

Transportation problems for intermodal networks: Mathematical models, exact and heuristic algorithms, and machine learning

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ABSTRACT

This paper presents a combinatorial problem called a pick-up routing problem with a three-dimensional (3D-PRP) loading constraint, clustered backhauls at the operational level, and train loading at the tactical level for an intermodal transportation network. A two-phase approach, called clustering first, packing-routing second, is proposed for use during the first stage. The clustering of backhauls is carried out using the k-means algorithm. A hybrid approach is provided, which combines the packing of orders by first solving a 3D loading problem for each cluster using machine learning with a best-fit-first strategy, with routing using a genetic algorithm. During the second stage, the train-loading problem is solved using a mixed integer programming approach to minimise the total costs by incorporating various cost types, in which detention and demurrage costs are taken into account. All solution approaches are computationally evaluated on real-world data provided by an international logistics firm and new randomly generated instances. Comparisons are carried out using both exact solution methods and heuristic approaches, and the proposed approach was shown to be more effective for real-world problems.

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1. Introduction

In recent years, intermodal problems related to decisions such as transport mode selection, vehicle routing (VRP), load planning, and consolidation have gained substantial attention in the transportation sector. An intermodal network design that ensures good solutions to multiple decisions is an important challenge. In this context, most researchers have focused on vehicle-routing problems and its variants, which are practical issues in the area of intermodal transportation. 3D-PRP is a variant of one of the most discussed vehicle-routing problems concerning practical and theoretical importance. Regarding the practical aspect, 3D-PRP has many real-world applications that are particularly relevant for logistics companies dealing with distribution and loading issues. 3D-PRP is of significant value from a theoretical aspect because it includes two NP-hard problems: the pick-up routing problem and three-dimensional loading.

Train transportation plays a key role in intermodal networks, providing the efficient movement of items. There has recently been growing interest in shifting the transportation modes from road to rail. Pre- and post-haulage in the road transportation have a larger cost per tonne-km (Bergqvist & Behrends, 2011). Rail transport ensures a reduction in external costs (Janic & Vleugel, 2012).

Although both 3D-PRP and train loading problems have been separately discussed, there is a need to coordinate these problems in the present paper. The combination of different levels is necessary because 3D-PRP is a precondition of a train loading problem. Backhaul orders are packed during the 3D-PRP stage and the packed orders are then assigned to trains.

The present paper addresses the interactions between 3D-PRP and a train loading problem for an intermodal transportation network including road and rail transportation modes. During the first stage, road transportation is provided for the 3D-PRP, which handles the clustering of backhauls by incorporating the latitude and longitude of the loading cities using the k-means algorithm, the picking up of the orders, a feasible loading of the orders, and vehicle routing. During the second stage, rail transportation is examined for the train-loading problem, in which consolidated orders are assigned to trains with a focus on reducing the penalty and demurrage costs.

Our motivation for this paper is derived from the packing first, routing second approaches proposed by Bortfeldt and Homberger (2013) and Reil, Bortfeldt and Mönch (2018). We modified this approach by first using the clustering of backhauls for a fast computational time, then packing using machine learning for a feasible loading pattern with four loading dimensions, and finally applying vehicle routing using a genetic algorithm. The packing phase also handles four dimensions (length, width, height, and weight). Therefore, this phase can be called a four-dimensional

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loading problem (4D loading). As the main contribution of this paper, we combine operational and tactical levels of decision making with a two-stage approach for considering the picking up of orders from customers in the hinterland, and then loading the orders into the vehicles using a 3D bin packing formulation for the operational and tactical levels to assign these order groups to trains. The combining of two different levels of decision (operational-tactical) is called a “vertical integration” (Pishvae, Farahani & Dul-laert, 2010). Several researchers have provided the benefits of combining different decision levels (Lerhlaly, Lebbar, Allaoui, Ouazar & Affi, 2016). The combination of levels ensures a bridging of the gap between academic and real-world problems. In addition, to the best of our knowledge, this is the first study integrating a genetic algorithm and a machine learning approach to solve 3D-PRP. We provide a new principle, namely, clustering first, packing-routing second for 3D-PRP. We consider various cost variants by incorporating penalty and demurrage costs for the train loading problem and the four loading dimensions, making it more challenging than the three loading dimensions for a 3D loading problem. A holistic view is presented regarding the cost minimization and utility maximization simultaneously. Finally, we compare exact solution approaches, open-source coding approaches, and heuristic approaches on real-world data using an international logistics firm and new randomly generated instances.

The remainder of this paper is organised as follows. The next section presents a literature review, and Section 3 describes the materials and methods applied. Section 4 presents the proposed solution approaches. Section 5 presents the computational results. Finally, Section 6 provides some concluding remarks regarding this study.

2. Literature review

Many published papers related to intermodal transportation are based on determining the mode choices (Bierwirth, Kirschstein & Meisel, 2012; Min, 1991; Serper & Alumur, 2016) and a comparison of transportation modes (Barnhart & Ratliff, 1993) and load planning (Bauer, Bektaş & Crainic, 2010; Bruns & Knust, 2012). The

combination of operational and tactical levels of decision-making related to intermodal transportation is presented for the first time in this paper. 3D-PRP and train loading problems have been studied intensively but independently. Thus, a literature review can be divided into two groups:

2.1. Studies related with pick-up routing problems with 3D loading constraints

VRP with real-world constraints have attracted the attention of both researchers and practitioners during the last few years. However, VRP with clustered backhauls and 3D loading was addressed by only Bortfeldt, Hahn, Männel and Mönch (2015) and Reil et al. (2018). In the present article, PRP with clustered backhauls and 3D loading including orientation, stacking, weight and clustering constraints are considered, suggesting that these constraints are more realistic. Papers considering some of these constraints are summarised in Table 1. Bortfeldt and Homberger (2013) merely considered the orientation, stacking, and weight constraints for the problem. Each box has its own weight, and 90° rotations are permitted as well as in this work. Zachariadis, Tarantilis and Kiranoudis (2013) designed a vehicle routing problem under loading constraints, in which 90° rotations are allowed for all boxes. Zu, Qin, Lim and Wang (2012) introduced a vehicle routing problem with 3D loading constraints imposed based on the item fragility, weight, and orientation. Clustered backhauls, which were considered in the work of Reil et al. (2018) are also contribution of this work. Reil et al. (2018) dealt with this issue regarding the precedence relationship between clustered linehauls and backhauls while clustering of backhauls was carried out using the k-means algorithm for a fast computational time. Additional constraints such as LIFO, support by Tao and Wang (2015), load bearing by Ceschia and Schaerf (2013), fragility by Lacomme, Toussaint and Duhamel (2013) were presented. We also provide a two-stage mathematical model for 3D-PRP (see Section 3). 3D-PRP can be formulated into two stages it includes two NP-hard problems as mentioned in Ruan, Zhang, Miao and Shen (2013). Gendreau, Iori, Laporte and Martello (2008) presented

Table 1
Overview of papers dealing with vehicle routing problems with 3D loading constraints.

Paper	Problem characteristics	Objective	Orientation	Stacking	Weight	Clustering	Solution approach
Bortfeldt (2012)	Vehicle routing with 3D loading	Total travel distance and total computation times	X	–	X	–	Tabu search
Bortfeldt and Homberger (2013)	Packing first, routing second	Total travel distance and vehicle numbers	X	X	X	–	Two stage heuristic
Ruan et al. (2013)	Routing first, packing second	Total transportation cost	X	–	X	–	Proposed Heuristic
Gendreau et al. (2008)	Routing to check the loading	Total travel distance	–	X	X	–	Tabu search
Junqueira, Oliveria, Carravilla and Morabito (2013)	Vehicle routing with 3D loading	Minimum cost delivery routes	X	–	–	–	Mathematical modeling
Ceschia and Schaerf (2013)	3D Packing	Empty linear space	X	–	X	–	Local search heuristic
Lacomme et al. (2013)	Routing with 3D Packing	Total transportation cost	X	–	X	–	GRASP × ELS algorithm
Tao and Wang (2015)	Routing that calls the loading	Utilisation rate of container	X	–	X	–	Tabu search
Tarantilis et al. (2009)	Combined routing and 3D-packing	Minimum cost set of routes	X	–	X	–	Tabu search
Zachariadis et al. (2013)	Vehicle routing with loading arrangement	Utilisation rate of pallet volume	X	–	–	–	Local search heuristics
Zu et al. (2012)	Vehicle routing with loading sub problem	Total transportation cost	X	–	X	–	Tabu search
Reil et al. (2018)	Packing first, routing second	Total travel distance	X	X	X	–	Packing first, routing second heuristic
Presented study	Clustering first, then packing and routing	Total travel distance and number of vehicles	X	X	X	X	Clustering first, then packing-routing heuristics

two variants of the problem: one for routing and the other for feasible loading.

Most commonly, many of the published papers provide heuristic approaches. The algorithm proposed by Gendreau, Iori, Laporte and Martello (2006) determines the routes using an outer Tabu search and solves the bin packing with an inner Tabu search. Tarantilis, Zachariadis and Kiranoudis (2009) presented Tabu search and a guided local search for routing, six packing heuristics for loading. A Tabu search for routing and two packing heuristics for loading were presented by Zu et al. (2012). The two-stage heuristic, which is the motivation of our study, was provided by Bortfeldt and Homberger (2013) and Reil et al. (2018) using packing first, routing second (PIR2) approaches while we also used the bin packing solver in order to obtain more optimum and fast packing plans.

2.2. Studies related with train freight assignments

Train freight assignments are a sub-problem of a train planning problem. A few papers that have solved the freight-to-train assignment problem are provided herein. In the present paper, a mixed integer programming approach is used to solve the freight-to-train assignment problem. In contrast to Xiao, Pacht, Lin and Wang (2018), who uses heuristic approach for a block-train assignment to determine the train service and travel plans, most of the literature developed linear integer models. Feo and Gonzales-Velarde (1995) provided an integer-linear programming to assign two trailers to a single wagon, which is a limitation of their study. Corry and Kozan (2008) also developed a linear integer problem for a load-planning problem regarding the train length, load pattern restriction, and handling time. Most commonly, the overall aim is considered as minimising the loading time, maximising the train usage, as mentioned in Bruns and Knust (2012). Anghinolfi and Paolucci (2014) evaluated the train loading by taking into account the distances between containers. However, container handling time, weight distribution are also regarded in the work of Corry and Kozan (2006). But in reality, it is necessary to regard the penalty and demurrage costs for real-world conditions. In this work, the total costs by incorporating various cost types, in which detention and demurrage costs are taken into account (see Section 3.2).

3. Materials & methods

3.1. Problem description

In this section, we describe the 3D-PRP and train loading problems in detail. The first stage is based on the idea that orders of each clustered backhauls are packed using a 3D bin packing formulation and the vehicle routing problem is solved. A simple representation is given in Fig. 1. During the second stage, the packag-

ing orders are allocated to the trains when considering real-world constraints.

The 3D-PRP is defined as follows:

Carrying units are considered with identical containers or trailers with length L , depth D , height H , and weight W . Each clustered backhaul $numClusters$ requires 3D orders with length L , depth D , height H , and weight W . Loading cities are denoted by $V=(0,1,\dots,n)$, and the depot is represented by node 0. The orders are divided into two groups: export and import containers. Export containers, which can be defined as the containers transported from the customers in the hinterland to the depot (Sterzik & Kopfer, 2013), are considered. Each order is loaded within the loading space. The loading space and weight of the orders cannot exceed the vehicle space and weight. Each order lies in the vehicle orthogonally. Fragile orders can be stacked on other fragile orders. Orders that are non-fragile cannot be loaded on top of fragile orders (Ruan et al., 2013). This limitation is valid for our problem. Each order can be rotated by 90° horizontally. Each vehicle starts and completes its tour at the depot. Each clustered backhaul is visited once to pick up the orders.

In the present paper, in addition to decisions in terms of 3D-PRP, the assignment of packaging orders to the block trains is considered during the second stage. The considered network, including both road and rail transportation, is presented in Fig. 2. A real-life application is presented to demonstrate the practical value of this study. The aim of this study is to develop effective solutions regarding this complex intermodal network concerning its practical importance.

The first stage is dominated by road transportation, in which trucks are used to pick up orders from the loading cities. The main aim of this stage is to increase the efficiency by reducing the usage costs of the vehicles and achieve a high capacity utilisation of the load units, such as trailers and containers. Thus, a holistic view is put forward considering both minimum cost and maximum utilization of carrying units. The second stage is related to rail transportation, in which block trains are used to transfer the carrying units. The purpose of train-load planning is to ensure the efficient delivery and timely availability of the carrying units with a main focus on a reduction of the total cost. In the objective function, the aim is a minimisation of the demurrage, usage and detention costs. The main constraints considered in this problem are capacity and assignment constraints.

The presented models reflecting practical requirements and the proposed solution approaches can be used by freight forwarders and logistics operators dealing with container delivery and loading. The proposed models are highly relevant to actual practice when considering both inland and international transportation networks.

3.2. Mathematical model approach

In this section, we start by discussing all problems using mathematical modelling approaches to find the exact

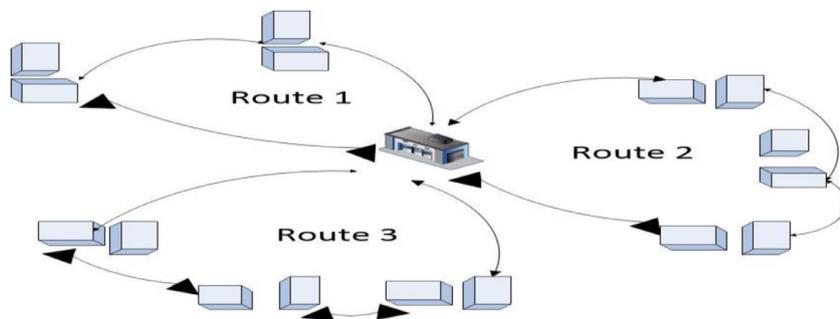


Fig. 1. Clustering of loading cities and 3D bin loading.



Fig. 2. Intermodal transportation network in presented study.

solutions. This mathematical modelling is based on an approach by Ruan et al. (2013), in which 3D-PRP can be divided into two groups, one for pick-up routing and the other for 3D packing. In addition, clustering the loading points by incorporating the latitudes and longitudes is our contribution to this particular approach. We suppose the (x, y) coordinates of the loading points, and each order i is assigned to k clusters. Before employing the developed k-means algorithm, a random assignment is employed using random clusters along the coordinates m_{kxy} , the coordinates of the points p_{ixy} , the cluster number of point c_i , the total number of clusters num , the order numbers assigned to cluster n , the centroid cnt_{kxy} , the squared distance d_{ik} , and the closest distance to the cluster, $close_i$. The decision variable X_{ik} is an assignment of points to clusters. The mathematical formulation is shown below:

Clustering function:

$$\text{objective} = \frac{1}{n} \sum_{i=1}^n \sum_{k=1}^{num} \|p_{ixy} - c_{kxy}\|^2 \quad (1)$$

In the objective function, the aim is a minimisation of the distance of the loading points. Thus, each point is assigned to the closest cluster.

* Stage 1

A random assignment of the points is as follows:

$$c_i = \text{uniformint}(1, num)$$

$$x_{ik} = c_i$$

*Stage 2

The centroids are calculated as follows:

$$n_k = \text{sum}(X_{ik}, 1);$$

$$cnt_{kxy} = p_{ixy}/n$$

* Stage 3

*The points are reassigned as follows:

$$d_{ik} = \sum_{i=1}^n \sum_{k=1}^{num} \|p_{ixy} - c_{kxy}\|^2$$

$$close_i = d_{ik}$$

After formulating the clustering of loading points, a pick-up routing problem (PRP) is formulated. PRP calls for the routes of vehicle k with capacity Q_k , which visits a set of customers $N = (1, 2, \dots, n)$. All locations are shown as (i, j, l) , where $i, j, l \in N$ and $i \neq j, i \neq l$. Here, c_{ij} is the distance measured by the generalized cost. Generalized cost is composed by price between location i and j (distance multiplied by cost per km) and time (generalized time

between l and j multiplied by the price parameter of the average value of time). p_i is the load amount picked up from point i . Given k identical vehicles, each has a fixed cost F .

Decision Variables

U_{ik} : Upper limit of load amount picked up from point i with vehicle k (unit)

$$X_{ijk} = \begin{cases} 1, & \text{if vehicle } k \text{ goes to point } j \text{ from point } i \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ik} = \begin{cases} 1, & \text{if vehicle } k \text{ picks up from point } i \\ 0, & \text{otherwise} \end{cases}$$

$$y_k = \begin{cases} 1, & \text{if vehicle } k \text{ is used} \\ 0, & \text{otherwise} \end{cases}$$

$$\min z = \sum_{k=1}^K \sum_{i=1}^I \sum_{j=1}^J c_{ij} X_{ijk} + \sum_{k=1}^K F * y_k$$

$$\sum_{i=0}^I X_{ilk} = \sum_{j=0}^J X_{ljk} \quad l = 1, \dots, n; k = 1, \dots, K; l \neq i; i \neq j \quad (1)$$

$$\sum_{k=1}^K \sum_{j=0}^J X_{ijk} = 1 \quad i = 0, \dots, n; i \neq j \quad (2)$$

$$0 \leq U_{ik} \leq Q_k \quad i = 1, \dots, n; k = 1, \dots, K \quad (3)$$

$$U_{jk} \geq U_{ik} + p_j * z_{jk} - (1 - X_{ijk}) * Q_k \quad Q_k \quad i = 1, \dots, n; j = 1, \dots, n; k = 1, \dots, K \quad (4)$$

$$\sum_{j=1}^J X_{0jk} \leq y_k \quad k = 1, \dots, K \quad (5)$$

$$\sum_{j=1}^J X_{j0k} \leq y_k \quad k = 1, \dots, K \quad (6)$$

$$\sum_{j=0}^J X_{ijk} = z_{jk} \quad i = 1, \dots, n; k = 1, \dots, K; i \neq j \quad (7)$$

$$\sum_{i=1}^I z_{ik} * p_i \leq Q_k \quad k = 1, \dots, K \tag{8}$$

$$\sum_{i,j \in U} X_{ijk} = W - 1 \quad k = 1, \dots, K \tag{9}$$

$$X_{ijk}, z_{ik}, y_k \in (0, 1), U_{ik} \geq 0 \tag{10}$$

The objective function minimises the total travel cost and number of vehicles. Constraint (1) is a flow conservation; when a vehicle arrives at a node, it must travel from that node to another one. Constraint (2) ensures that each node is visited once. Constraint (3) ensures that the upper limit of the pick-up amount cannot exceed the vehicle capacity. Constraint (4) balances the pick-up amount transferred from one node to another. Constraints (5) and (6) ensure that vehicles start and end at the depot. Constraint (7) ensures that the vehicle picks up from a point if the vehicle goes to that point. Constraint (8) ensures that the picked-up amounts cannot exceed the vehicle capacity. Constraint (9) is a sub-tour constraint. Constraint (10) is a non-negativity constraint in which the decision variables should be greater than or equal to zero. A binary variable can only take on a value of zero or one.

Before formulating the 3D loading problem, we discuss the indices and parameters. The notation is based on that by Chen, Lee and Shen (1995). Let P order (1,..., P), where K is a set of available carrying units (1,..., K). Each order has a loading space l_p , w_p , h_p , and each carrying unit has a loading space L_k , W_k , H_k . The utilisation cost and capacity of the carrying units k are C_k and Q_k .

Decision variables:

o_{kp} : Assignment of orders to the carrying units

$$a_{pr} = \begin{cases} 1, & \text{if order } p \text{ is left of order } r \\ 0, & \text{otherwise} \end{cases}$$

$$b_{pr} = \begin{cases} 1, & \text{if order } p \text{ is right of order } r \\ 0, & \text{otherwise} \end{cases}$$

$$c_{pr} = \begin{cases} 1, & \text{if order } p \text{ is front of order } r \\ 0, & \text{otherwise} \end{cases}$$

$$d_{pr} = \begin{cases} 1, & \text{if order } p \text{ is behind of order } r \\ 0, & \text{otherwise} \end{cases}$$

$$e_{pr} = \begin{cases} 1, & \text{if order } p \text{ is on of order } r \\ 0, & \text{otherwise} \end{cases}$$

$$f_{pr} = \begin{cases} 1, & \text{if order } p \text{ is under of order } r \\ 0, & \text{otherwise} \end{cases}$$

x_p : Coordinate x of order p ($p= 1, \dots, P$),

y_p : Coordinate y of order p ($p= 1, \dots, P$),

z_p : Coordinate z of order p ($p= 1, \dots, P$),

$$\min z = \sum_{k=1}^K \sum_{p=1}^P o_{kp} * C_k \tag{1}$$

$$x_p + l_p \leq x_r + (1 - a_{pr}).M \quad \forall p, r \quad p < r$$

$$x_r + l_r \leq x_p + (1 - b_{pr}).M \quad \forall p, r \quad p < r \tag{2}$$

$$y_p + w_p \leq y_r + (1 - c_{pr}).M \quad \forall p, r \quad p < r \tag{3}$$

$$y_r + w_r \leq y_p + (1 - d_{pr}).M \quad \forall p, r \quad p < r \tag{4}$$

$$z_p + h_p \leq z_r + (1 - e_{pr}).M \quad \forall p, r \quad p < r \tag{5}$$

$$z_r + h_r \leq z_p + (1 - f_{pr}).M \quad \forall p, r \quad p < r \tag{6}$$

$$a_{pr} + b_{pr} + c_{pr} + d_{pr} + e_{pr} + f_{pr} \geq o_{kp} + o_{kr} - 1 \quad \forall p, r \quad p < r \tag{7}$$

$$x_p + l_p \leq L_k + (1 - o_{kp}).M \quad \forall p, \beta \tag{8}$$

$$y_p + w_p \leq W_k + (1 - o_{kp}).M \quad \forall p, \beta \tag{9}$$

$$z_p + h_p \leq H_k + (1 - o_{kp}).M \quad \forall p, \beta \tag{10}$$

$$x_p, y_p, z_p \geq 0, a_{pr}, b_{pr}, c_{pr}, d_{pr}, e_{pr}, f_{pr}, o_{kp}, \in (0, 1) \tag{11}$$

The objective function minimises the utilisation cost of the carrying units. Constraints (1)–(6) provide the order locations considering the x, y, z coordinates. Constraint (7) ensures that two orders in a carrying unit must be only one of the directions described above. Constraints (8)–(10) ensure that the loading spaces of the orders cannot exceed the loading spaces of the carrying units. Constraint (11) is the non-negativity constraint in which decision variables should be greater than or equal to zero. A binary variable can only take on a value of zero or 1.

In the train-loading problem, let us consider a set of trains ($i=1, \dots, I$) and a set of carrying units ($j=1, \dots, J$). Before their assignments to the trains, the carrying units are assumed to be transferred from a ship. Thus, the shipping day $ship$ with tolerance num is incorporated into the model. Train capacity b_i must not be exceeded. Each train has g_i working days and tr_i departure days that must be respected. The train usage cost is f_{ij} when the carrying units are assigned to the trains. An extra cost is defined by the detention cost p_j and demurrage cost cst when the due date d_j is not ensured. The other parameter is the utilisation a_{ij} .

Decision Variables

w_i : Demurrage (day)

$$x_{ij} = \begin{cases} 1, & \text{if } i \text{ trains is assigned to } j \text{ carrying units} \\ 0, & \text{otherwise} \end{cases}$$

s_j : Detention (day)

$$\min z = \sum_{i=1}^I f_{ij} * X_{ij} + \sum_{j=1}^J s_j * p_j + \sum_{i=1}^I w_i * cst \tag{1}$$

$$\sum_{i=1}^I X_{ij} = 1 \quad (j = 1, \dots, J) \tag{2}$$

$$\sum_{j=1}^J x_{ij} * a_{ij} \leq b_i \quad i = 1, \dots, I \tag{3}$$

$$w_i = \sum_{j=1}^J x_{ij} * (ship + num - tr_i) \quad i = 1, \dots, I \tag{4}$$

$$g_i \leq d_j + s_j + (1 - x_{ij}) * M \quad i = 1, \dots, I; \quad j = 1, \dots, J \tag{5}$$

$$X_{ij}, u_i \in (0, 1), s_j, w_i \geq 0 \tag{6}$$

The objective function (1) minimises the usage cost of the carrying units, the detention cost, and the demurrage cost. Constraint (2) is an assignment constraint that ensures that each carrying unit must be assigned to one train. Constraint (3) ensures that train capacity cannot be exceeded. Constraint (4) corresponds to the demurrage cost. Constraint (5) ensures that the number of train transportation days cannot exceed the total travel days of the carrying

```

K-means (A,  $\mathbf{B}_i$ )  $\rightarrow$  (B, C)

Repeat

     $\mathbf{B}_{previous} \leftarrow \mathbf{B}_i$ ;

    For all  $i \in [1, N]$  do

         $c(i) \leftarrow \arg \min d(\mathbf{a}_i, \mathbf{b}_i)$ 

    For all  $j \in [1, k]$  do

         $\mathbf{b}_j \leftarrow \text{avg } \mathbf{a}_i, c(i) = j$ ;

Until  $B = \mathbf{B}_{previous}$ 

```

Fig. 3. Pseudo-code of k-means clustering.

units assigned to the train. Constraint (6) is a non-negativity constraint in which the decision variables should be greater than or equal to zero. A binary variable can only take on a value of zero or 1.

4. Proposed solution approaches

As previously mentioned, 3D-PRP is one of the most well-known NP-hard problems. Computational complexity of the problem is examined. The complexity of the total decision variables is calculated $2n^2k+3nk+2k$ and the complexity of the total constraints is calculated $2n^2k+3nk+2k$ for PRP. The complexity of the total decision variables is calculated $12n^2+2kp+3p$ and the complexity of the total constraints is calculated $6n^2+n^2k+3kp$ for 3D. Real-world data including 103 nodes (n), 20 vehicles (k) and 4444 orders (p) cannot be solved by exact algorithmic approaches within a reasonable amount of time. Therefore, we present heuristics, meta-heuristics, and machine learning approaches to solve these problems. In the present paper, the clustering of the loading points is solved using the k-means algorithm; the 3D bin packing problem is dealt with using machine learning with a best-fit-first strategy, which is considered more effective than other packing solutions (Yang & Mu, 2018); and routing section is addressed using a genetic algorithm. A heuristic approach developed to integrate these three methods is presented to solve the combinatorial problem.

4.1. K-means clustering algorithm

K-means clustering ensures the assignments of n objects into k clusters, where the initial cluster number is assigned before the algorithm starts. Fig. 3 shows a representation of k-means clustering. The clustering starts with an initial cluster number, $numClusters$, or the use of the k-means algorithm to choose the initial cluster number. The next step is the computation of the distances between the objects p_i and the cluster center c_k . The assignment of each object to the clusters with the closest centroid then proceeds. The step is repeated until the maximum number of iterations is reached.

K-means uses the squared Euclidean distances given by:

$$\text{Minimise sum} = \sum_{i=1}^n \text{distance}(\mathbf{p}_i - \mathbf{c}_k)$$

The pseudo-code of k-means is depicted in Fig. 3. Dataset N , the initial k clusters, cluster centroids, and the cluster label are represented as A , \mathbf{B}_i , B , and C , respectively.

Lastly, we produce a DataforR list of cluster solutions including *oid* (order codes), *sku* (clusters), and loading spaces (l, d, h, w) for a 3D packing phase.

4.2. Machine learning for 3D bin packing

In this subsection, the orders of each cluster are packed in a corresponding carrying unit. A 3D problem for each carrying unit *bin* is defined based on the length l , weight w , depth d , and height h , and the set of orders *it* is defined by the length l , weight w , depth d , and height h . Initially, orders *it* are loaded into the same carrying unit *bin*. A list of loading positions is generated in descending order of l , d , h , and w , respectively. The aim of this order is to load larger orders first. At the beginning of the heuristics, the loading place of the carrying unit (0, 0, 0) is available. Orders are loaded without any constraint violations until all orders are packed into carrying units. Then, orders are loaded into a carrying unit using best-fit-first heuristics. Given the orders and carrying units, the solver searches for the optimum packing plans to minimise the number of vehicles and maximise the volume utilisation. The loading process is as follows (Algorithm 1):

Algorithm 1 Procedure of generalised 3D bin packing algorithm.

```

Inputs: Clustered orders from k-means clustering algorithm
Outputs: Order positions into the vehicles
#- bpp_solver: output: packing solution
#-sn
# sn bpp_solution packing solution <list>
# it item <data.table>
# oid: order id <integer>
# sku: stock keeping unit as it id <character>
# tid: ticket id - a unique id within oid <integer>
# otid: order id x ticket id - a unique identifier indicates that it with the same
      tid can be packed into one bin <character>
# - bid: bn id <integer>
# - x, y, z it position in bid bin <numeric>
# - l, d, h it scale along x, y, z <numeric>
# - w it weight <numeric>
# - bn bins <data.table>
# - id bn id <character>
# - l bn length limit along x-coordinate <numeric>
# - d bn depth limit along y-coordinate <numeric>
# - h bn height limit along z-coordinate <numeric>
# - w bn weight limit along w - a separate single dimension <numeric>
sn <- gbp::bpp_solver(it = it, bn = bn)

```

City_1	City_2	City_3	City_4	City_5	City_6	City_7	City_8	City_9	City_10
City_1	City_8	City_3	City_4	City_5	City_6	City_7	City_2	City_9	City_10

Fig. 4. Swap operator representation.

4.3. Vehicle routing using genetic algorithm

The genetic algorithm (GA) used for the vehicle routing problem provides specific procedures. Firstly, we produce an initial population, which includes chromosomes in a random manner. Secondly, each population member is evaluated, and the first generation is found. Thirdly, we initialise some genetic algorithm operators to obtain better generations. Various mutation operators such as flip, swap, and slide are selected to mix the routes. Using a swap operator, I and J locations are chosen, and their positions are swapped (Bestroute (k, [I J])=Bestroute (k, [J I])). Fig. 4 shows the swap representation, where City_2 and City_8 positions are swapped.

With a flip operator, I and J locations are chosen, and their positions are flipped (Bestroute (k, [I J])=Bestroute (k, J:-1: I)). With a slide operator, I and J locations are chosen, and their positions are slid (Bestroute (k, [I J])=Bestroute (k, [I+1: J I])). This process is repeated to optimise the objective function. The pseudocode for the GA is as follows (Algorithm 2):

Algorithm 2 Pseudocode for genetic algorithm.

```

Input: popSize, numIter, Pmutation
Output: optRoute, minDist
//InitializePopulation of routes randomly with a function random()
for k:= 2 to popSize do
  if (k=1) then
    - An initial population pop randomly
    - Current best solution is pbest from pop
  else
    Initialise the population popSize with pbest
  end if
//GA
While (max iteration has not been reached) do
  For l:=1 to popSize do
    - Selection of best route p2 from popSize
    -Reduce the total distance of p2
    -Best solution pbest=p2
    - Perform mutation on the best route to get three new routes
  End for
  Evaluate solution pbest with evaluate function
  If minDist < globalMin Then Update the best solution pbest end if
  OptRoute= BestSolution
End while

```

4.4. General layout of the proposed approach

Our proposed approach integrates a k-means algorithm, machine learning, and a GA. K-means applies clustering heuristics to produce the initial clusters for the 3D loading phase. We obtain a dataset including clusters for the loading points. The 3D loading problem using machine-learning best-first-fit heuristics is then discussed. Finally, the routing phase is addressed using a GA. A general layout of the three different types of algorithms applied for 3D-PRP is as follows:

```

//First stage: Clustering
//cluster locations with k-means clustering algorithm:
for each city (pick-up location) do
  if (customer is a backhaul) then
    -find the k-nearest neighbours by latitude and longitude
    - store the result clusters dataforR
  end if
end for
//Second stage: Packing
// Use clusters dataforR
for i:= 1 to numclusters do
  solve 3D bin packing instance given by length l, depth d, height h, and
  vehicle ids;
  store 3D packing plan 'Result.txt'
endfor
//Third stage: Routing
// Use the data processed by R
Initialise the population
While iteration<=itermax do
  Iteration=iteration+1
  Evaluate each population member
  Find the best individuals in the population
  Perform mutation operators to find new individuals
  Evaluate the fitness of new individuals and place them

```

5. Computational results

To solve the real-world data for 3D-PRP, the hybrid algorithmic approach was executed on a computer with an Intel 3.6GHz CPU with 16 GB of RAM. As previously mentioned, 3D-PRP is one of the most well-known NP-hard problems. Exact algorithmic approaches cannot solve real-world problems that include a large dataset within a reasonable amount of time. Thus, small-sized test instances including customer sets, vehicles with corresponding orders, and medium-sized test instances are generated. We divide 3D-PRP into two groups: 3D and PRP. Based on mathematical models, namely, the commercial optimisation solver GAMS and Open Door Logistics software, both the 3D and PRP problems are solved. Meta-heuristics and machine learning approaches solve a real-world instance containing 4444 orders and newly generated medium test instances containing 994 orders. We compare the performances of the exact method (two-stage approach), open-source coding, and the proposed approach (first clustering, then packing-routing).

5.1. Results of the exact algorithmic and open source software for small-sized instances

We start by presenting the results for small-sized instances related to 3D-PRP. The results were obtained using both open-source coding and a mixed integer programming (mip) approach. We focus on the total travel distance, number of vehicles for routing section, and the loading positions for the loading section. Firstly, by means of the proposed k-means algorithm, 20 loading points of the orders are clustered, and eight clusters (orders) are formed. Next, the orders are loaded onto the vehicles with 3D loading constraints. Finally, the optimal routes for vehicles are obtained. The computing time for an instance is 0 s for clustering, approximately 34 s for routing, and 60 s for loading. Fig. 5 shows the positions

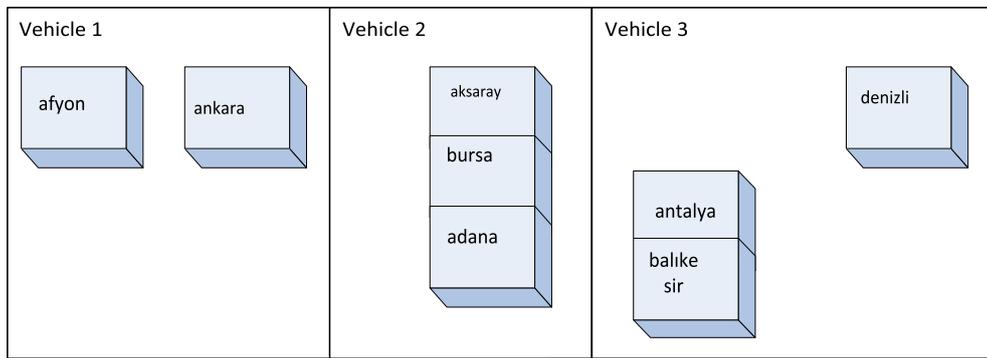


Fig. 5. Positions of the orders into the vehicles.

	vehicle-id	stop-id	job-id	vehicle-name	stop-number	stop-name	type	stop-address	stop-latitude	stop-longitude
1	2-1	P1		truck1-1	1		stop	adana	36,992	35,331
2	2-1	P3		truck1-1	2		stop	aksaray	38,369	34,022
3	2-1	P7		truck1-1	3		stop	bursa	40,269	29,074
4	2-1	End_2		truck1-1	4	End_2	depot		40,975	29,257
5	2-2	P5		truck1-2	1		stop	antalya	36,928	30,784
6	2-2	P8		truck1-2	2		stop	denizli	37,783	29,1
7	2-2	P6		truck1-2	3		stop	balikesir	39,655	27,889
8	2-2	End_2		truck1-2	4	End_2	depot		40,975	29,257
9	2-3	P2		truck1-3	1		stop	afyon	38,757	30,535
10	2-3	P4		truck1-3	2		stop	ankara	40,123	32,63
11	2-3	End_2		truck1-3	3	End_2	depot		40,975	29,257

Fig. 6. Routes created using open-source coding approach.

Table 2
Routes and pick-up quantities obtained from GAMS commercial solver.

Routes			
Truck Depot-Afyon-Ankara-depot			
Truck Depot-Adana-Aksaray-Bursa-depot			
Truck Depot-Balikesir-Denizli-Antalya-depot			
Picked up quantities (unit)			
Cities/vehicles	Truck 1	Truck 2	Truck 3
Adana		2	
Afyon	10		
Aksaray		7	
Ankara	4		
Antalya			10
Balikesir			1
Bursa		10	
Denizli			6

Table 3
Comparison of exact solution approach and ODL for routing sub-problem.

Instances	Exact method		ODL	
	<i>nv</i>	<i>ttd</i>	<i>nv</i>	<i>ttd</i>
1	1	2908	1	0.2
2	2	4325	2	3
3	3	4407	3	22
4	4	5065	4	33

visually. The orders are located based on their *x*, *y*, *z* coordinates. Thus, the optimum location planning is obtained.

We can see from Table 2 that the starting point for each vehicle is a depot. Note that we make sure that each truck is formed by incorporating the capacity and number of orders. In addition, the order locations are also important when determining the truck routes.

The results from open-source coding are similar to the results by the mip solver. The pick-up routing problem is solved using the open-source coded program Open Door Logistics (ODL). Given the vehicle numbers, the addresses and pick-up quantities are input for the system, and the routes are then generated. We can see from

Fig. 6 that the open-source software applies 3D-PRP using similar *nv* and *ttd* with the mip solver.

The computing time is approximately 34 s for the mip solver, whereas the computing time is approximately 22 s for ODL. Fig. 7 shows a map including three routes of orders. We can conclude that the optimum routes under the vehicle capacity distances are generated using ODL.

Table 3 shows that a comparison of both methods when considering computing times (*ct*) is fair because the *nv* and *ttd* values and routes are similar. Fig. 8 shows comparisons of GAMS and ODL, in which the computing times increase when the number of orders is increased. We can also observe that the ODL heuristics becomes faster for routing the vehicles.

5.2. Results of proposed solution approach for medium data

There are no other real-world data or test instances for our problem, and a randomly generated test instance is implemented in addition to the given case study. The parameters are created

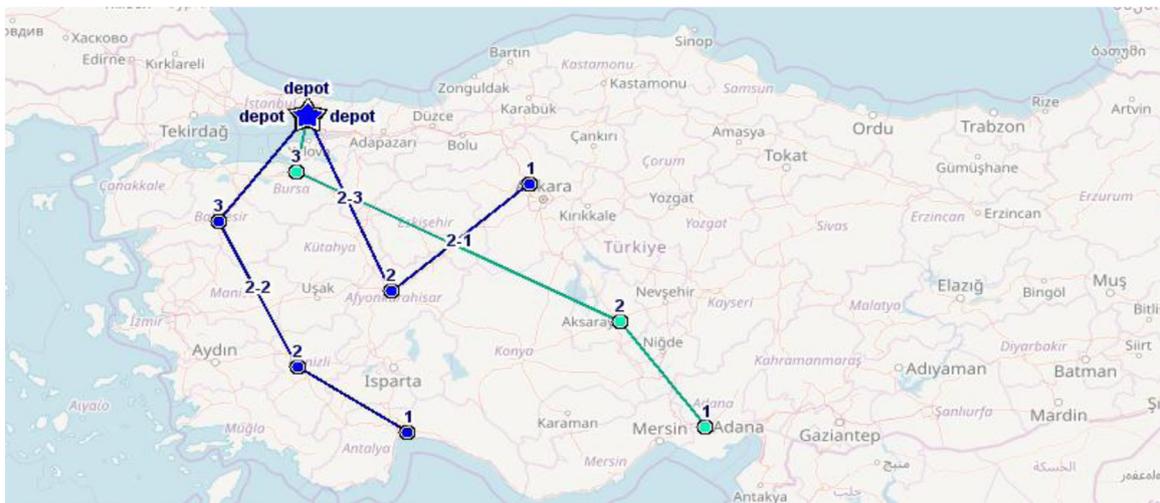


Fig. 7. Map result of routes created using open-source coding approach.



Fig. 8. Comparison of computing times for GAMS and ODL.

Table 4
Random generation parameters for medium-sized test instances.

Parameters	Values
Order latitude	UNIF(10)+35
Order longitude	UNIF(10)+27
Package quantity	Rand(10)
Weight	UNIF(9000)+1000
Volume	UNIF(29)+1
Width	Rand([60 120])
Height	Rand([50 250])
Depth	Rand([50 200])
Vehicle weight	Rand([20,000 30,000])
Width	Rand([2 3])
Height	Rand([2 3])
Length	Rand([10 13])

through a uniform distribution in MATLAB, as shown in Table 4. The order latitude, longitude, weight, and volume values are created using a uniform distribution. The other parameters are randomly created. All parameters are created when considering real-world data.

The results were obtained from employing the proposed approach (clustering first, then packing-routing) on a medium test instance. The results demonstrate that 12 carrying units (*nv*) are used, and the total travel distance (*ttd*) is 25.3225 km. In addition, the orders in the same cluster are placed into the same vehicle. These are compared with the values obtained using the exact method and the GA heuristics. However, it is fair to compare the running times because the data size is different. We also demonstrate in Fig. 9 the order positions when loaded into Vehicle 1 for Cluster 1. Considering the loading coordinates, 29 orders have been

located onto Vehicle 1. There are no violations regarding the loading spaces.

Fig. 10 shows the routes of the carrying units loaded onto the trucks. Vehicle 1 for Cluster 1 travels to the order locations according to the latitudes and longitudes.

5.3. Results of the proposed solution approach for larger data

In this subsection, we present the computational results obtained for 3D-PRP. The vehicle numbers, order numbers, and positions of the orders for all clusters are described in this section. Our results show that four clusters are formed, in which all orders are located by considering the *x*, *y*, *z* coordinates. For instance, in Cluster 1, all orders are loaded onto four types of carrying units. We can see from Table 8 that the number of vehicles (*nv*) and total travel distance (*ttd*) are larger when compared to the medium test instance. We also demonstrate the order positions loaded onto Vehicle 1 for Cluster 1 in Fig. 10. Considering the loading coordinates, 31 orders were located on Vehicle 1. We report the clustering performance over two instances. The packing results were strongly improved by the clustering heuristics. Improvements of up to 60% and 45% are possible for *nv* and *ttd*. We can also see that the GA heuristics become faster for the input processed through machine learning.

Fig. 12 shows the routes of the carrying units loaded onto the trucks. Vehicle 1 for Cluster 1 travels to the order locations according to the latitudes and longitudes.

5.4. Experiment design

The design of the experiments was applied to justify the model behaviours under various conditions for the 3D-PRP results. A factorial design is provided, and the results are presented in Table 5.

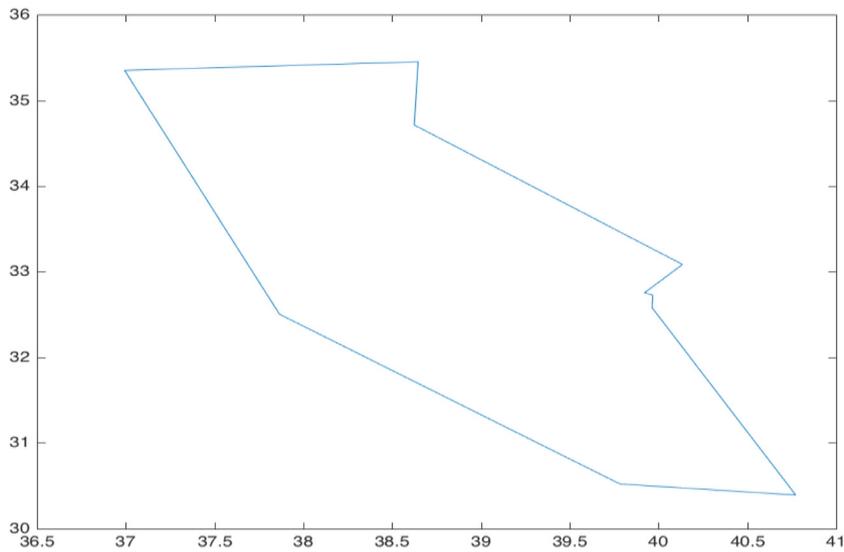


Fig. 12. Optimal route of Vehicle 1 for Cluster 1.

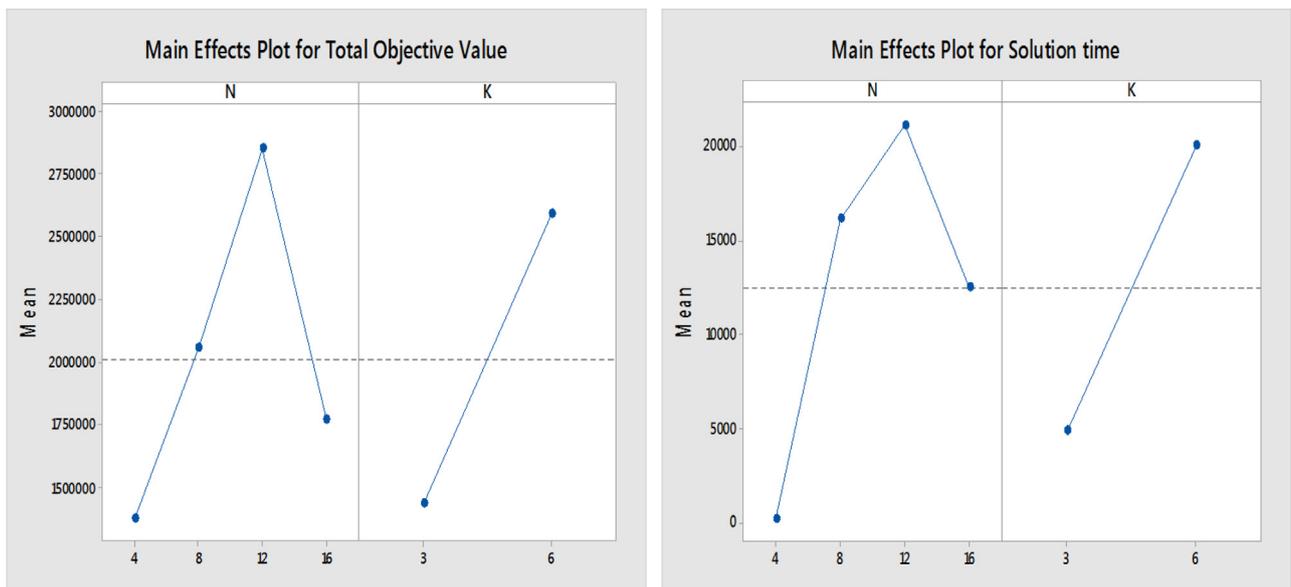


Fig. 13. Effects of number of nodes and periods on the objective value and solution time for 3D-PRP.

Table 5
Two-stage 3D-PRP results.

N	K	PRP objective value	3D loading objective value	Total objective value	Solution time
16	3	259,686	4900	264,586	35
12	6	3415,200	7520	3422,720	18,567
8	3	3322,100	4500	3326,600	15,345
16	3	568,935	45,670	614,605	67
16	6	2485,700	3400	2489,100	45,467
4	6	1657,643	5400	1663,043	654
8	6	456,345	23,300	479,645	125
12	3	2215,200	4670	2219,870	12,430
8	3	836,595	4556	841,151	3456
12	3	2067,895	12,200	2080,095	7890
16	6	3659,874	48,900	3708,774	4356
4	3	562,569	3400	565,969	8
4	3	1564,569	3500	1568,069	15
8	6	3574,569	7800	3582,369	45,453
12	6	3658,945	12,300	3671,245	45,400
4	6	1688,945	5600	1694,545	250

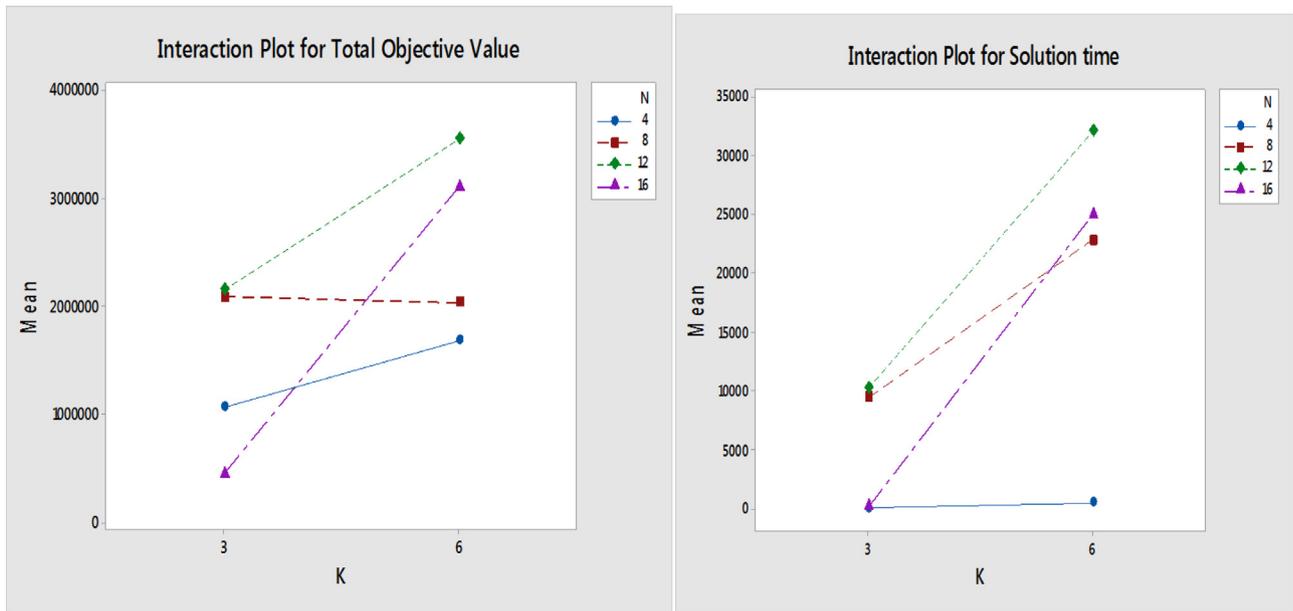


Fig. 14. Interactions between number of nodes and periods on the objective value and solution time for 3D-PRP.

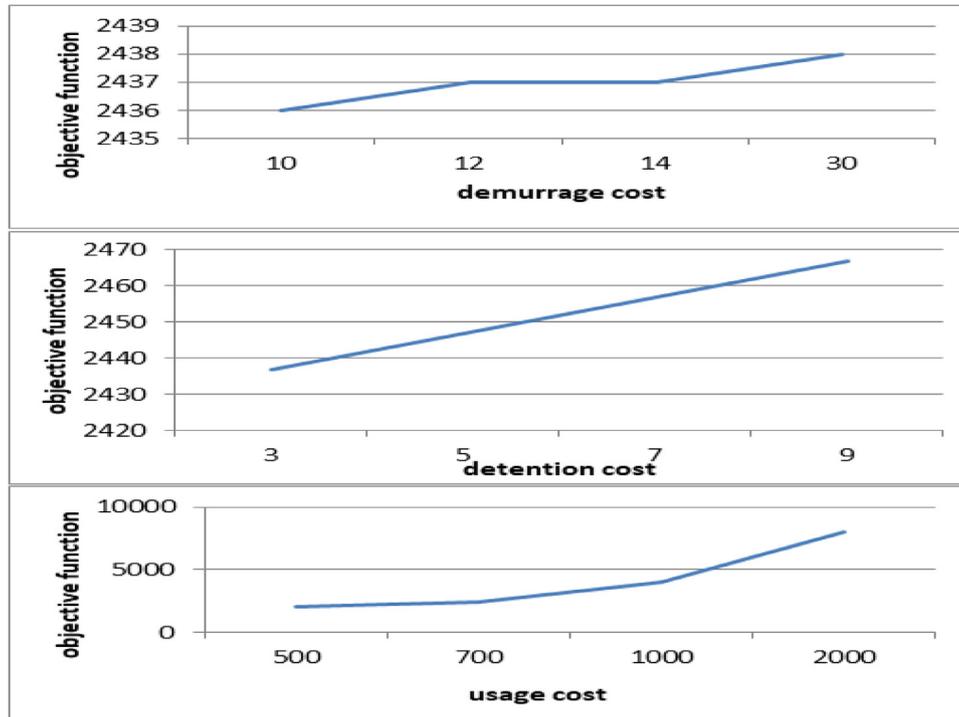


Fig. 15. Sensitivity analysis regarding the effects of parameters on the objective function.

The number of nodes, including four levels (4, 8, 12, and 16), and periods, including two vehicles (3, 6), were chosen as factors. Thus, a 4×2 type factorial design was obtained. Two replications were applied for each experiment. The response variables were chosen as the total objective value involving the PRP and 3D loading values and the solution time.

The main effects plot in Fig. 13 shows the effects of the numbers of nodes and vehicles in the problem. The objective value increases with an increasing number of nodes and periods until the number of nodes is 16. The solution time is affected based on the increasing number of periods. The results of the solution time are similar to those of the objective value.

Interactions of the numbers of nodes and periods on the problem are demonstrated in Fig. 14. The objective function is not significantly affected with eight and four nodes. However, for 16 and 12 nodes, the number of periods affects the objective value. However, the solution time is not significantly affected when the number of nodes is less than 16.

5.5. Comparison of the methods with different instances

The methods used in these instances were compared based on the number of vehicles (nv) and the total travel distance (ttd), as shown in Table 6. There are no other real-world data or test

Table 6
Comparison of mathematical modelling, the proposed approach, and open-source coding approach.

Instances	Two-stage approach		Proposed approach (First cluster, then packing-routing)		Open-source coding	
	<i>nv</i>	<i>ttd</i>	<i>nv</i>	<i>ttd</i>	<i>nv</i>	<i>ttd</i>
Small data	3	4407			3	4407
Medium data			12	25.3225		
Larger data			14	47.2043		

Table 7
Train assignments.

Trains	Detention	Assignment of Vehicle 1	Assignment of Vehicle 2	Assignment of Vehicle 3	Assignment of Vehicle 8
Trieste-Koln	0.515		X	X	X
Trieste-Ludwigshafen	0.322	X			

instances for our realistically sized instance. Thus, it is fair to compare the results of real-world and generated medium-sized instances. We can conclude that *nv* and *ttd* increase based on the order size, and clustering the backhauls ensures less travel distance. The results are as follows: *ttd* is 4407 km for small data, approximately 25 km for medium data, and approximately 47 km for larger data, and *Nv* is 3 for small data, 12 for medium data, and 14 for larger data.

5.6. Results of the train assignment problem

As mentioned above, the intermodal transport network proposed in the present study consists of road and rail transportation modes. The first stage of the intermodal transport network focuses on road transportation. The results of this stage are discussed Sections 5.1–5.3, and the output of the 3D-loading is the input of the train assignment problem. The carrying units (trailers or containers) of orders packed with 3D loading constraints are optionally assigned to the block trains for two different train stations. The carrying units are transferred by Roros in Turkey to Trieste, and then from Trieste to Koln or Ludwigshafen. Vehicle 1 is assigned to Trieste-Ludwigshafen, and the other vehicles are assigned to Trieste-Koln. The results are shown in Table 7.

Our results indicate that the proposed exact approach can solve realistic instances within a reasonable amount of time. We can conclude that the demurrage and detention affect the delays for Vehicles 2, 3, and 8. Orders are delivered to the customers with delays of 1, 2, and 3 days. We analysed the performance of the algorithm based on a sensitivity analysis, as shown in Fig. 15 (a, b, c). We can see from these figures that the objective function is mostly sensitive to the usage costs of the trains, and the demurrage and detention costs are negligible. Thus, it is not surprising to obtain an increase in the total cost when the usage costs of the trains are added.

6. Conclusion

In this study, we considered intermodal network problems combining pick-up routing problems with three-dimensional (3D-PRP) loading constraints, clustered backhauls at the operational level, and train loading at a tactical level. To the best of our knowledge, the first cluster, then packing-routing described herein is the first of this type of approach. A main challenge is the proposed solution method in which four expert systems are employed to solve the combinatorial problems. Four small-sized instances are solved to optimality using GAMS and ODL. An open-source coding approach was compared with the exact solution method. The results show that ODL heuristics can solve the routing problem within seconds. To solve realistic-sized instances, we proposed hybrid meta-heuristics including k-means heuristics for clustering, a

machine learning approach for 3D loading, and a GA for PRP. We proposed a new mathematical formulation for the train loading, which considers demurrage and detention costs.

This paper also presented both academic and practical implications. Regarding the academic aspects, the paper provided a new approach, called first cluster then packing-routing for 3D-PRP, which is of significant value from a theoretical aspect because it includes two NP-hard problems: the pick-up routing problem and 3D loading. In addition, this is first time a machine learning approach for a 3D loading problem has been provided. Regarding the practical aspects, freight forwarders and decision makers should develop effective solutions for more complex intermodal networks. 3D-PRP plays a key role in real-world distribution logistics in which a container delivery of large items and loading is important. 3D-PRP has many transportation applications with intermodal means of transportation, including road, rail, and marine networks.

This paper has a limitation considering only road and rail transportation modes used between Turkey and European customers. To generalise the results, other regions can be added to the network to compare all alternative solutions. In addition, backhaul items were considered for this paper. This paper can be extended by considering both linehaul and backhaul items. Separate compartments can be assigned for these items using the variable neighbourhood search from Bortfeldt et al. (2015). The application of clustering first, packing-routing second is based on the assumption that the k-means clustering is used to cluster the backhaul customers using the Euclidean distance. However, Bortfeldt and Homberger (2013) consider customer combinations with a high-volume utilisation. Customer combinations that avoid packing losses, long travel distances can be used for future studies. For future research, pick-up routing with 3D loading can be extended under various constraints such as the time-window concept and delivery options to obtain more realistic solutions. The proposed load-planning models can be extended by incorporating the fleet size, empty container repositioning, and fleet expansion decisions. Furthermore, exact fuzzy-based exact approaches from von Westarp and Schinas (2016) that can handle the uncertainty of transport demands, transit times, freight capacities, and cost parameters may also be incorporated as a future study. During the train loading stage, consolidated orders are shipped using ro-ro. In this paper, the marine environment of ro-ro (waves, wind, and storm) and the ro-ro speed are negligible. However, considering these conditions is highly relevant to actual practice.

Conflict of interest

None.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.eswa.2019.06.023](https://doi.org/10.1016/j.eswa.2019.06.023).

Credit authorship contribution statement

Elifcan Göçmen: Conceptualization, Methodology, Software, Resources, Data curation, Writing - original draft, Investigation.
Rızzvan Erol: Conceptualization, Methodology, Writing - original draft, Supervision, Data curation, Validation, Visualization.

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