handling cost and higher shipping capacity, the maritime transportation system offers significant advantages over air transportation systems. However, in recent years, the cargo usage rates and container traffic have also increased, causing a heavy burden on sea ports' space for loading/unloading, traffic disruption, thus a significant increase in the cargo dwelling times. According to UNCTAD's report, in 2019, the growth of maritime trade was 0.5%. Also, the growth of global traffic in the field of containers in ports has been 2%. One of the most effective solutions to alleviate the problem in the seaport, when its expansion is often infeasible, is the construction of dry ports in the hinterland.

Dry ports are typically constructed in a landlocked area, interconnected directly to a seaport via road or rail transportation systems, and thus often operate as a center of intermodal rail-road logistics. Acting as the inland terminals, the dry port's functions are similar to that of a seaport. As a trans-shipment facility for cargo export, import, and transit, dry ports are equipped with facilities to manage transactional operations like billing, coordination between importers and exporters, as well as customs services.

Dry ports act as the hubs, connecting all origin/destination cities, also known as the nodes. In some countries, several dry ports may be connected one another forming a large and complex logistic network. The use of hub-based logistic networks has many benefits, notably the consolidation of cargo shipment, leading to reduced transportation costs, traffic, and air pollution.

When constructing a dry port, one critical concern is deciding its location within a transportation network. The location decision is a long-term and strategic one, considering all aspects prior to any investment commitments. These aspects include the consideration of connecting the cities to the dry port as their hub. Deciding the location of the hub and the allocation of the cities (nodes), the cargo traffic volume between the nodes, time constraints of cargo delivery from/to nodes, and all the transportation costs within the network imply an optimization problem.

Postal companies, telecommunication and airline industries are the traditional adopters of hub and spoke networks, though other industries such as maritime and freight transportation have now caught up (Farahani et al., 2013).

In this section, firstly, the review papers in the field of hub and spoke network that were published from 1994 to 2021 have been investigated: O'Kelly and Miller (1994) presented a

structured review of hub network design problems up to 1993 and provided some examples of different network design models. Alumur and Kara (2008) discussed a review of hub location problems prior to early 2007. They classified hub location models considering over one hundred papers. Farahani et al. (2013) provided a review of different types of hub location problems from 2007 up to 2012 by investigating over one hundred and fifty papers. Basallo-Triana et al. (2021) reviewed over one hundred papers about intermodal network design in the hub location problem; furthermore, they provided some directions for the future study based on the modeling of intermodal transportation systems.
Moreover, in some fields of the hub and spoke network, many papers have been published over the past years. Some of the most cited articles are considered here, too:
Contreras et al. (2011) investigated an un-capacitated hub location problem with uncertain demand and transportation cost. Survey performed by Vieira and Luna (2016) provided an outline for designing solution techniques, modeling approaches and applications of the logistics hub location problems. Mahmutogullari and Kara (2016) explored a hub location problem in a competitive condition. In their problem, the market is considered to be a duopoly. Musavi and Bozorgi-Amiri (2017) studied a sustainable hub location problem. They considered product perishability and amount of CO2 emission in a food supply chain. Dukkanci et al. (2019) considered 'green' issues as part of HLP's objective to reduce CO2 emission whilst maintaining the high service level. Mohammadi et al. (2019) investigated the effect of uncertainties on deliveries by studying the single allocation hub location problem. They aimed to minimize the maximum transportation time and the total cost of the network. Monemi et al. (2021) developed a hub location problem in multi-period condition which deals with the distribution of humanitarian aid in war-ridden areas. Rostami et al. (2021) presented a two-stage single allocation hub location problem considering allocations as second stage decision. Wu et al. (2022) presented hub location- allocation routing problem to design express service system. In their network, the flows of parcels and mails are exchanged via local tours and hubs.

In order to lower the transportation cost, in HLP, the goods are shipped from their origin to destination through the hub, instead of direct connections between origin and destination nodes (O'Kelly and Miller, 1994). However, it is sometimes necessary to have a direct connection between nodes if it is proven more efficient and cost effective (Ishfaq and Sox, 2010). De Sa´ et al. (2018) considered the possibility of incorporating the direct connections between nodes in their mathematical model, while Choi et al. (2018) examined a hub-and-spoke network using the same assumption.

Tsao and Thanh (2019) proposed a multi-objective programming approach for the sustainable network design of a dry port, aiming to minimize the cost, reduce environmental impacts and address social issues. Wei and Dong (2019) prepared a bi-objective mixed integer programming model to connect the maritime and inland networks in cross-border logistics via dry ports. Qiu and Lee (2019) studied the transportation pricing in a dry port using the Stackelberg game to formulate their problem where the dry port developer and shipper are considered the leader and follower, respectively. Facchini et al. (2020) applied a non-linear mathematical model to identify the number of containers in a seaport and dry port to minimize the running cost as well as carbon impact costs. Fazi et al. (2020) designed a network consisting of a dry port and several seaport terminals to avoid over trucking and find the best allocation of containers to barege.

The previous studies show that different decision-making methods have been considered for determining the location of dry ports. Also, some mathematical models have been developed to optimize the location and allocation of dry ports. However, it can be observed that in most studies, only one level of decision maker has been considered, whereas in reality more than one decision maker is in different levels. In the transportation network design, there are typically two players (government and freight forwarders) and these players act upon two main issues. The government/authority, on the one hand, who has the jurisdiction over the transportation network, sets some regulations to reduce the flow of goods to its minimum, utilizing direct connections among nodes, and offers incentives to investors to locate dry ports in preferred locations that overall will minimize the air pollution. On the other hand, the freight forwarders/shippers may use the network to transport the goods through all available routes to minimize the total transportation cost. In this instance, a bi-level approach is deemed necessary, considering adopting the bi-level programming in a mathematical optimization model.

Previous work in bi-level programming span across many areas and contexts. Parvaresh et al. (2013), for example, proposed a p-hub median problem using a bi-level approach under purposeful disruptions. The leader aimed to minimize transportation costs and located the hubs. On the other hand, follower identified those hubs with the loss of service efficiency. To solve the problem, two algorithms based on simulated annealing were applied. Angelo and Barbosa (2015) presented a production-distribution planning problem using bi-level programming. They studied the use of the approximate method in the second level and its effect on the values of the objective function in the first level. Parvasi et al. (2017) used bi-level programming to present a mathematical model for a bus routing problem. Ghaffarinasab and Atayi (2018) applied bi-level programming in the context of security in the hubs. They aimed to minimize damage to the system by considering the network keeper (the leader) in the first level and the attacker (a follower) in the second level. The problem is solved by an exact method based on enumeration. Kolak et al. (2018) presented a bi-level model to address sustainability issues in the case of traffic authority management. Hassanpour et al. (2019a, 2019b) implemented a bi-level mixed integer linear programming to design a closed-loop supply chain network pertinent to government policies. The government and the private sectors were considered as a leader and followers, respectively. The leader aimed to collect used products and satisfy minimum demand. On the other hand, the followers tried to maximize their profits. Gao(2019) presented a bi-level stochastic model to rebalancing multi-commodity models. In the first level the goal is to reduce the level of dissatisfaction in crisis situations and the goal of the second level is to reduce transportation time. Mirzaei et al. (2019) presented a bi-level location-allocation nonlinear model that was solved by different types of enumeration approaches, branch-and-bound and the clustering method.

Similarly, Labbe et al. (2019) proposed a mixed integer linear model of bi-level programming on which the leader aimed to select some locations among possible points. The follower chooses its location in a continuous structure in the lower level. This model is solved by using the Benders decomposition algorithm. Abareshi and Zaferanieh (2019) presented a bi-level p-median facility location problem that the leader tries to minimize location cost and the follower determines allocation decisions. Qiu and Xu (2019) presented a bi-level model for pricing of rail shuttle service and scheduling. Dry port and shippers are considered at the first and second levels, respectively. In their study, operational decision-making is considered. However, in this paper, both strategic and operational level decisions are considered.

Table1. Investigating the research gap in the literature

Reference	Solution method				Modeling approach				Time consideration in transportation	Air pollution consideration	Transportation mode			product type		Decision variables type
	Exact	Meta-heuristic	Heuristic	Matheuristics	bi-level	Location-allocation	Game	Others			Railway	Roadway	Airway	perishable	others	
Abbasi and Pishvaee, (2018)	✓					✓				✓	✓	✓			✓	Location, Allocation, Flow
Nguyen and Notteboo, (2016)								✓		✓	✓	✓			✓	-
Ka, (2011)								✓				✓			✓	-
Tsao and Thanh, (2019)	✓					✓			✓	✓	✓	✓			✓	Location, Flow

Qiu and Lee, (2019)	✓						✓				✓				✓	Number of deliveries, Delivery cycle time, Breakpoint quantity price discount
Facchini et al., (2020)			✓					✓	✓		✓	✓			✓	Number of containers
Wei and Dong, (2019)		✓						✓	✓		✓					Number of containers, Number of vehicles
Qiu and Xu, (2019)			✓		✓				✓		✓				✓	Rail transportation charge, Rail shuttle service time interval, Delivery cycle time, Number of deliveries
Fazi et al., (2020)		✓						✓			✓				✓	Allocation, Export and import quantity, Time barge, Routing
Kurtuluş, (2022)	✓					✓				✓	✓	✓			✓	Transportation, Number of empty containers, Flow
This paper				✓	✓	✓			✓	✓	✓	✓		✓		Location, allocation, Routing (direct and indirect rout), Flow

Some of the studies related to this paper are summarized in Table 1. Most of them focus on the definition of dry port, but only a few focus on dry port mathematical modeling. None of the studies in the literature have fully investigated the use of bi-level models for locating dry ports based on a hub and spoke network. Furthermore, only two papers (Qiu and Lee, 2019; Qiu and Xu, 2019) have modeled the problem using the bi-level programming or game theory-based approach. In both papers, nonetheless, the dry port was considered as a leader and the freight forwarders as follower.

In this paper, the transportation network of the dry port is modeled in a bi-level programming approach in the strategic and operational time horizon. The government's decision is considered at the first level, and freight forwarders' (followers') are considered at the second level. This paper showed that the use of bi-level programming approach leads to the reduction of air pollution through the correct choice of routes.

This paper considers transportation time, air pollution and intermodal rail-road transportation using the bi-level approach by considering government regulation to get closer to the real world. Also, some products shipped through the dry port are considered perishable. Finally, the direct route variable (without crossing the dry port) is also considered in the variables. Tsao and Thanh (2019) just considered Location and Flow variables. Qiu and Lee (2019) considered Number of deliveries, Delivery cycle time and Breakpoint quantity price discount variables. Fazi et al. (2020) considered Allocation, Export and import quantity, Time barge and Routing variables. Kurtuluş, (2022) considered Transportation, Number of empty containers and Flow variables. In addition to Direct and indirect route variables, Location, allocation and Flow variables are also considered in this paper.

And finally, the problem is solved by matheuristic method by decomposing the mathematical model. All these innovations are accompanied by the fact that the mathematical model presented in this paper is quite special and unique.

Figure 1 illustrates one of the ideas in this paper whereby the direct connection among nodes in the network is possible. Freight forwarders may choose the direct connection for their shipment, despite the government's higher cost and preference to utilize dry ports as hubs due to environmental sustainability benefits. However, this significantly saves transportation time, especially in the case of managing perishable products.

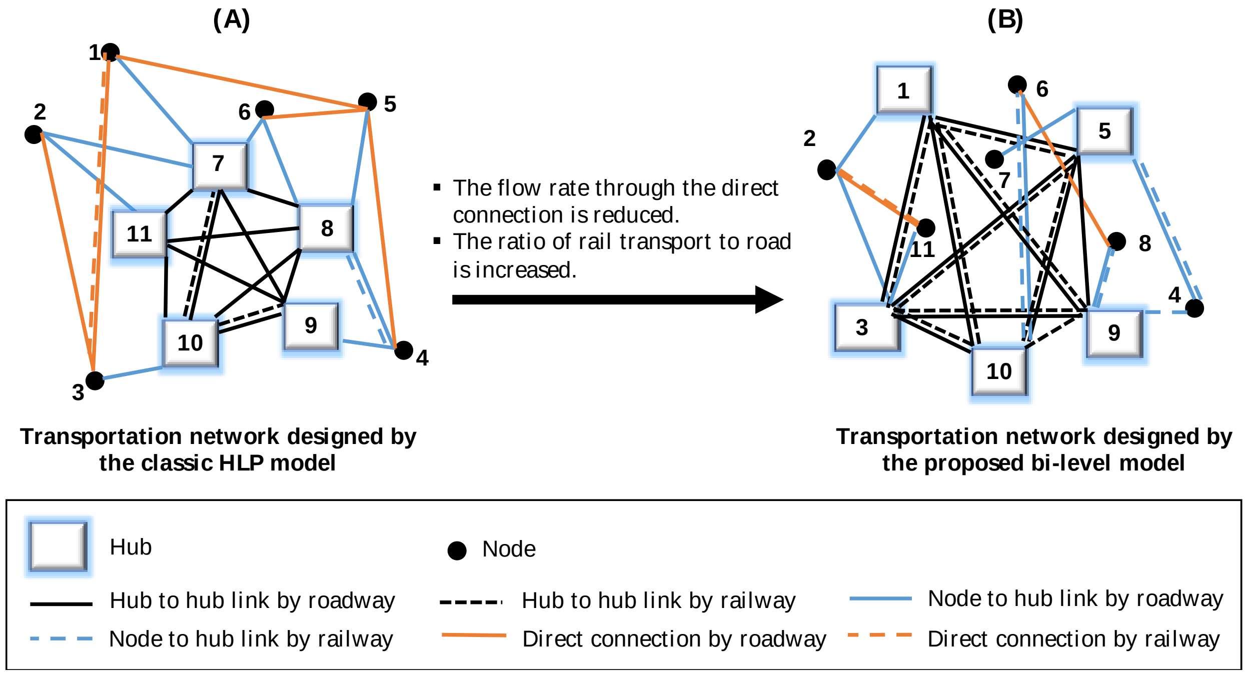

Figure 1. Illustrative example on the main idea of this research

This paper seeks to design a transportation network that will help reduce the shipping volume through a direct connection. The proposed bi-level model is demonstrated in section (B) of Figure 1. By comparing the proposed network in Section (B) with the traditional one in section (A), it can be seen that the number of direct connections will be decreased, significantly. For a better understanding, a brief explanation of the steps of this research is illustrated in Figure 2.

The main contributions of this paper are as follows:

- Presenting a novel hub location-based model via a bi-level programming approach for locating dry ports in a transportation problem.

- Considering direct connection possibility between cities in a hub and spoke network.
- Focusing on the ratio of rail to road transportation and try to increase it in a mathematical model.
- Considering time in the transportation network, making the model more suitable for perishable products.
- Using a matheuristic algorithm to solve the dry port location problem more efficiently.
- Using Karush–Kuhn–Tucker reformulation of the bi-level programming.

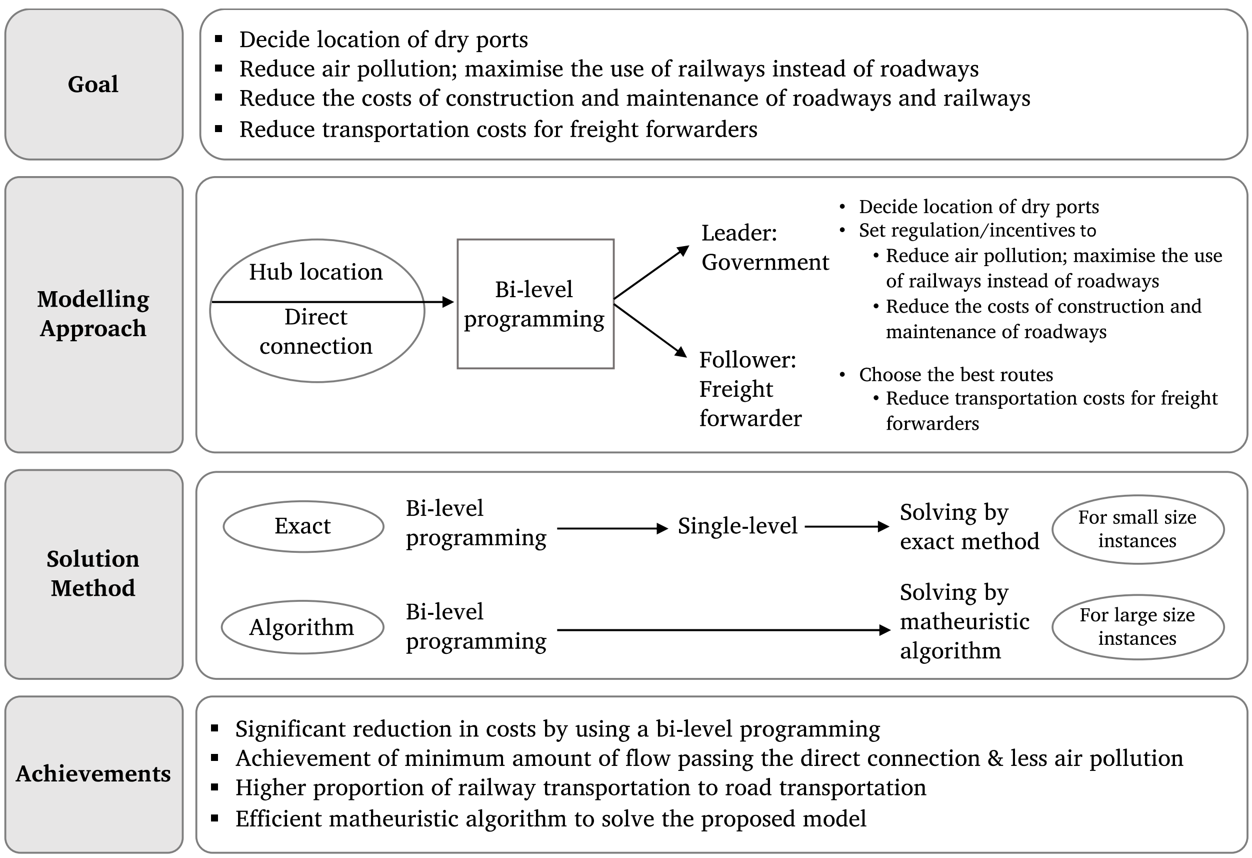

Figure 2. Illustrative brief explanation of the steps of this research

This paper is structured as follows: In Section 2, the problem description will be described, and in section 3, a bi-level hub location model for locating the dry ports will be presented. Then via using the KKT condition, the bi-level model will be replaced with single-level model and finally linearized. A matheuristic solution algorithm is presented in section 4. Section 5 illustrates the numerical results obtained by proposed algorithm via some real and generating data. Finally, this research is concluded by giving some outlooks for future studies in the last section.

2. Problem description

In classic hub models, at least one hub must be crossed between the two nodes of origin and destination. However, in real models, such as transport studies in dry ports, it is not always feasible to cross the hubs to reach the destination. For this reason, in transporting commodities that are perishable, thus shipping time is critical; these commodities are often sent directly without using the dry ports. Direct connection reduces transportation time but it is usually more costly than through dry ports. However, the government prefers goods pass through dry ports for a variety of reasons, including reduced fuel consumption and air pollution. The difference between the interests of the government and the freight forwarder makes a difference in their goals. This issue is taken into account by presenting a mathematical model in this section.

This paper presents a bi-level hub location model with the possibility of the direct connection between a pair of nodes. As shown in Figure 3, at the first level, the government decides on the dry port's location with the aim of minimizing the costs for both dry ports construction and maintenance of the transportation infrastructures. In addition, the government intends to increase the ratio of rail transportation to road transportation by setting some regulations. Freight forwarders are in the second level, and aim to minimize the total transportation cost by choosing the optimal routes for their shipping.

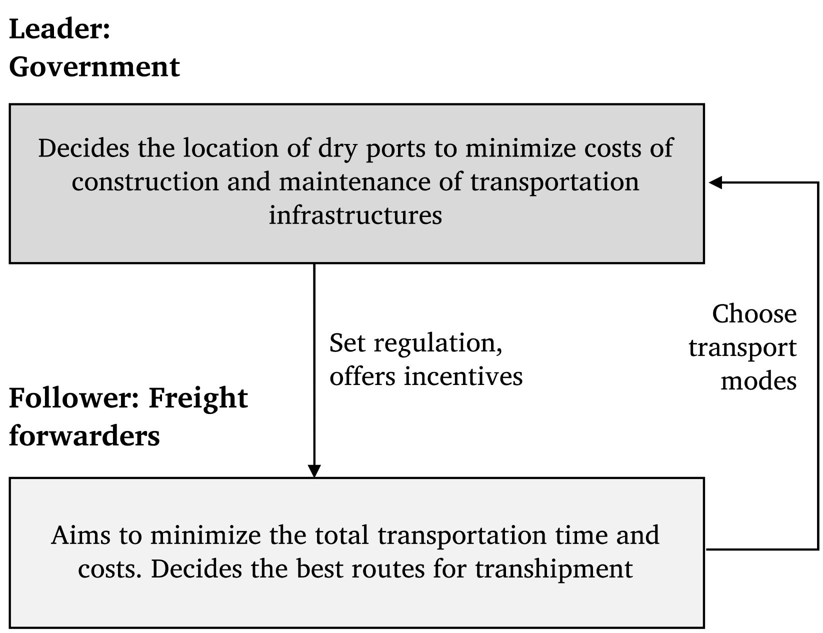

Figure 3. An illustration for the bi-level structure of the study

The main assumptions of this study are as follows:

- The number of dry ports is pre-defined.
- The capacity of the dry port is unlimited.
- Multiple allocation strategy is possible between hubs and nodes.
- Direct connection between nodes is allowed.
- Each cargo occupies a percentage of the rail and road route to move.
- Multiple cargoes can move from one route at a time.
- Some goods are perishable.
- Some rail and roadways already existed while others needed to be constructed.

In the context of the hub location problem, the construction cost is not considered in the literature if the problem belongs to the p-median problems while it aims to locate P hubs in the network (Farahani et al., 2013; Skorin-Kapov et al., 1996). However, the construction cost is considered in the model for the median problems, so the number of hubs is one of the decision variables in such studies. As the number of dry ports has been pre-defined, it belongs to the p-median location problems category. Therefore, the construction cost of hubs (dry ports) is not considered in the proposed model. Although the construction might be done by private investors, government may set some regulations or incentives to ensure that the overall objectives related to the transportation network or pollution rate will be achieved. In some cases, the government made the decision on the location of dry ports (Tsao and Thanh, 2019), and in others, government initiatives affect the institutional environment of dry port constructions (Gujar et al., 2019; Haralambides and Gujar, 2011). In the proposed model, the cost of construction and maintenance of railways and roadways is considered in the objective function of the first level. Because of various issues, including security, the railways and roadways must be under the jurisdiction of the government (Haralambides and Gujar, 2011).

Sets, parameters and decision variables of the proposed mathematical are presented in Table 2.

Table 2. Parameters and decision variables

Sets	
N	Set of nodes ($N = \{1, \dots, n\}$)
I	Set of origin nodes
J	Set of destination nodes
K, L	Set of potential nodes to establish dry ports ($K, L \in \{N\}$)
M	Set of transportation modes (m=1: railway, m=2: roadway)
Parameters	

p	Number of dry ports to be constructed
c_{ik}^{m}	Construction and maintenance costs between two nodes such as i and k with transportation mode m
T	Maximum allowed delivery time between an origin to destination
f	Cost of violation of the allowed time (T) for sending goods from origin to destination nodes
A	The ratio of rail transportation to road transportation
q^{m}	Unit transportation cost when the flow passes through the dry ports with transportation mode m
q'^{m}	Unit transportation cost when the flow passes via direct connection with transportation mode m ($q'^{m} = \beta q^{m}$)
β	The increased cost factor in direct connection ($\beta \geq 1$)
d_{ik}^{m}	Distance between node i and k with transportation mode m
w_{ij}	Amount of flow between nodes i and j
t_{ik}^{m}	Transportation time of sending goods from node i to k with transportation mode m
b	Amount of budget considered for construction and maintenance of routes between dry ports.
γ^{m}	Capacity of every pair of nodes in transportation mode m
α	Inter-hub discount factor ($\alpha \leq 1$)
Decision Variables	
z_{ik}	A binary variable that equals to 1 if node i is allocated to dry port k, and 0 otherwise
x_{ijkl}^{m}	A binary variable that equals to 1 if the flow from node i to node j is routed via dry ports k and l, with transportation mode m, and 0 otherwise
y_{ij}^{m}	A binary variable that equals to 1 if a direct connection is created between nodes i and j, with transportation mode m, and 0 otherwise
$u1_{ijkl}^{m}$	A continuous variable that shows the amount of flow between nodes i and j through dry ports k and l, with transportation mode m
$u2_{ij}^{m}$	A continuous variable that shows the amount of flow through nodes i and j with a direct flow using the transportation mode m

3. Mathematical modeling

Using the above notations, the mathematical formulations of a bi-level hub (dry port) location problem are shown below:

The first level:

$$\boldsymbol{Min\ Z_1} = \sum_i \sum_j \sum_k \sum_l \sum_m x_{ijkl}^{m}\left(c_{ik}^{m} + c_{kl}^{m} + c_{lj}^{m}\right) + \sum_i \sum_j \sum_m y_{ij}^{m} c_{ij}^{m} \quad (1)$$

$\boldsymbol{s.t.}$

$$z_{ik} \leq z_{kk} \qquad \forall\, i, k \quad (2)$$

$$\sum_k z_{kk} = p \quad (3)$$

$\sum_l x_{ijkl}^m \leq z_{ik} \quad \forall\, i,j,k,m$ (4)

$\sum_k x_{ijkl}^m \leq z_{jl} \quad \forall\, i,j,l,m$ (5)

$\sum_k \sum_l x_{ijkl}^m + y_{ij}^m = 1 \quad \forall\, i,j,m$ (6)

$\sum_i \sum_j \sum_k \sum_l \sum_m x_{ijkl}^m \left(c_{ik}^m + c_{kl}^m + c_{lj}^m\right) + \sum_i \sum_j \sum_m y_{ij}^m \left(c_{ij}^m\right) \leq b$ (7)

$\sum_i \sum_j \sum_{m\neq 2} \widehat{u2}_{ij}^m + \sum_i \sum_j \sum_k \sum_l \sum_{m\neq 2} \widehat{u1}_{ijkl}^m \geq A(\sum_i \sum_j \sum_{m\neq 1} \widehat{u2}_{ij}^m +$ (8)
$\sum_i \sum_j \sum_k \sum_l \sum_{m\neq 1} \widehat{u1}_{ijkl}^m)$

$z_{ik}\,, x_{ijkl}^m\,,\; y_{ij}^m \in \{0,1\}$ (9)

The second level:

$\boldsymbol{Min\, Z_2} = \sum_i \sum_j \sum_k \sum_l \sum_m u1_{ijkl}^m * q^m\left(d_{ik}^m + \alpha * d_{kl}^m + d_{lj}^m\right) + \sum_i \sum_j \sum_m u2_{ij}^m *$ (10)
$q'^m(d_{ij}^m) + Max\{0, ((\sum_k \sum_l \left(t_{ik}^m + t_{kk}^m + t_{kl}^m + t_{ll}^m + t_{lj}^m\right) * \hat{x}_{ijkl}^m) - T) * f\} +$
$Max\left\{0, (\left(\left(t_{ij}^m\right) * \hat{y}_{ij}^m\right) - T) * f\right\}$

$\boldsymbol{s.t.}$

$u1_{ijkl}^m \leq \gamma^m * \hat{x}_{ijkl}^m \quad \forall\, i,j,k,l,m$ (11)

$u2_{ij}^m \leq \gamma^m \hat{y}_{ij}^m \quad \forall\, i,j,m$ (12)

$$\sum_k \sum_l \sum_m u1_{ijkl}^m + \sum_m u2_{ij}^m = w_{ij} \qquad \forall\, i,j \tag{13}$$

$u1_{ijkl}^m\,, u2_{ij}^m \geq 0$ (14)

Two terms of the objective function in the second level are non-linear, so they can be linearized as follows (s and s' are the negative continuous variables for linearization):

$s = Max\{0, ((\sum_k \sum_l \left(t_{ik}^m + t_{kk}^m + t_{kl}^m + t_{ll}^m + t_{lj}^m\right) * \hat{x}_{ijkl}^m) - T) * f\}$ (15)

$s' = Max\left\{0, (\left(\left(t_{ij}^m\right) * \hat{y}_{ij}^m\right) - T) * f\right\}$ (16)

$Min\; Z = s + s'$ (17)

$\boldsymbol{s.t.}$

$s \geq ((\sum_k \sum_l \left(t_{ik}^m + t_{kk}^m + t_{kl}^m + t_{ll}^m + t_{lj}^m\right) * \hat{x}_{ijkl}^m) - T) * f \quad \forall\, i,j,m$ (18)

$s' \geq \left(\left(\left(t_{ij}^m\right) * \hat{y}_{ij}^m\right) - T\right) * f \quad \forall\, i,j,m$ (19)

$s, s' \geq 0$ (20)

At the first level, in the objective function (1), the first and second terms are the total cost of constructing and maintaining rail and roadways through the dry port and via direct connection, respectively. Eq. (2) guarantees that a node can only be allocated to an established dry port. Eq. (3) ensures that the number of established dry ports to be P. Eq. (4) and Eq. (5) ensures that all the flow between an origin-destination node can be routed from allocated dry ports only. Eq. (6) guarantees that all flows pass through dry ports or via a direct connection between origin and destination nodes. Eq. (7) ensures that the costs of constructing and maintaining railways and roadways not to be exceeded the allocated budget. Eq. (8) expresses the current regulation set by the government so that the proportion of rail-to-road transport to be exceeded the pre-specified A percent.

At the second level, in the objective function (10), the first and second terms are the total cost of flow through the dry ports and via direct connections, respectively, and the two last terms in the objective function represent the cost of violation of the delivery time limit (T) for sending goods from origin to destination nodes. Eq. (11) and Eq. (12) ensure that the amount of flow passing through the dry ports and via direct connection does not exceed the maximum available capacity of the railways and roadways, respectively. Eq. (13) represents the coverage of the total flows (demands).

One of the effective ways to work with bi-level programming is by using the Karush-Kuhn-Tucker (KKT) technique. Various papers have used and introduced this approach to convert the bi-level problem to the one-level model (Sinha et al., 2019; Allende and Still, 2013; Dempe and Zemkoho, 2012; Dempe and Zemkoho, 2014; Sinha et al., 2017). In this model, the lower level is linear and its variables are continuous so it is convex and it can be replaced by the KKT conditions. In this paper, it is necessary to compare the matheuristic algorithm with the exact method. To solve the model in the exact format, the KKT technique is required. Table 3 shows defined additional variables for the KKT condition.

Table 3. Decision variables

Variables	
$\lambda 1, \lambda 2, \ldots, \lambda 9$	Lagrangian variables
$Y1, Y2, \ldots, Y9$	Linearization variables

So, the equivalent single-level model using the KKT conditions adhering to Table 3 is as follows:

$$\boldsymbol{Min\ Z_1} = \sum_i \sum_j \sum_k \sum_l \sum_m x_{ijkl}^m \left(c_{ik}^m + c_{kl}^m + c_{lj}^m\right) + \sum_i \sum_j \sum_m y_{ij}^m \left(c_{ij}^m\right) \tag{1}$$

$\boldsymbol{s.t.}$

(2)- (9)

(11)- (14)

(18)- (20)

$$q^m\left(d_{ik}^m + \alpha * d_{kl}^m + d_{lj}^m\right) = -\lambda 1_{ijklm} - \lambda 3_{ij} + \lambda 8_{ijklm} \qquad \forall\, i,j,k,l,m \tag{21}$$

$$q'^m * d_{ij}^m = -\lambda 2_{ijm} - \lambda 3_{ij} + \lambda 9_{ijm} \qquad \forall\, i,j,m \tag{22}$$

$$-1 = -\lambda 4_{ijm} - \lambda 6 \quad \forall\, i,j,m \tag{23}$$

$$-1 = -\lambda 5_{ijm} - \lambda 7 \qquad \forall\, i,j,m \tag{24}$$

$$\lambda 1_{ijklm}(u1_{ijkl}^m - \gamma^m * x_{ijkl}^m) = 0 \qquad \forall\, i,j,k,l,m \tag{25}$$

$$\lambda 2_{ijm}(u2_{ij}^m - \gamma^m y_{ij}^m) = 0 \qquad \forall\, i,j,m \tag{26}$$

$$\lambda 4_{ijm}(s - ((\sum_k \sum_l \left(t_{ik}^m + t_{kk}^m + t_{kl}^m + t_{ll}^m + t_{lj}^m\right) * x_{ijkl}^m) - T) * f\ )) = 0 \qquad \forall\, i,j,m \tag{27}$$

$$\lambda 5_{ijm}\left(s' - \left(\left(t_{ij}^m\right) * Y_{ij}^m\right) - T\right) * f\ ) = 0 \qquad \forall\, i,j,m \tag{28}$$

$$\lambda 6.\, s = 0 \tag{29}$$

$$\lambda 7.\, s' = 0 \tag{30}$$

$$\lambda 8_{ijklm}(-u1_{ijkl}^m) = 0 \qquad \forall\, i,j,k,l,m \tag{31}$$

$$\lambda 9_{ijm}\left(-\, u2_{ij}^m\right) = 0 \qquad \forall\, i,j,m \tag{32}$$

$$\lambda 1, \lambda 2, \lambda 4, \lambda 5, \lambda 6, \lambda 7, \lambda 8, \lambda 9 \geq 0 \quad , \lambda 3 : free \tag{33}$$

The linear form of constraints (25)-(32) is as follows:

$$\lambda 1_{ijklm} \leq M * Y1_{ijklm} \qquad \forall\, i,j,k,l, \tag{34}$$

$$(u1_{ijkl}^m - \gamma^m * x_{ijkl}^m) \geq M * (1 - Y1_{ijklm}\ ) \qquad \forall\, i,j,k,l, \tag{35}$$

$$\lambda 2_{ijm} \leq M * Y2_{ijm} \qquad \forall\, i,j,m \tag{36}$$

$$(U2_{ij}^m - \gamma^m Y_{ij}^m)\ \geq M * (1 - Y2_{ijm}) \qquad \forall\, i,j,m \tag{37}$$

$$\lambda 4_{ijm} \leq M * Y3_{ijm} \qquad \forall\, i,j,m \tag{38}$$

$$(s - ((\sum_k \sum_l \left(t_{ik}^m + t_{kk}^m + t_{kl}^m + t_{ll}^m + t_{lj}^m\right) * x_{ijkl}^m) - T) * f\ )) \geq M * (1 - Y3_{ijm}) \qquad \forall\, i,j,m \tag{39}$$

$$\lambda 5_{ijm} \leq M * Y4_{ijm} \qquad \forall\, i,j, \tag{40}$$

$$\left(s' - \left(\left(t_{ij}^m\right) * y_{ij}^m\right) - T\right) * f\ ) \geq M * (1 - Y4_{ijm}) \qquad \forall\, i,j,m \tag{41}$$

$$\lambda 6 \leq M * Y5 \tag{42}$$

$$s \geq M * (1 - Y5) \tag{43}$$

$$\lambda 7 \leq M * Y6 \tag{44}$$

$$s' \geq M * (1 - Y6) \tag{45}$$

$$\lambda 8_{ijklm} \leq M * Y7_{ijklm} \qquad \forall\, i,j,k,l,m \tag{46}$$

$$(-u1_{ijkl}^{m}) \geq M * (1 - Y7_{ijklm}) \quad \forall\, i,j,k,l,m \tag{47}$$

$$\lambda 9_{ijm} \leq M * Y8_{ijm} \quad \forall\, i,j,m \tag{48}$$

$$\left(-\, u2_{ij}^{m}\right) \geq M * (1 - Y8_{ijm}) \quad \forall\, i,j,m \tag{49}$$

$$Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8, Y9 \in \{0,1\} \tag{50}$$

4. Matheuristic solution algorithm

The mathematical model presented in this paper belongs to the NP-hard class (Moore and Bard, 1990). Solving this problem in a large-scale and in a reasonable time is one of the most important issues. There are different methods to solve this problem in the literature. Bagloee et al. (2018) implemented the hybrid machine-learning and optimization method to solve their bi-level problem. Matheuristic algorithm is one of the efficient methods that has received more attention for its high performance recently (Fonseca et al., 2016; Lin and Ying, 2016; Alekseeva et al., 2016; Fanjul-Peyro, 2017; Nishi et al., 2017; Grangier et al., 2017; Moussavi et al., 2019). Privileged articles have also been published on location and network with this method (Li et al., 2017; Aksen and Aras, 2013; Stefanello et al., 2015; Ghaffarinasab, 2018). Matheuristic combines mathematical programming techniques and heuristic/metaheuristic algorithms. One of the most important benefits of this method is the reduction of computational time.

In the matheuristic algorithm proposed in this paper, the whole model is first decomposed to master and sub-problems. The location decisions are made in the master problem and the remaining variables are decided in the sub-problem. A Genetic Algorithm (GA) is used as the solution method for the master problem, which determines the locations of the dry ports. To achieve this, a set of initial location must be generated. Then allocations based on proximity to location must be determined. After calculating the fitness function based on the second level of mathematical model and checking its feasibility, parents are selected, and the crossover operation is performed. After checking for repetition of the new member, this solution is saved, and the stop condition is checked. After reaching the stop condition, the location variables in the main problem are fixed, and the objective function of the main problem is calculated. In this part, because some variables are fixed in the problem, the number of variables is reduced and due to the reduction of the size of the problem, the computational time is significantly reduced. The rest of the variables will be obtained by fixing the location variables in the main problem to construct the sub-problem. The following procedure is illustrated the main steps of the proposed matheuristic algorithm. An integer solution representation is used for the sub-problem, which determines the hubs, as indicated in Figure 4.

The proposed matheuristic solution algorithm

Input parameter of the model

$z_{kk} = \{\}$

While the termination condition of matheuristic algorithm is not met **do**

Generate the initial set of location Z_{kk}

Determine allocations based on proximity to locations

Calculate the fitness function based on the second level

If the solution is feasible, **then**

$z^*_{kk} \leftarrow z_{kk}$

else

Fitness function $\leftarrow \infty$

end if

While the termination condition of GA is not met **do**

Randomly select two parents (chromosome) for crossover based on the roulette wheel method

Perform crossover operation

If the new member repetitious **then**

Fitness function $\leftarrow \infty$

else

Determine allocations based on proximity to locations

Calculate the fitness function based on the second level

$z^*_{kk} \leftarrow z_{kk}$

end if

end while

fixed the variable z^*_{kk} in the main problem

calculate the objective function of main problem (KKT)

Save the solution

end while

For example, according to Figure 4, selected hub nodes are 7, 8, 9, 10, and 11. Then, the allocations of nodes to hubs decisions are made based on proximity to location by doing the analysis of the second-level of model. Finally, the fitness function can be calculated.

7	8	9	10	11

Figure 4. Solution representation

In each iteration, after the locations are specified by the algorithm, a main problem with determined values for dry ports locations is solved. This will dramatically reduce the number of variables and, thus, the computational time. For example, in a sample with 10 nodes and 4 hubs, the number of variables is 122191, but solving this problem with the proposed algorithm reduces the number of variables in the main problem to only 24991 (79.5% reduction). This is because the set members of K and L have been reduced from 10 to 4 by solving the sub-problem.

One of the most important operations in the genetic algorithm is crossover. For this GA algorithm, the one-point crossover is used. After selecting a pair of parents by the roulette wheel method, one point is selected randomly, and the crossover operation is done as illustrated in Figure 5.

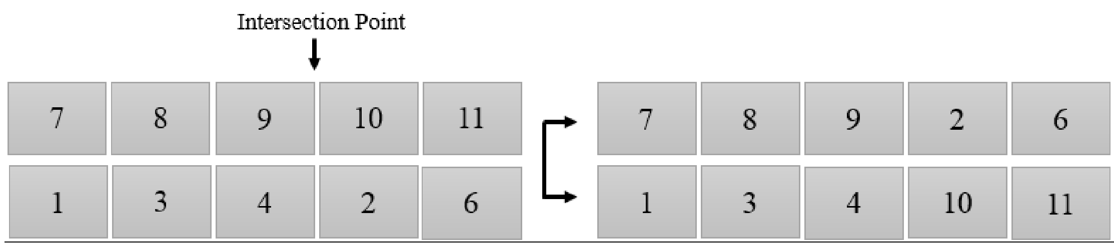

Figure 5. An illustrative example of the crossover operation

In this research, the maximum iteration number is considered as a terminate condition in the genetic and the matheuristic algorithms. Moreover, some parameters such as crossover rate, population size, and maximum generation in the genetic algorithm need to be tuned appropriately to reach optimal and efficient solutions. These parameters have been tuned using the Taguchi method.

5. Computational results and discussion

The proposed mathematical model has been solved by the exact method and algorithm in 12 instances. The instances are grouped into four sets of different sizes. There are three examples in each set that contain a different number of dry ports. The number of dry ports in each example is determined by the ratio of dry ports to total nodes, similar to research previously done on a real case. Some parameters, such as P,C_{ik}^{m}, d_{ik}^{m} and W_{ij} are derived from a real transportation case, but other data were unavailable and thus were estimated. The computational tests have been carried out on a computer with Intel Core i5 CPU with 2.5 GHz clock speed and 6 GB of RAM. The proposed models are solved by linking the GAMS (version 24.1.3) with the CPLEX solver and MATLAB (version 15a). The results of the calculation are presented in Table 4.

Table 4. Results of computational analysis to solve the problem with a comparison

Instance	Total number of nodes	Number of dry ports	Objective Function value		GAP (%)	Computational time(s)	
			Cplex in GAMS	matheuristic algorithm		matheuristic algorithm	Exact (Cplex)
1	10	2	253,477.16	253477.16	0	175.81	11.92
2	10	3	242,747.36	242747.38	0	272.57	12.92
3	10	4	241,114.46	241114.46	0	396.30	13.80
4	20	4	4,684,045,930.52	4,687,840,007.72	0.081	1,250.56	365.22
5	20	5	4,188,567,868.42	4,192,211,922.46	0.087	1,122.26	381.42
6	20	6	3,774,407,570.35	3,777,804,537.16	0.09	1,540.38	392.31
7	30	6	49,171,353,902.62	49,225,442,391.91	0.11	2,150.54	1265.35
8	30	7	34,572,452,841.32	34,624,311,520.58	0.15	2,453.36	1274.58
9	30	8	16,826,168,771.15	16,853,090,641.18	0.16	2,147.89	1300.01
10	50	11	Out of memory	5,214,164,187,148.11	-	54,200.32	-
11	50	12	Out of memory	4,148,568,685,312.36	-	52,145.87	-
12	50	13	Out of memory	2,536,558,723,648.36	-	53,103.78	-

As can be seen from the results, the proposed matheuristic algorithm can solve all the small, medium and large instances in a reasonable time, while in the large instance, the exact algorithm cannot solve it. Moreover, the GAP never exceeded from 0.2 percent in each instance. This demonstrates the efficiency and the robustness of the proposed matheuristic algorithm.

The necessity of applying a bi-level approach is studied by comparing the results of 3 instances, both with and without bi-level approaches, to the proposed model. Without the bi-level programming, the objective function of the leader (Eq. (1)) and all the leader's and follower's constraints (Eq. (2)-Eq. (9) and Eq. (11)- Eq. (14)) are considered in the model. To illustrate this, at first, the model is solved in a single-level format, and the results are fixed in a bi-level format. The results of single and bi-level analysis have been reported in Table 5. Given that the problem is minimization, the examples using bi-level format provide better results than those that are not using this format. This means that when the problem is defined using the bi-level programming approach, there is a significant reduction in costs. One of the reasons of the increased cost is due to the flows through the direct connection. By defining the model in the form of bi-level programming, the amount of flow passing through the direct connection reaches its minimum value.

Table 5. Results of comparing using and not-using bi-level programming approach

Instance	Total number of nodes	Number of dry ports	Objective Function value	
			Fixing the result of the single-level format in the bi-level format	bi-level format
1	10	4	1,068,975.56	241,114.46
2	20	6	134,856,583,241.32	3,774,407,570.35
3	30	8	70,653,595,358.48	16,826,168,771.15

The transportation sector is one of the world's leading causes of air pollution, and researchers have attempted to tackle the issues using various methods (Li and Shue, 2004). One of the important goals of this paper was to design a network that would reduce air pollution, which was done by increasing the proportion of rail to road transport (Lin et al., 2017). The impacts are vast (Song et al., 2016; Zheng et al., 2019; Gu et al., 2019). Some research has also emphasized the reduction of air pollution by using other methods such as road pricing (Miguel et al., 2017) and the optimal tax rate for carbon (Chen e al., 2020).

To estimate the emission of transport, several methods such as Well to wheels (WTW), Tank to wheels (TTW), etc., can be applied (Cai et al., 2017; Gilpin et al., 2014; Rahman et al., 2015). The total emissions per transport can be obtained by the WTW method for both rail and roadway. In this study, a real case in Iran has been used as a basis to calculate the cost of air pollution. The method is a simplified version of the WTW by considering the experts' opinions. The cost of air pollution in the railway is considered 2.5 IRR per ton-kilometer, and the roadway cost is considered 10 IRR per ton-kilometer. Note that this cost has been calculated for a certain period of time in the mentioned case and may need to be updated for different countries and in different time periods based on factors such as inflation rate etc.

Figure 7 illustrates the good performance of the network designed in this paper to reduce air pollution costs in different volumes. The volume of each flow is taken from different instances in different sizes. The figure also shows the reduction of the cost of air pollution while the network is designed in the bi-level format. With the increase in flow rate (increasing the size of the problem), the cost increase in the single-level format is greater than the bi-level one. This occurs since the leader objective is considered only with all constraints of the two players in the single level model. This will lead to achieve the least rail to road ratio. However, by considering a bi-level model, objectives for both players will be investigated and the follower would like to decrease the transportation costs due to usage of more rail ways and consequently it will lead to achieve rial to road ratio greater than the predefined value (A). Sensitivity analysis confirms that using a bi-level model will lead to achieve less carbon emission due to use of more rail ways comparing to the single level model. It should be noted that in case of setting the ratio with a very large value will lead to achieving similar carbon emission by using both models.

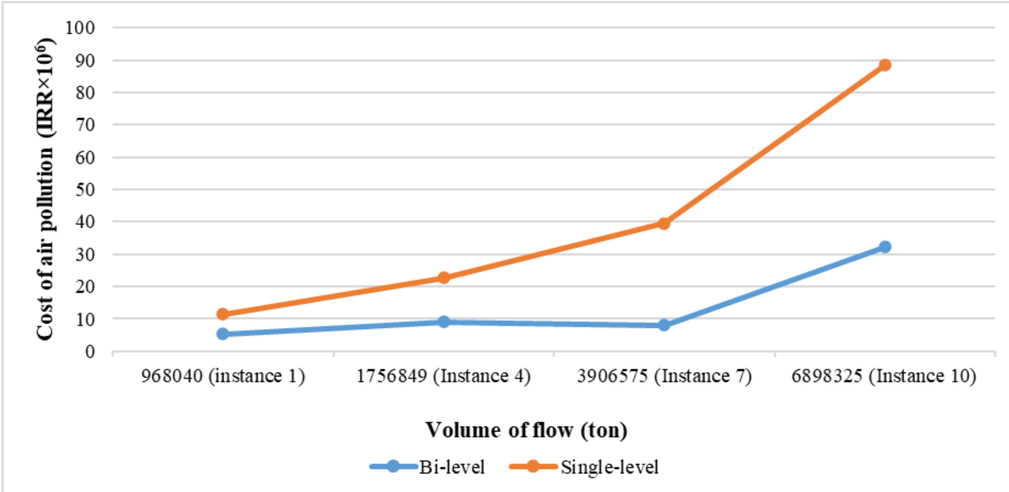

Figure 7. Air pollution reduction in designed network

One of the important issues considered in this paper is to allow the direct connection between the nodes. The government's preference is to pass all flow through dry ports because of the logistical rules and reduction in fuel consumption and air pollution. However, for the convenience of transportation and time saving, the freight forwarders prefer to transport the goods directly rather than through dry ports. To achieve this, the government has considered lowered transport costs through dry ports (see α and β in the mathematical model). This is illustrated by the sensitivity analysis shown in Figure 8. By increasing β, the flow through direct connection will be decreased. This means that if the government does not increase the cost of direct connection, the freight forwarders would ship all their goods directly as far as capacity was allowed through a direct connection, which is not in line with the government's logistical standards. To solve this problem and achieve the logistical goals, strict oversight of the costs associated with hub-to-hub routes and direct connection routes must be done.

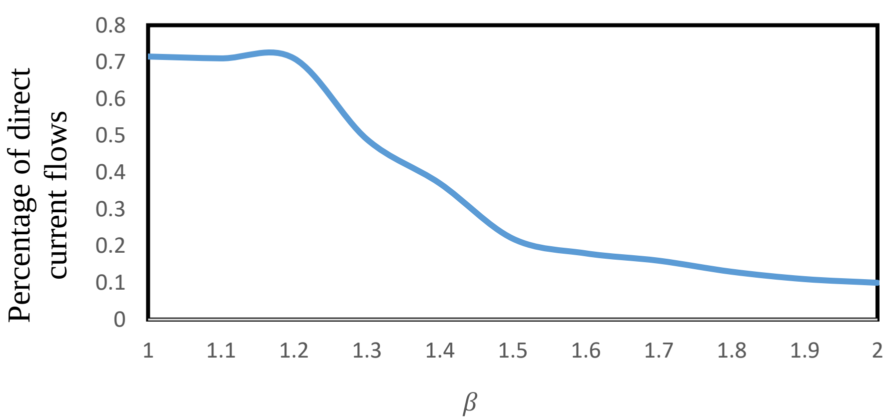

Figure 8. Sensitivity analysis of the shipping cost effect on direct connection rate

One of the reasons of going toward direct transport by freight forwarders is its time saving aspect. Generally, there are three categories of reasons that encourage fast shipment of products: the first one is that customers expect to receive their product as quickly as possible for various reasons such as market competitiveness, health-related issues, emergency situations, and etc. The second category is for goods that should be transported quickly due to their nature. Perishable goods can be classified in this category. The third one refers to the problems that arise in the network because of unanticipated issues such as route breakdowns, accidents, and etc. that require freight forwarders to use direct routes. The proposed model is generic and can be applied to all types of products which must be transported quickly for different reasons.mentioned categories. The first two categories depend on the maximum allowable delivery time parameter (T), which is relevant to the perishability characteristics of the product, such as evaporation, loss of utility, spoilage rate, etc. (Amorim et al., 2013). The last category is dependent on the transportation time parameter i.e., t_{ik}^{m}. The following sensitivity analysis has been done to have a better interpretation on this issue. This sensitivity analysis is about parameters of t_{ik}^{m} and T by increasing parameter β in each change. As shown in Figure 9, it was concluded that by increasing the parameter t_{ik}^{m} or decreasing the parameter T, the number of direct transportations that are used in this network is increased. As a result, air pollution should also increase due to the more usage of direct road routes.

The cost of direct transportation can be a good mechanism to control this issue. The analysis confirms that by increasing the value of the direct transportation cost factor (β), it partially prevents using more direct transportation in the network and consequently less air pollution occurs.

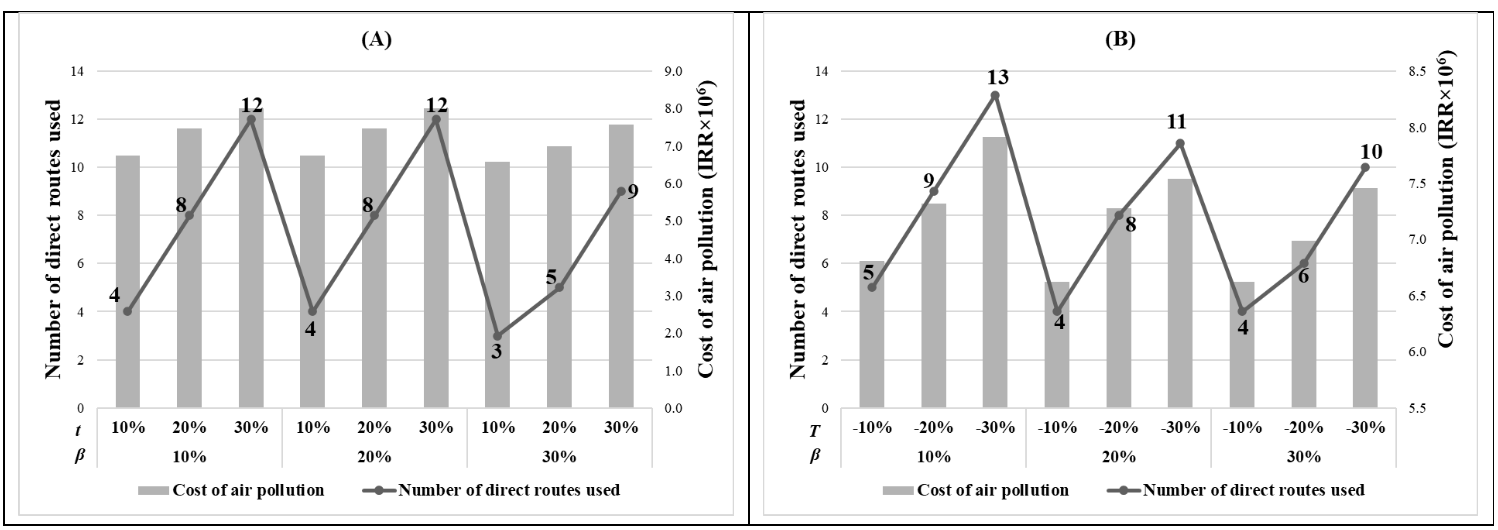

Figure 9. Sensitivity analysis of the transportation parameters on the direct routes: (A): sensitivity analysis of the transportation time (B): sensitivity analysis of maximum allowable delivery time

The following analysis is investigated to show the importance of intermodal rail-road in the network. For this purpose, the network has been investigated considering a single mode of transportation (i.e., only railway or roadway). The results have been compared with an intermodal rail-road network reported in Table 6. The results show that if the network is only based on the railway, air pollution is significantly reduced, but the total delay in deliveries increases. On the other hand, if the network is only based on the roadway, the amount of total time delays will be decreased because of direct transportation and less waiting times, while the amount of air pollution will increase, significantly. However, by utilizing an intermodal network, a tradeoff is obtained between transportation delays and the amount of air pollution. This analysis confirms the suitability of the intermodal dry port network.

Table 6. Sensitivity analysis of the intermodal rail-road network

Railway network			Roadway network			Intermodal rail-road network		
Air pollution cost (Million Rials)	Total cost of network (Million Rials)	Total delay time(day)	Air pollution cost (Million Rials)	Total cost of network (Million Rials)	Total delay time (day)	Air pollution cost (Million Rials)	Total cost of network (Million Rials)	Total delay time (day)
2.4201	12057	3256	9.6804	30524	1123	6.80923	24114	2296

In the presented model, there is an important parameter called A, which represents the ratio of rail to road transportation and is considered to be given by the government. This parameter will ensure to achieve less air pollution levels because of using railway routes. A sensitivity analysis was performed by changing its value from 0.2 to 0.8 in order to evaluate its impact on the network structure and air pollution changes. By increasing the parameter (A), the amount of flow through the railway increases. In most cases, transportation time increases due to the nature of rail transportation. In these cases, if the network has a tight time limit for delivery of goods, then using of direct routes will be an alternative for the network to reduce transportation time. This issue is well shown in Table 7. As expected, the results show that by increasing parameter A, the amount of rail transportation increases and of course the total amount of air pollution decreases. Changes in the value of A in the network structure even have an impact. So, as can be seen in Table 7, the location of dry ports also changes in some cases. Therefore, the proper determination of parameter A is very important, because it may impact on both players decisions, i.e., the leader and follower.

Table 7. Sensitivity analysis of ratio of rail to road transportation

Ratio of rail to road transportation (A)	Follower decisions					Leader decision
	Number of utilized direct routes	Amount of flow		Air pollution cost		Change in the location of dry ports
		through railway (ton)	through roadway (ton)	of roadway (Million Rials)	total (Million Rials)	
0.2	4	193608	774432	7.74432	8.22834	yes
0.4	5	307216	660824	6.60824	7.37628	no
0.6	5	363015	605025	6.05025	6.95779	no
0.8	7	430240	537800	5.378	6.4536	yes

Another important issue in the proposed model is the government's approach to using more railways than roadways. The government may consider giving subsidies for rail transportation so the cost of railway transport can be reduced. As shown in Figure 10, by reducing the subsidy of railway freight costs, the volume of railway traffic is still higher than roadway before point 25. At point 25, where the costs of rail and road transport are equal, the freight forwarders may prefer to use the roadway instead of the railway. If the costs of railway and roadway are equal, the freight forwarders get more profit by using the roadway with less transport time.

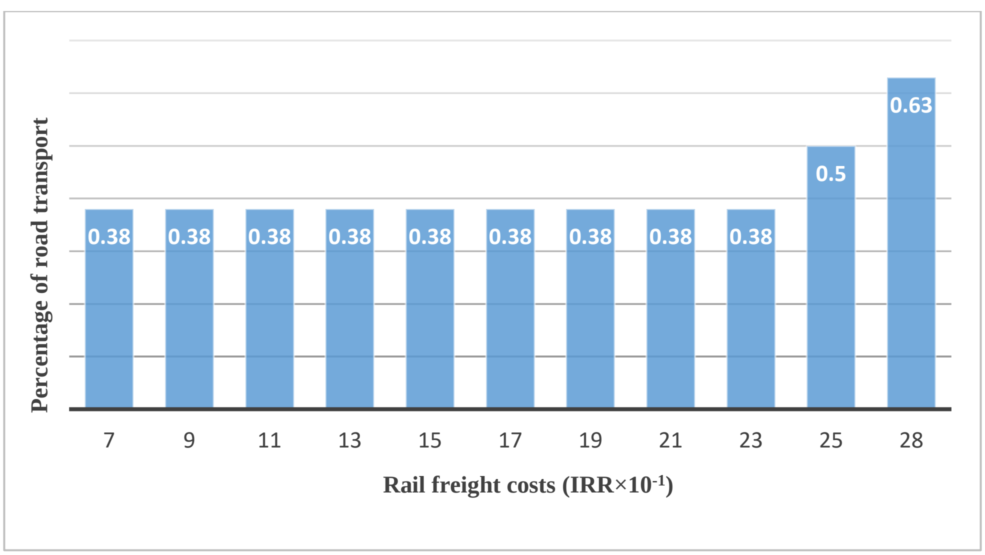

Figure 10. Sensitivity analysis of the rail transportation subsidy

Due to the convenience of road transportation, freight forwarders often choose to use the road instead of the rail. Therefore, one of the most important measures that needs to be taken by the government is to offer adequate subsidies to the rail transport sector, increasing fleet repair, and decommissioning of outdated fleets.

6. Conclusion

This paper considered an intermodal rail-road p-hub median problem utilizing a bi-level programming approach for locating the dry ports. At the first level, the government as the *leader* decided on the dry ports locations in such a way as to minimize the construction and operational costs between dry ports and also to increase the use of railway system. At the second level, freight forwarders as followers tried to minimize the transport costs by deciding on the optimal routes for their transportation. One of the important issues considered in the given hub model was the possibility of the direct link between the origin and destination nodes (i.e. dry port, seaport and hinterland) in the real world. The government is interested in transporting all or a large volume of goods through dry ports to consume less fuel and reduce environmental pollution; on the other hand, freight forwarders intend to use direct routes between origin and destination nodes in order to reduce the travel time. The proposed bi-level model well tackles this conflict between the interests of the government and freight forwarders. A matheuristic algorithm based on GA was proposed for solving this model. Some numerical examples utilizing both real and generated data were designed, and the results showed the robustness and efficiency of the proposed algorithm with respect to the optimality GAP and computational time. The proposed transportation network can significantly reduce the amount of flow passing through the direct connections; thus, it can be effective on air pollution reduction.

For future research, more stakeholders such as private sector investors, seaports, and dry ports can be considered in this game. Some parameters, such as transit times, demand in the destinations, and transportation costs, can be assumed to be uncertain. Developing a new bi-level model considering rail to road transportation ratio (A) as another variable for the leader in the transportation network design can be considered as another direction for the future study.

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