ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

Elifcan GÖÇMEN

OPTIMIZATION MODELS OF INTEGRATED LOAD CONSOLIDATION AND TRANSPORTATION MODE SELECTION PROBLEM ON INTERMODAL NETWORK

DEPARTMENT OF INDUSTRIAL ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Doctor of Philosophy by the board of jury on 24/07/2019.

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ABSTRACT

PhD THESIS

OPTIMIZATION MODELS OF INTEGRATED LOAD CONSOLIDATION AND TRANSPORTATION MODE SELECTION PROBLEM ON INTERMODAL NETWORK

Elifcan GÖÇMEN

ÇUKUROVA UNIVERSITY
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This thesis deals with clustering, three dimensional bin packing, pick-up routing, train assignment and transport mode assignment problems for intermodal transportation networks. The research problem is called pick-up routing problem with a three dimensional (3D-PRP) loading constraints, clustered backhauls at operational level, and train loading and transport mode selection at tactical level for an intermodal transportation network. During the first stage, we propose a hybrid approach, which packs the orders firstly using machine learning, then routing using a genetic algorithm approach. During the second stage, a mathematical model is formulated to solve the train-loading problem to minimize the total costs by incorporating various cost types, in which detention and demurrage costs are taken into account. Allocation of export containers to transportation modes is also provided. A fuzzy-based approach is performed to determine the risk weights of the transportation modes. Developed graphical user interface allows the end-user to control the calculations visually. Computational results for real-world data and new randomly generated instances reveal that the proposed approaches produce high-quality solutions.

Key Words: Intermodal transportation, pick-up routing problem with three dimensional bin packing, heuristic approach, mathematical modelling

ÖZ

DOKTORA TEZİ

İNTERMODAL AĞDA BÜTÜNLEŞİK YÜK KONSOLİDASYONU VE TAŞIMA MODU SEÇİMİ PROBLEMİNİN OPTİMİZASYON MODELLERİ

Elifcan GÖÇMEN

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Bu tez, intermodal taşımacılık ağında kümeleme, üç boyutlu kutulama, toplamalı rota, tren atama ve taşıma modları atama problemlerini ele almaktadır. Araştırma problemi, 3 boyutlu yükleme kısıtlı toplamalı araç rotalama problemi, operasyonel seviyedeki kümelenmiş taşıma ve intermodal taşımacılık ağı için taktiksel seviyede tren yüklemeleri ve taşıma mod seçimi olarak adlandırılmaktadır. İlk aşamada, öncelikle siparişleri makine öğrenmesi ile paketleyen, ikinci olarak genetik algoritma yaklaşımıyla rotalama yapan hibrit bir yaklaşım önermekteyiz. İkinci aşamada, bekleme ve gecikme maliyetlerinin göz önüne alındığı çeşitli maliyet tiplerini içeren toplam maliyeti en küçüklemek için tren yükleme problemini çözmek amacıyla matematiksel bir model formüle edilmektedir. İhraç konteynırların taşıma modlarına atanması da ele alınmaktadır. Taşıma modlarının risk ağırlıklarını belirlemek için bulanık temelli bir yaklaşım uygulanmaktadır. Geliştirilen grafik ara yüzü hesaplamaların görsel olarak kontrol etmek için son kullanıcıya izin vermektedir. Gerçek dünya verileri ve yeni rastgele üretilen örnekler için hesaplamalı sonuçlar, önerilen yöntemlerin yüksek nitelikli çözümler ürettiğini ortaya çıkarmaktadır.

Anahtar Kelimeler: İntermodal taşıma, üç boyutlu kutulamalı toplamalı rotalama, sezgisel yaklaşım, matematiksel modelleme

EXPANDED ABSTRACT

In recent years, importance of transportation logistics on supply chain network has shown a substantial increase. Thus, transportation problems are hot research topics for both logistics companies and researchers dealing with logistics operations. Transportation problems incorporating load planning, fleet sizing, load consolidation, vehicle routing etc. are evolving domain in the area of the logistics. Loading and vehicle routing operations are one of the most vital parts of the logistics planning. To make these planning parts sound, integrated loading and routing operations should be conducted within the area of logistics and transportation. Simultaneous loading and routing problems are also challenging to make scientific sound. Loading the items is one of the most labour and expensive operation. The loading problem is related to packing the maximum number of items onto the carrying units. The problem should take into consideration various parameters such as orientation, stability, and fragility. The decision maker also has to evaluate the item and vehicle characteristics. The routing problem is taken into consideration considering vehicle routing problem (VRP) formulations. Pick-up routing problem can be considered as a special variant of the VRP. In these problems, customers are divided into two groups: line haul and backhaul customers. Backhaul customers require pick-up operations. Pick-up vehicles start and complete their routes in the warehouses. This study is divided into two groups: one for a combinatorial problem named 3D-PRP loading constraints, clustering loading points during the first stage, and train assignments during the second stage, the other stage is for an intermodal route and transportation mode choice for an intermodal transportation system. The study needs a combinatorial optimization for an optimal packing, and vehicle routing for minimizing the total travel distance then capacitated train loading and transport mode selection. The case study for an international logistics firm is conducted with large-scale instances. We can summary firstly the first problem group. We provide mathematical models for

clustering the order locations, pick up routing and three-dimensional bin packing and transport mode choice problems. Small sized problems are solved to show the model effectiveness for clustering and 3D-PRP. Eight customer nodes in the firm inland are chosen as the small sized instance. More customer nodes cannot solve by the exact solution methodology in a reasonable time. By the problem complexity and larger data, exact solution methods do not ensure real case requirements. Therefore, in the first stage, k-means algorithm is coded for clustering the backhauls firstly; next, we propose a hybrid approach, which packs the orders first by providing a 3D loading problem at each cluster using machine learning, routing second by genetic algorithm. In the second stage, a mathematical model is formulated to decide the train loading for packed orders of the first stage and the problem is solved optimally. Proposed methods are applied on real world data obtained from a transport company and produced instances. Both mathematical modelling approaches and heuristics are compared and the proposed hybrid approach generates good quality solutions for the real world applications.

The second problem is related with sustainable intermodal transportation problem. Sustainability issues are forcing the logistics companies to handle the risk parameters for the intermodal network system. In the current studies, traditional constraints such as capacity, distance are basically included into the problems. Otherwise, instead of the transporting the cargos timely and optimally, transporting considering human and environmental risks are vital importance of human living. Traffic congestion, pollution, environmental concerns factors must be handled for the sustainable transport systems. In this context, the study considers economic, social and environmental risk parameters, which play a key role for a sustainable transport. Transport modes have risk issues that threat both the human living and the environmental balance. Processes realized in the intermodal systems cause to various risky results. Assignment of exported containers to transport modes, considering various risk factors with a focal point to minimization the transport costs is addressed. Mixed integer programming based mathematical model is presented to determine how to allocate the carrying units to the various transport modes. Besides, a fuzzy-based method is applied to decide human and environmental risk values of the transport modes. Risk weights are used for finding the optimum allocation of modes. The study is the first by applying fuzzy based approach regarding new risk weights for an intermodal transportation problem. Each transportation mode is handled with human risks (human accidents, deaths) and environmental risks (emission value, noise pollution) by decision makers with allocation of numerical assignments. Then, these outputs of each transport modes are defined 'inputs' in the mathematical model. The highest risk score is obtained by the road transport. Road transport has a major share in human deaths, traffic accidents, noise pollution and high emissions. Thus, road transportation with highest risk weights could be considered. Risk scores of rail transport with the lowest risk weights and maritime transport with the medium risk weights are obtained. Regarding these risk weights and transportation costs, optimal mode assignment is provided. Due to the effectiveness of the risk weights, total demands could not met by road transportation. Some demands require to be transported by intermodal transport. Within the evolving domain of an intermodal network, a systematic comparison of transportation modes and the modelling of intermodal transportation based on economic, human, and ecological factors are provided for the logistics firm. The computational results provide that transportation modes more economical and environmentally friendly are presented in the study.

Intermodal transportation is the transportation of carrying units with various transportation modes without any change on the carrying units. Transportation mode choice, load allocation, distribution processes are handled simultaneously, and this situation increase the complexity of the problem. We handle the intermodal transportation including highway and railway transportation. In the first stage, road mode is used for hinterland customers to pick up the orders with 3d loading constraints and vehicle routing. Backhauls are clustered according to the latitude and longitude values of loading cities with k-means algorithm. Then, routing problem is solved with vehicle capacity and loading spaces. In the second step, consolidated orders are assigned to the train lines. Final step is intermodal route and transportation mode selection problem. The transportation modes used in this step are truck, train and Ro-ro. The difficulties of intermodal transport can be explained as follows: (i) intermodal transport consists of multiple modes of transport, with each mode having its own characteristics, (ii) multiple decision modes and multiple decision mechanisms with different purposes in multimodal transport management, (iii) line planning and load planning involve very large amounts of load, fleet size, multiple time periods and high levels of uncertainty (iv) limited data access, the size of the problem, the difficulty of high-throughput efforts. For the complexity of these problems, there are limited published papers.

This study provides both theoretical and practical implications. Considering this theoretical aspect, this study presents the novel approach named first cluster then packing routing for 3D-PRP, which is of great value from an academic aspect since it involves two NP-hard problems: PRP and 3D loading. It is first time to provide a machine learning approach for 3-D loading problem. Best-fit-first strategy is applied to bin packing formulation and weight dimension is added to the 3-D loading. The problem is transformed to 4-D loading with this contribution. In addition, researchers suggest that the performance scores addressed as risk factors in the study can be included as inputs to the mathematical models. This study is the first to include the outputs of fuzzy based approach as inputs to the mathematical model presented in the last step. Regarding the practical aspect, freight forwarding companies and decision makers would make a break to produce high quality solutions for inland operations and more complex intermodal network systems.

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NOMENCLATURE AND ABBREVATIONS

PRP	: Pick up routing problem
3D	: Three dimensional loading
3D-PRP	: Three-dimensional pick up routing problem
GA	: Genetic algorithm
FTA	: Fault Tree Analysis
FMEA	: Failure Mode and Analysis
MIP	: Mixed integer programming
CPU	: Central processing unit
TL	: Turkish lira
UNIF	: Uniform distribution
KM	: Kilometre
VRP	: Vehicle routing problem
FTL	: Full truckload
LTL	: Less than truckload
TEU/TU	: Twenty-foot equivalent unit
AHP	: Analytic Hierarchy Process
ANN	: Artificial Neural Network
ICT	: Inland container transportation
L	: Length
W	: Width
H	: Height
D	: Depth
WHO	: World Health Organization
ODL	: Open Door Logistics
m_{kxy}	: random cluster indicator
p_{ixy}	: coordinates of the points

c_i	: cluster number of the point
num	: total number of clusters
$\mathbf{cntr}_{kxy}$	: centroid indicator
d_{ik}	: squared distance
$close_i$	: distance closest cluster
X_{ik}	: assignment of points to clusters indicator
Q_k	: capacity indicator
p_i	: load amount indicator
F	: fixed cost indicator
U_{ik}	: upper limit of load amount
X_{ijk}	: travelling indicator
z_{ik}	: picking up indicator
y_k	: truck usage indicator
p,P	: order index, number of orders
k,K	: carrying unit index, number of carrying units
l_p , w_p , h_p	: order loading spaces
L_k , W_k , H_k	: carrying unit loading spaces
$\mathbf{C}_k$	: utilization cost
$\mathbf{Q}_k$	: capacity of carrying units
i,I	: index of supply points, number of supply points
j,J	: index of seaports, number of seaports
m,M	: index of customers, number of customers
p,P	: index of train stations, number of train stations
t,T	: index of time periods, set of time periods
$\mathbf{De}_{imt}$	: Export demand indicator
$\mathbf{C1}$, $\mathbf{C2}_{ij}$, $\mathbf{C3}_{jp}$	: cost of transportation modes
$\mathbf{Cap}_{ij}$,$\mathbf{Cap}_{jp}$	: capacity of transportation modes
$\mathbf{d}_{im}$ $\mathbf{d}_{jm}$ $\mathbf{d}_{jp}$	: road distance, rail distance

$\mathbf{M_{ijt}}$	: Maximum limit on number of Roro
$\boldsymbol{\gamma}$	: mode weight indicator
$\mathbf{X_{imt}}$ $\mathbf{Y_{ijmt}}$ $\mathbf{Z_{ijpmt}}$ $\mathbf{Ro_{ijt}}$	: amount of TUs
$\mathbf{NB_{jpt}}$ $\mathbf{NR_{ijt}}$	:number of block train and Roros

1. INTRODUCTION

In recent years, load consolidation and transportation mode selection problem for intermodal transportation network have been attracted considerable attention. Container based transportation and load consolidation are vital importance for the logistics companies to revise the traditional logistics management. Effective load planning and transportation processes are crucial to decide whether or not the logistics company takes into account the customer requirements.

Intermodal transportation plays a key role in the load transportation market. New trends including economic and environmental components are forcing to the market. Intermodal transportation is basically divided into three stages. Short haul stage and end haul stage are related with the road transportation for the pick-up and delivery operations. Long haul transportation involves the intermodal transportation. A representation of these stages is depicted in Figure 1.1.

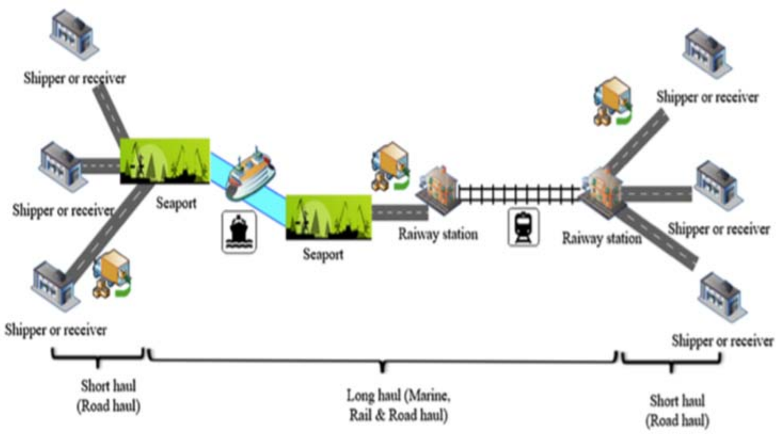

Figure 1.1. A simple representation of the intermodal stages (Baykasoğlu and Subulan, 2016)

In this study, intermodal transportation problem is a highly complex considering 3D-PRP and transport mode choice. During the pre-haul stage of the intermodal transportation, the problem is dominated by the road transportation, in which trucks are used to pick the orders and vehicle routing. During the long haul stage, both road and rail, and intermodal transportation are used. The problems are of practical interest on intermodal network. Logistics companies deal with real world applications combining loading and vehicle routing. The problems are of theoretical interest because of considering a combinatorial problem called 3D bin packing and VRP.

1.1. Background and Motivation

Over the last decades, effective and efficient logistics activities have become a highly competitive issue. Due to the increasing new trends such as the fourth industry revolution, various transport modes in the logistics system, the changing roles of ports, logistics concept has been redefined. Logistics is defined as the processes of planning, implementing and managing the transportation of goods, inventories, goods or information between starting point and final destination (Akarcay, 2011). Besides, logistics companies are aware of that logistics services require a mixture of various characteristics. Service availability, distribution time, route planning, feasible loading are some of these requirements. The development of effective logistics activities is fostered by rapidly increasing and variable demands of customers and increasingly competitive environment. Companies dominated in the field of logistics also focus on logistics and supply chain, global resource utilization, logistics outsourcing. These companies should be a part of the global distribution channel and logistics chain to improve loading and unloading operations to obtain a major share in this market.

Logistics companies also need to improve effective transport routes and networks to control transport costs, manage freight forwarder-customer relationships, manage risk, improve quality and performance, integrate land-sea interfaces, and improve environmental performance. In addition to efforts by the companies, researchers are also aware of transforming to intermodal transport systems to increase the efficiency of the logistics and supply chain. Intermodal problems including line planning, load planning and consolidation are increasingly attracted by both researchers and practitioners. Transport modes play a key role in the economies of countries. Therefore, countries also have to develop their transport modes oriented to macroeconomic objectives. Stop points of transport modes such as ports, airports and train stations, which are critical places to consolidate the freights and transfer them, requires to be focused by the government. In addition to economic aspects, sustainable environmental development issues should be addressed in the field of transportation sector. Environmental concerns, regulations, government policy force the universe to take measures. Thus, these problems require simultaneous multiple decisions regarding the ecological factors. Decisions as transportation mode choice concerning sustainable issues, transport operations and load consolidation increase the complexity of the problem. Thus, in the literature, most researchers have concentrated on uni-modal transportation networks.

Load planning and transportation mode selection problems for intermodal transportation network have been attracted considerable attention. These problems are dealt with by the researchers with various modelling and solving approaches. However, both of the transportation processes of the inland and external region are investigated by few researches. In addition, load consolidation and transport mode assignments are not mostly considered in the literature. Otherwise, limited papers, which involve strategic, tactical and operational decision levels simultaneously, are available.

Load planning and transportation mode selection problems for intermodal transportation network are examined on three phases. Figure 1.2. depicts the locations related with the proposed problems. First problem is related with the inland operations of the international logistics company. The company requires to improve the hinterland operations to export the orders effectively. The operations should be organized and the orders in the locations should be picked up with clustering and 3d loading constraints. Second problem is solved after getting the results from the first problem. Train allocation problem should be solved to obtain a tactical plan. Third problem is independently solved from the other problems. The third problem includes an intermodal transportation mode choice between European customers and inland customers.

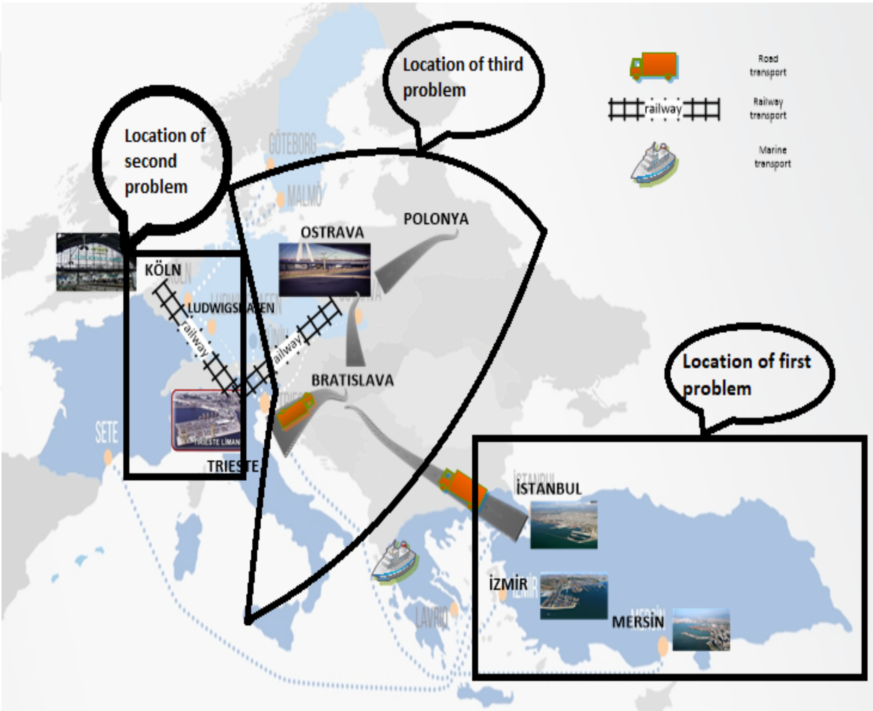

Figure 1.2. A depiction of the locations in the intermodal network

1.2. Inland Container Transportation (ICT)

Globalization and demand fluctuations change the role of freight transportation. Container volumes are increasing day by day and expected to increase further. Therefore, to develop an effective and sustainable inland container transport system is focal.

The inland region is defined as an economic and effective market area where a port sells its services and offers interaction between customer points (Slack, 1993). Van Klink and Van Den Berg (1998) describe this region as an inland area serving from the ports. Inland regional transport is the major share of all cost items for door-to-door container transportation. A large number of ports are widening the areas of the backward zone, and this brings about competition.

Although road transport is still the dominant mode of transport, alternative modes are also evolving. Many ports are turning to alternative modes to reduce container traffic. Rail-road transport modes are the most efficient combined mode considering both financially and environmentally.

The sharing of the transportation modes between the regions is distinctive for various ports, which have an impressive effect on the port area and material types. For example, utilization rates of hinterland transportation modes are 47% for Hamburg Port, 35% feeder, and 18% rail; In Rotterdam Port: 50% truck, 40% feeder and 10% rail; In Hong Kong Port: more than 90% truck, less than 10% feeder; In Singapore Port: 20% truck, 80% feeder (Yalçın, 2005). There are few good port applications, in which the container transport processes are effective and the loading unloading operations are successful. Container traffic in the UK ports has been increasing rapidly in the last 20 years and this increase will be a record increase in the future. Main major ports in the UK are Felixstowe, Southampton, London, Medway, and Liverpool. Although road links connected to these ports have high quality infrastructure, increased traffic and environmental conditions have forced to alternative transport options. Hinterland container transportation has increased with the infrastructure of the railway lines since 1998. The port of Gothenburg is located in Sweden and it is a gateway to other Scandinavian countries. Although this port often dominates the road transport sector, the railway is also used to a considerable extent. By the successful applications of the Rail port system, many ports are oriented to the Rail port terminals. The greatest success of this system is its cost effectiveness, service availability, shorter availability times and flexibility. The Port of Rotterdam is a gateway to countries such as Germany, Luxembourg and France. This port is the largest container terminal in Europe. In 2002, it changes the goals for the port strategy. These goals include expansion of the backward region, developments in information and communication technology, focusing on internal transport and rail transport. In order to develop the railway transportation in the port's regional transport, a new line has been developed that connects with Germany. Increasing the capacity of Rotterdam's freight flows and to reduce transport costs is expected. The goal of the port for the year 2035 is to increase the train transportation performance by 20 per cent. Turkey should develop the ICT systems to ensure high quality solutions in the logistics market.

Many researchers have provided the basic conditions of the well-organized inland transportation system. Efficient determination of the system requirements for the transport structure, good coordination of the actors in the transport chain and the services provided by freight forwarders should be provided. The actors in the inland transportation chain are presented in Table 1.1 as follows:

Table 1.1. Important actors of inland region

Inland	Actors
Marine way	Marine operators Port firm Terminal operator Freight forwarder Customer
Railway	Railway operators Railway firm Railway terminal operator Infrastructure director Freight forwarder Customer
Highway	Highway firm Freight forwarder Customer

1.3. Intermodal transportation

Intermodal transport is defined as the transport of cargo by various transportation modes in the same carrying unit. Intermodal line is started with transporting the cargo by truck. Then, the cargo is loaded into the ships and transporting the cargo with the train line or trucks is followed. Intermodal transport is a sub-section of multimodal transport. Multimodal transport is divided into three sub-divisions: preliminary, main and final transportation.

Preliminary transportation includes the transportation between customer and the terminal, the main part includes transportation from the terminal to the other terminal, and the final part includes transportation from the terminal to the customer. The main part is usually the longest section and covers the railway or maritime route, while the preliminary and final sections include trucks and door-to-door carriage (Nossack and Pesch, 2013). 25% and 40% of the total costs in multimodal transport are related with the trucking operations of the transport chain. (Macharis and Bontekoning, 2004). Nooteboom and Rodrigue (2005) also state that maritime transportation costs are consisted of the shares between 40% and 80% of internal transport. The elements of multimodal transport are:

1.3.1. Container

The containers are one of the carrying units that are grouped into export and import containers considering customer requirements. Import containers are called by this name because the containers unloaded from the ships are transported to the customer points in the hinterland. Export containers are called by this name because the containers in the customer points are distributed to the terminal by the road transportation (Sterzik and Kopfer, 2013). Either container is transported between the customer points and the terminal or they are transported by railway transport to the train stations within the terminal. Containers are also divided into FTLF, FTLB, and LTL. FTLF and FTLB containers are full truckload containers; LTL containers are less than truckload containers.

Container sizes are standardized. Due to practical utilization of the container, container transportation is evolving in the logistics sector. Various types of containers are produced. Loads are usually loaded into containers of 20 feet in length, equivalent to TEU (Twenty Equivalent Units) and 40 feet in length, equivalent to FEU (Forty Equivalent Unit). The dimensions of a standard container determined by ISO are shown in Figure 1.3.

CONTAINER				Volume	Loading Volume	Max. Loading Weight	Self-weight
Size	Length (m)	Width (m)	Height (m)	m^3	m^3	t	t
20 TEU	6,096	2,438	2,591	32	29	24	1,8-2,4
40 FEU	12,192	2,438	2,591	65	59	30,48	2,8-4,0

Figure 1.3. Container sizes defined by ISO (Bartan, 2007)

Standard containers 20 ' is designed for general loads, it can be used for dry loads (Figure 1.4.). The containers are suitable to all loads that can fit inside the container for door-to-door transportation (Bartan 2007).

Figure 1.4. Standard container -20 TEU (Bartan 2007)

Standard containers 40 ' can take a load of 2x20 TEU containers as volume (Figure 1.5.). It is mostly used for textile sector, but preferred for transports with a low weight (white goods, tobacco, textiles, food, etc.).

Figure 1.5. Standard container - 40 TEU (Bartan 2007)

1.3.2. Transportation Modes

Inland transportation is carried out in a hinterland region, in which trucks, ships, and aircraft and train vehicles are used to transfer the containers. In the multimodal transportation, trucks are mostly used because they provide door-to-door carriage. The other type of vehicle used in this system is train. Trains are advantageous in terms of transporting cargoes in a reasonable time and environmental impacts comparing to trucks on the highway. The most important part in multimodal transportation is sea transportation. Ro-Ro ships are usually used for this transportation. These vehicles offer the possibility of moving loads within the same ship to their destination without loading, unloading or handling. Finally, there is another option: air transport. This transport is also preferred for transporting light and high-cost cargoes by incorporating other conditions such as deterioration, expiration date. A comparison table of transport modes is depicted in Figure 1.6.

In addition to multimodal transport is used to serve customers using multiple transport vehicles, transport systems such as single mode transport and combined transport are available. In the single-mode transport, a single transport vehicle is preferred. Road transport is frequently used due to the ease of loading and unloading and the economic structure of short distances. In addition to these advantages, there are disadvantages in terms of usage of trucks due to environmental and cost constraints. In addition to advantages such as low cost marine transportation have risks due to damage to the environment, limited settlement within ports and criticism of arrival times. As mentioned above, the air transport is the most costly transportation mode besides the high security and speed. Railway transport is advantageous because it can carry heavy loads safely, and it is not much affected by environmental conditions, and it is a fixed-price transport. This transport has high handling costs.

	Marineway Transport		Railway Transport	Highway Transport
	Main line	Intermediate line		
Container Number	Large	Medium	Small	One by one
Services	Regular, periodic	Regular, periodic	Regular, periodic	Irregular, non-periodic
Handling	Limited	Limited	Limited	Unlimited
Pre-planning of handling	Feasible	Feasible	Feasible	Infeasible

Figure 1.6. Comparison of transportation modes (Yalçın, 2005)

1.3.3. Other transportation modes

As mentioned above, multimodal transport is preferred mostly by using more than one means of transportation, while transport systems such as single mode transport and combined transport are also preferred. In single mode transport, transport is carried out using a single transport mode. Road transport is frequently used due to the ease of loading and unloading operations, the width of the transportation network and the economic structure at short distances. Besides these advantages, they have disadvantages in terms of environmental and cost constraints. In addition to advantages such as the lowest cost structure and lack of customs shortage in maritime transport, it is disadvantageous due to environmental conditions, damage to ports and limited availability of arrival times. As mentioned above in the aircraft transport, the unit is the most costly transport on weight and stands out in high safety and speed. Railway transportation has the advantage of being able to carry heavy loads safely, not affected by environmental conditions and being fixed-price transportation; infrastructure shortages are disadvantageous due to reasons such as high handling costs.

1.4. Vehicle Routing Problem

ICT is classically handled as vehicle routing problem. In the problem, the network is formed with container flows. This network is transformed into a multi-node or time-window vehicle routing problem in real case problems (Wang and Yun, 2013).

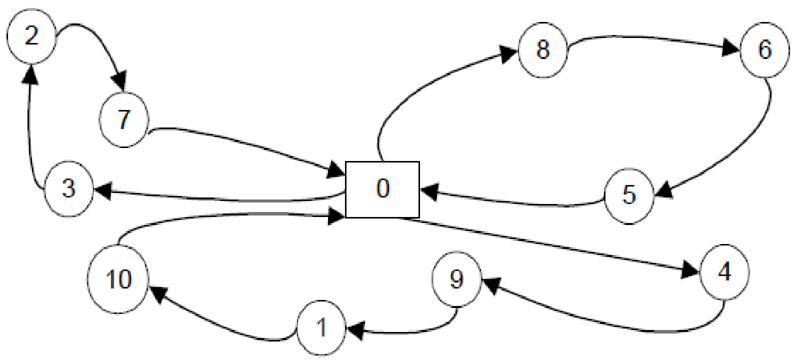

Figure 1.7. The network of a vehicle routing problem (Pereira, Tavares et al. 2002)

Vehicle routing problems (VRP) is first studied in 1959 (Toth and Vigo 2002). Vehicle routing problems include the routing of vehicles to minimize cost and durations between two points. The vehicle routing problem is actually G (V, A) and a basic network is represented in Figure 1.7.

1.4.1. Classical Vehicle Routing Problem

There are three basic assumptions in classical vehicle routing problems (Liong, Ismail et al. 2008):

- Each city should receive service from a single vehicle.
- Vehicle starts and ends the routing in the same warehouse.
- Some capacity, time etc. constraints should be provided.

Some of the restrictions in the literature are as follows (Laporte 1992):

- Capacity Constraints: This constraint ensures that the sum of the orders to be transferred does not exceed the vehicle capacity. This problem is named capacity restricted vehicle routing problem.
- City Constraint: This constraint indicates that number of city points to be stopped at each route.
- Total Time Constraints: Route lengths can be smaller than the previously defined maximum length value. This period should be considered to include transport and waiting times. This problem is called a time or distance restricted vehicle routing problem.
- Time Window: This constraint requires that travelling is performed within a certain time [a, b].
- Priority Relations: These constraints force a city to receive services before city j.

All mentioned constrains force the problem to be more difficult (NP-hard). The general formulation of vehicle routing problems can be defined as follows in Figure 1.8.

$$Min\ z = \sum_{i \neq j} d_{ij} * x_{ij} \quad (1)$$

$$\sum_{j} x_{ij} = 1, \forall i \in V \quad (2)$$

$$\sum_{i} x_{ij} = 1, \forall j \in V \quad (3)$$

$$\sum_{i} x_{ij} \geq |S| - v(S), \quad \{S{:}S \subseteq V \setminus \{1\}, |S| \geq 2\}, \quad (4)$$

$$x_{ij} \in \{0,1\}, \forall i,j \in E; i \neq j \quad (5)$$

Figure 1.8. The general formulation of vehicle routing problem (Laporte, 1992)

In the basic mathematical model, d is the distance or cost parameter and x is the transportation between cities. As mentioned earlier, there is no capacity constraint here. (1) Equality means the objective function, minimization of the total distance or of the cost. (2), (3) the obligation of each city to receive service; (4) is sub tour constraint (5) shows the range of decision variables.

1.4.2. Vehicle routing problem types

The vehicle is divided into several types due to application of routing problems and some other special cases. These are (Düzakın and Demircioğlu 2009):

- Mixed Capacity Vehicle Routing Problem: Each vehicle can have a different capacity in a mixed capacity vehicle routing problem.

- Vehicle Routing Problem with Multiple depots: Distribution company has multiple depots to serve customer points. Because customer points are clustered around the warehouses, the distribution problem can be modelled as a separate VRP. However, if customers and depots are mixed together, vehicle routing with multi depots must be solved. In this problem, vehicles are assigned to depots and each vehicle starts its tour in the warehouse, serves the customer, and finishes its tour in the same warehouse.
- VRP with Split Demand: VRP with split demand allows multi vehicles to service the same customer.
- VRP with Uncertain Demand: This problem is a VRP where demand is uncertain. When the delivery agent arrives at the customer, it becomes clear what the customer's demand will be.
- Vehicle Routing Problem with Returns: This type of vehicle routing problem includes the return of some parts of the products, such as deposits, packaging and pallets. In this case, vehicle capacities should be calculated by taking into account the parts to be returned from the customers.
- VRP with Time Window: In this problem, the distribution firm has to serve each customer at a certain time interval.
- Asymmetric VRP: The problem contains the distances from the warehouse to the customer point and the distances from the same customers to the warehouses. In this case, the cost matrix is not symmetrical.

1.5. Operational and Tactical Transportation Problems for Intermodal Transportation Networks

Over the last decades, intermodal network studies considering the transportation mode choice, vehicle routing problem, load consolidation have gained attraction in the domain of the logistics sector. These problems require high quality solutions to solve because of their complex structure. An optimal intermodal transportation system, which provides best solutions oriented to the need for customers, is a focal challenge regarding the practical and academic implications. In this context, most researchers have investigated the VRPs and its variants, which are part of the real world applications in the intermodal transport systems. 3D-PRP is a key part and mostly studied VRPs regarding practical and academic aspect. Considering the practical impact, 3D-PRP is related with many real-world scenarios of the logistics firms dealing with delivery and loading processes. 3D-PRP is also important considering an academic impact since it involves two NP-hard problems: PRP and 3D loading.

Railway transport is a key component for the intermodal transportation to provide the optimal distribution of goods. Recently, there is an increasing interest to shift the transport modes from highway to railway transportation. Road transportation related costs account for 25-40% of the total costs in the intermodal networks (Macharis and Bontekoning, 2004). Because of that, it is valuable to research the rail transportation based problems. While both of the 3D-PRP and the train assignment problem have been investigated respectively, coordinating the problems are required for an integrated network.

This study investigates the integrations between 3D-PRP and transport mode assignment problems for the intermodal transport system-involving truck and train mode. In the first step, truck vehicle is used for the 3D-PRP, which provides clustering loading cities, regarding latitude and longitude values of these cities using k-means algorithm, picking up the orders, and an optimal loading of the orders and vehicle routing. In the second step, railway transport is handled of the train assignment problem, in which consolidated orders are allocated to the trains with a focus on reducing the detention and demurrage cost parameters (Gocmen and Erol, 2019).

Our motivation for this presented study is of the papers proposed by Bortfeldt and Homberger (2013) and Reil et al (2018) with packing first, routing second approaches. We modify this approach by clustering backhauls first for fast computational time, then bin packing by machine learning for a feasible loading pattern with four loading dimensions and vehicle routing by genetic algorithm. The loading phase also includes four dimensions (length, width, height and weight). Thus, this phase can be called as four-dimensional loading problems (4D loading). The main outputs of this problem solution are four-folds:

- We combines operational and tactical levels of decision making with a two-stage approach considers picking up the orders from the hinterland customers, then loading the orders into the carrying units with three dimensional bin packing formulation for the operational level and tactical level for assigning these consolidated orders to the trains.
- To the best of our knowledge, this is the first study that integrates the genetic algorithm and machine learning approach to solve the 3D- PRP.
- A novel principle: clustering first, packing-routing second for the 3D-PRP is proposed.
- Various cost variants by incorporating detention and demurrage costs for the train assignment problem and four loading dimensions, making more challenging than three loading dimensions for 3D loading problem.
- Exact solution approaches, intelligent software for vehicle routing named ODL and heuristic approaches on real case data by an international logistics firm and new randomly generated instances (Gocmen and Erol, 2019).

1.6. Intermodal Transportation Problem

The importance of sustainable intermodal transportation problems have showed raising increase. Intermodal transportation is movement of goods by multiple transport modes in the same container (Oudani et al, 2014). Intermodal transportation problems include various sub problems such as mode selection, load planning and distribution. These problems are NP hard problems. Thus, single-mode transport systems are mostly handled. The transportation modes used in the intermodal networks are trucks, ships, trains and airplanes. Road transportation is mostly preferred option in Turkey. However, losing of 10,000 people are recorded each year (WHO, 2018). High emission values are observed and negative effects on human and environment increase in Turkey. These situations foster the sustainability issues for the logistics sector. Transport systems are evaluated considering environmental impacts (Lopez-Navarro, 2014). Intermodal transportation is evaluated to provide efficient and sustainable solutions (Jugovic et al, 2011). However, verification of this information has not provided (Janic, 2007). Trucks and truck-ship-train combinations competing each other to provide more sustainable transportation (Mostert and Limbourg, 2016). Road transport mode has been accepted as an important option to the intermodal transport due to the improvements (Janic, 2008). However, transport mode shifts such as road-rail are supported to reduce negative impacts (Janic and Vleguel, 2012). Intermodal problems involve the classical constraints in the literature. Intermodal route and mode choice problems are associated with capacity, distance, time and cost constraints. Not only transportation goods in a reasonable time and economically is critical but also transportation by incorporating social and ecological risks is vital.

Transportation vehicles with high-risk impacts are treats for all universe. The used transport modes are truck, train, ship and airplane. Airplane is not included to our study. Airplane has an advantage with fast travelling. However, it is considered as carbon intensive transport mode (Gennaro et al, 2016). Emission values related to air mode have shown an increasing trend (Sguoris et al, 2011). The other treat of emission values is road transport (Li et al, 2016). Truck is preferred in the inland operations. Loses of 1.25 million lives are realized with road accidents (WHO, 2013). High noise pollution is another negative result of this mode. The modern highway infrastructures increase the truck transports and more trucks are equal to more congestion. Trains are used for heavy bulks to minimize the transport costs. Environmental issues do not affect the rail transport highly. Trains also service the customers with one of the transportation modes. They travel between train terminals and truck is required for door-to-door transportation. Marine transportation is an alternative for heavy bulks and international logistics. Marine vehicles are affected by the environmental conditions. All transportation modes should be evaluated by considering all characteristics of the modes. Organizing the more sustainable transport systems is necessary for sustainable universe. Minimum social and ecological risks related to transport modes are aims for the sustainable transport system. Therefore, we handle two risk groups including social and ecological risks. Social risks are human deaths and accidents; ecological risks are noise pollution and emission values. Both of these main risk groups involve various sub groups. Collisions, driver faults, congestion and route infrastructure are sub-groups of social risks. Air toxics and particles, fuel efficiency, travelling time are the other sub groups. These main and sub-groups are evaluated by the decision makers who record the transportation system results. The scoring is conducted with linguistic variables. Each transport mode is assigned to the risk weight by the fuzzification method. The ecological results are very difficult to measure. This problem requires fuzzy method (Tuzkaya, 2009). Fuzzy method is provided to decide the risk weights. Thus, both of the economic assignment and the social-ecological assignment to the transport modes and routes are obtained. The papers related with intermodal systems consider the cost, capacity and time characteristics of the transportation modes. Few papers consider the risk issues in this network. The findings can make economically and environmentally sound. Outputs of the problem are provided as follows:

- Allocation of orders to the transportation modes and routes are achieved by developed mathematical model including multi-product and multi-period. Thus, modal shift mentioned in (Islam et al, 2011) is obtained with our new modelling approach.

- Various criteria should be handled as input to the mathematical modelling approach (Hanaoka and Kunadhamraks, 2009). Risk weights are used as indexs in the objective function.
- Both mathematical modelling and artificial based approaches should be handled for the intermodal networks (Serper and Alumur, 2016). Both of them are used for our problem. Fuzzy results are compared with the findings in (Tuzkaya and Onut, 2008). Similar best and worst transport mode alternatives are obtained.

1.7. Aim of the Thesis

Decisions include clustering, pick up routing, three dimensional bin packing on intermodal transportation and transport mode choice can ensure more effective load planning. The main aims of the study are given below:

- To provide a load planning problem that integrates simultaneous decisions like clustering, pick up routing and bin packing, train assignment
- To present a sustainable intermodal transport network problem based on social, economic and ecological risks
- To guide the logistics firms for their decision making processes about the transportation networks
- To find novel solution methods scientifically sound for intermodal networks

We can summary our aim in the system diagram shown in Figure 1.9. In the system diagram, system inputs, outputs, processes and performance criteria are handled.

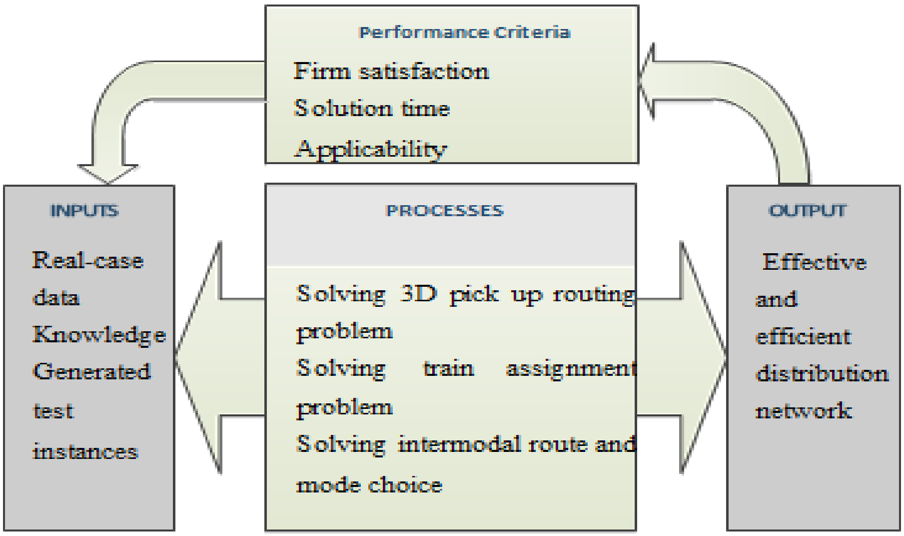

Figure 1.9. System diagram for our aim representation

1.8. Scope

In this study, coordinated operational and tactical problems for an intermodal network are solved. Mathematical models are presented for these problems. For larger and medium instances, heuristic and machine learning approaches are applied. The intermodal network focused on this study has some characteristics:

- An intermodal network is consisted of logistics firm, customers, transport modes, carrying units, and orders.
- Export demands are considered in the study. Import demands are not included.
- Export demands are exactly known and regarded as deterministic.
- Carrying units mentioned above are trailers or containers.
- Distribution is carried out by road, rail and maritime transportation.
- Block trains have fixed time schedules.

The 3D-PRP problems have some characteristics:

- The total distance that vehicle can travel is limited for the first problem.
- The distances between two points are calculated by generalized cost instead of Euclidean distance.
- Single firm and multi customers in the hinterland are assumed.
- Distribution is carried out by road transportation.

1.9. Steps and Organization of the Thesis

The thesis consists of the following stages:

- Decision-making process of the problem: This step is started with identifying our goal and gathering information related with the area.
- Review of previous papers: Papers focused on problems such as assignment to line planning, routing and transport modes in multimodal transport and single-mode transportation are examined. Formulations and methodologies of the problem definitions are examined.
- Description of the problem: The problem is described verbally and mathematically. Parameters, decision variables, constraints and assumptions are determined at this step.
- Model solution: The best solution approach is chosen for the problem and heuristic approaches are recommended for larger scale problems.
- Mathematical modelling: A mathematical model is developed and coded for modelling software.
- Case study: A real case study is examined and the mathematical model is solved by the firm’s real data.
- Heuristic method: A heuristic or meta-heuristic method is used for larger test instances.

- Analysis of the results: The effects of the problem parameters are analysed under different conditions and the sensitivity of the proposed model is evaluated.
- Conclusion: The results of the proposed problems and methods are evaluated and recommendations for future studies are presented.

1.10. Outline of the Thesis

This thesis comprises five main sections. This first section is introduction consists of twelve sub sections including the background and motivations, aim, scope, steps, problem definitions, contributions, outline of this thesis. In Section 2, literature review is provided. Discussions of the literature reviews for each problem are provided. In Section 3, material and methods are presented. Section 4 presents findings and discussions. Results of the thesis and future research directions are provided in Section 5.

1.11. Original Contributions

- A two-stage approach for both the operational level, that considers picking up the orders from the hinterland customers, then loading the orders into the carrying units with three dimensional bin packing constraints and tactical level for assigning these order groups to the trains is proposed.
- Intermodal transportation involving road, rail and maritime transport modes is presented. A user interface is developed for end users in this stage.
- A novel approach including clustering first, then bin packing by machine learning with four loading dimensions and VRP by genetic algorithm.
- A holistic approach including minimization of total costs and maximization for utility of carrying units is presented.

- Comparing exact solution approaches, intelligent software for vehicle routing and heuristic approaches for presented real case data by an international logistics firm and new randomly generated instances to validate the solution methods are conducted.
- In the mathematical model for VRP, generalized cost instead of a cost proportional to the distance is incorporated. This would deem the problem generally more complex to solve. In the literature, Euclidian approach is fundamentally misleading in the applications, as the 'distance' depends on the generalized cost (cost, time and bias) not the geometric distance.
- Researchers suggest that the performance factors could be included to mathematical modelling formulations. This is the first study to handle the results of fuzzy-based method as inputs to the objective function in the model. A fuzzy method is presented to examine the mode weights regarding human and ecological risks (Gocmen and Erol, 2018).
- A mathematical programming model that deals with allocation of orders to the various transport modes with multi-customers, multi supply points, multi-periods is provided to guide the freight forwards on the strategic decisions.

2. LITERATURE REVIEW

The pick-up routing with 3D loading and assignment problems are mostly handled separately. For this reason, previous works are discussed in three sections. Coordination of these problems provides a more efficient supply chain. Many of the current studies concerning intermodal transport are based on deciding the mode selections (Min, 1991; Bierwirth et al., 2012; Serper and Alumur, 2016), comparison of transport modes (Barnhart and Ratliff, 1993, load planning (Bruns and Knust, 2012; Bauer et al, 2010). To the best of our knowledge, combining operational and tactical levels of decision-making concerning intermodal transport is firstly provided in the study. 3D-PRP and mode assignment problem have been handled separately. Thus, preliminary works can be classified as three sections (Gocmen and Erol, 2018). First section is the papers dealt with pick-up routing problem with 3-D loading constraints at operational level while the second is about train-freight assignments at tactical level. The third section is about sustainable intermodal mode choice.

2.1. Studies Related With 3D-PRP

2.1.1. Studies Related with ICT

ICT problems involving fleet management, route planning, and truck loading have been investigated by many researchers. Table 2.1. summarizes the papers including inland container transportation problems.

Jula et al (2001), examine a problem involving container movements with trucks. The problem is handled as a travelling-salesman problem with time window constraint. The problem decides the truck routes and minimizes the total distribution costs. Dynamic programming based exact solution method is presented to solve the problem. Two-level approach is conducted to obtain the optimum solutions. The method yields successful results for 15-20 nodes. For large-scale problems, a hybrid method including dynamic programming and genetic algorithm is developed. The experimental results show the efficient solutions of the genetic algorithm.

Jula et al (2005), focus on the truck-scheduling problem involving transferring containers between port terminals, warehouses and customers. Time constraints at the start and end-points for the containers carried by trucks are available. The problem is a version of the traveling salesman problem, but also similar to the full truck-load problem. While deciding the routes of trucks, minimizing the total distribution costs is aimed. For large-scale problems, they have developed a hybrid method that includes dynamic programming and genetic algorithm.

Coslovich et al (2006), study the fleet management in the container transport industry and the company has tried to minimize costs from the eyes of the container transport company. In the paper, the costs are divided into three main categories: routing cost, truck and driver assignment costs, and container placement costs. The formulation is modelled as an integer programming problem and proposed method problem is based on dividing three separate sub-problems. The problem is applied for an Italian container carrier.

Imai et al (2007), solve the full container vehicle routing problem based on Lagrange relaxation and obtain optimal solutions. It involves two sub-problems: classic allocation problem and general allocation problem. Since the general assignment problem is based on a boxing problem. The developed heuristic has been tested on problem samples and has been observed to be effective for large-scale problems.

Namboothiri and Erera (2008) focus on management of truck fleets that present picking up and distribution services of containers through an assignment-based process. To provide solutions, they aim to plan container transport operations by an integer programming approach. The approach decides the order of pick up and distribution for daily transport operations with minimum transport costs. With the developed framework, the effects of access control systems on transport companies are observed. By the incorrect access time intervals, service shortages and reductions of number of customers are observed.

Zhang et al (2009) address a time-window transport problem, involving time windows at the start and end points of containers and the positioning of empty containers. Due to the difficult structure of the problem, a cluster method and tabu research algorithm has been handled to solve this problem. The approaches are compared with the exact solution method. Optimum results are found for small problems by the mixed integer modelling.

Kopfer et al (2010) optimize the transport of containers in a single-terminal. Two different models have been proposed for different scenarios in the system where the transportation is conducted with limited number and homogeneous trucks. In the first scenario, empty containers can only be used by their owners, while in the second scenario the use of empty containers by random and different owners is discussed. By comparing the two scenarios, the benefits of container sharing are observed.

Zhang et al (2010) deal with the truck scheduling by multi-storages and multi-terminals. In the study, a company with trucks and empty containers is handled between customers and terminals. In the network, empty containers are stored and trucks are parked in multiple storage locations. The problems discussed in this study are solved to decide where the empty container will be distributed after the import of the full container and where the empty container will be collected for the full export container. Total processing times of trucks have been minimized. The problem is mathematically formulated with the graphical formulation (Figure 2.1). This problem is a type of the classic travelling salesman problems with time-window and a window partitioned solution method has been developed.

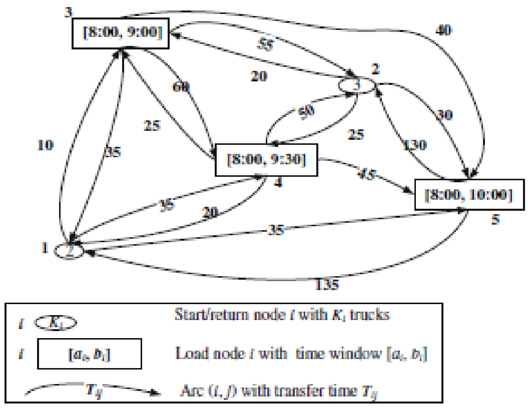

Figure 2.1. Example of network representation (Zhang et al, 2010)

Zhang et al (2011) discuss container-handling problems with empty container constraints. The area covered in the study is export-oriented and includes the movement of full export, full import and empty imported containers. Each container has time windows at the start and end-points. The initial numbers of empty containers in the tank are known. Total processing times including waiting times of all trucks are minimized. The problem is primarily formulated on a graphical model, and then modelled mathematically. The problem can be defined as a resource-constrained, time-window travelling salesman problem. An advanced heuristic based on tabu research has been developed.

Sterzik and Kopfer (2013) present the problem of internal container distribution including the transportation of all containers between a large number of terminals, warehouses and customers. A truck company uses a large number of homogeneous trucks to serve customers, for import and export containers. In the case of time constraints, vehicle routing, scheduling and empty container positioning are solved simultaneously and the total processing times of the trucks are minimized. This problem is solved by the heuristics and effective on small and large-scale samples.

Lai et al (2013) provide a new vehicle routing problem with load compartment, heterogeneous loaded trucks in container transportation. In the study, some trucks carry only one container and some of them carry two containers. At the same time, there are two customer classes as importer and exporter. Customers can be visited by multiple times. The linear integer programming model is developed for this problem. They have also developed a heuristics using Clarke-Wright algorithm and local searches for the initial solution.

Nossack and Pesch (2013), discuss the truck-scheduling problem in multimodal container transport where containers are transported between customers and container terminals. In this system, a transport company with various warehouses and trucks obtains the transport requests. In the study, the trucks and orders are chosen to minimize the all processing times under the time windows. The problem is formulated as a full loaded picking up and distribution problem with time windows constraint and two-stage heuristic approach is proposed.

Funke and Kopfer (2016), work on a problem involving pre-transport and final transport of multi-mode container transport. Containers are transported between terminals, customers and company as full or empty. The full containers are defined with the start and end-points, the empty containers are defined with the unknown start and end points. While the problem of truck routing is solved, assignments of cargo demands to empty containers are conducted. A mathematical model that assigns the containers to both demands and truck routes is solved for 40 and 20 containers. The model has been applied for two purposes, minimizing total travel distance and total truck operation time.

Table 2.1. Papers related with ICT

Paper	Problem	Methodology
Jula et al, 2001	Truck routing problem	Genetic algorithm
Jula et al, 2005	Truck routing problem	Genetic algorithm
Coslovich et al, 2006	Truck routing problem	Developed mathematical model
Imai et al, 2007	Truck routing problem	Developed heuristics
Namboothiri and Erera, 2008	Pick up delivery decisions of trucks	Integer programming
Zhang et al, 2009	Travelling salesman problem including truck transportation and empty container placement problem	Tabu search
Zhang et al, 2010	Truck scheduling problem	Developed mathematical model
Kopfer et al, 2010	Hinterland container transportation problem	
Zhang et al, 2011	Hinterland container transportation problem	Tabu search
Sterzik and Kopfer, 2013	Hinterland container transportation problem	Tabu search
Nossack and Pesch, 2013	Truck scheduling problem	Developed heuristics
Lai et al, 2013	Truck routing problem	Developed heuristics
Funke and Kopfer, 2016	Truck routing problem and empty container problem	Mixed integer programming

2.1.2. Studies Related with 3D-PRP

Pick up routing problems with real-world constraints have gained attraction by both the academicians and freight forwarders in the last few years. Clustering loading cities, time windows, loading constraints are included in terms of 3D- PRP in the literature. The papers consider those constraints are summarized in Table 2.2 (Gocmen and Erol, 2019). The 3D loading constraints on orientation, stacking, weight are considered by Bortfeld and Homberger (2013), Reil et al (2018) while ensuring two of these constraints by Ruan et al. 2013, Gendreau et al 2008, Ceschia et al 2013, Lacomme et al 2013, Tao and Wang (2015), Zachariadis et al (2013), Zhu et al (2012).

Table 2.2. Overview of papers dealing 3D-PRP

Paper	Problem characteristics	Objective	Orientation	Stacking	Weight	Clustering	Solution approach
Bortfeld, 2012	Vehicle routing with 3D loading	Total travel distance and total computation times	X	-	X	-	Tabu search
Bortfeld 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 et al. 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 x 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
Zhu 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

Few papers have stressed the importance of loading constraints for 3D pick up routing in the recent years. Mannel and Bortfeld (2018) propose a pick-up delivery problem, which includes reloading ban and loading constraints. The contribution of the reloading ban ensures better results for travel time. Bodis and Botzheim (2018) discuss an order picking routing problem based on pallet loading constraints. They present a bacterial memetic algorithm and compare it with Simulated annealing algorithm. Wei et al (2018) investigates the combination of loading, clustering and pick up routing is only rarely presented. Both clustered backhauls and loading are considered by Bortfeldt et al (2015). Few published papers present heuristics methods. Tabu search method is performed by Gendreau et al (2006), Tarantilis et al (2009), Bortfeldt (2012), Tao and Wang (2015), Zhu et al (2012). The proposed algorithm by Gendreau et al (2006) decides the routes with tabu search, bin packing is solved with inner tabu search. Tarantilis et al (2009) presents the tabu method with guided local search. A tabu search based on two packing heuristics for freight transport industry is presented by Zu et al (2012).

Various heuristics are provided for PRP with 3d loading constraints. Simulated annealing is proposed by Junqueira and Morabito (2015), whereas Fuellerer et al (2010) present an ant colony algorithm.

Two-stage heuristic that is our motivation is presented by Bortfeldt and Homberger (2013) and Reil et al (2018) with packing first, routing second (P1R2). Reil et al (2018) extends the approach with backhaul customers.

2.2. Studies Related with Train Freight Assignments

Trainload allocations are a variant of load planning problems. A few papers that solve the load-to-train allocation problems are presented. Feo and Gonzales-Velarde (1995) provide a trailer-train wagon assignment problem. They aim to allocate the trailers to one wagon and it is limitation for the papers. Corry and Kozan (2006) discuss a trainload-planning problem which each container is assigned to a wagon and there are no weight restrictions for the wagons. They consider load holding time and weight distribution. Corry and Kozan (2008) also present a freight-planning problem including train lengths, load restrictions, handling times. They develop an integer linear problem. Bruns and Knust (2012) consider weight constraints of wagon configurations for the train-planning problem. Three different integer-programming models are developed in order to maximize train usage and to minimize the loading time to the trains in the storage area. Anghinolfi and Paolucci (2014) evaluate the train assignment considering the distances between container positions. Xiao et al (2018) present a block train allocation to decide the train services and traveling plan. They use a combined genetic and tabu search algorithm.

2.3. Studies Related with Intermodal Transport Mode Choice

Intermodal network has been studied by many researchers. Exact solution approaches and meta- heuristic solutions are provided (Min, 1991; Choong et al, 2002; Chang, 2008; Bauer et al, 2010; Verma et al, 2012; Tierney et al, 2014; Serper and Alumur, 2016; Baykasoğlu and Subulan, 2016). Most papers consider only economical and time aspects for these problems. Table 2.3. summarizes the papers.

Min (1991), focuses on the transport mode choice with a multi-objective approach. A target-programming model that provides the best combination of different modes of transport and provides the best flow between modes is presented. The model is a multi-objective technique for deciding solutions and meets both objectives and risks associated with the objectives. For deciding between transport modes, cost, market share, transport lengths, equipment capacities, risk-based comparison are considered.

Barnhart and Ratliff (1993), study single-mode road transport and the rail / road combination. The study aims minimizing the all costs of transport and minimizing costs of transportation. In this first phase of the study, while the minimum cost routing is solved by the shortest way finding procedure, the second step is searched for by optimal matching algorithm.

Boardman et al (1997), develop decision making to decide the most cost-effective transport mode between the start and end-points. They use GIS software to analyse the region. With the shortest path algorithm, they have minimized both time and cost. They use the average transport rates as a cost indicator for each transport mode.

Choong et al (2002), evaluate the effect of the planning time on mode choice and empty containers. In addition to providing the optimum transportation of containers, minimizing the total costs related to empty container transportation is aimed. Long planning horizon is observed as best option for the transport modes.

Macharis and Bontekoning (2004), propose a framework of the operations research opportunities used in multimodal freight transport. In this study, finding answers to questions such as what are the problems that make multimodal transport interesting and which operations research techniques are used. In addition, papers according to operator types and time horizon of operations are classified in the study. A classification matrix is obtained by the combination of these two categories.

Chang (2008), focuses on a number of operational issues in an international multimodal network. The problem is formulated with time windows, multi-objective, multi-mode, multi-load flow problem. The characteristic features of the problem are the multi-objective structure, which minimizes the time and traveling cost, the distribution times and the effect of the economies of scale on the calculation of the transport quantity. A mathematical model that meets three characteristics has been developed.

Caris et al (2008), investigate the planning issues in multimodal transport. They emphasize the strategically level problems including terminal layout and network. They state that there are not enough scientific publications for planning problems at operational level. In addition, they classify the planning problems by incorporating decision levels.

Caris and Janssens (2009), discuss the distribution problem involving the pre-transport and final transport stages of multimodal container transport with time-windows. The two-stage heuristics is presented for the first solution, and the solution is developed with the local search heuristics. Although the initial heuristics implementation causes a variation of the fixed cost and variable cost, the heuristic is effective in reducing overall cost and quality of the solution.

Verma and Verter (2010), present the two-objective mathematical method to find an optimal transport plans for the transport of dangerous and non-dangerous goods in the multi-mode transport network. Routing the trains and train service choice decisions are related with customer based service times. The study aims minimizing the all costs of transport and the total risks associated with dangerous materials.

Bauer et al (2010), discuss the multimodal transport network planning, which takes into account environmental conditions such as greenhouse gas effects. The study presents two important decisions such as how often and when to run the services and the decision of the flow of products. They have implemented real train freight transportation by adding environmental conditions, multi-product and capacity network design approaches to load transportation planning problems.

Yang et al (2011), develop a multi-mode network optimization model to find the best route between China and Indian Ocean. They also use an coordinated cost and target-programming model for purposes such as cost minimization, transit times.

Bierwirth et al (2012), present a mathematical model for the tactical level problem of multimodal transport. Service choice, mode selection, multimode terminal choice and load planning for the train operations are added to the model.

Cho et al (2012), formulate a intermodal routing problem using weighted shortest path model. In order to obtain solutions considering costs and times, they have implemented the label placement procedure, which is a variant of dynamic algorithm.

Verma et al (2012) have tried a two-objective problem to route multimodal transports in the transport of dangerous cargos. Aim of the study is to minimize the all transportation cost while minimizing the risk of hazardous material. As the contributions of the study to the literature, the first application of dangerous cargo transportation with multiple terminals by train, truck and the traffic outputs at various ports and the decision of the loading parameters on the trains are presented. For the problem, a mathematical model is provided and tabu search is used to solve this model.

Bruns and Knust (2012), study on freight planning in multi-mode container terminals. They aim to maximize the use of trains and to assign cargo to train wagons to minimize installation-transportation costs. In the study, they use an integer linear programming and got very quick results.

Wang and Yun (2013), examine a problem involving container movements between customer locations, terminals and warehouses. They propose a multiple-mode and time-windows constraint in which containers are transported by road and rail transport. They develop a graphic model and provide a hybrid tabu search. In the graphical model, the two time windows for containers are combined. For small sized problems, programs such as Cplex could find optimum solutions. For larger-scale problems, hybrid tabu research has provided near-optimal solutions.

Garcia et al (2013), examine a container-based multimodal transport including truck, train and ocean transportation. The multimodal transportation problem is divided into two sub-problems using a combination of operations research and artificial intelligence techniques. In the first problem, the cost of trucks and containers is assigned to services. In the second stage, each service is formulated as a planning problem by selecting the best transport mode and fulfilling the collection and distribution demands for each service.

Yun et al (2013), study a container transport problem with a warehouse, a port terminal, a station and four different types of containers with time windows. A graphical model is presented to formulate and illustrate the problem, and a mathematical model is developed. Hybrid annealing is also applied for large-scale problems. Contribution of the study is presented as the implementation of multi-mode train and truck transport and the development of the annealing simulation algorithm.

Tierney et al (2014), present a new mathematical model of terminal transport analysis in new and expansion decision ports. The model helps ports to analyse the effects of the new restructuring, the placement of terminals and vehicle investments for transport. In this study, by determining the number of models, traffic jams, multiple vehicle types, loading / unloading time, taking into account the terminal structure, container distribution delay has been minimized. The study is carried out at the ports of Hamburg and Rotterdam and provides important information on long-term decision-making.

Reşat and Turkay (2015), propose two-dimensional mathematical modelling for intermodal transportation design and operation problems. Congestion on road is also addressed. In the paper, an increased € restricted approach is presented to provide better solutions for costs and distribution time.

Li et al (2015), develop a multi-mode load network model for multi-stage load planning. Transportation times, train schedules, limitations of physical structure are included in the model. To handle changeable transportation demands and traffic situations, a new method is addressed and various scenarios are analysed by different experiments.

Demir et al (2015), use the multi-dimensional mixed integer linear model for the sustainable intermodal transport network including route plans. They deal with the uncertainty of circulation. Average approximate algorithm is presented to provide transportation solutions, along with transportation costs and sustainable aims.

Ghane-Ezabadi and Vergara (2016), develop a multi-mode logistics management model. They have focused on terminal layout, transport mode and route choice problems. Two-step optimization approach is used to obtain precise solutions for large-scale problems in a short time.

Febbraro et al (2016), provide a novel agent-based modelling approach to solve the load-planning problem of the multimodal load transport system. In this study, they propose an optimization method to ensure minimum cost and maximum reliability. System dynamics are modelled by discrete event simulation. Load distribution plans are created with an approach called rotating horizon algorithm.

Serper and Alumur (2016), examine a network involving different types of vehicles and alternative modes of transport in central networks. The aim to decide the capacities and placements of the centres with minimum total cost, to decide the modes of transport to serve these centres, assign them to centres and to decide which type of vehicles are available on the centre network to route the demand. The total cost consists of establishing centres with different capacities, purchasing and operating costs, transportation costs and material handling costs. To solve the problem, a mixed integer mathematical model has been developed and a variable neighbourhood search algorithm has been developed. The heuristic algorithm is tested with data from a Turkish network.

Baykasoğlu and Subulan (2016), address a freight planning problem for a real-world implementation of a logistics firm. They have proposed a mathematical model to solve the multiple-objective, multiple-mode and multiple-period problem. In addition to minimization of all costs, transit times and carbon dioxide emissions are minimized.

Risk aspect is considered by a paper about transporting hazardous materials for the intermodal network (Xie et al, 2012). Few papers handle safety, and security issues for the intermodal system. Fuzzy AHP, ANN, Topsis, Fuzzy Delphi and Fuzzy Electre methods are applied in these problems, respectively (Tian and Cao, 2017; Kunadhamraks and Hanaoka, 2008; Qu and Chen, 2008; Moon et al, 2015; Wang and Yeo, 2016). Other sustainability solutions are presented by some papers. Industry 4.0 is included to mathematical modeling approach for more sustainable network chain (Banyai et al, 2018). The other important parameter “energy efficiency” is included to obtain more efficient supply chains. Mathematical modelling is provided to schedule the deliveries. Heuristic approach ensures the optimal solution for the energy efficient solution (Banyai, 2018). Emission values are also incorporated for the networks. Cap-and-trade system with stochastic demand is presented (Yuan et al, 2018). Green solutions are provided to minimize emission values (Brandenburg, 2015). Goal programming is applied to design a supply chain considering emission values and disruption risks (Mari et al, 2014). However, risk weights have not been included using fuzzy approach. Risk model is developed for rail transportation (Glickman et al, 2007). Risk analysis is conducted for hazardous materials of rail-road transportation (Bubbico et al, 2006). Hazardous items are considered for intermodal transportation. Minimization of total transport cost and risks are aimed by incorporating population and affected people (Verma and Verter, 2010). Hazardous goods are evaluated for intermodal network and regional accident data is used (Raemdonck et al, 2013). Risk studies related to road transportation are Fabiano et al, 2002; Huang et al, 2004; Guo and Verma, 2010; Yang et al, 2010; to rail transportation are (Winslott Hiselius, 2005; Verma, 2009; Reilly et al, 2012; Liu et al, 2014); to intermodal transportation is (Reniers and Dullaert, 2013).

The above-mentioned papers present the classical intermodal solutions including green supply chains, minimizing total costs, etc. Few papers provide risk based approaches for the intermodal networks. The study evaluates the social, economic, and environmental risks for intermodal network decisions.

Table 2.3. Submitted papers of intermodal transportation

Paper	Problem	Method
Min, 1991	Multi-objective approach focuses on the transport mode choice and decides transport modes	Chance constrained target programming model
Barnhart and Ratliff , 1993	Comparison of train / land combination and single-mode road transport and routing problem	Developed algorithm
Boardman et al., 1997	Deciding the combination of the most cost effective transport mode choice	Developed algorithm
Choong et al., 2002	Transport of containers minimizing the total costs associated with empty containers	Integer programming approach
Macharis and Bontekoning, 2004	A review of research opportunities used in multi-modal freight transport	Classification matrices
Chang, 2008	Multi-objective, multi-modal, multi-product flow problem with time windows	Mathematical model Developed heuristic
Caris and Janssens, 2009	A time-window pick-up and delivery problem involving pre-transport and final transport stages of multi-modal container transport	Developed two stage heuristic

Bauer et al, 2010	Multi-modal load transportation problem considering environmental conditions	Mixed integer programming model
Verma and Verter, 2010	finding the most appropriate transport plan for the transport of hazardous and non-hazardous materials	Iterative decomposition based solution detection
Yang et al., 2011	A multimodal network optimization problem to find optimal route	Target programming
Bierwirth et al., 2012	Transportation mode selection, multimodal terminal selection and cargo consolidation	Mixed integer model
Cho et al., 2012	The problem of formulating multi-objective, multi-modal problem with time window and weighted shortest path model	Dynamic programming
Verma and ark, 2012	Multi-modal transport that minimizes total cost of transport while minimizing risk due to hazardous substances at the same time.	Tabu search
Bruns and Knust, 2012	The problem of train loading in multimodal terminals	Integer linear programming
Wang and Yun, 2013	A problem involving container movements between customer locations, terminals, repositories	Tabu search
Zhang et al., 2011	Container transport problem to minimize total processing times, including waiting times of trucks	Tabu search
Garcia et al., 2013	Multimodal transport problem involving truck, train and ocean transport	Improved algorithm

Yun et al., 2013	A container transport problem involving four different types of containers with one depot, one port terminal, one station and a time window	Mixed integer model Simulated annealing
Tierney et al., 2014	The problem of minimizing container deployment delay for terminal transport analysis	Integer model
Resat and Turkay, 2015	Multimodal transport network and operational problem	Developed heuristic
Demir and ark, 2015	Green multi-modal transport network problem	Improved algorithm
Li et al., 2015	Multimodal load network and multimodal load transportation model for multi-stage freight transport planning	Simulation
Ghane-Ezabadi and Vergara, 2016	Station settling, transport mode and route selection problems	Improved algorithm
Febbraro et al., 2016	Planning problems in multimodal freight transport system	Agent based programming, Simulation
Serper and Alumur, 2016	Deciding on the modes of transportation, the type of vehicles	Mixed integer mathematical programming Developed algorithm
Baykasoğlu and Subulan, 2016	Multi-objective, multi-modal and multi-period load planning problem	Mixed integer mathematical programming Developed heuristic
Presented study	Intermodal problem including road and rail modes and transport mode choice	Mixed integer mathematical programming

2.4. Evaluation of Relevant Studies

Pick-up routing problems with 3D loading, train assignments and intermodal transportation decisions are widely studied in the literature. However, there are still many areas to investigate by the researchers. The aim of this study is fulfil these gaps. Load planning problems that are handled separately may cause increasing operational costs and using capacities redundantly. In addition, environmental concerns and legal obligations force the logistics firms to consider intermodal transportation systems. Firms should be responsible to evaluate social and ecological risks of transportation modes. A research gap is available considering these risk groups on the transportation modes.

Most of the studies provide mathematical modelling approaches for solving these problems. However, solving large-sized problems is hard in a reasonable time due to the NP-hard structure of the problems. Therefore, meta-heuristic approaches are applied.

3. MATERIAL AND METHOD

3.1. Material

In the study, a real life application is presented to demonstrate the efficiency and validity of the proposed approaches. The datasets, which have been used in both the 3D-PRP and intermodal transportation mode selection problem, are provided by EKOL Logistics 4.0. The international logistics company leads to intercontinental logistics services containing intermodal services. The company provides best transportation solutions for containers, finished products, and industrial products to the global firms and brands. Our motivation is related with company's intermodal transportation system and inland operations. Intermodal transportation is started by transporting of carrying units from Turkey ports to Trieste port by marine transport. Carrying units are assigned to the block trains at train station in Trieste. Arriving carrying units are unloaded from block trains. Then, they are transferred by road transportation to the centres of Ostrava, Cologne and Ludwigshafen. The intermodal transport network of the company, which is handled in the study, is depicted in Figure 3.1.

The dataset, which is used in the first stage, is provided by R & D department of the company. The dataset is divided into two groups: one is related with order dimensions and the other includes the carrying unit dimensions, which can be found in the appendix A and B. The order dataset is divided into 14 columns representing various properties. Orders are defined via their code, loading city, quantity, gross weight, volume brut, width, height, depth, stack ability properties. Loading cities are addressed by the postcode, longitude, and latitude properties. Vehicles used in the study are named as carrying units that have tare weight, width, height, and length properties. In this stage, in addition to real case data, random generated test instances are used. Small sized problems are solved by GAMS optimization software and an intelligent software for vehicle routing named Open Door Logistics executed on an Intel CPU 3.6 GHz with 16 GB RAM. Medium sized problems and real world data are solved by MATLAB software package, RStudio software.

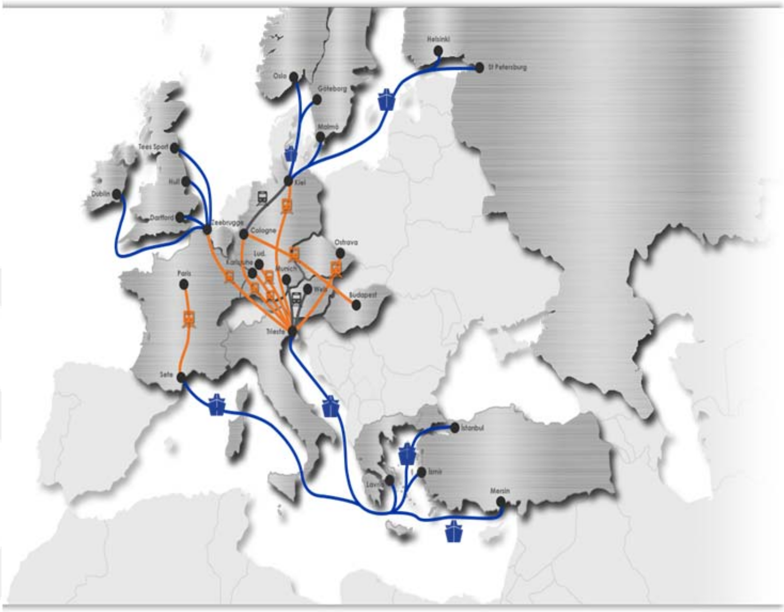

Figure 3.1. Company's multimodal logistics network configuration (Ekol Logistics, 2018)

Main component of the second stage is illustrated in Figure 3.2. Model component includes MILP and Fuzzy based approach. The data component consists of real life data. Then, GUI is for the end users.

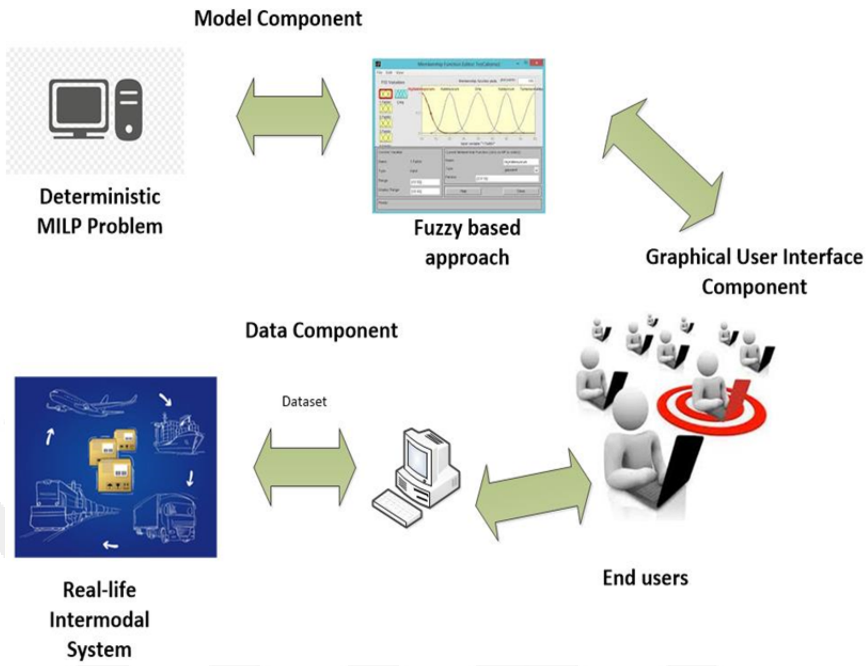

Figure 3.2. Main components for the intermodal transportation problem

The dataset, which is used in the second stage, is related with the intermodal transportation network includes one marine port- Trieste in Europe, a port-İstanbul in Turkey, three train stations with block trains. There are three round trips per week from Istanbul port to Trieste port and one round trip between İzmir and Sete ports. Each turn takes 60 hours and the tour is provided by the company's own Ro-ros. Each ship has 249 gigantic trailers or 45 ft. capacity. Every week, the company operates 6-day transit block trains between Istanbul and Europe. Thus, it consumes fewer litres of fuel and carbon dioxide than road transport. The block train capacity is 32 trailer-containers with a minimum of 8 trains per month. The intervals of other parameters are depicted in Table 3.1. The intermodal transportation mode selection problem is solved by GAMS optimization software executed on an Intel CPU 3.6 GHz with 16 GB RAM.

Table 3.1. Data ranges of the logistics company

Parameters	Range
Export demands of customers (TU/Month)	0-350
Maritime transportation cost by RoRo (€/TU)	600-1600
Railway transportation cost of per block train (€/TU)	20.000-25.400
Road transportation cost by trucks per kilometer (€ TU/km)	1.5
RoRo capacity (TU)	175-240
Train capacity (TU)	28-32
Truck capacity (TU)	10-20
Road distance between supply points in Turkey and customers in Europe (km)	560-5120
Road distance between Ostrava train station and customers in Europe (km)	65-3225

3.2. Method

In this section, 3D-PRP and intermodal problems are explained. 3D-PRP is consisted of two sub-problems: one for PRP, one for 3D packing. The mathematical modelling approach is motivated from (Ruan et al, 2013), in which 3D-PRP can be grouped into two parts. Sub-problems are solved both separately and co-ordinately. All mathematical formulations and the proposed solution approaches are provided in this section. In addition to mathematical modelling approaches, heuristic methodology is proposed in this section.

3.2.1. Problem Formulations

3.2.1.1. Objective Function

The objective function of the 3D-PRP and train loading problems aims to minimize total cost for pick up and deliver carrying units. The cost items are handled as follows:

- Generalized cost: It is composed by price between locations (distance multiplied by cost per km) and time (generalized time between I and j multiplied by the price parameter of the average value of time).
- Utilization cost of the vehicles for routing: The cost includes the fixed cost of usage and utilization decision of the vehicle.
- Utilization cost of the carrying units: This cost is related with the usage rates of different types of carrying units. The utilization cost is minimized by providing a feasible loading of the orders into the carrying units.
- Demurrage cost: This cost is defined as the penalty cost for exceeding time in the terminal station.
- Detention cost: This cost is defined as the penalty cost for exceeding time outside of the terminal station.

The objective function of the intermodal mode and route selection problem aims to minimize the total transportation costs. The cost items are handled as follows:

- Road transportation cost: This cost includes the amount of export demands, travel distance, road transportation cost per km per TU and mode weight
- Maritime and road transportation cost: This cost includes the amount of export demands, travel distance, road transportation cost per km per TU and mode weight

- Maritime, rail and road transportation cost: This cost includes the amount of export demands, travel distance, road transportation cost per km per TU and mode weight
- Maritime transportation cost: This cost includes the amount of export demands, maritime transportation cost per TU and mode weight
- Rail transportation cost: This cost includes the number of block trains, rail transportation cost per block train and mode weight

3.2.1.2. Constraints

In this section, constraints that are considered in the mathematical models are divided into four sub-groups: vehicle routing, 3-D bin packing, train assignment, intermodal transportation mode selection.

Vehicle routing constraints

- Flow conservation constraint addresses that when a vehicle arrives at a node, it must travel from that node to another one.
- Each customer node is visited once.
- Truck capacity cannot be exceed.
- Each tour start and end at the depot.

3-D-bin packing constraints

- Order locations considering the x, y, z coordinates are handled in the model.
- Two orders in a carrying unit must be only one of the directions.
- The loading spaces of the orders cannot exceed the loading spaces of the carrying units.

Train assignment constraints

- Assignment constraint that ensures that each carrying unit must be assigned to one train
- Train capacity cannot be exceed.
- Number of train transportation days cannot exceed the total travel days of the carrying units assigned to the train.

Intermodal mode selection constraints

- Export customers are serviced by direct road transport or intermodal transport. The sum of the number of products by road and number of products by intermodal line is equal to the demands of the export customers.
- Balance constraint that ensures the number of products between the starting and final points.
- The number of products transported between two points cannot exceed truck, Roro and Train capacity.

3.2.1.3. Problem Characteristics

The 3D-PRP is characterized as follows (Gocmen and Erol, 2019):

- Carrying units are defined as containers and trailers with length L, depth D and height H.
- Each cluster numClusters requires three-dimensional orders with length L, depth D and height H and weight W.
- Loading cities are denoted by V: = (0,1,…, n) and the depot is represented by the node 0.

- The orders are grouped as export and import containers. Export containers, which are considered to be transferred from the customer points in the hinterland to the warehouses (Sterzik and Kopfer 2013) are considered.
- We discuss the 3-D loading related constraints as the following:
- Each order is loaded considering loading dimensions. The loading dimensions and weights of the orders couldn't exceed the carrying unit dimensions and weights.
- Each order is placed into vehicle orthogonally.
- Fragile orders are stacked on the fragile orders. Orders, which are non-fragile, cannot be loaded on top of fragile ones (Ruan et al. 2013). This limitation is valid for our problem.
- Each order can be rotated by 900 horizontally.
- The non-overlapping orders are considered.

The intermodal problem characteristics are consisted of export containers, multi- ports, multi- customers, multi- stations, and demands for the containers in each period. The problem takes into account the export containers to transport orders ousing the Roro, Truck, or Truck–Train transportation combinations.

Transport modes utilized for this network are as follows:

- Roro-Train combination: Transferring the containers is conducted by Roro between Turkey and Trieste ports, by train to Ostrava.
- Roro- Truck combination: Transferring the containers is conducted by Roro between Turkey and Trieste ports, then to Ostrava, Bratislava, and Poland with road transport.
- Truck: Transferring the containers is conducted by truck between Turkey and Ostrava, Bratislava, and Poland.

3.2.1.4. Assumptions

This study is conducted to decide optimal load planning for an intermodal transport system. Strategic level decisions such as train; roro scheduling, and design of the network are not handled in the study. Transportation mode selection and route selection, utilization of the modes are decided. The first stage including 3D-PRP and train assignment problems contains daily planning; the other stage is of six-months planning horizon. The assumptions of the problems are presented as bellow:

- Load planning is conducted in Turkey in the pre-haulage of the intermodal network. Long-haul transportation is conducted between Turkey and Europe. End haul is not considered in the study.
- Export containers are handled in the study. Import containers are not included.
- Delayed demands are allowed for only train assignment stage. However, a penalty cost is available in this situation.
- All vehicles and carrying units are homogenous.
- Block trains are used for railway transport and they have fixed time schedules.
- Customer demands, transportation costs are known.

3.2.2. Modelling and Solution Approaches

As previously mentioned, 3D-PRP is one of the most well-known NP-hard problems. Exact solution approaches cannot solve the real-case problems including real case dataset. Thus, heuristics, meta-heuristics and machine learning approaches are proposed to solve the problem within reasonable time. In the study, clustering the loading points are solved by k-means algorithm; three dimensional bin packing problem is handled with machine learning using best-fit-first-strategy that is considered as more effective than other packing solutions (Yang and Mu 2018); routing section is addressed by genetic algorithm. A developed heuristics approach integrating these three approaches is provided to solve the combinatorial problem (Gocmen and Erol, 2019). Then, intermodal mode selection problem is solved via deterministic MILP. The steps of the solution approaches are depicted in Figure 3.3.

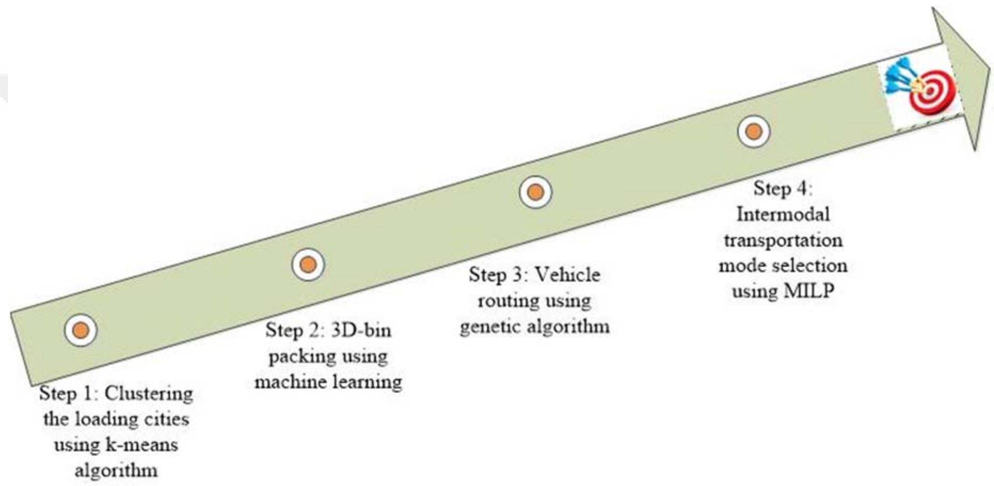

Figure 3.3. Steps of the solution approaches for the problems

We start by presenting the clustering phase. Here, the loading points are clustered in a corresponding cluster.

3.2.2.1. K-Means Clustering Algorithm

K-means clustering ensures the assignments of the **n** objects into **k** clusters, where an initial cluster number is assigned before the algorithm starts. Figure 3 gives a representation of the k-means clustering. The clustering starts with an initial cluster number *numClusters* or using k-means algorithm to choose the initial cluster number. The next step is computation of the distances between the objects $\boldsymbol{p_i}$ and the cluster center c_k. Assignment of each object to the clusters with the closest centroid is proceeding. The step is repeated until the maximum number of iterations is reached (Gocmen and Erol, 2019).

We employ k-means algorithm that uses a heuristics that finds the initial cluster centres. The k-means algorithm is as follows:

- Choose the initial cluster number from the data set, X. The first centroid is called c_1.
- Compute all distances to c_1. Distance between c_1 and new observations are computed and each observation is assigned to the cluster *numClusters*. Select each centroid by the distance to the closest center.
- Repeat step 3 until *numClusters* are chosen as initial centroid.

K-means uses the squared Euclidean distances given by:

Minimize sum= $\sum_{i=1}^{n} \text{distance}(p_i\text{-}c_k)$

Pseudo-code of K-means is depicted in Figure 3.4. N dataset, initial k clusters, cluster centroids and cluster label is represented by *A*, B_i, *B*, *C*, respectively.

$\text{Kmeans}(A, \boldsymbol{B_i}) \rightarrow (B, C)$

Repeat

$\boldsymbol{B_{previous}} \leftarrow \boldsymbol{B_i}$;

For all i ∈ [1,N] do

$c(i) \leftarrow \arg\min d(\boldsymbol{a_i}, \boldsymbol{b_i})$

For all j ∈ [1,k] do

$\boldsymbol{b_j} \leftarrow \text{avg}\ \boldsymbol{a_i}, c(i) = j$;

Until B=$\boldsymbol{B_{previous}}$

Figure 3.4. Pseudo-code of k-means clustering

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

3.2.2.2. Machine learning for three dimensional bin packing

Best packaging of thousands of orders is a challenging problem. In this subsection, the orders of each cluster are packed in a corresponding carrying unit by a machine approach. Packing each order into the smallest number of carrying units to obtain highest utilization value is aimed. We develop an open source R package gbp. Gbp optimizes the number of bins and utilization of them by incorporating length, width, height, weight constraints. This package is challenging with the best-fit-first strategy, considering weight, order split, none overlap, orthogonality constraints. A weighted k-medoids clustering algorithm is used to formulate the 3-D bin-packing problem. A 3-D problem for each carrying unit *bin* is defined by the length *l*, weight *w*, depth *d*, 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 same carrying unit *bin*. A list of loading positions is generated in descending order of l, d, h, w, respectively.

Let us consider a set of all feasible container sizes C= (l_i, d_i, h_i). w_j is the weight of the container and estimated and c_{ij} is the distance between containers. p is tuning parameter. p is tested between 0.25-1 values. The optimal packing plan is obtained in 0.50 value. Utilizaiton rate is obtained as %8.43. The problem is to solve this optimization problem:

The aim of this order is to load larger orders first. At the beginning of the heuristics, 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 carrying unit using best-fit-first heuristics. Given orders and carrying units, the solver searches for optimum packing plans to minimize the vehicle numbers and maximizing volume utilization. A loading process is depicted as follows:

Algorithm 1: Procedure of generalized 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 - an unique id within oid <integer>
# otid: order id x ticket id - an unique indentifier indicate it with 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)
```

3.2.2.3. Genetic Algorithm for the Pick-Up Routing Problem

GA for the vehicle routing problem provides specific procedures. Firstly, we produce an initial population, which includes chromosomes randomly. Secondly, each population member is evaluated, so the first generation is found.

Thirdly, we initialize some genetic algorithm operators to obtain better generations. Various mutation operators like flip, swap, and slide are selected to mix the routes. With swap operator, I and J locations are chosen; their positions are swapped. (Bestroute (k, [I J]) = Bestroute (k, [J I])) Figure 3.5. shows the swap representation; City_2 and City_8 positions are swapped.

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

Figure 3.5. Swap operator representation

Flip operator, I and J locations are chosen; their positions are flipped (Bestroute (k, [I J]) = Bestroute (k, J:-1: I). With slide operator, I and J locations are chosen; their positions are slided (Bestroute (k, [I J]) = Bestroute (k, [I +1: J I]). This process is repeated to optimize the objective function. Matlab code is depicted in appendix C. Pseudo code for GA is as follows:

Algorithm 2: Pseudocode for the Genetic Algorithm

```
Input: popSize, numIter, Pmutation
Output: optRoute, minDist
//InıtializePopulation 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
     Initialize the population popSize with pbest
     end if
//GA
     While (max iteration has not been reached) do
           For I :=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 Updata the best solution pbest
end if
           OptRoute- BestSolution
        End while
```

3.2.2.4. General Layout Of The Proposed Approach

Our proposed approach integrates k-means algorithm, machine learning and genetic algorithm. K-means applies clustering heuristics to produce initial clusters for 3-D loading phase. We obtain data set including clusters for loading points. Then 3-D loading problem is discussed by machine learning best-first-fit heuristics. Finally, routing phase is addressed by genetic algorithm. A general layout of three different types of algorithms applied for 3-D 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 three dimensional bin packing instance given by length l, depth d, height h and vehicle ids;
store three dimensional packing plan 'Result.txt'
endfor
//Third stage: Routing
// Use the data processed by R
Initialize 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

Researchers provide that performance index is incorporated as inputs in the mathematical model formulations (Hanaoka and Kunadhamraks, 2009). Sustainable intermodal network also needs both the mathematical modelling approach and artificial intellgence methods (Baykasoğlu and Subulan, 2016). Thus, a MIP model and a fuzzy-based approach are used for the proposed intermodal transportation network. Obtained results are evaluated by the firm experts. A MIP solver by General Algebraic Modelling System (GAMS) software is used to solve this problem in a reasonable time. Allocation of each order to each route and transportation mode is obtained. Fuzzy-based method gives the weights of each transport modes. This approach is applied by Matlab fuzzy logic designer. The decision makers score the transport modes based on the risk factors. They use historical data for each mode to score them.

3.2.2.5. Fuzzy-Based Approach

Human and ecological risks related with the transportation modes are evaluated considering historical data by the firm experts. Human risks (human accidents and deaths) and ecological risks (emission values and noise pollution) are handled as the inputs. Human risks are scored by considering accident reports. Ecological risks are scored by considering environmental reports. All risk factors are defined with linguistic definitions initially and they are fuzzified. Developed fuzzy approach is constructed by the fuzzy logic designer in Matlab. The output of the system is the risk weights of the transport modes. The proposed fuzzy design is shown in Figure 3.6. The designer is worked with a Mamdani inference system including inputs and outputs. Inputs are scored with linguistics variables called low, medium, and high by decision makers. They decide these definitions considering firm reports related with transportation modes. As an example, human accidents and deaths reported by the firm are evaluated and an assignment a linguistic variable for the transport mode is decided. The inputs depicted in the left hand of Figure 13 are fuzzified via membership functions. The transportation mode with lowest risk weight and cost is chosen for the network. This system considers the outputs as fuzzy sets. Inference consists of implication, aggregation, and defuzzification processes. A weight is assigned to each rule by implication process. Fuzzy sets of outputs are consolidated into a set by aggregation. Defuzzification combines the aggregate fuzzy set to a single number by the centroid calculation.

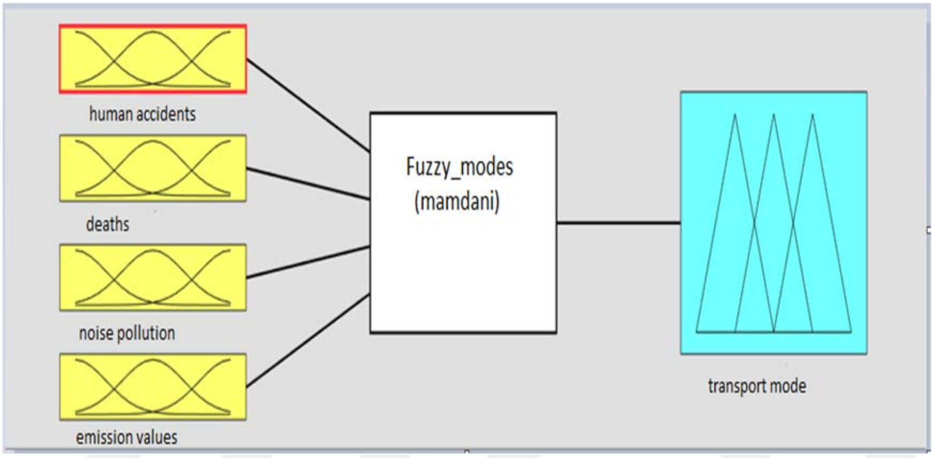

Figure 3.6. Design of developed fuzzy-based approach

The triangular membership function is depicted in Figure 3.7. This function is preferred for advantage of simplicity using straight lines. This function incorporates low, medium, and high variables. The figure depicts the membership functions of the chosen input and output variables. Variable ranges and membership function types are organized. Fuzzy numbers are proposed as low (0, 0, 1.5), medium (0, 1.5, 3), and high (1.5, 3, 3). Scores are assigned to inputs with linguistic variables. Fuzzy numbers representing the linguistic variables are assigned to the inputs (Gocmen and Erol, 2018).

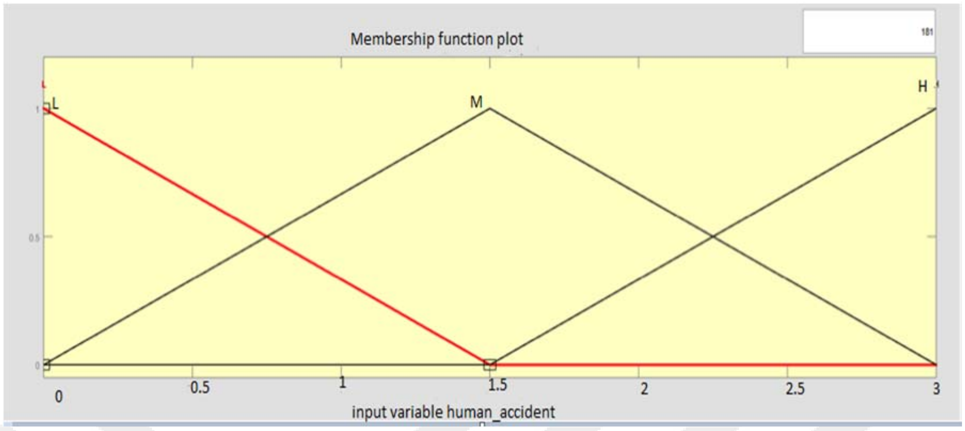

Figure 3.7. A depiction of membership function plot (MFP) for input variables

Fuzzy numbers are presented for the output as low (0, 0, 0.5), medium (0, 0.5, 1), and high (0.5, 1, 1). Figure 3.8. shows that the risk weight of output is decided by fuzzy numbers. By the results of the decision rules, a risk weight is obtained for each transport mode.

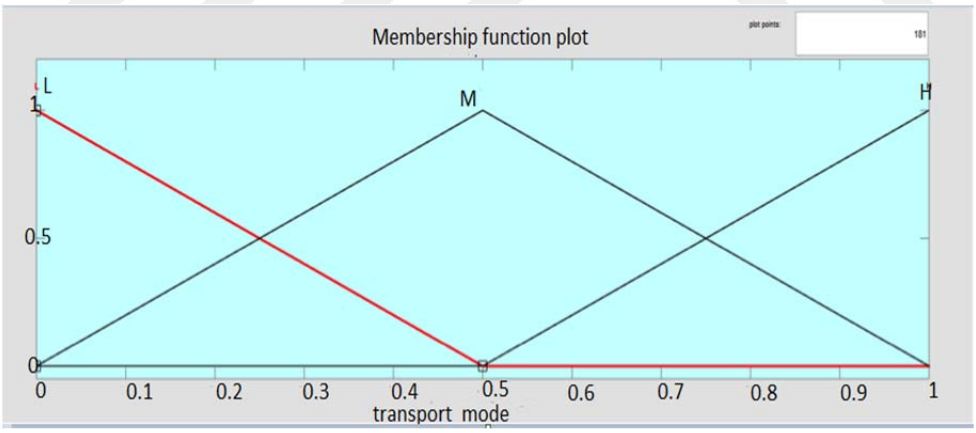

Figure 3.8. MFP of the output variable

100 decision rules for the international logistic firm are developed. All combinations of the linguistic variables are tried to find the risk weight. If–then rules are applied in this step. Some rules are shown in Figure 3.9.

A fuzzy if–then rule is formed as "if x is L then y is M." L and M are linguistic definitions. Low is represented as a number between 0 and 0.5. M is represented as a fuzzy set. After the fuzzification of the inputs, the "and" operator is applied shown in Figure 15. The "and" operator uses the minimum fuzzy number.

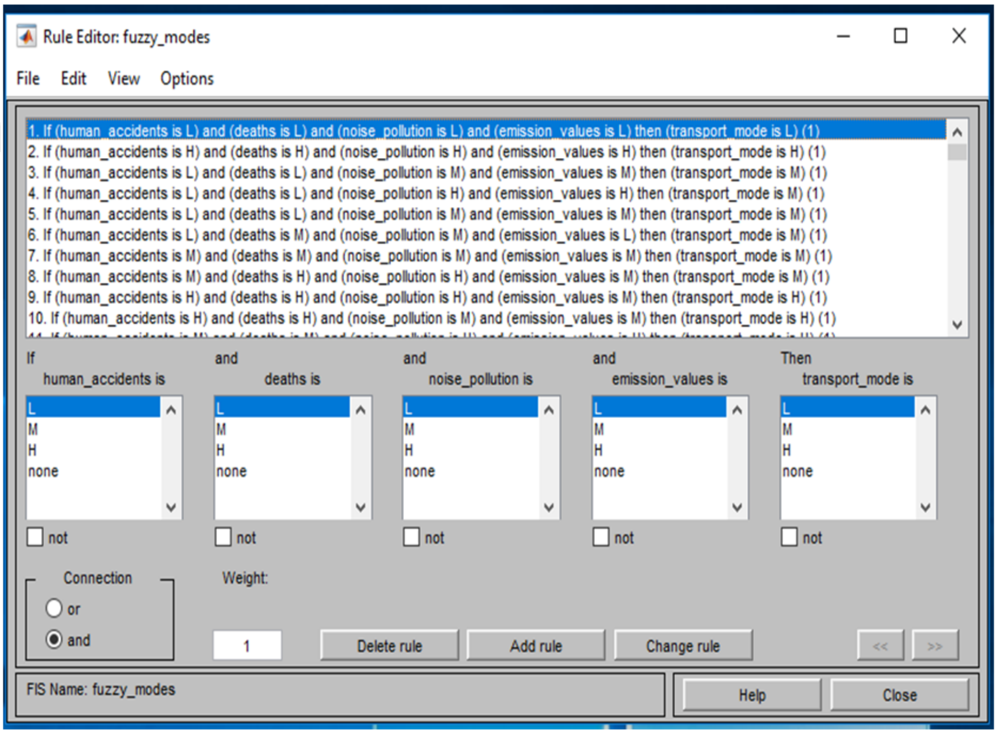

Figure 3.9. Decision rules formed for transport modes

Figure 3.10. displays the rule viewer that represents the fuzzy inference system. The rules are on the left of the rows. Yellow plots in the figure show the if section of the rules. Blue plots are presented as then section of the rules. Decision rules are tried by decision makers, and effects to the output are evaluated. When all inputs are increased, transport mode value also increases. When all inputs are defined as medium, the output weight takes a 0.5 value in Figure 3.10.

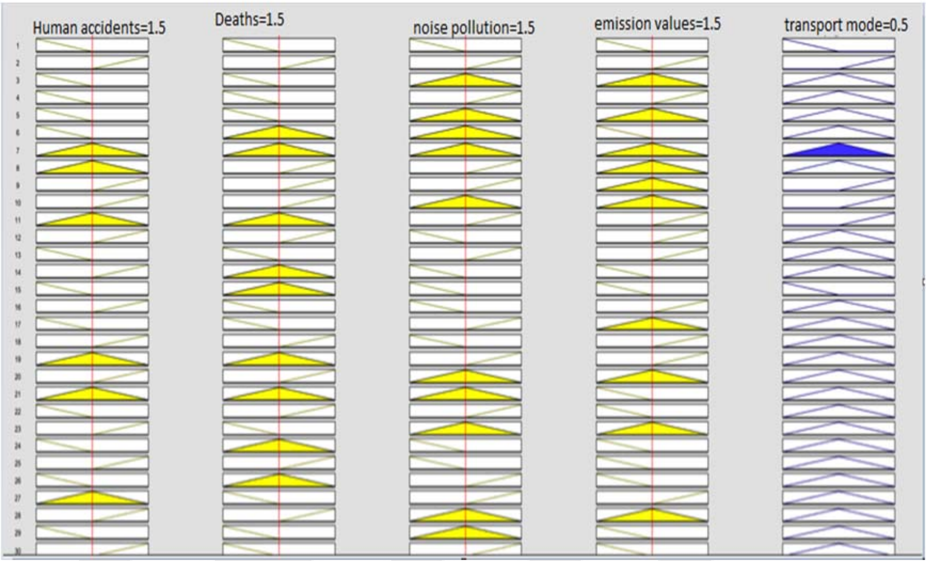

Figure 3.10. İnput and output values according to decision rules (with medium fuzzy numbers)

All inputs are given for road transport in Figure 3.11. Road transport is evaluated as the most risky mode by decision makers. Therefore, the inputs take a value of nearly 3 (high) and the output is nearly 1 (high risk weight). Human accidents, deaths, noise pollution, and emission are scored as 2.83, 2.93, 2.85, and 2.82 by decision makers. The risk weight is resulted as 0.727 for road transport. The risk weights of the rail and marine transports are 0.346 and 0.539.

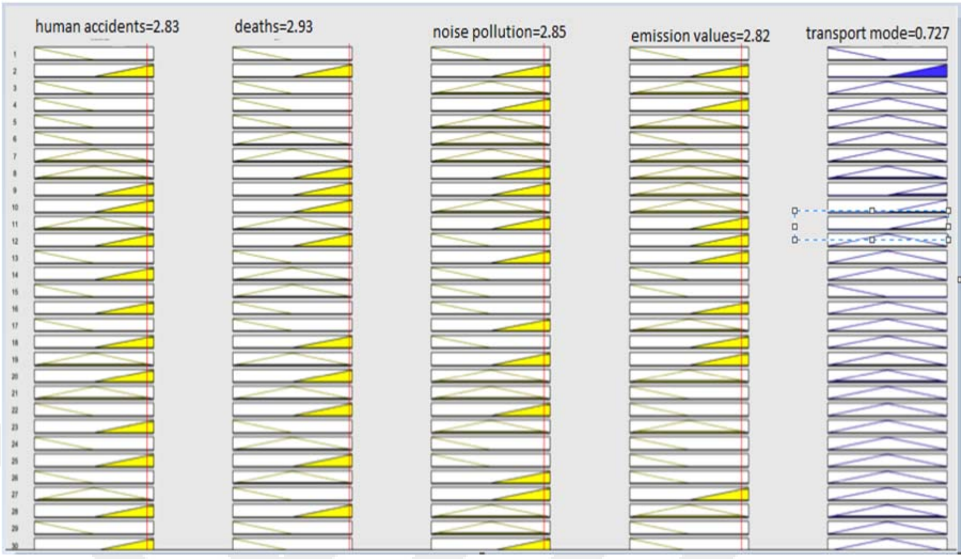

Figure 3.11. Input and output results regarding the decision rules (road transportation)

3.2.3. Mathematical Programming Model for Stage 1

In this section, the problems are discussed by using mathematical modelling approaches to find exact solutions. The mathematical modelling approach is motivated from (Ruan et al, 2013), in which 3D-PRP can be grouped into two parts, one for PRP, one for 3D packing. Besides, clustered loading points regarding latitude and longitude values are our contribution to this approach.

3.2.3.1. Notation for Clustering

We suppose (x, y) coordinates of the loading points and each order i is assigned to k clusters. Before using the k-means algorithm developed, the random assignment is used with random clusters along coordinates m_{kxy} , coordinates of the points p_{ixy}, cluster number of the point c_i, total number of clusters *num*, order numbers assigned to the cluster n, centroid $cntr_{kxy}$, squared distance d_{ik}, distance closest cluster, $close_i$ The decision variable X_{ik} is assignment of points to clusters. The mathematical formulation is as below (Eq. 3.1): Gams model is depicted in appendix E.

3.2.3.2. Objective Function

In the objective function, minimization of the distance of loading points is aimed. Thus, each point is assigned to the closest cluster. Clustering function;

3.2.3.3. Constraints

- Stage 1

$$\text{objective} = \frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{num}\left\| p_{ixy} - c_{kxy} \right\|^2 \qquad \text{Eq. (3.1)}$$

A random assignment of the points

c_i = uniformint(1,num)

$x_{ik} = c_i$

- Stage 2

Centroids are calculated

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

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

- Stage 3

Points are reassigned

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

$close_i = d_{ik}$

3.2.3.4. Notation for PRP

After formulating the clustering of loading points, PRP is formulated. Gams model is depicted in appendix F. PRP calls for the routes of vehicle k with capacity Q_k, which visits a set of customers N = (1, 2,…, n). All locations are shown as (i, j, l), where i, j, l ϵ N and i≠j, i≠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 I 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 k vehicle as a fixed cost *F (*Gocmen and Erol, 2019).

Decision Variables

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

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

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

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

3.2.3.5. Objective Function

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

The objective function minimizes the generalized cost and number of vehicles.

3.2.3.6. Constraints

$$\sum_{i=0}^{I} X_{ilk} = \sum_{j=0}^{J} X_{ljk} \quad l = 1, \dots, L;\ k = 1, \dots, K;\ \ l \neq i; i \neq j \qquad \text{Eq. (3.2)}$$

$$\sum_{k=1}^{K} \sum_{j=0}^{J} X_{ijk} = 1 \qquad i = 0, \dots . . I;\ \ i \neq j \qquad \text{Eq. (3.3)}$$

$$0 \leq U_{ik} \leq Q_k \qquad i = 1, \dots, I;\ k = 1, \dots, K \qquad \text{Eq. (3.4)}$$

$U_{jk} \geq U_{ik} + p_j * z_{jk} - (1 - X_{ijk}) * Q_k \quad i = 1, \ldots, I;\ j = 1, \ldots, J;\ k = 1, \ldots, K$ Eq. (3.5)

$\sum_{j=1}^{J} X_{0jk} \leq y_k \quad k = 1, \ldots, K$ Eq. (3.6)

$\sum_{j=1}^{J} X_{j0k} \leq y_k \quad k = 1, \ldots, K$ Eq. (3.7)

$\sum_{j=0}^{J} X_{ijk} = z_{jk} \quad i = 1, \ldots, I;\ k = 1, \ldots, K;\ i \neq j$ Eq. (3.8)

$$\sum_{i=1}^{I} z_{ik} * p_i \leq Q_k \quad k = 1, \ldots K$$ Eq. (3.9)

$\sum_{i,j \in U}^{J} X_{ijk} = W - 1 \quad k = 1, \ldots, K$ Eq. (3.10)

$X_{ijk}, z_{ik}, U_{ik} \geq 0$ Eq. (3.11)

Equation 3.2 is flow conservation that vehicle travels between two nodes. Equation 3.3 ensures that that each node is visited once. Equation 3.4 provides that the picked up amounts cannot exceed the vehicle capacity. Equation 3.5 balances the pick-up amounts transferred from one node to another. Equations 3.6 - 3.7 ensure that vehicles start and end at the depot. Equation 3.8 links the 3-D loading variable to PRP. Equation 3.9 allows that the vehicle capacity cannot be exceeded. Equation 3.10 is sub tour constraint. Equation 3.11 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.

3.2.3.7. Notation for 3D- loading

Before formulating the 3-D loading problem, we talk about the indices and parameters. The notation is based on Chen et al. (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 units have a loading space L_k , W_k , H_k. Utilization cost and capacity of k carrying units are C_k and Q_k. Gams model is depicted in appendix G.

Decision variables

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

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

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

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

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

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

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

x_p : x coordinate of p order (p=1,…,P),

y_p : y coordinate of p order (p=1,…,P),

z_p : z coordinate of p order (p=1,…,P),

3.2.3.8.Objective function

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

The objective function minimizes the utilization cost of the carrying units.

3.2.3.9. Constraints

$$x_p + l_p \leq x_r + (1 - a_{pr}).M \quad \forall p, r \;\; p < r$$ Eq. (3.12)

$$x_r + l_r \leq x_p + (1 - b_{pr}).M \quad \forall p, r \;\; p < r$$ Eq. (3.13)

$$y_p + w_p \leq y_r + (1 - c_{pr}).M \quad \forall p, r \;\; p < r$$ Eq. (3.14)

$$y_r + w_r \leq y_p + (1 - d_{pr}).M \quad \forall p, r \;\; p < r$$ Eq. (3.15)

$$z_p + h_p \leq z_r + (1 - e_{pr}).M \quad \forall p, r \;\; p < r$$ Eq. (3.16)

$$z_r + h_r \leq z_p + (1 - f_{pr}).M \quad \forall p, r \;\; p < r$$ Eq. (3.17)

$$a_{pr} + b_{pr} + c_{pr} + d_{pr} + e_{pr} + f_{pr} \geq o_{kp} + o_{kr} - 1 \quad \forall p, r, k \;\; p < r$$ Eq. (3.18)

$$x_p + l_p \leq L_k + (1 - o_{kp}).M \quad \forall p, k$$ Eq. (3.19)

$$y_p + w_p \leq W_k + (1 - o_{kp}).M \quad \forall p, k$$ Eq. (3.20)

$$z_p + h_p \leq H_k + (1 - o_{kp}).M \quad \forall p, k \qquad \text{Eq. (3.21)}$$

$$x_p, y_{p,} z_p \geq 0, \quad a_{pr}, b_{pr}, c_{pr}, d_{pr}, e_{pr}, f_{pr}, o_{kp}, \epsilon \qquad \text{Eq. (3.22)}$$
(0,1)

Equations 3.12 - 3.17 provide the order locations considering x,y,z coordinates. Equation 3.18 ensures that two orders in a carrying unit must be only one of the directions described above. Equations 3.19 - 3.21 ensure that the loading spaces of the orders cannot exceed the loading spaces of the carrying units. Equation 3.22 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.

3.2.3.10. Notation for Train Assignment Problem

Let us consider in the train-loading problem a set of trains (i=1,.., I) and a set of carrying units (j=1,…,J). The carrying units are assumed that they are unloaded from Roro in Trieste. The train loading is conducted in the seaport train terminal. Thus, shipping day *ship* with a tolerance *num* is incorporated to the model. Train capacity b_i must not be exceeded. Each train has working days g_i and departure days tr_i that must be respected. A train usage cost is f_{ij} when the carrying units are assigned to trains. An extra cost is defined by detention cost p_j, demurrage cost *cst* when due date d_j is not ensured. The other parameter is utilization a_{ij}.
Gams model is depicted in appendix H.

Decision Variables

w_i: Demurrage (day)

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

s_j: Detention (day)

3.2.3.11. Objective function

The objective function minimizes the usage cost of carrying units, detention cost and demurrage cost.

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

3.2.3.12. Constraints

$$\sum_{i=1}^{I} X_{ij} = 1 \qquad (j = 1, \dots J) \qquad \text{Eq. (3.23)}$$

$$\sum_{j=1}^{J} X_{ij} * aij \leq b_i \qquad i = 1, \dots\dots, I \qquad \text{Eq. (3.24)}$$

$$w_i = \sum_{j=1}^{J} X_{ij} * (ship + num - tr_i) \qquad i = 1, \dots\dots, I \qquad \text{Eq. (3.25)}$$

$$g_i \leq d_j + s_j + (1 - x_{ij}) * M \quad i = 1, \dots\dots, I;\ j = 1, \dots\dots J \qquad \text{Eq. (3.26)}$$

$$X_{ij}, u_i \in (0,1), s_j, w_i \geq 0 \qquad \text{Eq. (3.27)}$$

Equation 3.23 is assignment constraint that ensures that each carrying unit must be assigned to one train. Equation 3.24 ensures that train capacity cannot be exceed. Equation 3.25 corresponds to demurrage cost. Equation 3.26 allows that the train transportation day cannot exceed the total travel day of carrying units assigned to the train. Equation 3.27 ensures that decision variables are greater than zero point.

3.2.4. Mathematical Programming Model for Stage 2

This section presents a decision support system (DSS) including the allocation of the orders to the transport modes and routes combining fuzzy-based approach and mathematical model. DSS requires to handle all load planning processes for an intermodal network. A mixed integer linear programming model is formulated. The outputs of the presented model are optimal transportation mode and routes, optimal utilization of the vehicles. The notation denoted for the model is as follows (Gocmen and Erol, 2018):

3.2.4.1. Notation

Sets:

I: Set of supply points in Turkey, origin point for export transport

J: Set of seaports in Europe for export transport

M: Set of customer points in Europe (aggregated points)

P: Set of train stations in Europe

T: Set of time periods for planning horizon

Indices

i: index of supply points in Turkey ($i \in I$)

j: index of seaport points ($j \in J$)

m: index of customer points ($m \in M$)

p: index of train station ($p \in P$)

t: index of time periods ($t \in T$)

Parameters

De_{imt} : Export demand of of point m from point i in period t (unit)

C1: road transportation cost per km of per TU (TL/km*TU)

$C2_{ij}$: maritime transportation cost per TU from point i to point j (TL /TU)

$C3_{jp}$: rail transportation cost per block train from point j to point p (TL / block train)

Cap_{ij}: transportation capacity of RoRo from point i to point j (TU)

Cap_{jp}: transportation capacity of block train from point j to point p (TU)

d_{im} : road travel distance between i and m points (km)

d_{jm} : road travel distance between j and m points (km)

d_{jp} : rail travel distance between j and m points (km)

M_{ijt} : Maximum limits on number of Roros between i and j in period t

$\gamma^r, \gamma^m, \gamma^t$: risk value based on human and ecological risk factors of the transportation mode road, marine, train

Decision Variables

X_{imt}: amount of TUs from point i to point m by road transport in period t

Y_{ijmt}: amount of TUs by maritime and road transport in period t

Z_{ijpmt}: amount of TUs by intermodal line in period t

Ro_{ijt}: amount of TUs by maritime transport in period t

NB_{jpt}: number of block trains from point j to point p in period t

NR_{ijt}: number of Roros from point i to point j in period t

3.2.4.2. Objective Function

Objective Function:

$$\min z = \sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{t=1}^{T} C1 * X_{imt} * d_{im} * \gamma^r +$$

$$\sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} C1 * Y_{ijmt} * d_{jm} * \gamma^r +$$

$$\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} \mathrm{C1} * \mathrm{Z_{ijpmt}} * \mathrm{d_{pm}} * \gamma^{r} +$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} \mathrm{Ro_{ijt}} * \mathrm{C2_{ij}} * \gamma^{m} +$$

$$\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} \mathrm{NB_{jpt}} * \mathrm{C3_{jp}} * \gamma^{t}$$

The objective function minimizes the sum of the total transportation costs. First part of the equation is related to road transportation. There are three highway lines, in which trucks are used. These lines are between Turkey and Ostrava, Bratislava and Poland and between Trieste and Ostrava, Bratislava, Poland. The risk weights of the transport modes are evaluated considering human and ecological aspects by decision makers in the company. The risk weight of the road transport is expected to have highest risk than the other transport modes. The second part of the equation is related to marine and road transportation. Maritime transportation is conducted by the Ro-Ro ships. The third part of the equation is related to intermodal transportation including roro, train and truck. The fourth part is about only maritime transportation and the end part is of rail transportation.

3.2.4.3. Constraints

Total export transport demands are met by using road transportation and integrated roro and road, integrated roro, rail, road;

$$\mathrm{X_{imt}} + \sum_{j=1}^{J} \mathrm{Y_{ijmt}} + \sum_{j=1}^{J}\sum_{p=1}^{P} \mathrm{Z_{ijpmt}} \geq \mathrm{De_{imt}} \quad \forall \mathrm{i} \in \mathrm{I}, \forall \mathrm{t} \in \mathrm{T}, \forall \mathrm{m} \in \mathrm{M} \qquad \text{Eq. (3.28)}$$

Equation 3.28 ensures the meeting of the demands. Export customers are serviced by direct road transport and intermodal transport. The sum of the number of products by road and number of products by intermodal line is equal to the demands of the export customers.

$$\sum_{m=1}^{M} Y_{ijmt} \leq Cap_{ij} * M_{ijt} \qquad \forall i \in I, \forall t \in T, \forall j \in J \qquad \text{Eq. (3.29)}$$

Equation 3.29 ensures that the amount of containers transported between two points cannot exceed the Roro capacity.

$$\sum_{m=1}^{M} Y_{ijmt} = Ro_{ijt} \qquad \forall i \in I, \forall t \in T, \forall j \in J \qquad \text{Eq. (3.30)}$$

Equation 3.30 ensures to calculate the total amounts of containers transported by Roro to the seaports.

$$Ro_{ijt}/Cap_{ij} = NR_{ijt} \qquad \forall i \in I, \forall t \in T, \forall j \in J\} \qquad \text{Eq. (3.31)}$$

Equation 3.31 ensures the number of Roros used to transfer the load units.

$$\sum_{i=1}^{I} \sum_{m=1}^{M} Z_{ijpmt} \leq NB_{jpt} * C3_{jp} \quad \forall j \in J, \forall t \in T, \forall p \in P \qquad \text{Eq. (3.32)}$$

Equation 3.32 ensures the number of block trains used to transfer the load units.

$$X_{imt}, Y_{ijmt}, Z_{ijpmt}, Ro_{ijt}, NR_{ijt}, NB_{jpt} \geq 0 \qquad \text{Eq. (3.33)}$$

Equation 3.33 is a non-negativity constraint in which the decision variables should be greater than or equal to zero and take integer values.

3.2.5. Case Study

In this chapter, case study including 3D-PRP and train assignment problem are defined in detail. During the first step, loading cities are clustered and the orders of each clusters are loaded with three-dimensional bin packing constraints and VRP is solved. A basic representation is depicted in Figure 3.12. In the second step, the consolidated orders have been assigned to the trains by incorporating real-world constraints.

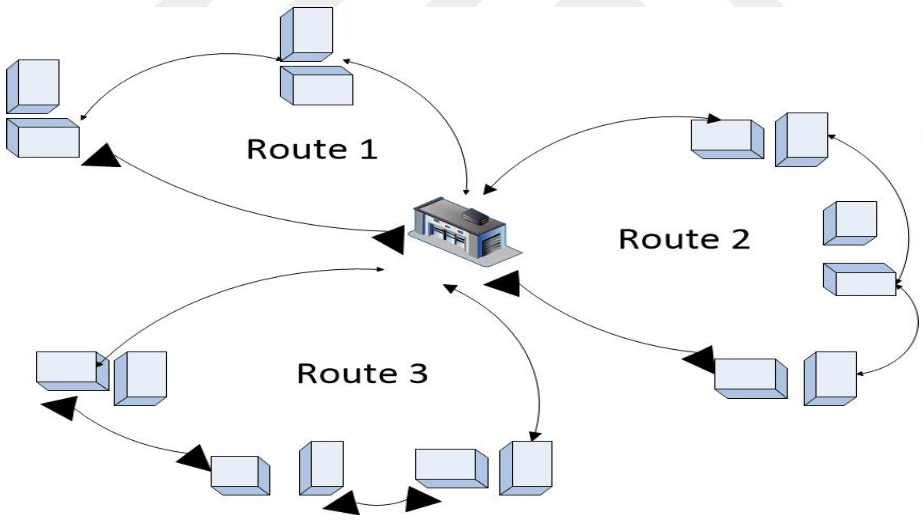

Figure 3.12. Clustering the loading cities and 3D bin packing

In the study, besides the decisions in terms of 3D-PRP, allocation of the consolidated orders to the block trains is dealt with in the second stage. The proposed network including both the road transportation and rail transportation is given in Figure 3.13.

Figure 3.13. Intermodal transportation network including both the road transportation and rail transportation

The first stage is dominated by highway transport, in which truck vehicles are preferred to picking the orders from the loading cities. The objective of this step is to increase the efficiency by reducing the utilization costs of carrying units and to provide high capacity utilization of caryying units such as trailers and containers. The second step is concerned the rail transport, in which block trains are preferred to transport the carrying units. The purpose of load-train planning is to provide efficient distribution and timely availability of the carrying units with a focus on the reduction of the total cost (Gocmen and Erol, 2019). We discuss the objective function as the following:

In the intermodal transportation problem section, a novel mathematical model for freight transportation provided. A sustainable model is formulated for tactical planning level of transportation management. The presented model includes transportation mode and route choice, utilization of transportation vehicles to minimize the total costs considering risk weights. A real case data is used to verify and validate the model. The different transportation modes including maritime vehicles (Ro-Ro vessels), rail transportation (block trains with fixed time schedules) are incorporated to the model. Ecological and human parameters are also involved. The international firm services its customers by direct road transportation, road-maritime transportation, and maritime–road–rail transportation combinations. Inland operations of the firm are conducted by road transport. Freight transport is between customers in the inland and customers abroad. Marine-road combination ensures the good flow in which truck transportation follows the Ro-Ro transportation. This combination restrains the tonnage restrictions on the highways. Then, goods are distributed between the terminals in Turkey and Europe. From there, goods are transferred by highway. Intermodal transportation with various different modes is ensured. Thus, effective and efficient good flows can be conducted in a more sustainable aspect.

Few papers consider environmental impacts of the usage transportation modes (Bauer et al, 2010; Ezabadi and Vergara, 2016). Caris et al (2013) indicates that evaluating the environmental effects of transportation modes plays a key role. Otherwise, human and ecological risks are available resulting from usage of each transportation mode.

The intermodal network for the proposed problem is depicted in Figure 3.14. Network is comprised of various parameters: container, customer, the freight forwarders, the port, train stations, transportation modes, risk weight of modes. Containers are grouped as export and import for the customer types and FTLF, FTLB, and LTL for the types. Import containers are transferred to the customer points in the hinterland. Export containers are transferred to port from the hinterland region (Sterzik and Kopfer, 2013). For the transfers, trucks or train line are used. Customers also grouped into two classes: import and export companies. Import companies are serviced by a flow from terminal to company and export companies send the containers to the terminal. Terminal is defined as intermediate region in which import containers start the flow; export containers arrive to be sent.

Optimal loading plans are generated by proposing solution approaches in a more sustainable manner.

The logistics forwarder aims to organize the freight transport by ensuring all constraints defined of the containers considering the risk weights and to provide effective and efficient load plans.

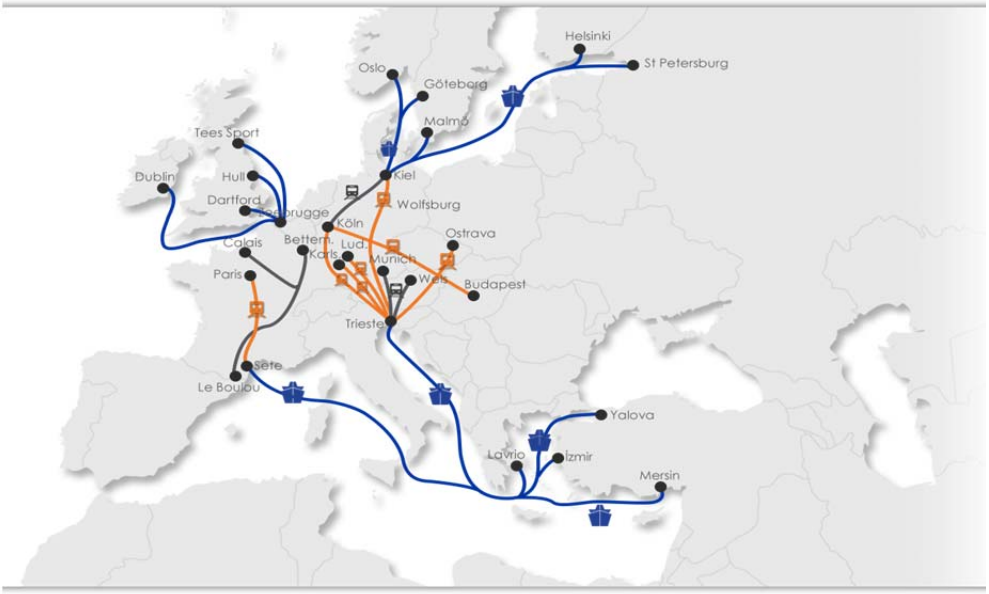

Figure 3.14. The proposed intermodal transportation network (Ekol, 2019)

Presented model aims to minimize the total cost regarding risk weights by incorporating transportation mode and route choice, utilization of transportation vehicles. Decision variables of the problem are transport mode and transport route choice that aims to minimize total cost and risks. The inland operations are not included in the presented model. Time and cost of loading/unloading and packing/unpacking are neglected (Gocmen and Erol, 2018).

4. RESULT AND DISCUSSION

4.1. Results of Stage 1

The hybrid algorithmic approach is executed on Intel CPU 3.6 GHz computer with 16 GB RAMS to solve a real- case data for 3D-PRP. As previously mentioned, 3D-PRP is one of the most well-known NP-hard problems. Exact algorithmic approaches cannot solve the real-case problems including large dataset in a reasonable time. Thereby, small-sized test instances including customer sets, vehicles with corresponding orders and medium-sized test instances are generated. We divide the 3D-PRP into two groups: 3D and PRP. By means of mathematical models, commercial solver Gams optimization software and Open Door Logistics software, both the 3D and PRP are solved. Meta-heuristics and machine learning approaches solve the real case instance containing 4444 orders and new generated medium test instances containing 994 orders. We compare the performances of exact method (two-stage approach), intelligent software ODL and proposed approach (First clustering, then packing-routing).

4.1.1. Results for Small-Sized Instances

We start by presenting results for small-sized instances related to 3D-PRP. The results are obtained using both of the open-source coding and mixed integer programming (mip) approach. We focus on the total travel distance, number of vehicles for routing section and loading positions for loading section. Firstly, by means of the proposed k-means algorithm, 20 loading points of the orders are clustered and 8 clusters (orders) are formed. Next, the orders are loaded to the vehicles with 3d loading constraints. Finally, optimal routes for vehicles are obtained. Computing time for instance is 0 seconds for clustering, around 34 seconds for the routing, 60 seconds for the loading. The results in Table 4.1. depicts the x, y, z coordinates of the orders into the vehicles.

Table 4.1.Loading spaces of small-sized orders for 3-D loading

Loading spaces/ loading points	x	y	z
ankara	35		
denizli	40	40	
aksaray			40
antalya			40
bursa			5

Due to aksaray, antalya and bursa cities are above of the orders, there are only z coordinates of them. Ankara and denizli cities are in the right positions of the others and there are x coordinates of them. Antalya is in front of the denizli; therefore there is y coordinate of the denizli order. Figure 4.1. shows the positions visually. The orders are located by their x,y,z coordinates. Thus, optimum location planning is obtained.

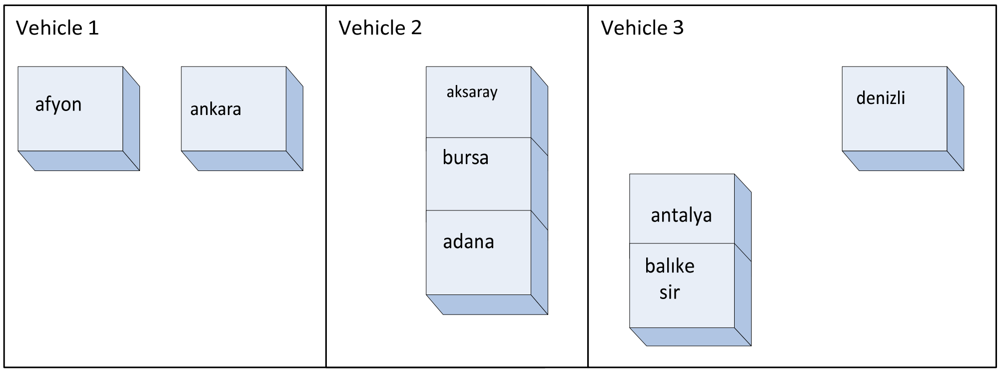

Figure 4.1. Positions of the orders into the vehicles

Table 4.2. Routes and pick-up quantities obtained from Gams commercial solver

Routes	
truck	Depot -Afyon-Ankara-depot
truck	Depot-Adana-Aksaray-Bursa-depot
truck	Depot-Balıkesir-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
balıkesir			1
bursa		10	
denizli			6

We see from Table 4.2. that starting point for each vehicle is depot. Note that we make sure that each truck is formed by incorporating the capacity and the amount of the orders. In addition, the order locations are also important to decide the truck routes.

The results by open source coding demonstrate that the results by mip solver are similar. Pick up routing problem is solved by an open source coded program called Open Door Logistics (ODL). Given vehicle numbers, addresses, picked up quantities are input for the system, and then routes are generated. We see from Figure 4.2. that open source software performs 3D-PRP by similar *nv*, *ttd* with mip solver.

	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	balıkesir	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

Figure 4.2. The routes generated by open source coding approach

Computing time is around 34 seconds in the mip solver, whereas computing time is around 22 seconds for ODL. Figure 4.3. depicts the map including three routes of the orders. We conclude that optimum routes under vehicle capacity distances are generated by ODL.

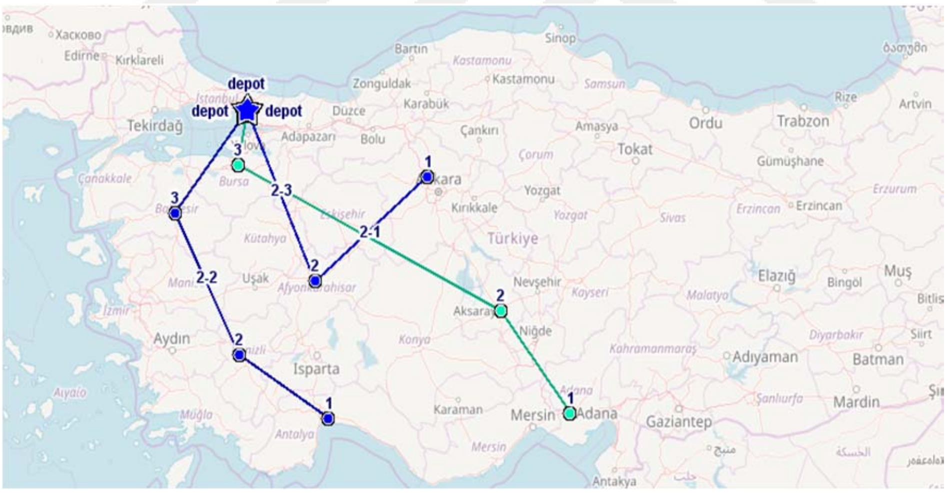

Figure 4.3. The map result of routes created by open source coding approach

Table 4.3. Comparison of exact solution approach and ODL for routing sub-problem

Instances	Exact method		ODL	
	nv	ttd	nv	ttd
1	1	2908	1	2875
2	2	4325	2	4280
3	3	4407	3	4407
4	4	5065	4	5054

Table 4.3. provides that a comparison of both methods considering nv, ttd values. For each instance, results are similar of both approaches.

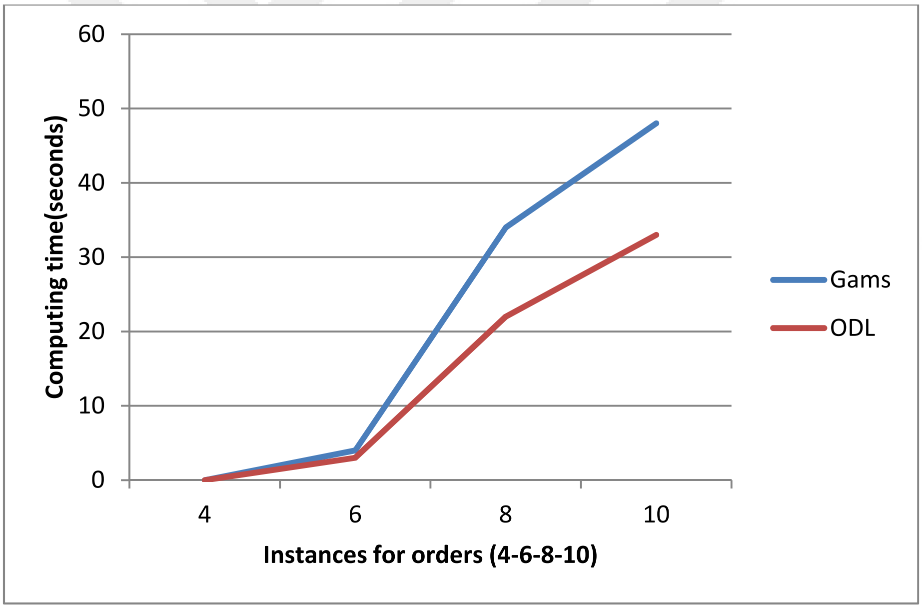

Figure 4.4. Comparison the computing times for Gams and ODL

Figure 4.4. depicts the comparisons of Gams and ODL, in which computing times increase when the number of orders is increased. We also observe that ODL heuristics becomes faster for routing the vehicles.

4.1.2. Results of Medium Sized Problems

There are no other real case data or test instances for our problem; randomly generated test instance is implemented in addition to given case study. The parameters are created by uniform distribution in Matlab shown in Table 4.4. Order latitude, longitude, weight, volume values are created using uniform distribution. The other parameters are created randomly. All parameters are created considering real case data.

Table 4.4. 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([20000 30000])
Width	Rand([2 3])
Height	Rand([2 3])
Length	Rand([10 13])

Results are obtained from employing the proposed approach (clustering first, then packing routing) on the medium test instance. The results demonstrate that 12 carrying units (*nv*) are used and 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 these values obtained by the exact method and GA heuristics. However, it is only fair to compare the running times since data size is different.

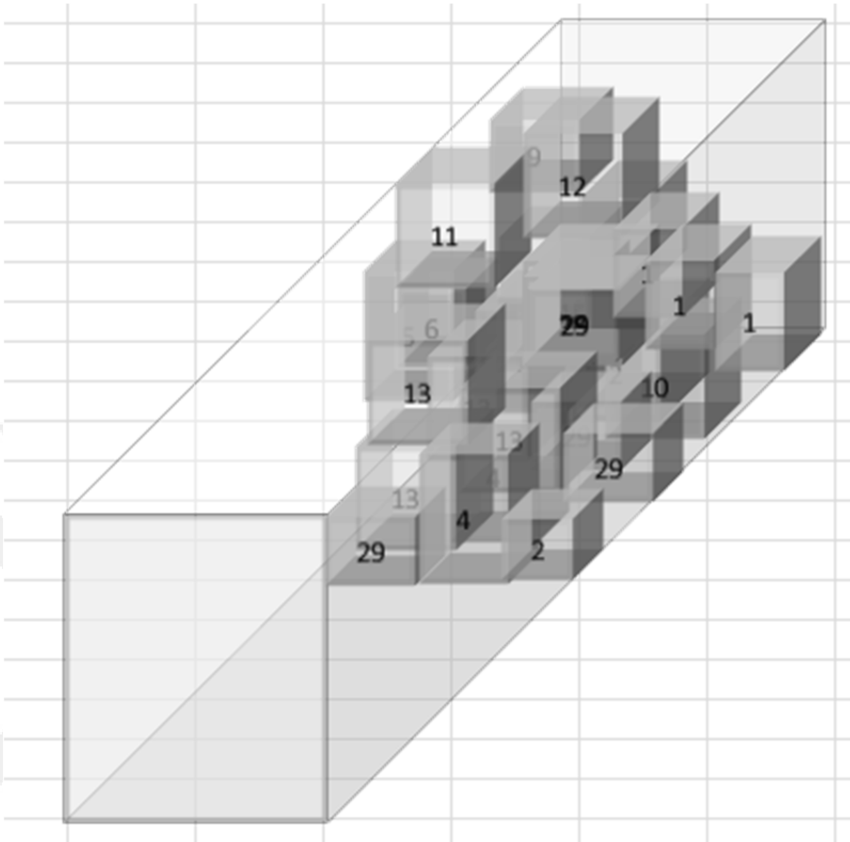

Figure 4.5. Order positions loaded into Vehicle 1 for Cluster 1 for medium data

We also demonstrate the order positions loaded into Vehicle 1 for Cluster 1 in Figure 4.5. and vehicle route for Vehicle 1 of Cluster 1 in Figure 4.6. Considering the loading coordinates, 29 orders have been located to the Vehicle 1.

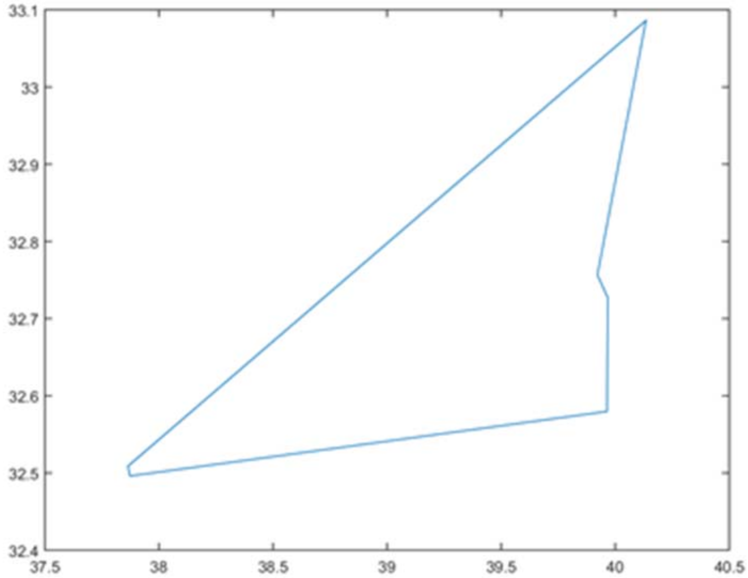

Figure 4.6. Optimal Route of Vehicle 1 for Cluster 1 for medium data

4.1.3. Results of case study

In this subsection, we present the obtained computational results for 3D-PRP. Vehicle numbers, order numbers and positions of the orders for all clusters are obtained in this section. Our results show that 20 clusters are formed, in which all orders are located by considering x, y, z coordinates. The results demonstrate that 14 carrying units (*nv*) are used and total travel distance (*ttd*) is 47.2043 km. The loading results are depicted in appendix I. For instance; In Cluster 1, all orders are loaded into four types of carrying units. We see from Table 4.5, the number of vehicle (nv) and total travel distance (ttd) is larger when compared to the medium test instance. We also demonstrate the order positions loaded into Vehicle 1 for Cluster 1 in Figure 4.7, Vehicle 8 for Cluster 2 in Figure 4.8, Vehicle 2 for Cluster 3 in Figure 4.9, Vehicle 1 for Cluster 4 in Figure 4.10. Considering the loading coordinates, 31 orders have been located to the Vehicle 1. We report the clustering performance over two instances. The packing results are strongly improved by the clustering heuristics. Improvements up to 60% and 45% are possible for *nv* and *ttd*.

We also see that GA heuristics becomes faster for the input processed by machine learning.

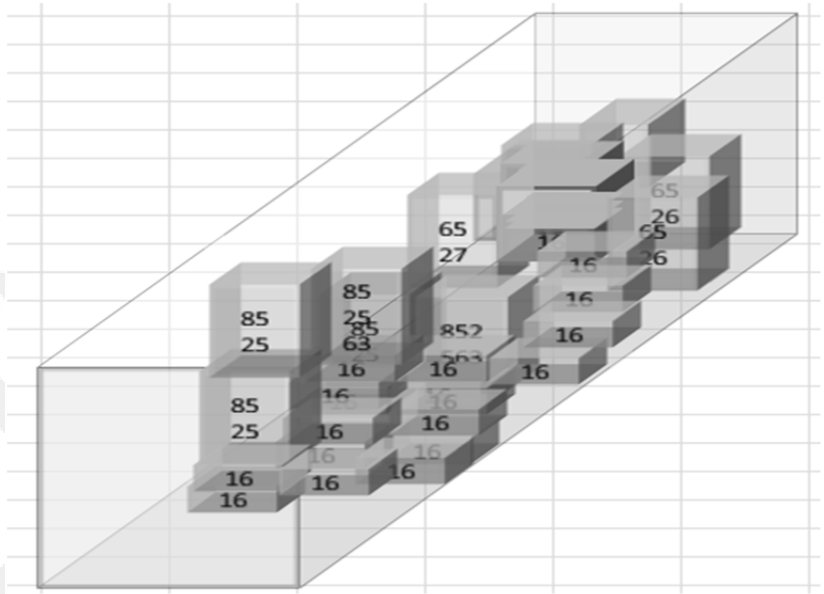

Figure 4.7. Order positions loaded into Vehicle 1 for Cluster 1

Figure 4.7. depicts the orders loaded to the trailer 1. The same orders are shown in the same colours. 85256394 orders are none stackable. 165264357 and 165267291 orders are stackable; thus, two orders are loaded above these orders. The utilization is improved significantly by 12.89%.

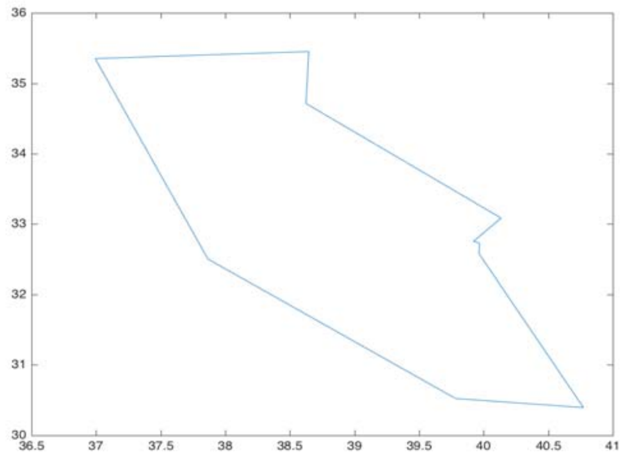

Figure 4.8. Optimal Route of Vehicle 1 for Cluster 1

Figure 4.8. shows the routes of the carrying units loaded to the trucks. The vehicle 1 for cluster 1 travels the order locations according to the latitudes and longitudes. The origin point is (40.7- 30.4) of the tour by truck. The truck starts and ends the tour in the same point.

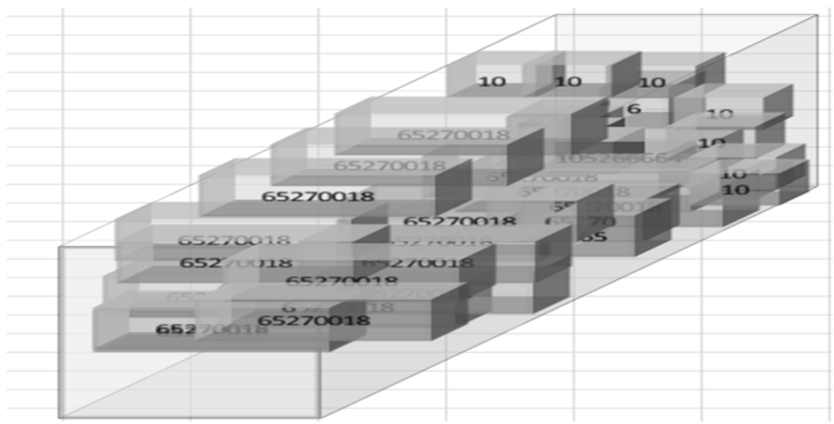

Figure 4.9. Order positions loaded into Vehicle 8 for Cluster 2

Figure 4.9. is about the order packing into the trailer 8 for cluster 2. Two groups of orders are packed into the trailer 8. The same orders are shown in the same colours. 105266664 and 65270018 orders are stackable. Thus, three orders are loaded above these orders. The utilization is improved significantly by 25.18%.

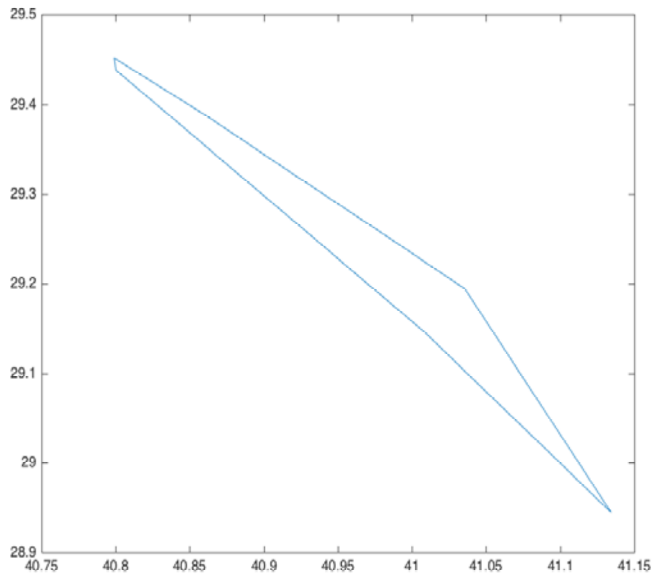

Figure 4.10. Optimal Route of Vehicle 8 for Cluster 2

Figure 4.10. shows the routes of the carrying units loaded to the trucks. The vehicle 8 for cluster 2 travels the order locations according to the latitudes and longitudes. The origin point is (41.14- 28.94) of the tour by truck. The truck starts and ends the tour in the same point.

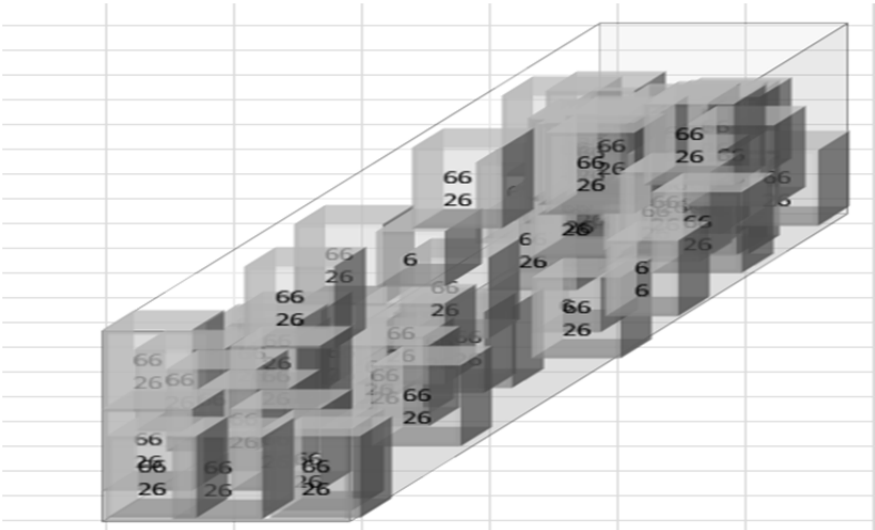

Figure 4.11. Order positions loaded into Vehicle 2 for Cluster 3

Figure 4.11. is about the order packing into the trailer 2 for cluster 3. 45 orders are packed into the trailer 8. The same orders are shown in the same colours. 66263740 orders are stackable. Thus, three orders are loaded above these orders. The utilization is improved significantly by 20.19%.

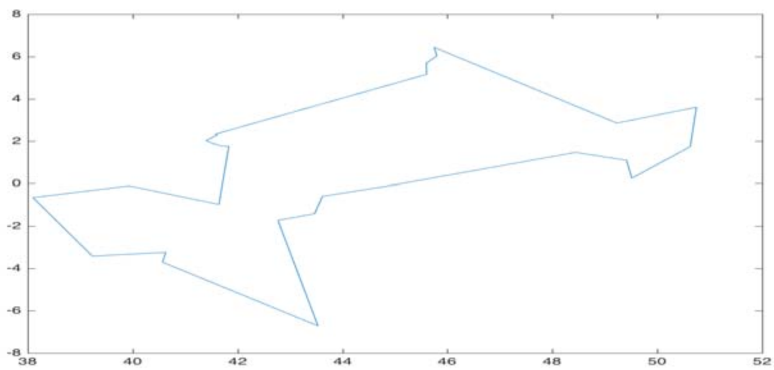

Figure 4.12. Optimal Route of Vehicle 2 for Cluster 3

Figure 4.12. shows the routes of the carrying units loaded to the trucks. The vehicle 2 for cluster 3 travels the order locations according to the latitudes and longitudes. The origin point is (43.7- 30.52) of the tour by truck. The truck starts and ends the tour in the same point.

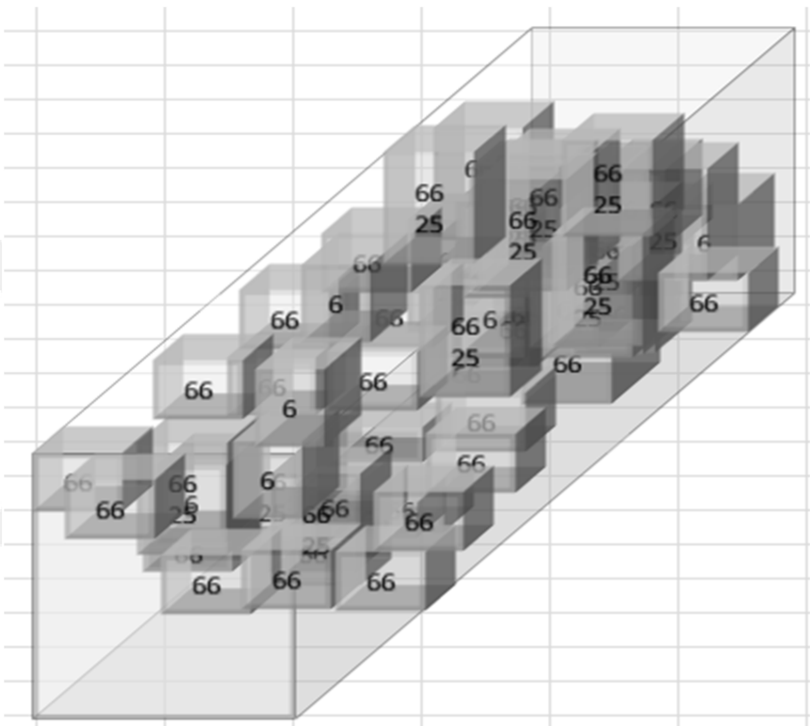

Figure 4.13. Order positions loaded into Vehicle 1 for Cluster 4

Figure 4.13. is about the order packing into the trailer 1 for cluster 4. 98 orders are packed into the trailer 1. The same orders are shown in the same colours. 66265435 orders are stackable. Thus, three orders are loaded above these orders.

Figure 4.14. depicts the all routes of the carrying units loaded to the trucks. Trailers 1,2,3,8 are used for cluster 1; trailers 1,2,3,8 are used for cluster 2; trailers 1,2 are used for cluster 3; trailers 1,2 are used for cluster 4.

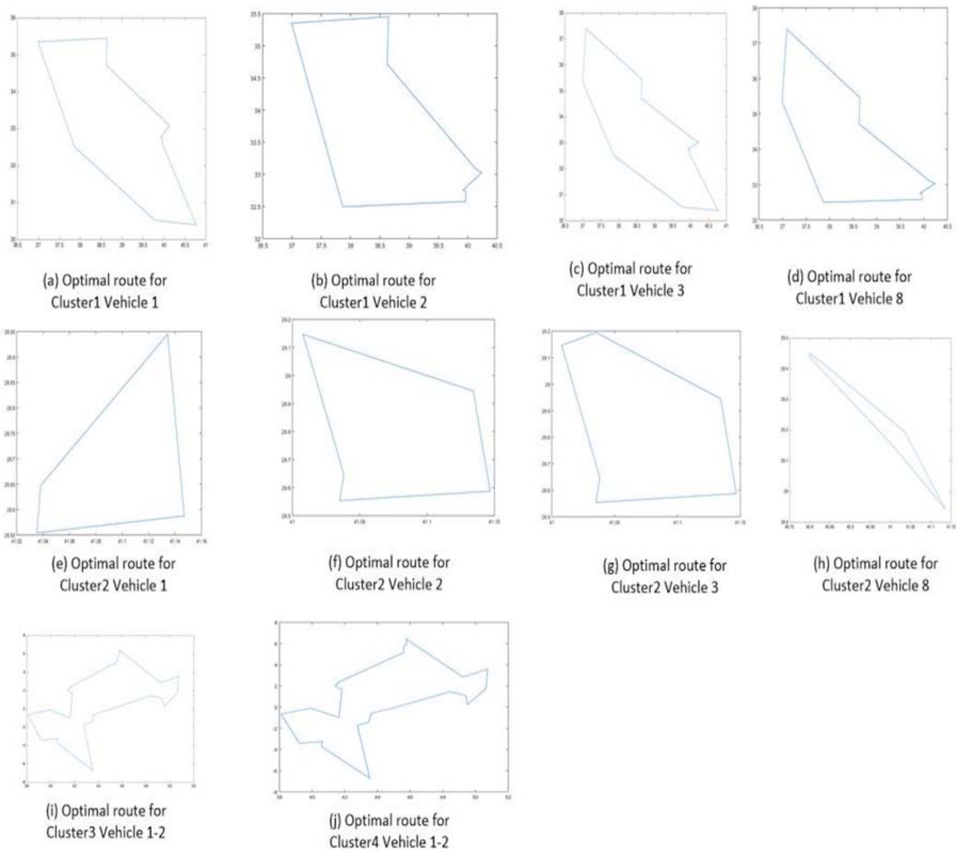

Figure 4.14. Optimal routes of vehicles for clusters

4.1.4. Comparisons of the Methods with Different Instances

The methods used in the instances are compared by number of vehicles (nv) and total travel distances (ttd) in Table 4.5. There are no other real case data or test instances for our realistic-sized instance. Thereby, it is only fair to compare the results of real-case instance and generated medium-sized instance. We can conclude that *nv* and *ttd* increases by the order size and clustering the backhauls ensures less travel distance. The results are as follows: ttd is 4407 km for small data, about 25 km for medium data, about 47 km for larger data. Nv is 3 for small data, 12 for medium data, 20 for larger data.

Table 4.5. Comparisons of mathematical modelling, proposed approach, open source coding approach

	Two stage approach		Proposed approach (First cluster, then packing-routing)		ODL	
Instances	nv	ttd	nv	ttd	nv	ttd
Small data	3	4407			3	4407
Medium data			12	25.3225		
Larger data			14	47.2043		

4.1.5. Results of the Train Assignment Problem

We mentioned above that the intermodal transport network proposed in the study consists of road and rail transportation modes. First stage of the intermodal transport network focuses on road transportation. The results of this stage are feasible packing plans and the output of the 3d-loading is input of the train assignment problem. 14 Carrying units (trailers or containers) of orders packed with 3d loading constraints are assigned to the block trains optional for two different train stations. Carrying units are transferred by Roros from Turkey to Trieste, then from Trieste to Koln or Ludwigshafen. In this stage, the maritime transport stage is not considered. Vehicle 1 is assigned to Trieste-Ludwigshafen; other vehicles are assigned to Trieste-Koln. The results are depicted for 4 carrying units in Table 4.6. The results for 16 carrying units are provided in appendix E.

Table 4.6. 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			

Our results show that the proposed exact approach can solve realistic instances in a reasonable time. We conclude that demurrage and detention affect the delays for vehicles 2, 3 and 8. Orders are delivered to the customers with 1, 2 and 3 days delays.

4.2. Results of Stage 2

Intermodal transportation has been increasingly investigated in the logistics sector in last few years. This problem is transport mode selection and load assignment by corporating risk factors. Proposed model uses the real world data of a large-scale international logistics firm to validate the model. The mathematical formulation is solved by GAMS optimization software, and a fuzzy based approach is applied by the Matlab fuzzy logic designer executed on an Intel CPU 3.6 GHz with 16 GB RAM. The mathematical model is solved in a reasonable time limit in GAMS. The fuzzy logic designer also provides to design our fuzzy inference system. The fuzzy logic software produces good solutions for a large number of inputs. The software has various sections such as a designer, a membership function editor, a rule editor, a rule viewer, and a surface viewer.

The results demonstrate that the logistics firm can reduce the total costs and present various opportunities to control the transportation network under risk parameters. The results in terms of total cost present optimal results. The results present that all demands should not be met with the same transportation modes. Regarding cost, human and ecological weights, demands should be met by various transportation carrying units.

Load plan is depicted in Figure 4.15. The export containers transported by different transportation modes are obtained. Total 443 TU containers are transferred by road transportation; total 3600 TU containers are transferred by maritime and road transportation; total 12300 TU containers are transferred by maritime, road and rail transportation.

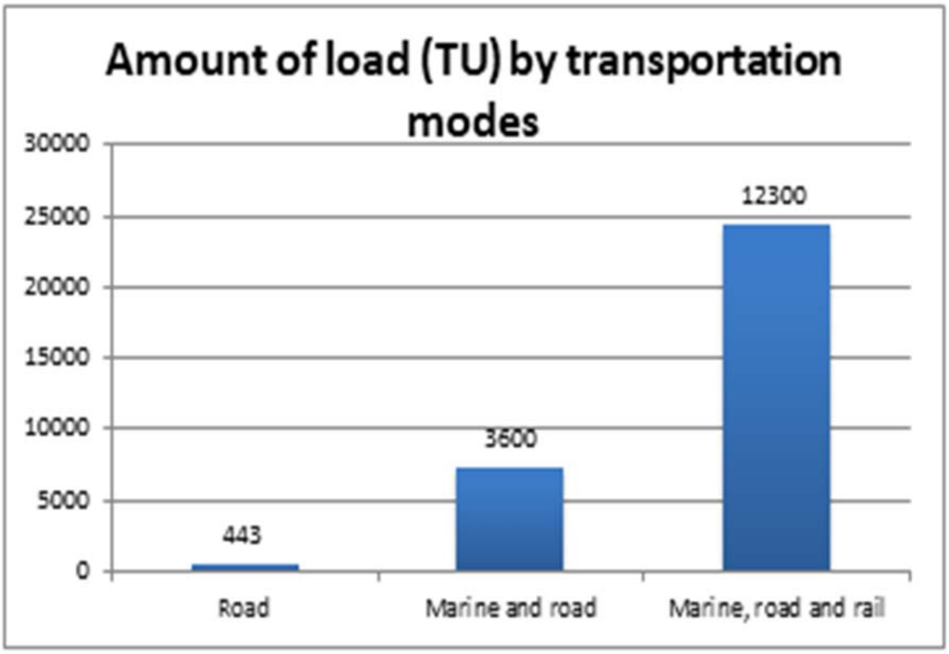

Figure 4.15. Amount of containers (TU) by various transportation modes

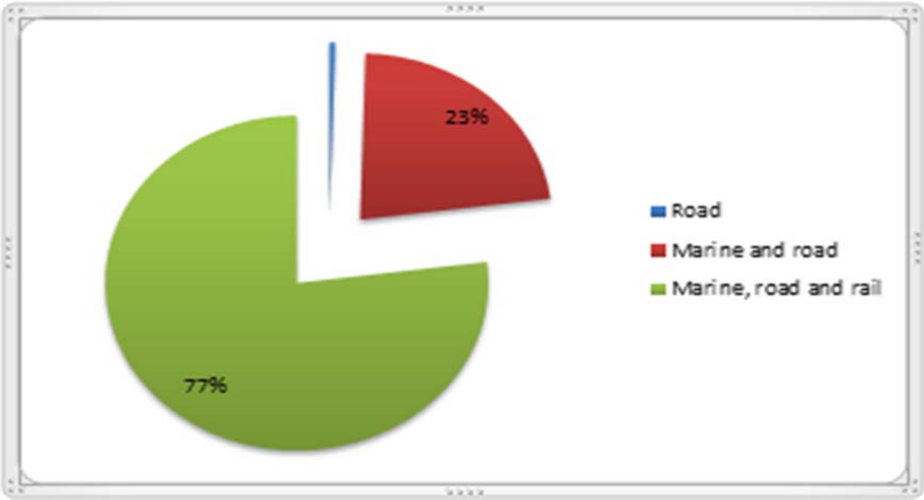

Figure 4.16. Total shares of the transportation modes obtained in the study

Intermodal transportation including marine, road, rail modes has the highest share in Figure 4.16. Road transportation has the lowest share that is used only for the TU transfer between Turkey supply point and Bratislava, Poland. Road transportation has the lowest share of transferring the containers because the risk weight of this mode is also effective on this result.

Export flow from Turkey to Ostrava, Bratislava, and Poland at each period can be found in Table 4.7. All demands of Bratislava and Poland from Turkey are not met by road transportation. Therefore, there is an export flow from Turkey port to the customers by different modes. Firstly, marine transport is used from the Turkey ports to the Trieste port by Roros; then, a train transportation to Ostrava is conducted. Finally, road transport is used to tranfer the containers. Therefore, intermodal transportation mode is used including maaritime-road and maritime-rail-road mode. All demands of Bratislava and Poland are provided at each period. The road transportation is not used in 1,2,3 periods between İstanbul and customers. The risk weights, road cost and road distance dominate the results.

Table 4.7. Amount of load transferred by transportation modes (TU)

Period	1	2	3	4	5	6
Amount of load transported by Roro						
İstanbul/Trieste	1520	730	545	450	534	522
Number of block trains						
Trieste/Ostrava	9	9	8	7	8	7
Amount of load transported by Road						
Ostrava/Customers	50	52	65	58	46	72
Amount of load transported by Road						
İstanbul/Customers	0	0	0	50	30	20

Monthly amount of export containers are depicted in Figure 4.17. An increasing pattern is available between period 1 and period 4. Then, a decreasing pattern is obtained.

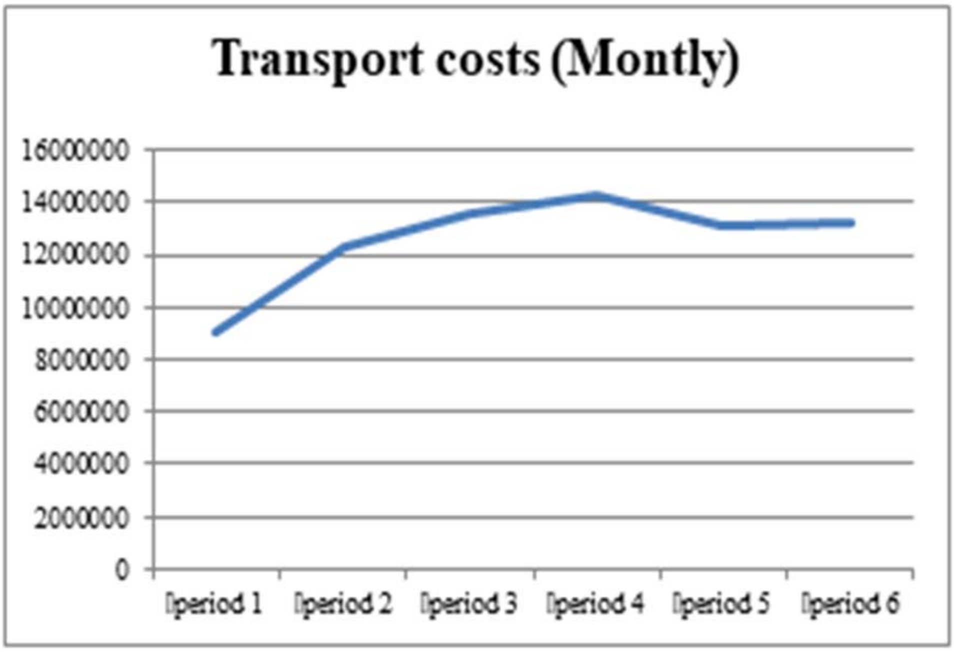

Figure 4.17. Monthly transport costs for each period

The results demonstrate thar weights, cost and distance are effective on the results and ensure the use of intermodal transportation modes. Without considering risk weights, all demands could be provided by road transport.

4.2.1. Graphical User Interface (GUI) for Real Life Application

Solutions of the intermodal transportation problem should respond quickly the end user. Thus, an interface called intermodal transportation planner has been proposed. Figure 4.18. is login screen of the software. This screen is about importing existing data. Main centres, transfer point, customers, products, transport modes and periods are decided. Each parameter is imported from Microsoft Excel. The GUI environment includes pushbuttons, list boxes, sliders components.

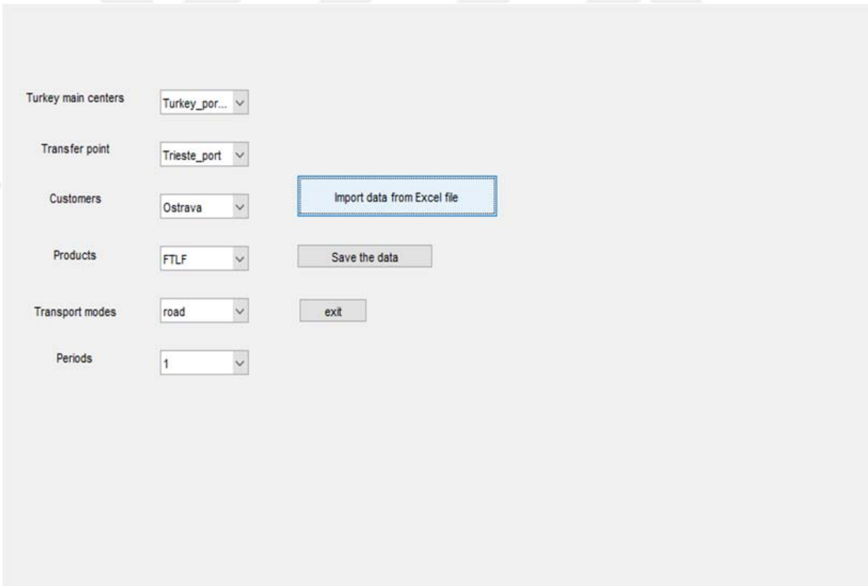

Figure 4.18. Login screen of intermodal transportation planner

Main centres, transfer points, customers, products, transport modes and periods are incorporated to the system. Data obtained by the logistics firm is imported from Microsoft Excel. Then, the data is saved in the system. The end user can import the data that will be controlled. In Figure 4.19-4.20, the results are analysed. The results are divided into two groups: number of vehicles used and total order flows to the customers. Number of vehicles and total order quantities are summarized in Figure 4.19. The graph depicts the number of vehicles used during the planning periods. Total number of transport modes and monthly usage of them are obtained by pushing the “show selected results”. The end user will use this form to plan the utilization of transportation modes. Thus, usage of the resources effectively can be ensured.

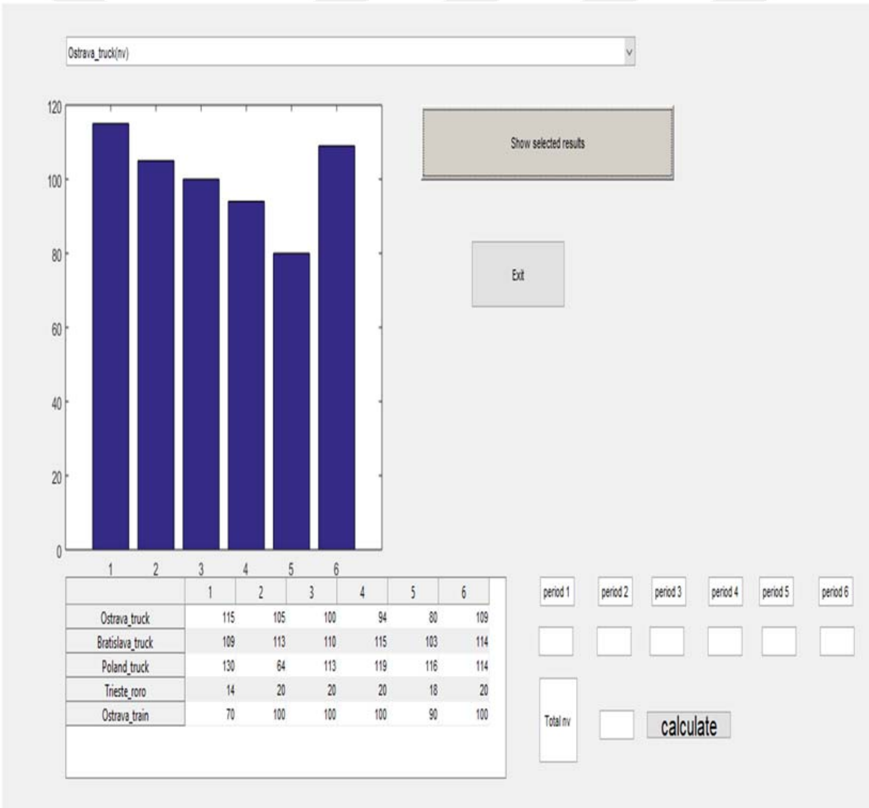

Figure 4.19. Results of intermodal transportation planner for number of vehicles

The other form shows total order quantities in Figure 4.20. In the form, order quantities are shown during the periods. In the case study, demands of customers including Poland, Bratislava and Ostrava should be met by transportation modes. The end user chooses the demand of the customer with button and the results including amounts of orders are depicted in the figure and table. Thus, following the orders is provided and customer requirements are met.

Figure 4.20. Results of intermodal transportation planner for total order flow

4.3. Computational Complexity of the 3D-PRP

Computational complexity of the mathematical model for 3D-PRP is related with the number of total decision variables and constraints. Both of the pick-up routing problem and the 3D loading problem is NP-hard. We examine the complexities of each problem. The complexity increases since the real case data includes a large number of variables and constraints.

4.3.1. Computational Complexity of the PRP

Computational complexity of the decision variables for pick up routing problem is summarized in the Table 4.8. The complexity of the decision variables is calculated by n^2 k+2nk+k regarding the index variables. The complexity of the binary decision variables is calculated by n^2 k +nk+k regarding the index variables. Since the number of decision variables are related with number of nodes, vehicles and periods, the problem complexity depends on these values. Real case problems including more nodes, vehicles and periods need more computational time.

Table 4.8. Complexity of the decision variables for the PRP

Variable	Number of nodes (n)	Number of vehicles (k)	Number of variables	Type of variable
U	n	k	nk	Continuous
X	n^2	k	n^2 k	Binary
Z	n	k	nk	Binary
y		k	k	Binary
	Total binary variables		n^2 k +nk+k	
	Total decision variables		n^2 k+2nk+k	

Figure 4.21. depicts the trend of the decision variables regarding number of vehicles and nodes. Decision variables increase exponentially by the increasing

number of vehicles and nodes. Thus, the real case problem cannot be solved in a reasonable time.

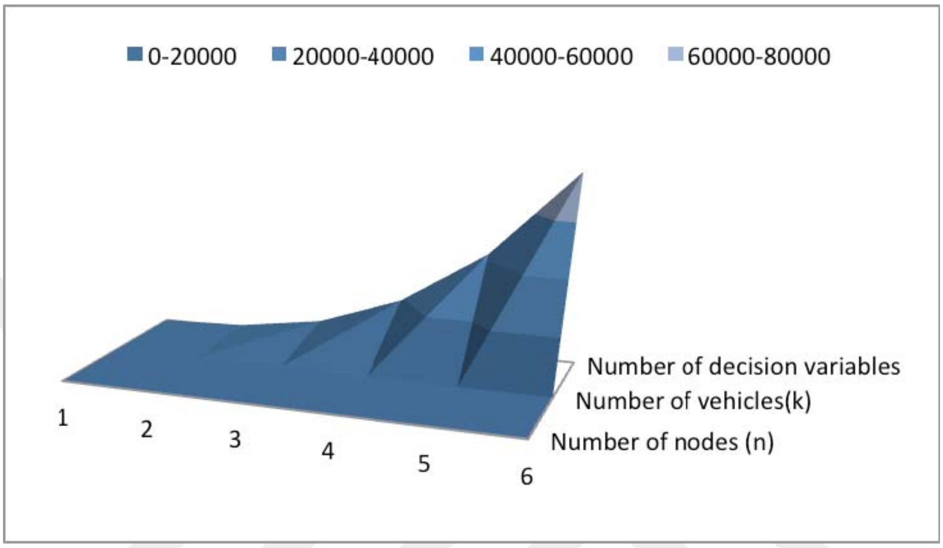

Figure 4.21. Changes on total decision variables regarding the number of nodes, vehicles

Computational complexity of the constraints is summarized in the Table 4.9. The complexity of the constraints is calculated by n^2 k+2nk+k regarding the index variables. Since the number of constraints is related with number of nodes, vehicles and periods, the problem complexity depends on these values. Real case problems including more nodes, vehicles and periods need more computational time.

Table 4.9. Complexity of the constraints the PRP

Variable	Number of nodes (n)	Number of vehicles (k)	Number of variables
1.constraint	n	k	nk
2.constraint	n		n
3.constraint	n	k	nk
4.constraint	n2	k	n2 k
5.constraint		k	k
6.constraint		k	k
7.constraint		nk	nk
8.constraint		k	k
9.constraint		k	k
Total number of constraints		n2 k +2nk+n+4k	

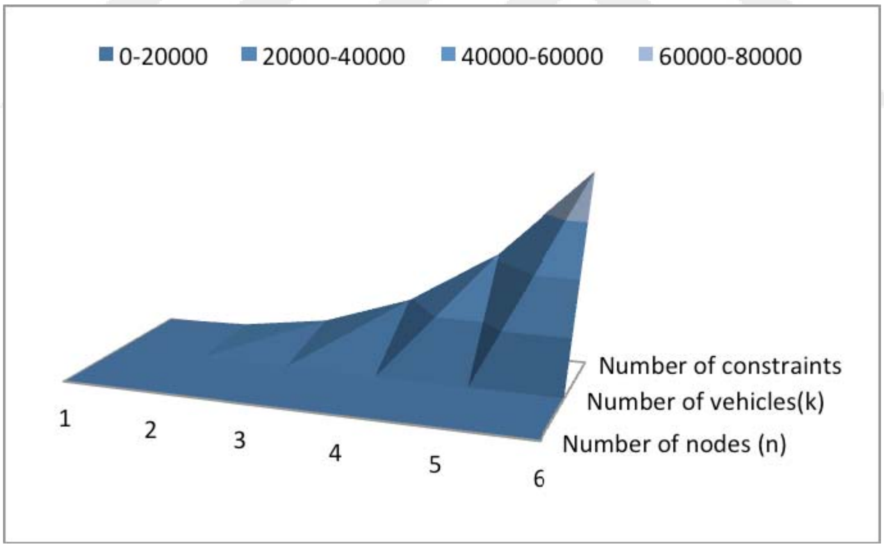

Figure 4.22. Changes on total number of constraints regarding the number of nodes, vehicles

Figure 4.22. depicts the trend of the constraints regarding number of vehicles and nodes. Constraints increase exponentially by the increasing number of

vehicles and nodes. Thus, the real case problem cannot be solved in a reasonable time.

4.3.2. Computational Complexity of the 3D loading

Computational complexity of the decision variables for 3D loading is summarized in the Table 4.10. The complexity of the decision variables is calculated by $6n^2 + kp + 3p$ regarding the index variables. The complexity of the binary decision variables is calculated by $6n^2 + kp$ regarding the index variables. Since the number of decision variables is related with number of nodes, vehicles and orders, the problem complexity depends on these values. Real case problems including more nodes, vehicles and orders need more computational time.

Table 4.10. Complexity of the decision variables for 3D loading

Variable	Number of nodes (n)	Number of orders (p)	Number of vehicles (k)	Number of variables	Type of variable
o		p	k	kp	Binary
a	n^2			n^2	Binary
b	n^2			n^2	Binary
c	n^2			n^2	Binary
d	n^2			n^2	Binary
e	n^2			n^2	Binary
f	n^2			n^2	Binary
x		p		p	Continous
y		p		p	Continous
z		p		p	Continous
		Total binary variables	$6n^2$ +kp		
		Total decision variables	$6n^2$ +kp+3p		

Figure 4.23. depicts the trend of the decision variables regarding the number of vehicles and orders. Number of decision variables increase exponentially by the increasing number of vehicles, orders and nodes. Thus, the real case problem cannot be solved in a reasonable time.

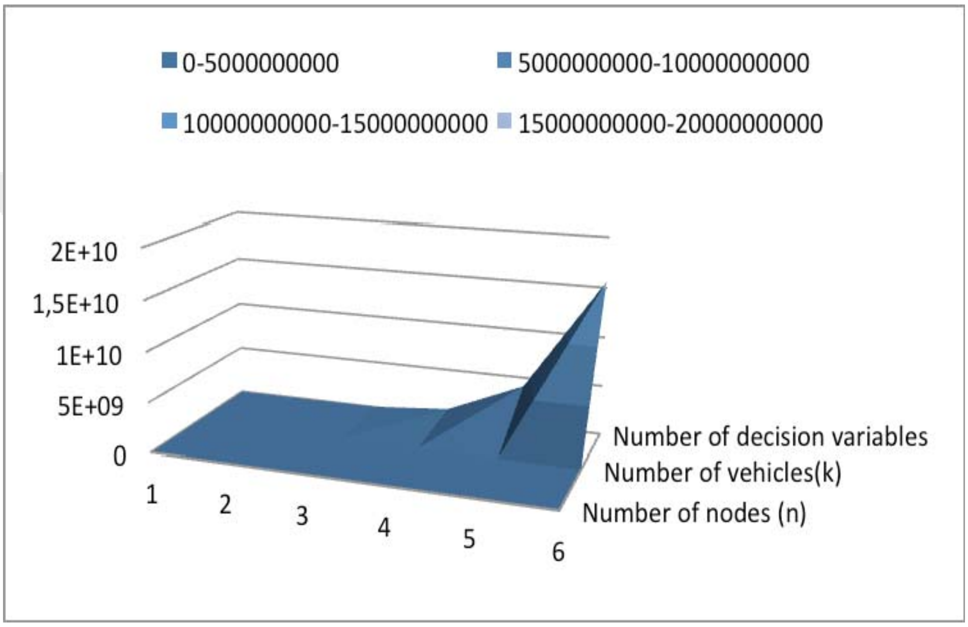

Figure 4.23. Changes on total number of decision variables regarding the number of nodes, vehicles for 3D loading

Computational complexity of the constraints is summarized in the Table 4.11. The complexity of the constraints is calculated by $6n^2 + n^2 k + 3kp$ regarding the index variables. Since the number of constraints is related with number of nodes, vehicles and orders, the problem complexity depends on these values. Real case problems including more nodes, vehicles and orders need more computational time.

Table 4.11. Complexity of the constraints for 3D loading

Variable	Number of nodes (n)	Number of vehicles (k)	Number of orders (p)	Number of variables
1.constraint	n^2			n^2
2.constraint	n^2			n^2
3.constraint	n^2			n^2
4.constraint	n^2			n^2
5.constraint	n^2			n^2
6.constraint	n^2			n^2
7.constraint	n^2	k		$n^2 k$
8.constraint		k	p	kp
9.constraint		k	p	kp
10.constraint		k	p	kp
	Total number of constraints		$6n^2 + n^2 k + 3kp$	

Figure 4.24. depicts the trend of the constraints regarding number of vehicles and nodes. Constraints increase exponentially by the increasing number of vehicles and nodes. Thus, the real case problem cannot be solved in a reasonable time. Exact solution methods cannot solve the larger data including large number of constraints. Thus, other solution methodologies such as meta-heuristics, machine learning are used to solve these real case problems.

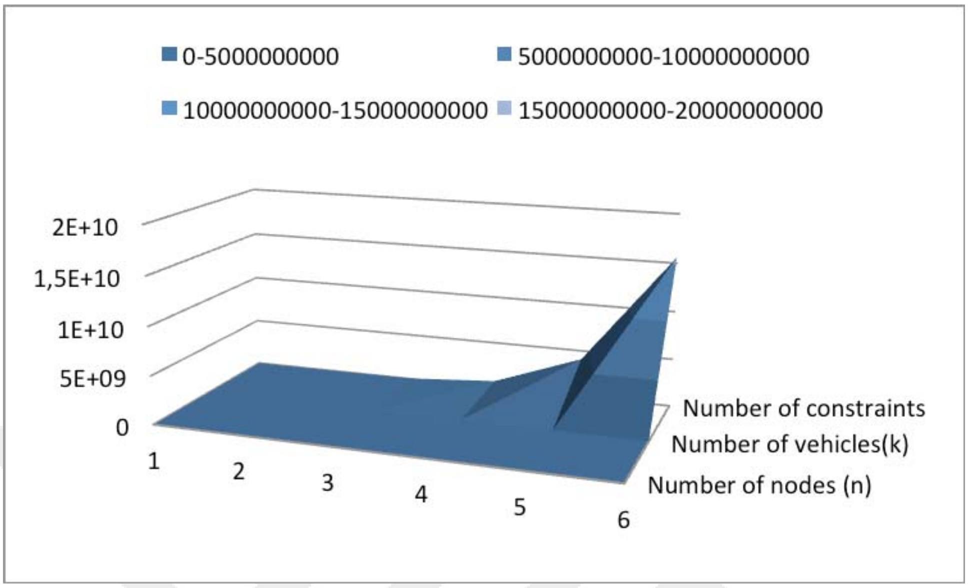

Figure 4.24. Changes on total number of constraints regarding the number of nodes, vehicles for 3D loading

4.4. Sensitivity Analysis

Sensitivity analysis is applied to show the effects of parameters on the objective function. The changes can be conducted on the coefficients and constraints of the objective function. In the real case studies, the values of the coefficients can include uncontrollable situations. Decision makers could make adjustments on these values. In order to show the changes of these values on the optimal solution, sensitivity analysis is preferred.

Train assignment model is complicated if the number of nodes, periods and vehicles are chosen. Therefore, demurrage, detention and utilization costs are chosen to measure the sensitivity of the model. We analyse the performance of the algorithm by sensitivity analysis in Figure 4.25 (a, b, c). Figures reveal that objective function is mostly sensitive to the train usage costs and demurrage and detention costs are negligible. Therefore, it is expected to obtain increasing total costs due to the usage cost of trains are included.

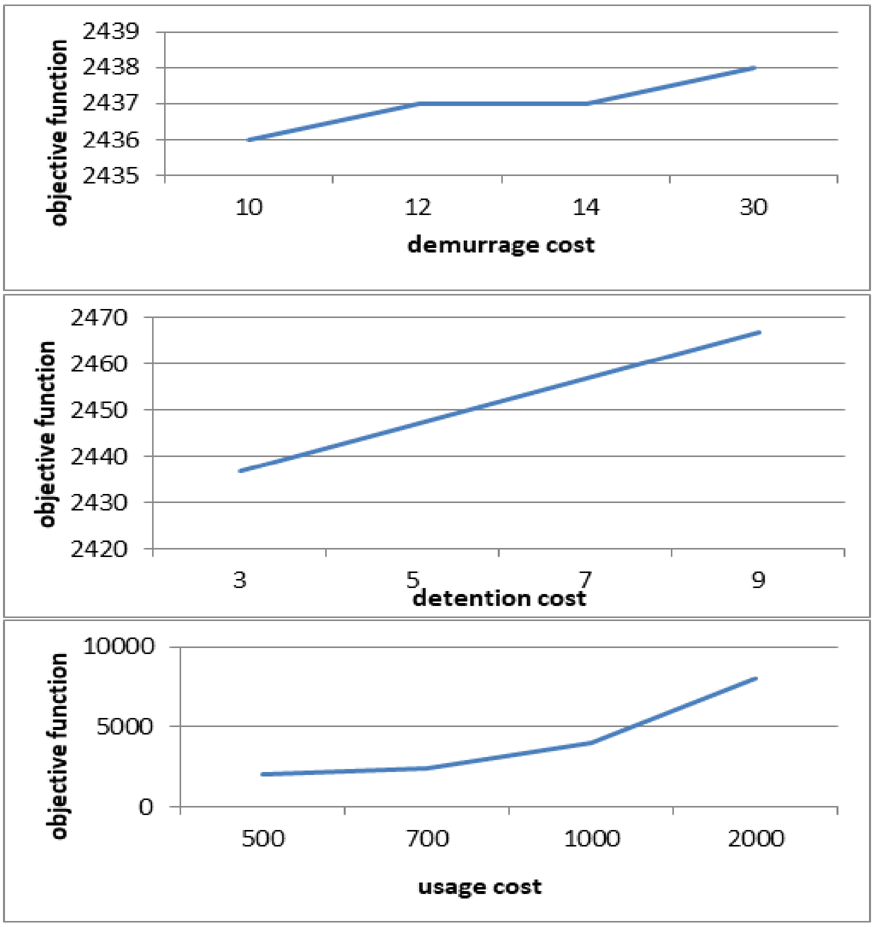

Figure 4.25. Sensitivity analysis for the effects of parameters on the objective function

An experimental design is applied to evaluate the effects of cost parameters. Three ratios are chosen as factors.

4.5. Scenario Analysis

Scenario analysis is performed to examine the model behaviours on various conditions for the intermodal transportation mode problem results. A factorial design is provided and results are presented. Number of nodes including four levels

(3, 6, 9, 12) and periods including two levels (6, 12) are chosen as factors. Thus, 4x2 type factorial design is obtained. Two replications are applied for each experiment. The response variables are chosen as objective value and solution time.

4.5.1. The Intermodal Transportation Mode Problem Results

The instances used in this scenario analysis are generated randomly. Thus, objective values are different with the same index values. However, the total transportation costs and solution time increase by the increasing number of nodes and periods. This result shows the NP hard structure of the problem. Average value of the objective function and solution time is obtained 16 179 002 366 money and 4.2 hours shown in Table 4.12.

Table 4.12. The intermodal transportation mode problem results

N	T	Objective Value	Solution time
12	6	1452813845	61
9	12	12712814818	24567
6	6	6412814818	11345
12	6	1022814818	156
12	12	6712814818	23467
3	12	10128148189	654
6	12	5112814818	357
9	6	6912814818	23400
6	6	4512814818	3456
9	6	17812814818	7890
12	12	17128148185	4356
3	6	1712814818	4
3	6	1714005127	5
6	12	5325641288	23453
9	12	14412814813	23400
3	12	5412814818	250
Average		16179002366	15078

Main effects plot depicts the effects of number of nodes and periods on the problem in Figure 4.26. The objective value increases with the increasing number of nodes and periods. When number of nodes is chosen as nine, the objective function takes the highest value.

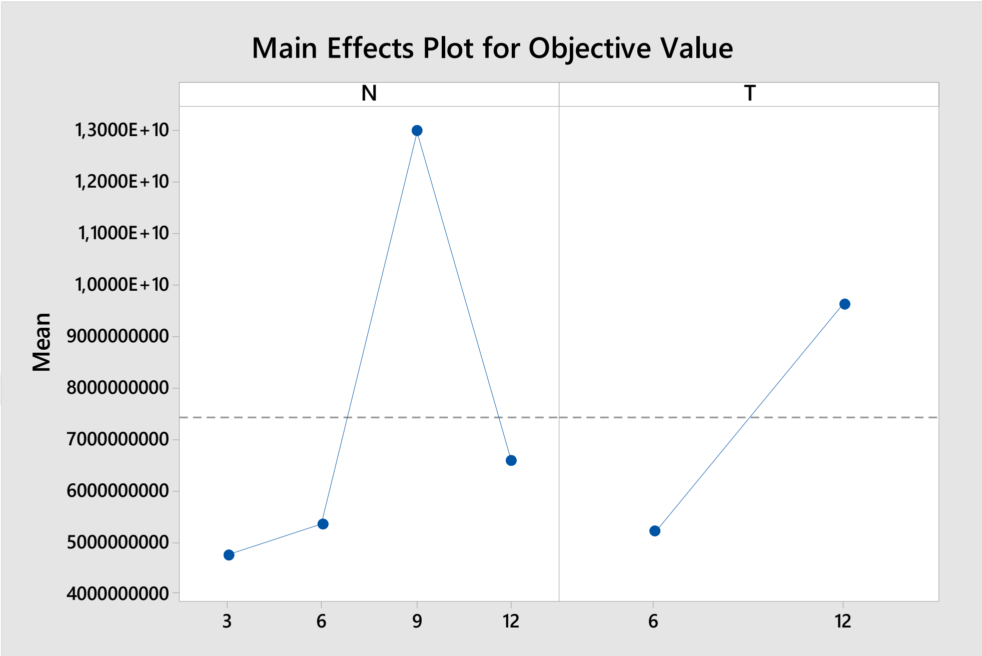

Figure 4.26. Effects of number of nodes and periods on the intermodal transportation problem

Main effects plot shows the effects of number of nodes and periods on the problem solution time in Figure 4.27. The solution time is not effected too much with the increasing number periods. The solution time results are similar to the objective value results. Until the number of nodes is reached to nine, the solution time increases. Highest value of the solution time is at nine. Then, the solution time decreases until the number of nodes reach the twelve nodes.

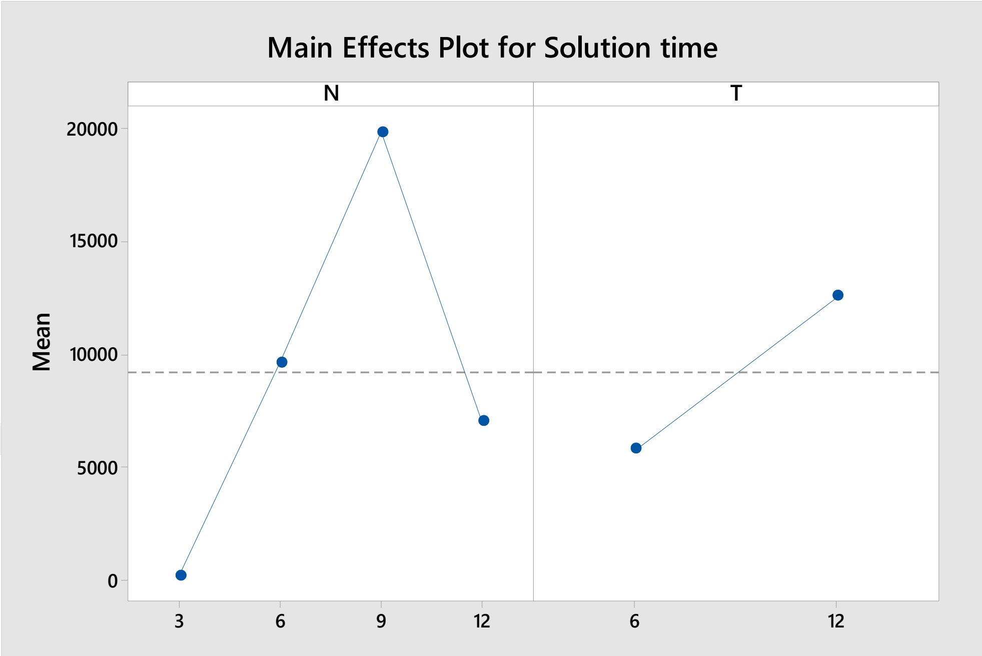

Figure 4.27. Effects of number of nodes and periods on the solution time for the intermodal transportation problem

Interactions of number of nodes and periods on the problem are demonstrated in Figure 4.28. Interactions between nodes 3, 6, 12 are available since there are intersection points. The objective function is not affected too much with the number of nodes six and nine. However, the number of nodes is chosen as three and twelve, number of periods effect the objective value. Objective value increases when the number of nodes are chosen as 3 and 12.

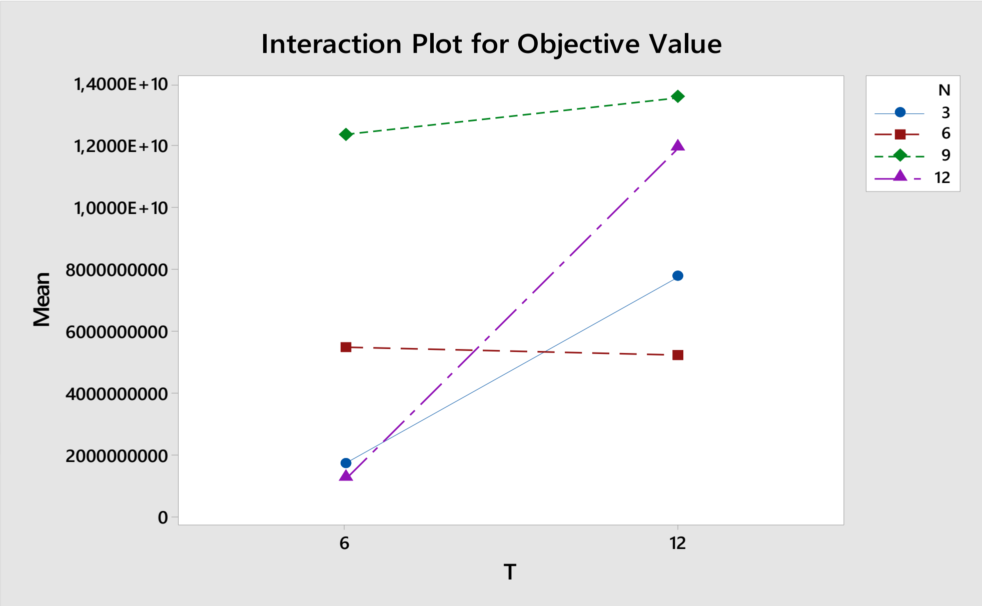

Figure 4.28. Interactions between number of nodes and periods on the intermodal transportation problem, objective function

Interactions of number of nodes and periods on the solution time are demonstrated in Figure 4.29. Interactions between nodes 3, 6, 12 are available since there are intersection points. The solution time is mostly effected with the number of nodes twelve. However, the solution time is not effected too much with the number of nodes under twelve.

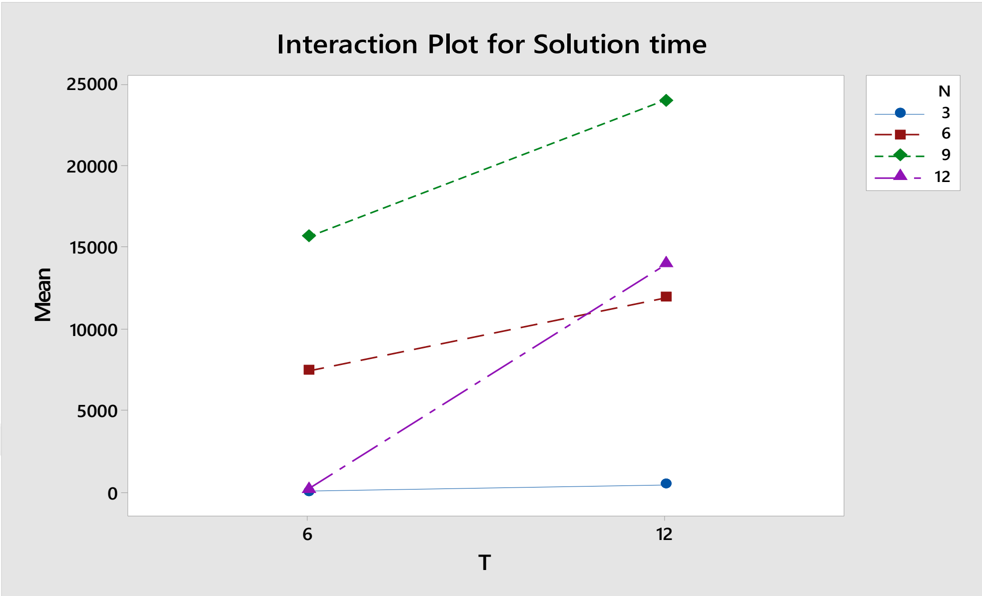

Figure 4.29. Interactions between number of nodes and periods on the intermodal transportation problem solution time

4.5.2.Two Stage 3D-PRP Results

A factorial design is provided and results are presented for 3D-PRP in Table 4.13. Number of nodes including four levels (4, 8, 12, 16) and vehicles including two levels (3, 6) are chosen as factors. Thus, 4x2 type factorial design is obtained. Two replications are applied for each experiment. The response variables are chosen as total objective value involving PRP and 3D loading values and solution time. For each problem, objective values are demonstrated and total objective value is also depicted. When the number of nodes and number of vehicles increase, total objective value and solution time also increases.

Table 4.13. Two stage 3D-PRP results

N	K	PRP Objective Value	3D loading Objective Value	Total Objective Value	Solution time
16	3	259686	4900	264586	35
12	6	3415200	7520	3422720	18567
8	3	3322100	4500	3326600	15345
16	3	568935	45670	614605	67
16	6	2485700	3400	2489100	45467
4	6	1657643	5400	1663043	654
8	6	456345	23300	479645	125
12	3	2215200	4670	2219870	12430
8	3	836595	4556	841151	3456
12	3	2067895	12200	2080095	7890
16	6	3659874	48900	3708774	43356
4	3	562569	3400	565969	8
4	3	1564569	3500	1568069	15
8	6	3574569	7800	3582369	45453
12	6	3658945	12300	3671245	45400
4	6	1688945	5600	1694545	250

Main effects plot depicts the effects of number of nodes and vehicles on the problem in Figure 4.30. The objective value increases with the increasing number of nodes and periods until the number of nodes is sixteen. When number of nodes is chosen as twelve, the objective function takes the highest value. Then, the objective value decreases until the number of nodes is reached to twelve. Increasing number of periods provides increasing objective value. Between 3 and 6 periods, an increasing pattern is available.

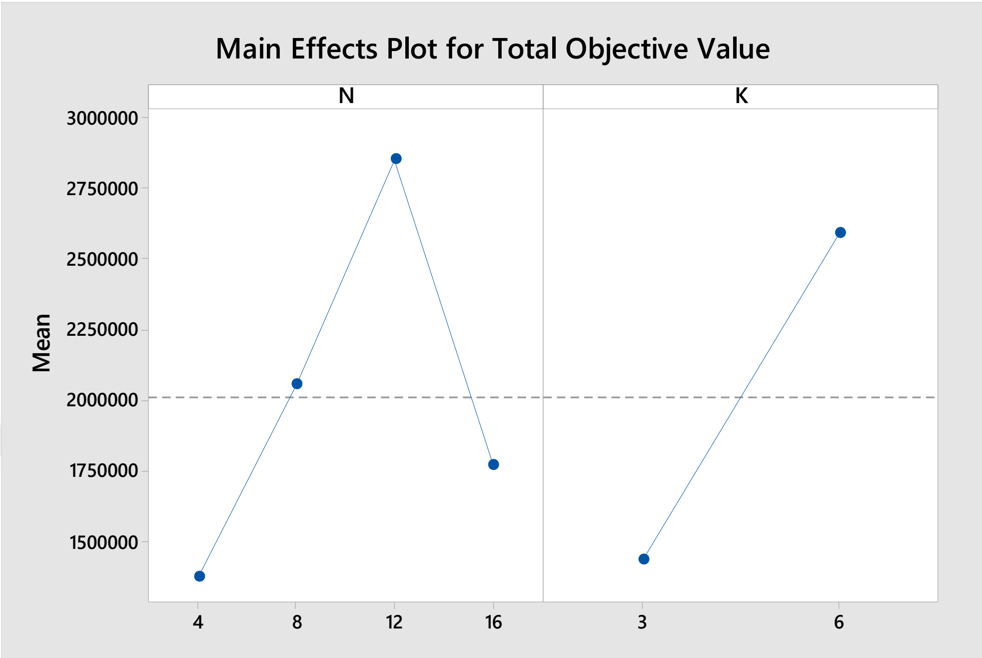

Figure 4.30. Effects of number of nodes and periods on the objective value for 3D-PRP

Main effects plot shows the effects of number of nodes and vehicles on the problem solution time in Figure 4.31. The solution time is effected with the increasing number periods. Increasing number of periods provides increasing solution time. Between 3 and 6 periods, an increasing pattern is available. The solution time results are similar to the objective value results. Until the number of nodes reaches the twelve, an increasing pattern for solution time is available. Then, a decreasing of the solution time is realized until to sixteen node.

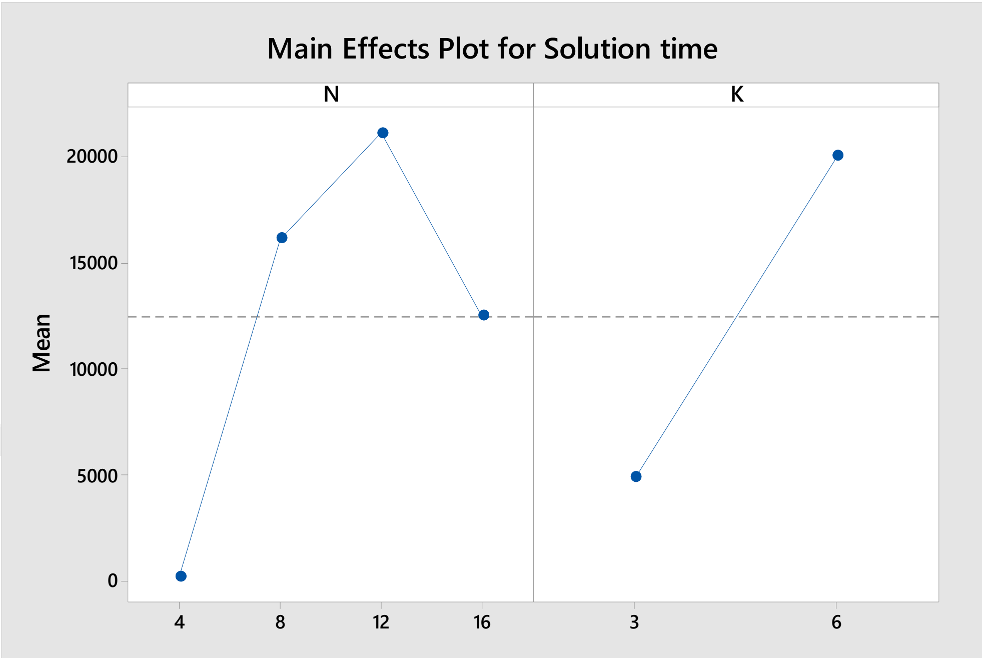

Figure 4.31. Effects of number of nodes and periods on the solution time for 3D-PRP

Interactions of number of nodes and periods on the problem are demonstrated in Figure 4.32. The objective function is not affected too much with the number of nodes eight and four. However, the number of nodes are chosen as sixteen and twelve, number of periods effect the objective value.

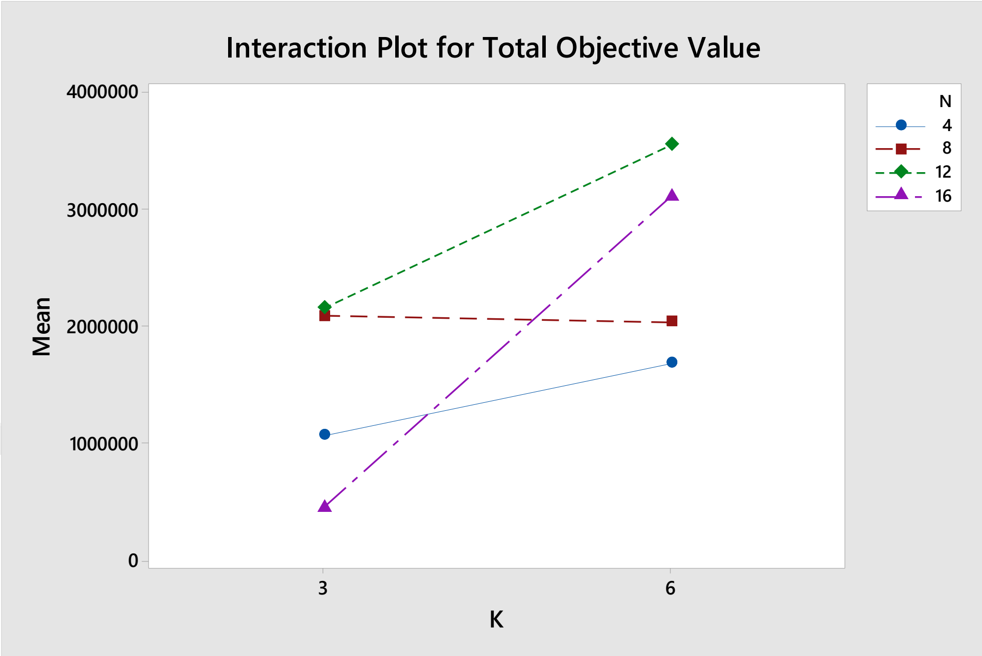

Figure 4.32. Interactions between number of nodes and periods on the objective value for 3D-PRP

Interactions of number of nodes and periods on the solution time are demonstrated in Figure 4.33. The solution time is mostly effected with the number of nodes sixteen. However, the solution time is not effected too much with the number of nodes under sixteen.

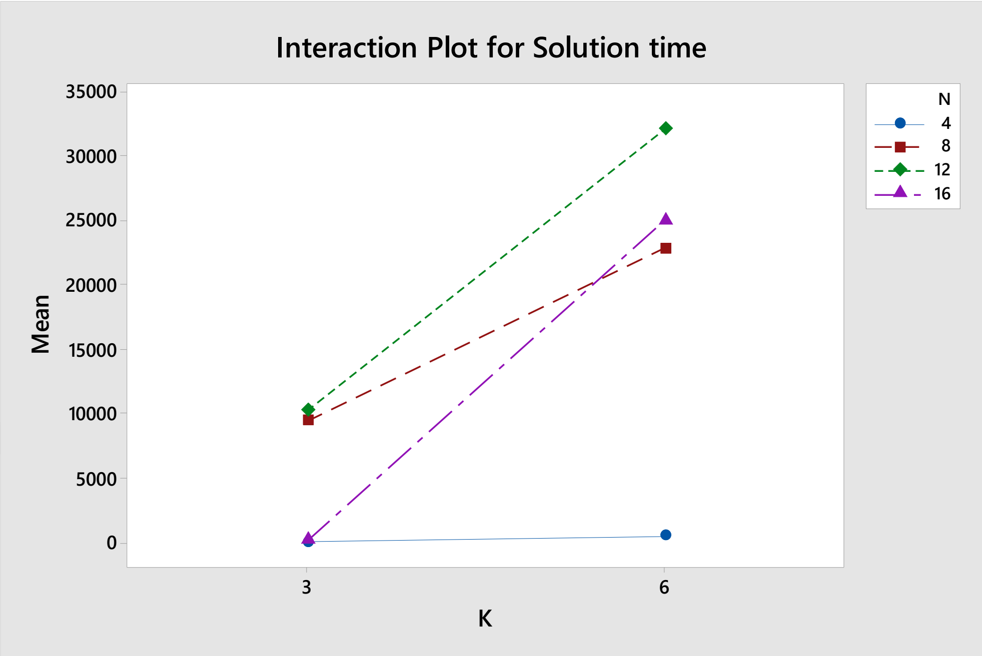

Figure 4.33. Interactions between number of nodes and periods on the solution time for 3D-PRP

4.6. Discussion

This problem is NP hard since it includes clustering, 3-D loading and pick-up routing. Solving this complex problem requires various solution approaches. Firstly, 3D-PRP is formulated as the mixed integer mathematical models. The models are formed as a two-stage approach, one for 3-D loading, the other for pick-up routing. Small instances are solved by exact solution methods in reasonable times. K-means algorithm is applied to cluster 102 coordinates into 8 clusters. Then, for each cluster, pick-up routing problem is solved. 3-D loading follows this step. Results are effective for the clustering the loading cities concerning the latitudes and longitudes. The locations are assigned to the nearest cluster. The orders in the locations are packed into the same vehicle. The small-sized problems are presented by both of the GAMS and ODL and the same outputs are obtained. Train assignment problem is formulated with the output of 3-D-PRP. The results show that demurrage and detention conditions are effective on the results. Demurrage and detention is related with the ship delays in the study. The ship is not included into the study. Preventing the delays related with ship, the sea conditions must be evaluated. Medium-sized and case study data are solved with heuristics and meta-heuristics. K-means clustering heuristics is applied to solve the clustering the locations. Then, the clustering section sends the data to Rstudio to solve the bin packing section. 4444 orders are packed into the carrying units according to the order and vehicle loading spaces. Finally, routing section is run with the output sent by the Rstudio. Results show that optimum loading and routing is obtained considering number of vehicles used and total travel distance.

Intermodal transportation has been increasingly investigated over the last decades because of human, economic, and ecological concerns. This study handles the assignment of demands to transport modes, i.e. transport mode choice considering economic, human and environmental factors as sustainable parts. The human and environmental risks are defined via linguistic descriptions by decision makers to decide transportation mode risk weights. The sub-classes of the human risk groups, i.e. vehicle collision, driver fault, traffic intensity, and route constructions, and the environmental risk group, i.e. the time spent in traffic, air toxics and particles, fuel efficiency, and ecosystem preservation, are examined to decide the linguistic descriptions of risk groups. Road transportation is obtained as the most risky transportation mode. Road transportation causes human deaths, accidents, and noise pollution and high emission values. Thus, road transportation has a highest risk weight. Rail transportation has a lowest risk weight, and maritime transportation has a medium risk weight. Regarding these risk weights and transport costs, optimal transport mode allocations are obtained. The proposed solution model is applied to the real world data of a large-scale international logistics firm to validate the model. Because the risk weights are effective on the transportation modes, export flow has not met all demands by road transportation. Some demands are provided by intermodal transportation. Research findings can differ from the current works by incorporating not only environmental factors but also human and ecological parameters for the transport sector to guide future researches. The theoretical contributions consist of designing a sustainable intermodal area, a systematic comparison of transportation modes, which is important in deciding the most optimal routes and modes, and the modelling of intermodal transportation based on economic, human, and ecological performances (Gocmen and Erol, 2018).

5. CONCLUSION AND FUTURE STUDIES

The thesis provides the intermodal transportation network optimization. Firstly, 3D - PRP constraints based on clustered backhauls are solved. A real world study is provided to demonstrate the validity of the proposed k-means clustering based machine learning and genetic algorithm solution approaches. In contrast to the compared methods, the proposed approaches handle both of the pick-up routing and bin packing taking simultaneously taken into account the effective solution methods according to the problem characteristics. Computational analysis has shown that the proposed approaches can produce effective solutions for decision makers.

Secondly, an intermodal transport model is presented considering fuzzy risks whose each transport mode is represented by fuzzy numbers. The decision maker can give decisions under different risk attitudes. Results have revealed that intermodal transportation is both the most efficient option for container transportation and may ensure economic, more humanist and environmental way. The experts of EKOL Logistics Inc. have announced that appropriate load plans can be generated via the proposed integer-programming model. Finally, it is also discovered that sustainable competitive advantage can be obtained by improving the logistics company's multimodal transportation planning mechanism with high level of customer satisfaction, environmental sensitivity and minimal cost.

In this problem, intermodal transportation integrating (3D-PRP) loading constraints, clustering backhauls at operational level and train loading at tactical level is studied. To the best of our knowledge, first cluster then packing routing is proposed for the first time. The main challenge is presented solution methods in which four expert systems are used to solve the combinatorial problems. Four small-sized instances are solved to optimality by Gams and ODL. An intelligent software for vehicle routing is compared with the exact solution method. Results reveal that ODL heuristics can solve the vehicle routing problem within seconds. For large-sized dataset, we have developed a hybrid meta-heuristics including k-means heuristics for clustering, machine learning approach for 3D-loading and genetic algorithm for PRP. We have proposed a novel mathematical model for the train loading which regards demurrage and detention costs. A sensitivity analysis is performed to examine the effects of these costs and train usage costs to the objective function. Results show that objective function is mostly sensitive to the utilization cost.

This paper also presents both theoretical and practical implications. Considering the academic aspect, this study provides a novel approach named first cluster then packing routing for 3D-PRP which is of great value from a theoretical aspect since it includes two NP-hard problems: Pick up routing problem and three-dimensional loading. Besides, it is first time to provide a machine learning approach for 3-D loading problem. Regarding the practical view, freight forwarders and decision makers would make a break to develop high quality solutions for more complex intermodal systems.

This paper has a limitation regarding only road and rail transport modes provided between Turkey and European customers. To generalize the results, the other regions could be included to the study to compare all alternative solutions. For future works, 3D - PRP can be extended with different constraints such as time window concepts, distribution options to obtain more solutions that are realistic. In the train loading stage, consolidated orders are shipped by maritime transportation, in which sea conditions are negligible. Thereby, delays related with the vessels affect the objective function. New methodologies combining the exact algorithmic approach and meta-heuristics can be provided.

We provide a container transportation system considering risk parameters on the transportation modes. The proposed mathematical model ensures human and economic solutions and cost reductions. The model is first to deal with social, economic, and environmental risk factors to determine transport modes. Fuzzy approach is applied for the transportation network before. However, using fuzzy risk numbers to determine the transport modes is first in this study. Decision makers assign scores to the risks using linguistic definitions. The findings obtained demonstrate that both the risk weight and transportation cost are important for a transport mode choice. The results show that without regarding risk weights, all demands of Ostrava could be met by highway. In addition, Roro- train combinations are used as an intermodal transportation since the risk weights are considered. Thus, effective and more sustainable intermodal network is ensured using the risk-based approach.

This study presents a novel approach coordinating a mathematical modelling method and a fuzzy-based method for transport mode choice. Risk parameters should be handled critically to decide these mode choices. Regarding the managerial aspect, logistics firms can provide more sustainable solutions and results help the freight forwarders and decision makers. Rail transportation should be preferred for since it has low risk weight.

However, this study only regards transportation modes for Turkey and European customer points, considering practical and academic aspects are available. Few papers have investigated the time, cost, and smart solutions to form a supply chain network. This present study presents both economic and human factors for determining transportation modes from Turkey to European customers. A real case application is applied to guide decision makers. Both a mathematical modelling approach and a fuzzy designer are used to realize these objectives. To generalize the results, other customer points could be included to the study to compare all alternative routes to determine the optimal route and mode. In future work, different social and environmental risk parameters, such as congestion, speed, reliability, and energy intensity, could be included to the study. In addition, air transportation could be included considering these risk parameters. Risk weights can be decided with other risk tmethods such as FMEA, FTA, and Fine-Kinney. This study can be reconsidered by incorporating the importation processes or both the import and export processes simultaneously.

5.1. Future Research Directions

- 3d-PRP could be extended with different constraints such as time-window concepts, distribution alternatives. Intermodal transportation can also include marine transportation that effects ship delays on train waiting times. Fourth Industrial Revolution for transportation networks need more dynamic and autonomous approaches. Agent based systems may be considered for the transportation network proposed in the paper.
- More social and environmental risk factors can be added to the system such as traffic congestion, speed, safety, energy. Also, air transportation could be included regarding air risk constraints.
- Risk weights can be obtained by other risk methods such as FMEA, FTA, Fine-Kinney, etc.
- Problem could be reconsidered regarding import and export processes simultaneously.
- In addition, backhaul items are 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.

- 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.

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APPENDIX

Appendix A- Order properties

Order code	Loading country	Loading postcode	Loading city	Loading latitude	Loading longitude	Package quantity	Gross weight	Volume brut	Width	Height	Depth	Stackable	Stackable count
065266989	TR	06750	Ankara	40,13522	33,08612	1	74,5	0,19	60	40	80	0	0
065267660	TR	34935	İstanbul	41,13434	28,9449	10	1850,1	13,5	80	110	120	1	2
065267939	TR	54200	Sakarya	40,757145	30,423738	10	1850,1	13,5	80	144	120	1	2
065269320	TR	06370	Ankara	39,9681	32,72678	1	630	1,04	93	99	113	0	0
065269474	TR	06105	Ankara	39,92222	32,756533	1	686,16	0,54	80	85	80	0	0
065269503	TR	41435	Kocaeli	40,8597	29,3887	1	220	0,48	55	72	120	1	2
065269620	TR	06760	Ankara	40,239536	33,029814	15	7524	10,09	60	82	80	1	2
065270018	TR	41435	Kocaeli	40,8597	29,3887	15	7524	10,09	82	82	103	1	2
065270519	TR	42050	Konya	37,87349	32,49615	1	190	2,04	85	185	130	0	0
085256394	TR	38210	Kayseri	38,64603	35,45206	2	1517	1,7	90	90	137	0	0
085268983	TR	42000	Konya	37,864252	32,508782	5	2246	1,32	60	55	80	0	0
085269355	TR	20280	Denizli	37,9106	29,1206	1	251	0,96	80	100	120	0	0
085269435	TR	16140	Bursa	40,2894	29,4454	9	6954	7,22	80	100	120	1	2
085269555	TR	34522	İstanbul	41,0382	28,6474	9	6954	7,22	80	45	110	1	2
085270421	TR	59520	Tekirdağ			9	6954	7,22	80	95	120	1	2
085271326	TR	34555	İstanbul	41,146872	28,58749	3	536	4,38	80	152	120	0	0
105253142	TR	45030	Manisa	38,62271	27,45211	2	3976	14,05	114	211	292	0	0
105253156	TR	45030	Manisa	38,62271	27,45211	1	531,4	1,3	80	135	120	0	0

105253176	TR	45030	Manisa	38,62271	27,45211	1	165	0,58	80	60	120	0	0
105253189	TR	45030	Manisa	38,62271	27,45211	4	10310	15,77	87	116	166	0	0
105253204	TR	45030	Manisa	38,62271	27,45211	4	10310	15,77	104	206	206	0	0
105253221	TR	45030	Manisa	38,62271	27,45211	4	10310	15,77	114	206	206	0	0
105255798	TR	45030	Manisa	38,62271	27,45211	6	1804	15,79	80	235	120	0	0
105255814	TR	45030	Manisa	38,62271	27,45211	6	1804	15,79	120	235	160	0	0
105260289	TR	06930	Ankara	39,9642	32,5797	2	1386	3,01	125	100	125	1	2
105265691	TR	41400	Kocaeli	40,8002	29,4381	2	1386	3,01	100	145	100	1	2
105265896	TR	34555	İstanbul	41,146872	28,58749	1	607	0,54	70	85	90	0	0
105266664	TR	41400	Kocaeli	40,8002	29,4381	36	5011,41	43,2	100	100	120	1	3
105266926	TR	35735	İzmir	38,54934	27,04586	9	3024	22,53	100	240	120	0	0
105267791	TR	16600	Bursa	40,4278	29,1594	9	3024	22,53	80	230	120	0	0
105268490	TR	59870	Tekirdağ	41,2346	27,70681	9	3024	22,53	85	250	125	0	0
105268882	TR	16600	Bursa	40,4278	29,1594	9	3024	22,53	100	240	120	0	0
105268886	TR	34555	İstanbul	41,146872	28,58749	9	3024	22,53	100	160	120	00	0
105268887	TR	34555	İstanbul	41,146872	28,58749	9	3024	22,53	90	240	125	0	0
105268892	TR	34555	İstanbul	41,146872	28,58749	9	3024	22,53	100	230	125	0	0
105268893	TR	34555	İstanbul	41,146872	28,58749	9	3024	22,53	80	140	120	0	0
105268915	TR	34555	İstanbul	41,146872	28,58749	9	3024	22,53	100	255	120	0	0
105269011	TR	27590	Gaziantep	37,09345	37,39318	8	3420	13,82	100	200	120	0	0
05269091	TR	34782	İstanbul	41,035395	29,1947	8	3420	13,82	100	120	120	0	2
105269332	TR	34555	İstanbul	41,146872	28,58749	8	3420	13,82	80	190	120	0	0
105269334	TR	34555	İstanbul	41,146872	28,58749	53	1126,5	1,99	26	15	70	1	0

105269338	TR	34555	İstanbul	41,146872	28,58749	53	1126,5	1,99	26	25	80	1	0
105269343	TR	34537	İstanbul	41,0352	28,5539	4	380	2	50	50	200	1	2
105269443	TR	34555	İstanbul	41,146872	28,58749	3	3330	4,32	100	120	120	0	0
105269450	TR	34555	İstanbul	41,146872	28,58749	1	62	0,29	60	60	80	0	0
105269899	TR	34935	İstanbul	41,13434	28,9449	13	1770	6,14	80	80	80	0	0
105270142	TR	34555	İstanbul	41,146872	28,58749	1	329	1,26	115	84	130	1	3
105270249	TR	34935	İstanbul	41,13434	28,9449	4	1120	4,76	80	124	120	1	2
165243134	TR	16600	Bursa	40,4278	29,1594	1	15	1	40	20	40	0	0
165243145	TR	16600	Bursa	40,4278	29,1594	1	290	1,15	80	120	120	0	0
165243673	TR	16600	Bursa	40,4278	29,1594	63	1319,78	4,67	23	23	140	1	0
165245308	TR	16600	Bursa	40,4278	29,1594	124	1963	11,9	40	40	60	1	0
165245313	TR	16600	Bursa	40,4278	29,1594	76	2009,65	15,77	53	38	103	1	0
165245471	TR	16600	Bursa	40,4278	29,1594	5	600	4,8	80	100	120	1	2
165247616	TR	35410	İzmir	38,3233	27,1261	11	1683	15,46	114	85	145	1	3
165251148	TR	16800	Bursa	40,48779	29,30976	2	1,58	0,41	53	38	103	1	2
165253525	TR	26110	Eskişehir	39,7607	30,5448	32	5266	44,96	114	85	145	1	3
165261051	TR	54000	Sakarya	40,772359	30,394132	159	2067	11,45	40	30	60	1	0
165262046	TR	54000	Sakarya	40,772359	30,394132	44	571,75	3,17	40	30	60	1	0
165263297	TR	16010	Bursa	40,18475	29,0613	292	2039	20,32	40	30	58	1	0
165263299	TR	16010	Bursa	40,18475	29,0613	105	900	5,04	40	20	60	1	0
165263300	TR	16010	Bursa	40,18475	29,0613	356	1992,44	17,09	40	20	60	1	0
165263901	TR	16600	Bursa	40,4278	29,1594	750	5000	11,58	21	21	35	1	0
165263908	TR	16600	Bursa	40,4278	29,1594	7	1675	19,17	115	200	115	0	0

165264332	TR	54000	Sakarya	40,772359	30,394132	7	1675	19,17	115	240	115	0	0
165264338	TR	54000	Sakarya	40,772359	30,394132	7	1675	19,17	115	205	115	0	0
165264344	TR	54000	Sakarya	40,772359	30,394132	104	651,87	3,74	40	15	60	1	0
165264348	TR	54000	Sakarya	40,772359	30,394132	47	591	3,38	40	30	60	1	0
165264357	TR	54000	Sakarya	40,772359	30,394132	19	166,88	1,37	40	30	60	1	0
165264366	TR	54000	Sakarya	40,772359	30,394132	12	3300	19,6	81	249	81	0	0
165264854	TR	26110	Eskişehir	39,7607	30,5448	7	4988	4,03	80	60	120	1	2
165264866	TR	16370	Bursa	40,225504	29,011933	24	4904	22,84	85	101	120	1	2
165264917	TR	26110	Eskişehir	39,7607	30,5448	24	4904	22,84	85	55	120	1	2
165266052	TR	01260	Adana	36,99274	35,35203	3	731	4,88	80	190	120	0	0
165266187	TR	54000	Sakarya	40,772359	30,394132	3	731	4,88	80	219	120	0	0
165267273	TR	50000	Nevşehir	38,6246	34,714	3	731	4,88	80	100	120	0	0
165267291	TR	50000	Nevşehir	38,6246	34,714	8	1957,08	5,39	80	90	120	1	2
165267295	TR	50000	Nevşehir	38,6246	34,714	8	1957,08	5,39	80	47	120	1	2
165267373	TR	45000	Manisa	38,6222	27,4297	8	1957,08	5,39	80	65	120	1	2
165267376	TR	45000	Manisa	38,6222	27,4297	8	1957,08	5,39	80	110	120	1	2
165267404	TR	45000	Manisa	38,6222	27,4297	130	916,66	6,24	40	20	60	1	0
165267763	TR	50000	Nevşehir	38,6246	34,714	1	271	0,58	80	60	120	0	0
165267807	TR	45000	Manisa	38,6222	27,4297	267	1702	9,44	80	140	120	0	0
165268788	TR	45000	Manisa	38,6222	27,4297	267	1702	9,44	80	200	120	0	0
165268850	TR	16600	Bursa	40,4278	29,1594	267	1702	9,44	80	140	140	0	0
165268851	TR	16600	Bursa	40,4278	29,1594	1	155	0,58	80	60	120	0	0
165269157	TR	26000	Eskişehir	39,785853	30,521574	2	370	0,94	65	60	120	0	0

165269901	TR	54000	Sakarya	40,772359	30,394132	10	862	5,65	82	56	123	1	2
165269929	TR	16315	Bursa	40,193667	28,839767	30	20923,5	30,54	75	85	115	0	0
165270057	TR	16140	Bursa	40,2894	29,4454	30	20923,5	30,54	110	70	110	0	0
165270060	TR	16260	Bursa	40,1762	29,097554	30	20923,5	30,54	85	80	110	0	0
165270082	TR	54000	Sakarya	40,772359	30,394132	30	20923,5	30,54	110	80	130	0	0
165270146	TR	16400	Bursa	40,092453	29,51552	30	20923,5	30,54	110	100	120	0	0
165270296	TR	59500	Tekirdağ	41,279317	27,970217	30	20923,5	30,54	110	75	120	0	0
165270450	TR	41480	Kocaeli	40,798941	29,451833	30	20923,5	30,54	80	90	115	0	0
165270452	TR	16140	Bursa	40,2894	29,4454	30	20923,5	30,54	110	75	120	0	0
165270489	TR	34775	İstanbul	41,00783	29,14677	30	20923,5	30,54	80	105	110	0	0
165270493	TR	41480	Kocaeli	40,798941	29,451833	30	20923,5	30,54	110	160	130	0	0
165270576	TR	16140	Bursa	40,2894	29,4454	30	20923,5	30,54	85	160	110	0	0
165270580	TR	45000	Manisa	38,6222	27,4297	30	20923,5	30,54	85	105	110	0	0
165270615	TR	45000	Manisa	38,6222	27,4297	30	20923,5	30,54	75	175	110	0	0
165270625	TR	16800	Bursa	40,48779	29,30976	30	20923,5	30,54	80	105	110	0	0
165270659	TR	16700	Bursa	40,219738	28,377944	30	20923,5	30,54	70	118	115	0	0

Appendix B. Properties of the caryying units

VEHICLE	CATEGORY	TARE_WEIGHT	WIDTH	HEIGHT	LENGTH
VH 1	TREYLER	17870	2,48	2,95	13,6
VH 2	TREYLER	26900	2,48	2,95	13,6
VH 3	TREYLER	28200	2,47	3	13,6
VH 4	TREYLER	28200	2,47	3	13,6
VH 5	TREYLER	28450	2,47	3	13,6
VH 6	TREYLER	28400	2,47	3	13,6
VH 7	TREYLER	28400	2,47	3	13,6
VH 8	TREYLER	31596	2,47	3	13,6
VH 9	TREYLER	31596	2,47	3	13,6
VH 10	TREYLER	27860	2,47	3	13,6
VH 11	TREYLER	31120	2,47	3	13,6
VH 12	TREYLER	27860	2,47	3	13,6
VH 13	TREYLER	28090	2,47	3	13,6
VH 14	TREYLER	27860	2,47	3	13,6
VH 15	TREYLER	27860	2,47	3	13,6
VH 16	KONTEYNER	29680	2,43	2,69	13,55
VH 17	TREYLER	28170	2,47	3	13,6
VH 18	KONTEYNER	29680	2,43	2,69	13,55
VH 19	KONTEYNER	29680	2,43	2,69	13,55
VH 20	KONTEYNER	29680	2,43	2,69	13,55

Appendix C. Matlab codes

```
% Read the package data (order number, locations) and remove
NaN values
clear;clc
lonLat = xlsread('order.xlsx','G2:H191');
[n,r,t] = xlsread('order.xlsx','B2:B191');
% for i = 1:length(t)
%     oCode(i,1) = str2num(cell2mat(t(i)));
% end
oCode = t;
indf = find(isnan(lonLat(:,1))==1);
lonLat(indf,:)=[];
oCode(indf,:) = [];

d = xlsread('order.xlsx','AA2:AF191');
d(indf,:)=[];
indf=[];
for i =1:size(d,1)
    if sum(d(i,3:end))==0
        indf = [indf;i];
    end
end
d(indf,:)=[];
lonLat(indf,:)=[];
oCode(indf,:) = [];

%% gives a unique ID to every package if they are multiple
for i = 1:size(d,2)
    indf = find(isnan(d(:,i))==1);
    d(indf,:) = [];
    lonLat(indf,:) = [];
    oCode(indf,:) = [];
end
lonLatf = [];
df = [];
oid = randperm(length(lonLat));
oidf = [];
sku = [];
n=0;
dataOrder = [];
oCodef = [];
for i=1:size(d,1)
    if(d(i,1))==1
        df = [df;d(i,2:end)];
        lonLatf = [lonLatf;lonLat(i,:)];
        oCodef = [oCodef;str2num(oCode{i})];
```

```
        oidf = [oidf;oid(i)];
        sku = [sku;1];
        n(i+1)=n(i)+1;
        m(i) = d(i,1);
    else
        df = [df;repmat(d(i,2:end),[d(i,1),1])];
        lonLatf = [lonLatf;repmat(lonLat(i,:),[d(i,1),1])];
        oCodef =
[oCodef;repmat(str2num(oCode{i}),[d(i,1),1])];
        oidf = [oidf;repmat(oid(i),[d(i,1),1])];
        tempsku = [];
        for j = 1:d(i,1)
            tempsku = [tempsku;j];
        end
        sku = [sku;tempsku];
        n(i+1)=n(i)+d(i,1);
        m(i) = d(i,1);
    end
end

%% Clustering according to locations
numClusters = 20;
[idc,c] = kmeans(lonLatf,numClusters,'EmptyAction','drop');
numClusters = length(unique(idc));
dataForR = [df idc];
nani = find(isnan(dataForR(:,6))==1);
dataForR(nani,:)=[];
lonLatf(nani,:)=[];
df(nani,:)=[];
dft(:,1:3) = df(:,3:5);
dft(:,4) = df(:,1);
df = dft;
oidf(nani,:)=[];
sku(nani,:)=[];
idc(nani,:) = [];
names = [{'oid'} {'sku'} {'l'} {'h'} {'d'} {'w'}];
data = [oCodef sku df idc]; % order code, unique code,
dimensions of the packages
% cluster numbers
% xlswrite('dataForR.csv',data)
save('dataForR.mat','data')

%% read data for the vehicles
[n,r,t] = xlsread('vehicle.xlsx');
datac = t(2:end,[10:12,9]);
clear data
for i = 1:size(datac,1)
```

```
    for j = 1:4
        data(i,j) = (cell2mat(datac(i,j)));
    end
end
data(:,1:3) = 100*data(:,1:3);
vid = [];
for i = 1:size(datac,1)
    vc = cell2mat(t(i+1,1));
    vid(i) = str2num(vc(4:end));
end
data = [vid' data]; % vehicle IDs, vehicle dimensions
% xlswrite('vehicles.csv',data)
save('vehicles.mat','data')

% This section sends the data to R for 3D bin packing
!R CMD BATCH /home/abbas/Rdocs/BinPacking/Main.r
RscriptFileName = 'Main.r';
Rpath = 'C:\Program Files\R\R-3.5.0\bin\R.exe'
RunRcode(RscriptFileName,Rpath);
Clc

% loads the data processed by R
load skuFile % unique stacking unit IDs
skuf=[];
textM = [];
count = 0;
fileID = fopen('Result.txt','w');
for i = 1:numClusters
    load(['OrderedFile_' num2str(i) '.mat']);
    bid = oit.bid; % vehicle ID assigned to orders
    xl = oit.x; yl = oit.y; zl = oit.z; % location of each
order inside the vehicle
    ubid = unique(bid); % unique vehicle IDs
    lonLatC = [];
    oidb = oit.oid; % unique order IDs
    for j = 1:length(ubid)
        xc = []; yc = []; zc=[];
        for k = 1:size(oit.sku,1)
            if strcmp(ubid(j),bid(k))==1
                skuf = [skuf;oit.sku(k)];
                oidh = oit.oid(k);
                skuh = oit.sku(k);
                indoid = find(oCodef==oidh);
                skuOh = skuO(indoid);
                for m = 1:length(skuOh)
                    A=cell2mat(skuO(indoid(m)));
                    B = cell2mat(oit.sku(k));
```

```
                    A = A (find (~ isspace (A)));
                    if strcmp(A,B)==1
                        lonLatC =
[lonLatC;lonLatf(indoid(m),:)];

                        textM = [textM;{['Vehicle: ' bid{k}
', Order ID: ' num2str(oCodef(indoid(m))) ...
                            ', SKU: ' B ...
                            ', x,y,z = {' num2str(xl(k)) ','
num2str(yl(k)) ',' ...
                            num2str(zl(k)) '}']}];
                        xc = [xc;xl(k)]; yc = [yc;yl(k)]; zc
= [zc;zl(k)];
                        count = count + 1;
                        fprintf(fileID,'%s\n',textM{count});
                    end
                end

            end
        end
        ux = unique(lonLatC(:,1));
        lonLatCf = [];
        for il = 1:length(ux)
            indl = find(lonLatC(:,1)==ux(il));
            lonLatCf = [lonLatCf;lonLatC(indl(1),1)
lonLatC(indl(1),2)];
        end
        clusters(i).vehicle(j).locations = [xc yc zc];
        clusters(i).vehicle(j).orderID = oit.sku;
        userConfig =struct('xy',lonLatCf,'showWaitbar',true);
        resultStruct = tsp_ga(userConfig);
        close all
        optRoute = resultStruct.finalXY;
        h = figure;
        plot(optRoute(:,1),optRoute(:,2))
        saveas(h,['OptimalRouteForClusterNumber_' num2str(i)
'_Vehicle_' ubid{j} '.png'])
    end
end
save('Clusters.mat','clusters')
fclose(fileID);
close all
```

Appendix D. Train assignments

	Triste-Cologne	Trieste-Ludwigshafen	Detention (day)	Demurrage (day)
Carrying unit 4	X		0.544	2
Carrying unit 5	X		0.235	0
Carrying unit 6		X	0	3
Carrying unit 7	X		2	0
Carrying unit 9		X	1	2
Carrying unit 10		X	0	0
Carrying unit 11		X	2	1
Carrying unit 12	X		2	3
Carrying unit 13	X		0.524	2
Carrying unit 14	X		0	3

Appendix E. GAMS Model of 3-D-bin packing

```
set k carrying units
set or orders
alias (kn, kn1) ;
Parameter
Qp(k) capacity
p(or) Length of order_x
q(or) Width of order_y
rr(or) Height of order_z
L(k) Length of carrying unit k
W(k) Width of carrying unit k
H(k) Height of carrying unit k
Cu(k) utilization cost
Scalar
M /1000000/
 ;
Binary variables
a(or, or1) left side constraint
b(or, or1) right side constraint
c(or, or1) front side constraint
di(or, or1) behind side constraint
e(or, or1) under side constraint
f(or, or1) over  side constraint
oo(k, or)
;
positive variables
xi(or)
y(or)
```

```
zi(or)
;
variables zmin;
Equations
obj
eq22(or)
conflict_control _1(or, or1)
conflict_control _2(or, or1)
conflict_control _3(or, or1)
conflict_control _4(or, or1)
conflict_control _5(or, or1)
conflict_control _6(or, or1)
conflict_control (k or, or1)
x_in_container (k, or)
y_ in_container (k, or)
z_ in_container (k, or)
allocation1(k, or)
allocation 3(k, or)
allocation 4(k, or)
allocation 5(k, or)
allocation 6(k, or)
allocation 7(k, or)
allocation 8(k, or)
allocation 9(k, or)
;

obj..     zmin =e= sum((k, or),oo(k, or)*Cu(k));
eq22(or).. sum(k, oo(k, or))=e=1;
```

```
conflict_control _1(or, or1) $(ord(or)<ord(or1)).. xi(or)+p(or)=l= xi(or1)+(1-a(or, or1))*M;
conflict_control u_2(or, or1) $(ord(or)<ord(or1))..xi(or1)+p(or1)=l= xi(or)+(1-b(or, or1))*M;
conflict_control u_3(or, or1) $( ord(or)<ord(or1)).. y(or)+q(or)=l= y(or1)+(1-c(or, or1))*M;
conflict_control _4(or, or1) $( ord(or)<ord(or1))..y(or1)+q(or1)=l= y(or)+(1-di(or, or1))*M;
conflict_control _5(or, or1) $( ord(or)<ord(or1)).. zi(or)+rr(kn)=l= zi(or1)+(1-e(or, or1))*M;
conflict_control _6(or, or1) $( ord(or)<ord(or1))..zi(or1)+rr(or1)=l= zi(or)+(1-f(or, or1))*M;
conflict_control (k, or, or1) $(ord(or)<ord(or1))..a(or, or1)+b(or, or1)+c(or, or1)+di(or, or1)+e(or, or1)+f(or, or1)=g=oo(k, or)+oo(k, or1)-1;
x_ in_container (k, or).. xi(or)+p(or)=l=L(k)+(1-oo(k,or))*M;
y_ in_container (k, or).. y(or)+q(or)=l=W(k)+(1-oo(k,or))*M;
z_ in_container (k, or).. zi(or)+rr(or)=l=H(k)+(1-oo(k,or))*M;
allocation (k, or).. oo("1","order")=e=1;
allocation 3(k, or).. oo("1"," order ")=e=1;
allocation 4(k, or).. oo("2"," order ")=e=1;
allocation 5(k, or).. oo("2"," order ")=e=1;
allocation 6(k, or).. oo("2"," order ")=e=1;
allocation 7(k, or).. oo("3"," order ")=e=1;
allocation 8(k, or).. oo("3"," order ")=e=1;
allocation 9(k, or).. oo("3"," order ")=e=1;
model BP_Container/all/ ;
option mip=cplex;
solve BP_Container using mip minimizing zmin ;
Display xi.l, y.l, zi.l, a.l, b.l, c.l, di.l,e.l, f.l, oo.l;
```

“

Appendix F. GAMS Model of VRP

```
option limrow=100 ;
option limcol=0 ;
option iterlim=100000000
option reslim=7200
Option Optcr=0.0
sets
 k vehicle
 i loading point
 alias (i, j)
 sets
 thisi(i)
;
table cc(i, j) road distance between loading points

 parameters
 Q(k) Truck capacities
 p(thisi) Picking up amounts
 ;
binary variables
 X(i, j, k)
 y(k)
 z(i, k) ;
variable
 n;
positive variables
```

```
 u(i, k)

 ;
scalar M large number /10000000/;
;
X.fx(i,i,k)=0;

equations

inflow_outflow(i, k)
travelling(thisi)
capacity(i, k)
capacity1(i,k)
origin(k)
end(k)
ub_for_u(k, i, thisi)
ub_for_uu(k,thisi)
last_E(thisi,  k)
cost
;
cost .. n =e= sum((k, i, j), (cc(i, j)*X(i, j, k)) +sum((k), y(k)*F)) ;

inflow_outflow(i, k).. sum(j, X(i, j, k))=e=sum (j, X(j, i, k));
travelling (thisi) .. sum((k, j), X(thisi, j, k))=e=1 ;
capacity (i, k).. u(i, k)=l=Q(k) ;
capacity1 (i,k).. 0=l=u(i, k) ;
ub_for_u(k, i, thisi).. u(thisi, k)=g= u(i, k)+ p(thisi)*z (thisi, k)-(1-X(i, thisi, k))*Q(k);
last_E(thisi,k).. sum(j,X(thisi, j, k))=e=z(thisi, k);
```

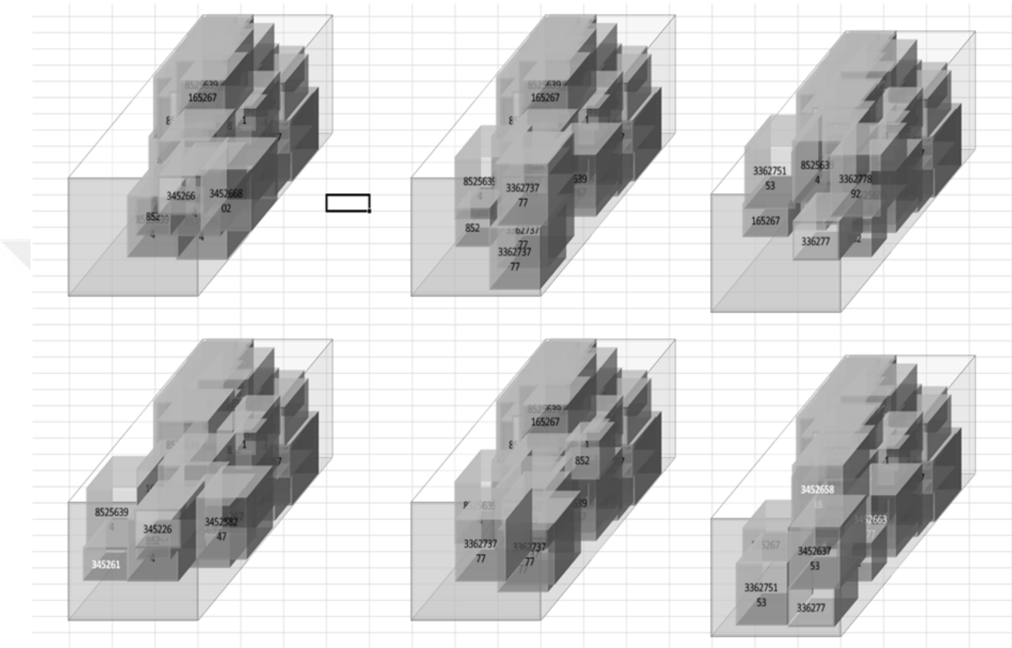
```
origin(k)..sum (j,x(0,j,k)=l=y(k);
end(k)..sum (j,x(j,0,k)=l=y(k);

ub_for_uu(k,thisi)..  p(thisi)*  sum(i,X(i,thisi, k))=l=Q(k);

model VRP_Containerr /all/ ;
solve VRP_Container using mip minimizing n ;
display
 X.l,  z.l, u.l,n.l
 ;
```

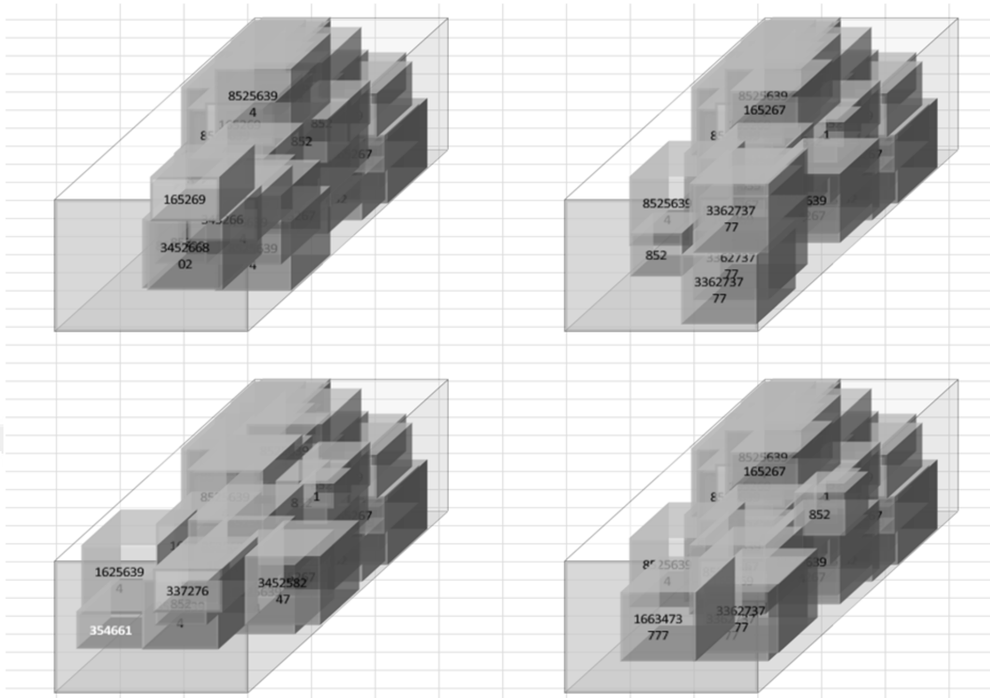
Appendix G. GAMS Model of train assignment

```
Set
  i        'trains'
  j        'carrying units'
  xopt(i,j) 'optimal assignment'

Variable
  x(i,j) 'assignment of i to j'
  z      'total cost of assignment'
  w(i)   'waiting days of trains'
  ;
Binary Variable x;
Integer Variable
s(j)   'delay of carrying units';

Table a(i,j) 'utilization of i train by  carrying units j'

Table f(i,j) 'cost of assigning  carrying units j to  train i'

Parameter b(i) 'available train capacities'
g(i) 'process days of train '
p(j) penalty cost of carrying units

d(j) due date of carrying units

M /100000000/

ship ship day from Turkey ports to Trieste
```

```
tr(i) train departure days
cst waiting cost in Trieste
w_objweight
w_objDelay
parameter num;
num =uniform() ;

Equations
   capacity(i) 'carrying units availability'
   choice(j)   'assignment constraint.. one carrying units per train'
   defz        'definition of total cost'
   penalty(i,j)
   chhe(i);

capacity(i).. sum(j, a(i,j)*x(i,j)) =l= b(i);
choice(j)..   sum(i, x(i,j)) =e= 1;
chhe(i)..     w(i) =e= sum((j),(x(i,j)*(ship+num-tr(i))));
penalty(i,j)..g(i)=l= d(j)+s(j)+(1-x(i,j))*M ;
defz..               z  =e=  sum((i,j),  f(i,j)*x(i,j))+  sum((j),  p(j)*s(j)*w_objDelay)+
sum((i,j),(x(i,j)*(ship+num-tr(i))*cst*w_objweight));

model TLP_Container /all/ ;
solve TLP_Container using mip minimizing z ;
display
 x.l,  z.l, s.l, w.l;
```

Appendix H. 3D- loading results




8525639
4
165269
3452668
02
165267
8525639
3362737
77
852
3362737
77
1625639
4
337276
3452582
47
354661
165267
852
1663473
777
3362737
77