A HYBRID MULTI-OBJECTIVE SYSTEM OPTIMIZATION APPROACH FOR RISK AND RESILIENT MANAGEMENT IN MULTIMODAL TRANSPORTATION MODELS

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ABSTRACT

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Master of Science Program in Industrial Engineering

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Although unimodal transportation is widely used in today's transportation operations, tendency to multimodal transportation is increasing because it offers the opportunity to reduce the total cost and time of transportation and at the same time provides resilience against the risks encountered during operations. Reducing the effects that transportation companies can face under different risk factors and determining which risk factors have a greater impact on company activities takes an important place in terms of planning activities. The hybrid solution approach created within the scope of this study aims to minimize the total transportation time, cost, and carbon footprint by using a multi-objective mathematical model, while simultaneously trying to minimize the total risk impact by taking into account the 7 predefined risk factors that can occur in multi-modal transportation activities. Developed multi-objective linear mixed integer optimization model is solved by using epsilon-constraint method and tested with real life data set. Pareto-solution sets are shared with decision makers and

decision makers have been enabled to plan and develop multimodal transportation activities under alternative risk factors for sustainable multimodal transportation activities. In addition, after performing size reduction to the obtained Pareto solution sets (cost, time, and carbon footprint) under obtained different risk factors, with the t-distributed Stochastic Neighbor Embedding (t-SNE) method, k-means algorithm is performed through machine learning and then alternative risk clusters are shared for users in sector.

Keywords: multimodal transportation, risk management, multi-objective optimization, supply chain management, t-SNE, clustering

ÖZET

ÇOK MODLU TAŞIMACILIK MODELLERİNDE RİSK VE DAYANIKLILIK YÖNETİMİ İÇİN ÇOK AMAÇLI HİBRİT BİR SİSTEM OPTİMİZASYONU YAKLAŞIMI

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Günümüz taşımacılık operasyonlarında tek modlu taşımacılık yaygın olarak kullanılmasına rağmen taşımanın toplam maliyetini ve süresini azaltma olanağı sunması, aynı zamanda operasyonlar sırasında karşılaşılan risklere karşı esneklik sağlaması sebepleriyle çok modlu taşımacılığa yönelim artmaktadır. Farklı risk faktörleri altında taşımacılık firmalarının uğrayacakları etkileri azaltmak ve hangi risk faktörlerinin firma faaliyetleri üzerinde daha büyük etkiye sahip olduğunu saptayabilmek planlama faaliyetleri açısından oldukça önemli konumdadır. Bu çalışma kapsamında oluşturulan melez çözüm yaklaşımı çok amaçlı matematiksel model kullanılarak toplam taşımacılık zamanını, maliyetini ve karbon ayak izini minimize etmeyi amaçlarken, eş zamanlı olarak önceden tanımlanmış çok modlu taşımacılık faaliyetlerinde ortaya çıkan 7 adet risk faktörünü göz önüne alarak toplam risk etkisini minimize etmeye çalışmaktadır. Geliştirilen çok-amaçlı doğrusal karma tamsayı optimizasyon modeli epsilon-kısıt yöntemi ile çözülerek gerçek hayat veri seti

ile test edilmiştir. Pareto-sonuç seti karar vericiler ile paylaşılmış ve karar vericilerin sürdürülebilir çok modlu taşımacılık faaliyetleri için alternatif risk faktörleri altında çok modlu taşımacılık faaliyetlerini planlaması ve geliştirmesi sağlanmıştır. Ayrıca, elde edilen farklı risk faktörleri altında elde edilen Pareto çözüm setleri (maliyet, zaman ve karbon ayak izi) t-dağıtılmış Stokastik Komşu Gömme (t-SNE) yöntemi kullanılarak boyut azaltımı yapıldıktan sonra makine öğrenimi sayesinde k-ortalama algoritması ile sektör kullanıcıları için alternatif risk kümeleri paylaşılmıştır.

Anahtar Kelimeler: çok modlu taşımacılık, risk yönetimi, çok amaçlı optimizasyon, tedarik zinciri yönetimi, t-SNE, kümeleme.

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CHAPTER 1: INTRODUCTION

The current COVID-19 outbreak has both severe and economic consequences across the globe and affects over all societies leading to dramatic changes in business actions and consumers behaviors. Many businesses are forced to shut down their operations, and this leads to an unprecedented disruption of commerce in most industries due to this outbreak case. Majority of companies and brands face many short-term challenges over management of the supply chain, the workforce, cash flow, consumer demand, sales, and marketing activities under these new circumstances. Therefore, all these risk factors and challenges over supply chains should be carefully investigated and analyzed in order to minimize future effects and improve the infrastructures against similar upcoming risk factors. While converting supply chain systems into more sustainable versions, risk sensitive and resilient operations should also be designed, developed, and used in daily operations. Transportation activities in fragile industries stand for an appropriate candidate for ignition point of this conversion process in transportation sector with a significant share of between 2% to 12% of gross domestic product (GDP) of countries (Gani, 2017). Total logistics cost has 8.5% of the U.S. GDP, according to the State of Logistics report for 2013 (Robinson, 2014). Logistics sector accounts for about 10% of European economy (EU Science Hub, 2021) with €12.3 billion worth of European logistics and industrial assets (White & Case, 2019). In the developing countries (such as Turkey), the logistics sector has about 12% share in the country's GDP, which is over ₺500 billion in 2019 (Utikad, 2020). Thus, the logistics sector has a significant share in the economies of both developed or developing countries and any minor improvement in logistics activities in terms of cost, time and sustainability perspective plays an essential role in this conversion stage. Many organizations try to convert and improve their transportation systems into more resilient and sustainable forms by searching new operational models and multimodal transportation systems are recently considered and chosen as one of the most suitable candidates for goals of sustainable transportation activities. Although, the level of operational planning and management of multimodal transportation is matured, parts about risk and resilient management in this new generation transportation models are not still studied and integrated thoroughly. Thus, one of the main novelties of this study is carefully to investigate potential risks and to highlight how these risks are affecting daily life of the logistics providers by proposing multi-objective multimodal freight transportation optimization model operating under different risk factors and to offer effective solutions to make logistics operations resilient against to various risk factors.

Under these considerations, the main novelties of this study are to:

- identify and categorize the main risk factors and perform quantitative measurements of those risk factors for multimodal transportation activities
- integrate those risk factors into the proposed optimization model for multimodal transportation considering total transportation time, cost, and environmental purposes in order to share alternative solution sets for decision makers or logistics providers such as supply chain director, logistic planner, logistic director, logistic operations manager, who are responsible of managerial decisions for logistic operations of company, under various risk conditions
- classify the potential risk factors based on effectiveness on cost, time, and environmental considerations by using machine learning techniques

There are several steps followed throughout this study. In Chapter 1, importance of risk management in supply chain and logistics activities, importance and share of logistics in supply chain, ways for making transportation efficient in the existence of risk, and novelty of this study are discussed. In Chapter 2, a detailed review of literature is presented in order to highlight the position of this study. Multimodal transportation optimization problems and risk management approaches studied in the literature, possible risk factors in the logistics are presented. Multi-objective considerations in these models and potential solution techniques are discussed. Additionally, dimension reduction and clustering techniques for transportation problems are mentioned. In Chapter 3, problem description, proposed model, solution approach for multi-objectivity, categorization of risks in the transportation and integration of those risks to the proposed multi-objective mixed integer linear programming model (MOMILP) implemented dimension reduction and clustering algorithm are covered. Data and network used in the scope of the proposed model are given in Chapter 4. Pareto solution sets of the proposed MOMILP model under different risk factors results, as well as results from dimension reduction algorithm and clustering algorithm are shared and discussed in Chapter 5. Finally, general assessment and discussion of the study are shared, and future improvements are explained in Chapter 6.

CHAPTER 2: LITERATURE REVIEW

Globalization of markets and significant technologic developments in information and communication technologies enable the globalization of supply chains (Maslarić, Brnjac, and Bago, 2016) and transportation activities takes an important role on responsiveness, efficiency, and performance of global supply chains (Paul et al., 2020). In this globalization process, transportation activities are responsible from the logistics operations in the longer distances between suppliers, producers, and customers. Thus, it gets inevitable importance to design and operate more efficient, effective, and innovative logistics systems for transportation activities (Beldek, and Aldemir, 2017). Unimodal and multimodal transportation are the two main transportation types used in logistics. While only one mode of transportation is utilized in unimodal type, there are at least two transportation modes such as road, rail, air, or water way used in intermodal transportation from starting point to destination point (Udomwannakhet et al., 2018). Multimodal transportation is gained attention and preferred commonly by the logistics providers (Beldek, and Aldemir, 2017) because it enables more efficient, reliable, flexible, and sustainable solutions for global transportation activities (Steadieseifi et al., 2014). Therefore, there are many studies conducted in the literature for multimodal transportation optimization problems. Yang, Low, and Tang (2011) proposes an intermodal network optimization model to choose the best freight route with different transportation modes from China to India and goal programming approach is used for multiple and conflicting objectives in the model. Resat, and Turkay (2015) designs an intermodal transportation network for the Marmara Region of Turkey. A bi-objective model with minimizing total delivery times and total transportation costs that considers traffic congestion on links for different transportation modes is presented and the ε-constraint method is used as a solution technique. Baykasoğlu, and Subulan (2016) proposes a sustainable intermodal freight transportation-planning model with time, cost, and environment objectives by considering transportation mode, service type selection, load allocation, and outsourcing. Fuzzy goal programming approach is applied for solution methodology. Furthermore, a real-life application is performed for a large-scale international logistics company in Turkey. Hao, and Yue (2016) propose a mixed integer linear programming model for a container multimodal transport system supported with a dynamic programming algorithm for optimal transport modes combination. Fazayeli, Eydi, and Nakhai (2017) and Rabbani, Sadri, and Rafiei (2016) present integer linear programming models for route selection with multimodal transportation and location routing problem. Both optimizing software tools and genetic algorithm are used as a solution technique to compare the results. Jian (2017) shares a mathematical model for the multimodal freight transportation problem based on a real-life case by taking shipping capacity limits, time slots and environmental issues into consideration. A sub gradient heuristic method based on lagrangian relaxation is developed for solution. Kaewfak, and Ammarapala (2018) develops a goal-programming model with cost, time, and risk minimization objectives for route selection problems in multimodal transportation. However, although multi modal transportation systems have such significant gains over operational conditions, they are very sensitive and vulnerable to insufficient transportation infrastructures (road, rail, maritime), usage of interconnected communication tools, as well as natural disasters and external threats. For example, few critical elements that could be defined as disturbances in multimodal transportation are: (World Economic Forum, 2021)

1. Policy Risks such as import/export restrictions, conflict, and political unrest. For instance, trucks carrying Turkish goods were held up at the Russian borders, import limitations or banning was applied by Russia due to a political conflict between Turkey and Russia (BBC, 2015).
2. Security Risks such as terrorism, crime issues etc. Such as, 9/11 terrorist attacks occurred in the U.S. led to border closure, stopping the port and airport activities, tighter controls, extensive security checks and as a result, widespread transportation delays, plant shutdowns and considerable cost to the U.S. were faced (Walkenhorst, and Dihel, 2002; North Carolina State University, 2005).
3. Technological Risks such as inadequate transport infrastructure and communication discontinuities. In Mombasa, ships waited to be loaded and unloaded for several days due to port strike by workers in 2015 and costing authorities millions of dollars (The East African, 2015).
4. Environmental Risks such as epidemics, natural disasters, bad weather conditions etc. For example, when two hurricanes called Katrina and Rita struck the U.S. Gulf Coast in 2005, the pipeline network used for oil and natural gas transport and Port of New Orleans, the largest export grain port of the US were shut down, key railroad bridges were ruined, some highways and airport

either collapsed or damaged and economic loss resulting from supply chain disruption was huge (Grenzeback, and Lukmann, 2007). Covid-19 pandemics worldwide impact such as border closures of countries, plant shutdowns, stopping the operation of ports disrupted global supply chains (Maritime Gateway, 2020).

Improvement of resilience and as well as inclusion of new generation risk management mechanisms into decision making processes get significant importance in management of the transport industry, because while eliminating risks from the systems, there will be significant gains over operational costs (like reduction of fuel consumptions, usage of environmentally-friendly transportation modes, inventory holding costs, etc.); reductions of greenhouse gas emissions (CO_2, NO_x, etc.); and improvements over social welfare (reduction of traffic congestions, traffic accidents, etc.). Therefore, the existing approaches in the design of risk management systems in supply chains, especially in multi modal transportation systems, do not provide enough quantitative information to assess risks and to examine which combinations of corrective actions contribute to risk measures. The control and improvement of resiliency and risk management in multimodal transport systems are highlighted limitedly in current academic studies. Therefore, there is no appropriate methodology developed to assess the resilience in multimodal transportation activities. For example, in the study of Vilko, and Hallikas (2012), risks affecting multimodal maritime supply chains are identified and categorized, as well as their resulting effects to the overall supply chain are presented using Monte-Carlo simulation. El Mokrini et al. (2016) presents a risk assessment model regarding logistics outsourcing risks and multi-criteria decision analysis for risk assessment is performed by using ELECTRE TRI. Choi, Chiu, and Chan (2016); Sayın, and Tekin (2017) study comprehensively about risk management of alternative risk types in logistics activities (such as; disruption risk management, operation risk control, disaster and emergency management, and logistics service risk analysis) and assesses implemented technologies towards these risks. Revilla, and Saenz (2017) presents the supply chain risk management strategies and their impacts on supply chain disruptions with an empirical analysis of case studies conducted in several countries. Senthil, Murugananthan, and Ramesh (2018) presents risk factors under nine major classes in reverse logistics activities by using multi-criteria classification methods. These risk factors are associated with environmental, operational (inventory, procurement, management, outsourcing), information and data security, and cultural activities. Rosyida, Santosa, and Pujawan (2019) mentions that when transportation network faces with a disruption, one of the best strategies is creating alternative routes and reducing the severe effects of disruptions for the continuity of logistical performance. Shi et al. (2019) provides a holistic view of sustainability in decision-making problems for the transportation industry by using CATWOE (customers, actors, transformation process, worldview, owners and environmental) analysis. Vilko, Ritala, and Hallikas (2019) shares a model to mitigate risks and recover the systems from disruptions along multimodal maritime supply chains. An analytical tool, which enables visibility and controllability of the risks, is designed to manage those risks. Li, Yang, and Chin (2019) investigates risk management for hazardous materials road transportation by proposing a fuzzy analytic hierarchy process, fuzzy failure mode and effect analysis for assessment of risks and nonlinear goal programming for the management of risks. Er Kara, Oktay Fırat, and Ghadge (2020) proposes a new model called data mining-based risk management model to identify, assess and mitigate different risk types in the supply chain. A case study example is used to show the implementation of the proposed model. Moreover, optimization models and their application on simulation environments (Ivanov, 2020; Ivanov, and Dolgui, 2021; Seck, Rabadi, and Koestler, 2015; Vieira et al., 2020; Oliveira et al., 2019) enhance the analysis of system behavior and functioning of strategies in more descriptive and predictive modes. Therefore, a simulation-based decision support system for real-time environmental and risk management will highlight the effectiveness of method in environmental impact mitigation and resilience improvement, also multimodal transportation will be analyzed under the influence of different types of perturbations, such as; vehicle utilization (lower load factors), price volatility (fluctuated exchange rates, fuel, capital), environmental regulations (GHG emissions), unpredictable traffic congestions, ICT inadequacy risk (unavailability of real-time data) about traffic congestions and weather conditions, etc.

Multimodal transportation problems include different conflicting objectives where while one is tried to be minimized, other(s) can be maximized or minimized in real-life cases. This tradeoff makes problems hard and complex to be solved under personal computer systems, also known as NP-hard (Mnif, and Bouamamaa, 2017). Thus, several solution techniques are presented in the literature. Although heuristic approaches are quite common, they have risk of stacking on the local optima. On the other hand, exact solution techniques towards multi-objective problems have the ability of obtaining optimal solutions. Hence, these techniques are also commonly used in literature. According to Hwang, and Masud (1979), there are three categories for solution of multi-objective mathematical models: the priori methods, the interactive methods, and the posteriori methods. In the priori methods, firstly, decision makers express their preferences and opinions for the objectives as setting goals or weighting the objectives then solution is found. However, it is possible that decision makers cannot make an accurate quantification of objectives in advance. In the interactive methods, decision makers are involved in the solution process and at each iteration information of decision maker's preferences is asked. Nonetheless, an acceptable solution cannot be reached, and these methods do not guarantee the Pareto-optimal solutions. In the posteriori methods, firstly, solutions to the problem are found then decision makers' opinion is taken for selection among the solutions. These methods are not popular because they are time consuming and require considerable computational effort. However, much more information can be conveyed to the decision maker and possibility of obtaining all efficient solutions make decision makers more confident for their final decision in this method. Thus, epsilon constraint method and the augmented epsilon constraint method, which is introduced later by Mavrotas (2009) as an improved version of epsilon constraint method, are two most widely used posteriori methods for multi-objective optimization models in general (Hwang, and Masud, 1979). Epsilon-constraint method is preferred by Demir et al. (2019); Heggen, Braekers, and Caris (2018) and Resat, and Turkay (2015) as an exact solution method for multi-objective models presented in their research. While Yakavenka et al. (2020) uses a goal programming approach for the multi-objective MILP model for the network design problem and Rasmi, and Turkay (2019) applied The Generator of ND and Efficient Frontier (GoNDEF) method as an exact solution technique to their model. Gazijahani et al. (2020) and Yu, and Solvang (2016) used augmented epsilon-constraint method. According to Mavrotas (2009), augmented epsilon-constraint method (AUGMECON) eliminates redundant iterations, weakly Pareto-optimal solutions, and this yields solution process to become faster and time-effective compared to epsilon-constraint method. Furthermore, epsilon-constraint method can work efficiently for finding Pareto solutions for continuous problems but not discrete-continuous problems while the new version, AUGMECON, can produce Pareto solutions for both problems. In addition, solution of multi-objective optimization problems results in too many solution points under Pareto frontiers and so that it will be so complex and inefficient for decision makers to choose one of them when multiple solutions and multiple criteria are emerged. Thus, there are various multiple-criteria decision making (MCDM) methods, which enables decision makers to choose most preferred solution alternative based on their preferences, introduced, and used in the literature. Simple additive weighting (SAW) (MacCrimmon, 1968), analytic hierarchy process (AHP) (Saaty, 1980), technique for order of preference by similarity to ideal solution (TOPSIS) (Hwang, and Yoon, 1981), elimination and choice translating reality (ELECTRE) (Roy, 1968), preference ranking organization method for enrichment evaluations (PROMETHEE) (Mareschal, Brans, and Vincke, 1984) are some of the popular MCDM methods used in the literature. While there are MCDM methods used and implemented in various studies in the existence of multiple criteria and multiple solution points, these methods require an extensive work in the scope of this study which will lead us to search for other solution alternatives for multiple criteria and solution points. In this regard, performing clustering operation will enable to cluster similar solution points. Hence, it will be more effective to offer solutions for decision makers upon their preferences. There are various algorithms presented for clustering high amount of data based on their feature. These algorithms are grouped as partition method, hierarchical method, density-based and grid-based method. Among them k-means, which is classified as a partition method, is mostly used and common algorithm because of its simplicity, fast response time and efficient computational time (Umargono, Suseno, and Gunawan, 2020). Nonetheless, multi-objective optimization solution sets generally include high dimensional data as the number of objectives increases, so to be able to perform clustering operation accurately, dimension reduction techniques that transform the data set into 2-dimensional data are needed. There are some commonly used techniques in this matter in the literature. T-distributed stochastic neighbor embedding (t-SNE) introduced by (van der Maaten, and Hinton, 2008) and principal component analysis (PCA) created by Hotelling (1933) are two well-known techniques used in the literature for dimension reduction. However, PCA is a linear dimension reduction technique whereas t-SNE can be implemented in also non-linear data sets, and Platzer (2013) proved that t-SNE perform better visualization than PCA for all criteria. For this reason, t-SNE is a popular and mostly preferred dimension reduction algorithm in the literature.

CHAPTER 3: METHODOLOGY

3.1. Problem Description

As previously mentioned in the introduction part, risk is inevitable in logistic operations and can be highly disruptive in terms of cost, time etc. Thus, management of risk in transportation activities and having a risk resilient transportation network takes an important place. Since multimodal transportation is gaining popularity and mostly preferred in logistics and decision makers are interested in not only cost but also time and carbon footprint resulted from their logistics operations. It is determined to construct a multimodal and multi-objective mixed integer linear programming model that takes risk factors into account. In this model, aim is to select the best route from a specified origin to a destination by using alternative transportation modes for a container and to decide number of containers to be carried in the chosen route. Time window consideration is also added to model because leaving and entering time of a container to a node is an issue and this will make the model applicable in real-life cases. Also, containers should be hold in inventories of the nodes and whether transhipment occurred or not in a node is examined due to its effect on transportation cost. Also, several assumptions are used while developing the proposed model.

- Only transportation of containers in multimodal network is taken into account.
- Size of container is taken as 20 TEU (Twenty-foot equivalent unit) and it is assumed that only one type of container is used.
- Average speed values are taken as free-flow speed limits in each transportation mode and traffic congestion on the ways and load factors are ignored.
- Travel times between two points for each transportation mode are calculated by dividing distances between these points by average speed values. For non-integer results, rounding up operation is made to the closest integer value and all travel times are taken as integer. For example, if travel time between point A and B is found as 3.83 hours then this value is rounded to 4 hours.
- European transportation network (between Turkey and Europe) is considered so the main and high volume capacitated, significant points in maritime and railroad transportation in intermodal network are selected and used in the model.

- Capacity of transportation for containers between two points is determined based on the Ro-Ro (combination of sea and road transportation) frequencies and RO-LA trips (combination of road and rail transportation) but no limitation is set for roadway capacity.
- Total time period is defined as 24 hours and time between two consecutive indexes *t and t+1* is set to 1 hour.
- Waiting times during handling operations of containers are discarded.

This model has three objectives to minimize total transportation time, cost, and carbon footprint. Total transportation time consists of transhipment time between nodes and total travel time of containers under different transportation modes. Cost objective includes (1) fuel cost spent for transportation of containers, (2) fixed cost per container due to vehicle usage in each transportation mode (3) transhipment cost between modes per container (4) material handling cost of containers in every node (5) inventory cost of keeping containers wait in the node for a transportation mode. Objective for the environmental effect of transportation considers total CO_2 emissions resulting from multimodal transportation of containers.

Figure 1 shows the visual representation of the methodology followed throughout this study. First, multi-objective mixed integer linear programming (MOMILP) model for multimodal transportation problem is developed and then several risk factors with the categorization and description of risks which will be exhibited in detail in the upcoming sections are integrated. Then, dimension reduction algorithm is applied to the Pareto solution sets obtained from MOMILP model. Lastly, risk clusters are obtained using a clustering algorithm.

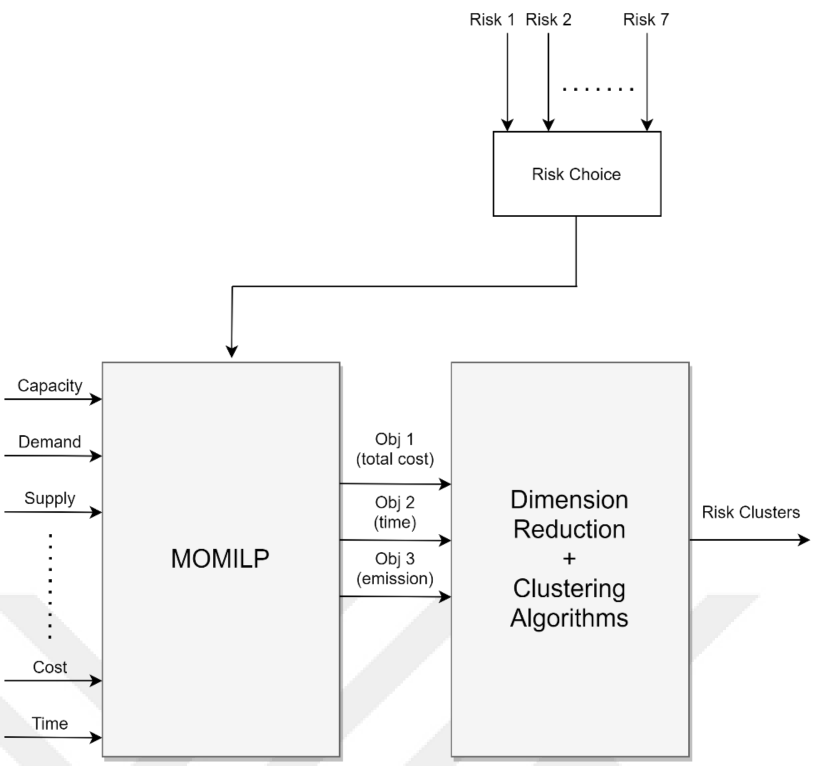

Figure 1. Visual representation of methodology

3.2. Model Formulation

Sets

i	Set of all nodes	$(i = 1, \ldots, I)$
j	Set of all nodes	$(j = 1, \ldots, J)$
h	Set of all nodes	$(h = 1, \ldots, H)$
k	Set of all transportation modes	$(k = 1, \ldots, K)$
m	Set of all transportation modes	$(m = 1, \ldots, M)$
t	Set of time units (hourly)	$(t = 1, \ldots, T)$
r	Set of risk categories	$(r = 1, \ldots, R)$

Parameters

$demand_{jkt}$	Demand at node j belong to mode k at time t *[unit]*
$dist_{ijk}$	Distances between node i and j with mode k *[km]*

$dcost_k$	Fuel cost per container per km travelled with mode *k* *[€/unit-km]*
$fcost_k$	Fixed cost of transportation with mode *k* per container *[€/unit]*
$hcost_{ik}$	Inventory holding cost per container at node *i* with mode *k* *[€/unit]*
$tscost_{km}$	Transshipment cost from mode *k* to mode *m* *[€]*
$tstime_{km}$	Transshipment time for transportation from mode *k* to mode *m* *[hour]*
$mhcost_{ik}$	Material handling cost per container on node *i* with mode *k* *[€/unit]*
cap_{ijk}	Capacity for containers to be transported from node *i* to *j* with mode *k* *[unit]*
$Invcap_{ik}$	Inventory capacity for containers at node *i* for mode *k* *[unit]*
M	Very large number
τ_{ijk}	Travel time from node *i* to node *j* with mode *k* *[hour]*
$clost$	Cost of unmet demand per container *[€/unit]*
$epsilon$	Very small number [10^{-6}]
f_2^{up}	Upper bound of second objective function
f_3^{up}	Upper bound of third objective function
δ_r	Capacity coefficient of risk r
$AvgEm_k$	Average emissions factor for mode k *[gCO_2/tonne-km]*
β	Average container capacity *[20 tons]*

Decision Variables

θ_{ijkt}	Containers transported from node *i* to node *j* with mode *k* with leaving time t
x_{ijkt}	Binary variable takes value 1 if there is a transportation from node *i* to node *j* with mode k with leaving time *t*, 0 otherwise
Iy_{ikt}	Containers on hand at node *i* with mode *k* at time *t*

ts_{ikmt}	Binary variable that will take value 1 if there is a change (transshipment) from mode k to mode m at node i in time t, 0 otherwise
$lost_{jkt}$	Demand of containers unmet at node j with mode k at time t
$slack_2$	Decision variable regarding to augmented ε-constraint method for second objective function
$slack_3$	Decision variable regarding to augmented ε-constraint method for third objective function

Model

$$\text{Min } f_1 = \sum_k fcost_k \sum_i \sum_j \sum_t \theta_{ijkt} + \sum_k dcost_k\left(\sum_i \sum_j dist_{ijk} \sum_t \theta_{ijkt}\right) + \sum_i \sum_k hcost_{ik} \sum_t Iy_{ikt} + \sum_i \sum_k mhcost_{ik} \sum_j \sum_t \theta_{ijkt} + \sum_k \sum_m tscost_{km} \sum_i \sum_t ts_{ikmt} + clost \sum_j \sum_k \sum_t lost_{jkt} \quad (1)$$

$$\text{Min } f_2 = \sum_i \sum_j \sum_k \tau_{ijk} \sum_t x_{ijkt} + \sum_k \sum_m tstime_{km} \sum_i \sum_t ts_{ikmt} \quad (2)$$

$$\text{Min } f_3 = \sum_k AvgEm_k \sum_i \sum_j dist_{ijk} \sum_t \beta\theta_{ijkt} \quad (3)$$

subject to

$$\sum_{i;\, i\neq j} \sum_k \theta_{ijk,t-\tau_{ijk}} + lost_{jkt} \geq \sum_k demand_{jkt} \qquad \forall\, j \in J,\, t \in T \quad (4)$$

$$\sum_{i;\, i\neq h} \sum_k \theta_{ihk,t-\tau_{ihk}} + \sum_k Iy_{hk,t-1} = \sum_{j;\, j\neq h} \sum_m \theta_{hjmt} + \sum_m Iy_{hmt} \qquad \forall\, h \in H,\, t \in T \quad (5)$$

$$\theta_{ijkt} \leq cap_{ijk} x_{ijkt} \qquad \forall\, i \in I,\, j \in J,\, k \in K,\, t \in T,\; i \neq j \quad (6)$$

$$Iy_{ikt} \leq Invcap_{ik} \qquad \forall\, i \in I,\, k \in K,\, t \in T \quad (7)$$

$$x_{ijkt-\tau_{ijk}} + x_{jhmt} \leq ts_{jkmt} + 1 \qquad \forall\, i \in I,\, j \in J,\, h \in H,\, k \in K,\, m \in M,\, t \in T,\; i \neq j,\, j \neq h,\, k \neq m \quad (8)$$

$$x_{ijkt-\tau_{ijk}} + x_{jhmt} \geq 2ts_{jkmt} \qquad \forall\, i \in I,\, j \in J,\, h \in H,\, k \in K,\, m \in M,\, t \in T,\; i \neq j,\, j \neq h,\, k \neq m \quad (9)$$

$$\sum_{k;\, k\neq m} \sum_m \sum_t ts_{ikmt} \geq 1 \qquad \forall\, i \in I \quad (10)$$

$$\theta_{ijkt},\ Iy_{it},\ lost_{jkt} \geq 0,\ x_{ikmt},\ ts_{ikmt} \in \{0,1\} \quad \forall\ i \in I, j \in J, k \in K, m \in M, t \in T \tag{11}$$

Equation (1) shows first objective function and aims to minimize total transportation cost including total fixed cost per container for vehicle usage, fuel cost, inventory holding cost, material-handling cost and transhipment cost among modes. Equation (2) aims to minimize total transportation time and Equation (3) aims to minimize total CO_2 emissions by using activity-based calculation explained in the McKinnon Report. There are two basic approaches represented by McKinnon, and Piecyk (2010) in their report for calculating total CO_2 emissions. These are activity-based and energy-based approach. Since necessary inputs for energy-based approach are not available due to the scope of the proposed model, activity-based approach is selected instead of energy-based approach. Constraint (4) ensures that the total cargo transported to a destination node can satisfy the demand of the node partially or totally and unmet demand will be lost demand for associated mode and period. Constraint (5) ensures conservation of flow on every node. Constraint (6) ensures that if there is transportation between two nodes then capacity of total containers to be transported cannot be exceeded. Constraint (7) limits the container number on hand at any node and any mode for each period. Constraint (8) and (9) check together whether there is a transhipment between two modes or not. Constraint (10) ensures that transhipment must be made at least once in each node. Lastly, Constraint (11) restricts sign and sets types of decision variables.

3.3. Augmented ε-Constraint Method

In Chapter 2, solution techniques for multi-objective mathematical models are reviewed. Among them, epsilon constraint method and augmented epsilon constraint method (AUGMECON) are most widely used generation or posteriori methods for solution of multi-objective optimization problems. AUGMECON is the improved version of epsilon constraint method, and it was introduced by Mavrotas (2009). Thus, augmented epsilon constraint method is selected as a solution approach to deal with multiple objective functions in this study. Some revisions are made on the model in this regard. Equation (1) which represents total cost is taken as prior objective function because cost has the highest importance for logistics companies. Then upper bounds for Equation (2) and (3) are found which are f_2^{up} and f_3^{up}, respectively. Furthermore, two slack variables are defined as decision variables and epsilon which is a very small-valued parameter is defined. Then, Equation (2) and (3) which are the time and emissions objectives are transformed to equalities by adding the slack variables and integrated to the model as constraints. After that, summation of slack variables is multiplied with epsilon value and this multiplication is subtracted from prior objective, objective function 1. By this way, model is turned into a form of single-objective model. These modifications are represented with below equations.

$$\text{Min } f_1 - epsilon\ (slack_2 + slack_3) \tag{12}$$

subject to

$$f_2 + slack_2 = f_2^{up} \tag{13}$$

$$f_3 + slack_3 = f_3^{up} \tag{14}$$

$$slack_2,\ slack_3 \geq 0 \tag{15}$$

Equation (4)-(11)

When the model is run, it is obvious that while other decision variables are aimed to be minimized due to cost factors, slack variables will be maximized to be able to minimize objective function (1). Consequently, increase in slack values lead to decrease in the value of objective function 2 and 3 that take place in equation 2 and 3. In the implementation of epsilon constraint method, one objective is taken as prior objective and other objective(s) are treated as constraints after setting their upper bound values while in AUGMECON method by means of introduced slack variables in epsilon constraint implemented model, weakly efficient solution points are not produced, redundant iterations are eliminated in the solution process, and this leads to less computational time.

3.4. Categorization of Risks

Logistics operations include several risk factors. These risk factors can cause severe disruptions in these operations. Thus, categorization and integration of potential risk factors into the proposed model take an important place in this matter. After making detailed literature research and taking logistics provider’s opinion, risks that can be encountered during transportation activities categorized into seven parts. Table 1 exhibits the categorization of specific risks for multimodal transportation activities under different risk classes. Epidemics, nuclear and natural disaster, and bad weather conditions belong to environmental risk category. Import/export restrictions and political unrest fall into policy risk category. Terrorism, crime issues and breakdowns on links are in the security risk category. While interpretation problems fall into operational risks category, capacity problems and labor shortage on links takes place in the supply risks and economic risks category, respectively. Lastly, information and communication discontinuities and inadequacy of transport infrastructure on links are in the technological risk category.

Table 1. Categorization of risks in logistics (Source: World Economic Forum, 2021)

Category	Risk
Environmental Risk	• Epidemics • Nuclear Disasters on node *i* • Natural Disasters on node *i* • Bad weather conditions on node *i*
Policy Risks	• Import / exports restrictions on node *i* for mode *k*
	• Conflict and political unrest
Security Risks	• Terrorism • Crime issues (sea piracy, pirate trade and organized crime) on node *i* for mode *k* • Breakdown issues on node *i* for mode *k*
Operational Risks	• Interpretation problems with documents, contracts, and permits on node *i* for mode *k*
Supply Risks	• Capacity problems on node *i* for mode *k*
Economic Risks	• Labour shortage on node *i* for mode *k*
Technological Risks	• Information and communication discontinuities on node *i* for mode *k* • Inadequacy of transport infrastructure on node *i* for mode *k*

After categorizing risks and performing specifications on each category, risks are written as constraints and integrated into the model (MOMILP). All seven risks are assumed to be active in a specific point (city) in the transportation network (represented as node in the proposed model) and all the direct links from that risk-active node to the other nodes are assumed to be affected. This effect is reflected in the model as reducing the capacity for number of containers to be transported from the risk-active node to the other nodes. However, it is assumed that transportation capacities of links from other nodes to the risk-active node are not affected. Furthermore, δ_r parameter, which is defined as the capacity coefficient factor of each risk in Section 3.1, can take value between 0 and 1. Value for each risk capacity coefficient is determined after discussing with the decision makers. Since proposed model considers a short period of time, these capacity coefficient factors are taken as constant values. Also, while expressing each risk as constraint, decision makers' opinion is taken. Table 2 illustrates how specific risks are converted into constraints and used in the proposed MOMILP model.

Table 2. Description of risks and associated constraints in the model

Risk #	Risk Description	Risk Constraint
Risk 1	Capacity reduction is made by multiplying the normal transportation capacities of each link (cap_{ijk}) with the capacity coefficient factor of risk 1 ($\delta\ (1)$) for each transportation mode during all time periods. For only risk 1 capacity is reduced to zero due to the stopping effect of this risk for the logistic operations. Thus, when risk 1 is emerged in a node in transportation network, no container can be sent from that risk-active node to the other nodes with any transportation mode during all time periods but normal capacity limitations (cap_{ijk}) are valid from other nodes to the risk-active node.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\ \delta_r$ $\forall\ j \in J,\ k \in K,\ t \in T;$ $i = i_1,\ r = 1$

Table 2 (Cont'd)

Risk #	Risk Description	Risk Constraint
Risk 2	Capacity reduction is made by multiplying the normal transportation capacities of each link (cap_{ijk}) with the capacity coefficient factor of risk 2 (δ *(2)*) for each transportation mode during all time periods. For example, when the value for δ *(2)* is set to 0.5, then capacity for number of containers (cap_{ijk}) to be transported in each direct link (from the risk-active node to the other nodes with each transportation mode) will be the half of normal transportation capacities of those links during all time periods but no change on the transportation capacities for the links from the other nodes to the risk-active node.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\, \delta_r$ $\forall\, j \in J,\, k \in K,\, t \in T;$ $i = i_1, r = 2$
Risk 3	Capacity reduction is made by multiplying the normal transportation capacities of each link (cap_{ijk}) with the capacity coefficient factor of risk 3 (δ *(3)*) for each transportation mode during all time periods.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\, \delta_r$ $\forall\, j \in J,\, k \in K,\, t \in T;$ $i = i_1, r = 3$
Risk 4	Capacity reduction is made by multiplying the normal transportation capacities of some links (cap_{ijk}) with the capacity coefficient factor of risk 4 (δ *(4)*) for a specific transportation mode and a specific time interval. For example, when the value for δ *(4)* is set to 0.5 and if it is determined that this risk will affect the operations in railway mode for 4 hours starting from t=0, then capacity for number of containers (cap_{ijk}) to be transported in direct links with railway mode (from the risk-active node to the other nodes) will be the half of normal transportation capacities of those links from starting time 0 to ending time 4 but no change on the transportation capacities for the links from the other nodes to the risk-active node.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\, \delta_r$ $\forall\, j \in J,\, t \in T;\, i = i_1,$ $k = k_1,\, t_1 \leq t \leq t_2,$ $r = 4$

Table 2 (Cont'd)

Risk #	Risk Description	Risk Constraint
Risk 5	Capacity reduction is made by multiplying the normal transportation capacities of each link (cap_{ijk}) with the capacity coefficient factor of risk 5 (*δ (5)*) for each transportation mode during all time periods.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\ \delta_r$ $\forall\ j \in J,\ k \in K,\ t \in T;$ $i = i_1,\ r = 5$
Risk 6	Capacity reduction is made by multiplying the normal transportation capacities of each link (cap_{ijk}) with the capacity coefficient factor of risk 6 (*δ (6)*) for each transportation mode for a specific time interval. For example, when the value for *δ (4)* is set to 0.5 and if it is determined that this risk will affect the operations for 4 hours starting from t=0, then capacity for number of containers (cap_{ijk}) to be transported in direct links (from the risk-active node to the other nodes for each transportation mode) will be the half of normal transportation capacities of those links from starting time 0 to ending time 4 but no change on the transportation capacities for the links from the other nodes to the risk-active node.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\ \delta_r$ $\forall\ j \in J,\ k \in K,\ t \in T;\ i = i_1,$ $t_1 \leq t \leq t_2,\ r = 6$
Risk 7	Capacity reduction is made by multiplying the normal transportation capacities of some links (cap_{ijk}) with the capacity coefficient factor of risk 7 (*δ (7)*) for a specific transportation mode during all time periods. For example, when the value for *δ (7)* is set to 0.5 and if it is determined that this risk will affect the operations in railway mode, then capacity for number of containers (cap_{ijk}) to be transported in direct links with railway mode (from the risk-active node to the other nodes) will be the half of normal transportation capacities of those links during all time periods but no change on the transportation capacities for the links from the other nodes to the risk-active node.	$\theta_{ijkt} \leq cap_{ijk} x_{ijkt}\ \delta_r$ $\forall\ j \in J,\ t \in T;\ i = i_1,$ $k = k_1,\ r = 7$

3.4.1. Integration of Risk 1

Risk 1 is the environmental risk category. This risk factor has a stopping effect on logistics activities when it occurs. For example, when there was a heavy snow, ice disrupting the transport in central and northern Europe, vehicles were struck at the traffic jam, highways were blocked and all of trucks and trains delayed for too long hours and railway services were cancelled (SDUT, 2021). Thus, after detailed research, it is decided that disasters and bad weather conditions that fall into this category can harm to the transportation modes and transporting any container from the points where this type of risk is active cannot be performed but only transportation of containers to the point. Therefore, while converting this risk into constraint, capacity for flow of containers that can be transported between two points for every transportation mode and every time unit is set to zero by multiplying the capacity with the related risk factor δ *(1)*. Equation for the constraint regarding to this risk can be seen in Table 2.

3.4.2. Integration of Risk 2

Risk 2 is the policy risk category. This type of risks generally arises because of political disagreements between countries. It is one of the examples that in February 2014, trucks passage was stopped at the Bulgaria border gate for two weeks due to a political unrest between Turkey and Bulgaria and waiting trucks created a queue over 10 kilometers (Hürriyet Daily News, 2014). Reducing the quote for the total transportation flow, closing the borders to prevent the passage of vehicles, or awaiting the vehicles for an unlimited length of time and causing delay of the deliveries are the other explicit examples of policy risks. Before coming to a decision about policy risk conversion into constraint, previous results and effects of this risk are analyzed from the past experiences of logistics companies and inquisition was also made with decision makers. Then, it is decided to reduce the flow capacity of containers that can be transported from the point, where this type of risk is active, for every transportation mode and every time unit and capacity of transportation for containers to the point is not restricted. This capacity reduction, which is denoted by δ *(2),* is specified by taking decision makers opinion and resulting equation for this risk is exhibited in Table 2.

3.4.3. Integration of Risk 3

Risk 3 is the security risk category. Terrorism is one of the examples that is in this risk factor. According to some news in Supply and Demand Chain Executive (2017), there were 346 terrorist attacks in total in 2016, and it is reported that

"The terrorism related to the Syrian conflict forced Lebanese officials to reroute $1 billion worth of exports and resulted in the loss of $754 million in revenue for the Jordanian trucking industry."

This one example can show how security risks can cause severe effects in logistics operations. Furthermore, after detailed research, it is concluded that this risk type is almost equally effective as risk type 1. Since risk 3 also can cause almost stopping effect on logistics operations from the points where those risks are concerned. For this reason, capacity for number of containers that can be transported from the risk active point was decreased for each transportation mode for all time by using risk factor, δ *(3),* which is close to zero whereas transportation of units to that point was not restricted. Logistics providers stated their approval for this matter, too. Constraint that stands for this risk type takes place in Table 2 with its description.

3.4.4. Integration of Risk 4

Risk 4 is the operational risk category. Examples of this risk type are ship collisions, lack of skilled workers, carelessness, and lack of motivation among the workforces (Vilko, and Hallikas, 2012). In the light of idea exchange with decision makers, it is determined that operational risks will reduce the capacity as risk 1 but can take shorter amount of time to resolve compared to other risk types. Hence, it is considered that operational risks will set the transportation flow capacity to zero for a specific transportation mode and for a short period of time. Based on this consideration, risk factor, δ *(4) that* will reduce the capacity of flow is taken zero and time limitation for this capacity reduction is added to the constraint as well. Equation formed for this risk type can be found in Table 2.

3.4.5. Integration of Risk 5

Risk 5 is the supply risk category. Stoppage with cargo on board, bottlenecks in transportation routes, employee strikes in ports and problems with custom clearance are some examples of supply risk (Vilko, and Hallikas, 2012). After detailed research, it is decided that this risk type will affect capacity of units to be transported from the point, where the risk is active, for each transportation mode for all time. Also, after making a comparison of this risk type effect with the other risk types, it is concluded that supply risk has the second lowest limiting impact on transportation capacity after risk 6, economic risk category. Therefore, risk factor *δ (5)* is specified under this consideration. After that, constraint representing this risk type is constructed by multiplying actual flow capacity with the risk factor *δ (5)*. This constraint can be seen in Table 2.

3.4.6. Integration of Risk 6

Risk 6 is the economic risk category. Currency fluctuations, sudden demand shocks, financial crisis are examples of this risk type (World Economic Forum, 2021). After meeting with decision makers, it is determined that economic risks have less disruptive impact on the transportation activities compared to other risk types and can take short amount of time to resolve. Hence, it is considered that operational risks can delimit the transportation flow capacity to a lesser extent and for a short period of time for each transportation mode. Based on this consideration, risk factor, *δ (6),* that limit the capacity of flow is taken bigger compared to other risk factors so that capacity reduction will not be in higher amount. Besides, time limitation for this reduction is added to the constraint. Equation formed for this risk type can be found in Table 2.

3.4.7. Integration of Risk 7

Risk 7 is the technological risk category. One of the examples of this risk factor is that increase in the usage of online systems brings possible cyber-attacks which can cause disruptions in information and communication and 41% of participants of a survey conducted in November 2011 faced with unplanned outages of IT or telecommunication systems (World Economic Forum, 2011). While forming the constraint for this risk type, inadequacy of infrastructure example, which falls into this category, was the focus. Thus, after taking the logistic provider’s opinion, it is decided that this risk type will yield a restriction on the capacity of total containers to be transported from the point where this risk is active by the amount of risk factor *δ (7)*, set by the decision maker, for a specific mode and for all time. Table 2 exhibits constraint regrading to technological risk.

3.5. Dimension Reduction Algorithm

t-Distributed stochastic embedding method (t-SNE) is a dimension reduction algorithm that is introduced by van der Maaten, and Hinton (2008), and it is one of the popular dimension reduction techniques used in the literature. This algorithm is used for transforming high dimensional data into 2- dimensional or 3-dimensional data. As a result of implementation of proposed model, 4-dimensional Pareto solution sets will be obtained with cost, time, emission, and risk factor dimensions. Thus, it will be required to use a dimension reduction technique that will transform dimension of embedded data set into 2-dimensional so that effective clustering can be performed. t-SNE is considered as an efficient algorithm due to its simplicity for implementation and better visualization outputs Platzer (2013), so for dimension reduction operation t-SNE is selected. In addition, there are several input parameters needed to apply this algorithm. Some of these input parameters are given in Table 3 with their descriptions.

Table 3. Parameters used in t-SNE algorithm

t-SNE Algorithm Parameters	Description
n_components	Desired dimension of the given data set
perplexity	Number of nearest neighbours
learning_rate	Training rate of algorithm
n_iter	Maximum number of iterations
init	Algorithm for initialization of the embedded space

As stated in Table 3, '*n_components'* is related to the dimension size that user aimed to obtain at the end. *Perplexity* is the parameter that the algorithm performance relies on the changes in this parameter according to van der Maaten, and Hinton (2018). This parameter generally takes value between 5 and 50. Moreover, '*learning_rate'* parameter and '*n_iter'* parameters are described as training rate of the algorithm and maximum number of iterations, respectively. Lastly, parameter '*init'* is used for initialization of the algorithm. Detailed explanations about this algorithm and all the other input parameters can be found in (scikit-learn, 2020). In the scope of this study, t-SNE algorithm will be utilized for the solution sets obtained from proposed model (MOMILP) as mentioned previously. It will be explained in Chapter 5, what values the input parameters take and reasons for selection of those parameter values in detail.

3.6. Clustering Algorithm

Data set that is acquired from the t-SNE algorithm results will be used for clustering so that decision makers can see various solutions with same features such as least time, high cost and low emission under different risk types. There is a need for a clustering algorithm in this regard. Thus, k-means algorithm is selected for clustering because k-Means is most widely used and popular clustering algorithm in the literature (Umargono, Suseno, and Gunawan, 2020). This algorithm is used for capturing similar data points and clustering them together. While doing this, clusters are distanced as far as possible. To be able to apply this algorithm, there are some input parameters needed and some of these parameters are given with their descriptions in Table 4.

Table 4. Parameters used in k-means algorithm

k-means Algorithm Parameters	Description
n_clusters	Number of clusters to create
init	Initialization of initial clusters
n_init	Number of times for running algorithm with different centroid seeds
max_iter	Maximum number of iterations
random_state	Random number for initialization of centroids

As presented in Table 4, '*n_cluster'* parameter is used to set number of clusters and this parameter takes integer values. *Init* parameter is used for selection of initial clusters. Parameter '*n_init'* represents number of times for running algorithm with different centroids. Lastly, while parameter '*max_iter'* stands for the maximum number of iterations, '*random_state'* parameter enables to choose random number initialization of centroids. Detailed explanations about this algorithm and all the other input parameters can be found in (scikit-learn, 2020). In the scope this study, k-means algorithm will be utilized for the data set resulted from t-SNE algorithm as mentioned previously. It will be explained in Chapter 5, what values the input parameters take and reasons for selection of those parameter values in detail.

CHAPTER 4: COMPUTATIONAL EXPERIMENTS

As it was mentioned in Chapter 3, proposed multi-objective mixed integer linear programming model is used to represent logistics activities between Turkey and Europe. Since real life problems includes too much complexity and this will make modelling hard, proposed model is designed and formed under important assumptions. However, these assumptions lead to the high amount of data requirements with different levels of complexities.

4.1. Data

4.1.1. Transportation Costs

In logistics activities, there are several parameters to be considered while forming a mathematical model of the current system. One of the main parameters in this sense is the cost. Transportation activities includes various cost types and each of them must be elaborated in a model as accurate as possible to be able to obtain more realistic results. MOMILP model which is presented in the methodology section considers different costs related to transportation such as fixed cost, fuel cost, inventory holding cost, transshipment cost and material handling cost per unit of container. In this sense, cost incurred in each transportation mode due to vehicle usage of per container is defined as fixed cost. Traveling cost of a container per km with each transportation mode is added to the model as fuel cost due to the transportation vehicle fuel usage. Cost of keeping a container in inventory under any transportation mode is defined as inventory holding cost. Lastly, handling cost of per container during the transportation is added to the model as material handling cost. To be able to determine values of these costs, several papers from the literature are reviewed and referenced, as well as operational data sets of some of the largest logistics providers in Turkey is also taken. Tables 5, 6 and 7 represent the fixed, fuel, inventory holding and material handling costs for alternative transportation modes. These tables are adapted from the reports on websites of Turkish Ministry of Commerce (T.C. Ticaret Bakanlığı, 2020) and Republic of Turkey State Railways (TCDD, 2020) and also studies of Baykasoğlu, and Subulan (2016); Resat, and Turkay (2015); Sun et al. (2018) and Wiegmans, and Janic (2019).

Table 5. Logistics costs for road transportation mode

	Logistics Costs for Road	Unit
Fixed Cost	1.20	€/TEU-km
Fuel Cost	0.38	€/TEU-km
Inventory Holding Cost	0.05	€/TEU-h
Material Handling Cost	2.71	€/TEU

Table 6. Logistics costs for rail transportation mode

	Logistics Costs for Road	Unit
Fixed Cost	685.00	€/TEU
Fuel Cost	0.23	€/TEU-km
Inventory Holding Cost	0.13	€/TEU-h
Material Handling Cost	21.13	€/TEU

Table 7**.** Logistics costs for sea transportation mode

	Logistics Costs for Road	Unit
Fixed Cost	987.50	€/TEU
Fuel Cost	0.03	€/TEU-km
Inventory Holding Cost	0.09	€/TEU-h
Material Handling Cost	126.00	€/TEU

Since multimodality is one of the focuses in this study. Transshipment costs, that is incurred while changing the mode of transportation in a node, are used, and shown in Table 8. These values in Table 8 are obtained from the study conducted by Resat, and Turkay (2015).

Table 8. Transshipment cost between transportation modes (€/TEU)

	Road	Rail	Sea
Road	56.7	113.3	99.7
Rail	113.3	90.7	170.0
Sea	99.7	170.0	113.3

4.1.2. Transportation Network

Multimodal transportation is mostly preferred and common way of transportation, especially in Europe. Thus, the MOMILP model is constructed by considering the intermodal network between Europe and Turkey. The map in the Figure 2 illustrates the network that is used for modeling the intermodal freight transportation between Turkey and Europe. Logistics provider's opinion was also taken before using the intermodal routes in the map.

Points exhibited in the map are defined as nodes to the MOMILP model and colored arrows represent the available transportation mode between two points. It is considered that there is highway connection between most of the points even if it is not denoted in the map. For instance, there is not any connection between Barcelona and Munich or there is only railway connection seen between Trieste and Budapest, so constructed model also considers that road transportation can be utilized between such points where no connection or only one mode connection exists. While modifying these networks between points, decision maker's advice is also sought.

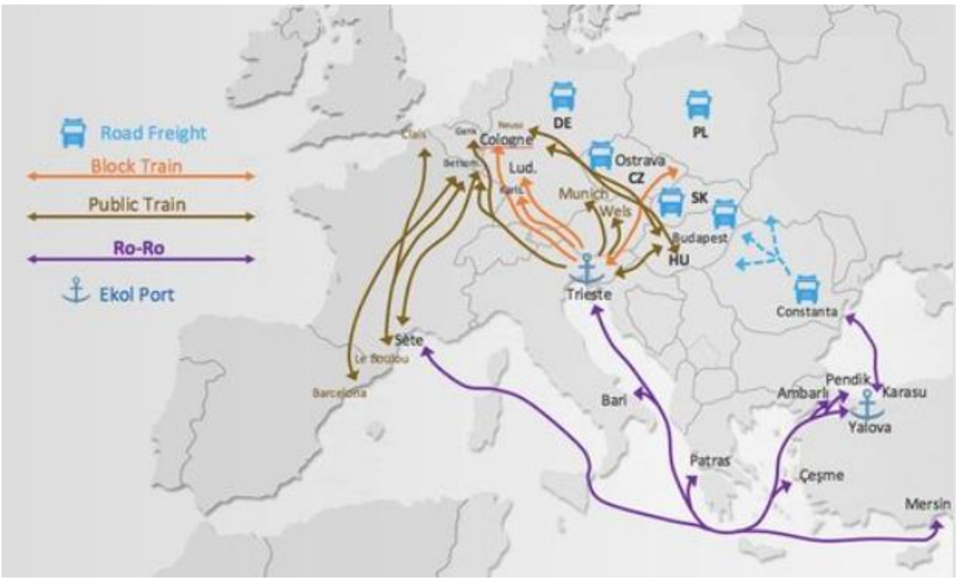

Figure 2. Intermodal network map between Turkey and Europe (Source: Ekol, 2019)

Distances between the points are collected for each existing transportation mode. Distances between nodes in roadway is obtained from (European Commission, 2020) and distance unit is in km. Distances between rail stations in railway is taken from (European Commission, 2021) and distance unit is in km. Distances between ports in sea way is found from (SEA-DISTANCES.ORG, 2021) and distance units are obtained as miles and then converted into kilometer. All these distances obtained for each transportation mode are divided by the free flow speed limits of corresponding mode to set travel time between two points with each transportation mode. These speed limits used in the calculation of travel times can be found in Table 9. Additionally, transshipment times used for the duration of mode change are shown in Table 10. These time values are adapted from the study of Resat, and Turkay (2015).

Table 9. Speed Limits (km/h) in each transportation mode

Transportation mode	Speed Limit (km/h)
Road	90
Rail	60
Sea	35

Table 10. Transshipment times between transportation modes

[hour]	Road	Rail	Sea
Road	0.1	0.12	0.17
Rail	0.12	0.4	0.17
Sea	0.17	0.17	0.7

Additionally, capacity for transportation of containers in each transportation mode is determined depending on each mode's conditions. While frequency of Ro-Ro vessel cruises, which is the combination of sea and road transportation, are considered for capacity of seaway transportation, trips for RO-LA, which is the combination of road and rail transportation, services are considered for the railway transportation. Since these voyages and services have a time schedule for departures at some certain time intervals so railway and seaway mode can be available at specific times. Thus, capacities for these transportation modes are set based on these considerations. Nonetheless, it is determined that there is no capacity limitation for road transportation and even if there is capacity constraint for the roadway transportation in the proposed model, that capacity value is set to a high value so that there will be no limitation for the transportation capacity for roadway. In addition, if a transportation mode does not exist between two points, then transportation capacity for containers is set to zero so that any flow cannot occur. Lastly, inventory capacities of each node, demand of each node and cost of each unmet demand are assumed after discussing with one the largest logistics providers of Turkey.

4.1.3. Emissions Factors

Green logistics is one of the main considerations in the model. Since transportation of every container result in carbon footprint depending on the transportation mode choice. It is aimed to integrate total carbon footprint, that transportation causes, to the model. In Chapter 3, it is pointed out that activity-based approach is selected for total carbon footprint of transport and CO_2 emissions factors in each transportation mode depending on per ton-km traveled must be set for this calculation. These factors that are used in Equation (3) are taken from McKinnon report (McKinnon, and Piecyk, 2011) and Table 11 shows emissions factor values regarding to transportation mode.

Table 11. Average Emissions Factors (Source: McKinnon, and Piecyk, 2010)

Transport Mode	gCO_2/tonne-km
Road transport	62
Rail transport	22
Short sea	16

CHAPTER 5: RESULTS

5.1. Mathematical Model Solution Results

Proposed MOMILP model and all other risk activated models are implemented in GAMS (GAMS Development Corporation, 2019). A computer with AMD Ryzen 5 3500U with Raedon Vega Mobile Gfx with 2.10 Ghz processor, and with 8.00 GB RAM is used for implementation of all models. Results are discussed in the subsections of this chapter.

5.1.1. Base Model (without any risk factor) Solution Set

Base model is the model where any effect of risk is not involved. It is mentioned in previous sections that constructed multimodal transportation model has multiple objectives. Thus, AUGMECON method (Mavrotas, 2009) is utilized in this matter. While using this method, model was run 100 times with different epsilon values yielding different results. Obtained Pareto frontiers that shows non-dominated solution points are reflected in Figure 3. When frontiers are examined, it can be concluded that objective function 1 (cost) has an inverse relationship with both objective function 2 (time) and objective function 3 (emissions) because decrease in the value of one causes some amount of increase in the value of the other. Nonetheless, time and emissions objectives are positively related where one’s value is decreased, other’s value is also decreased or vice versa.

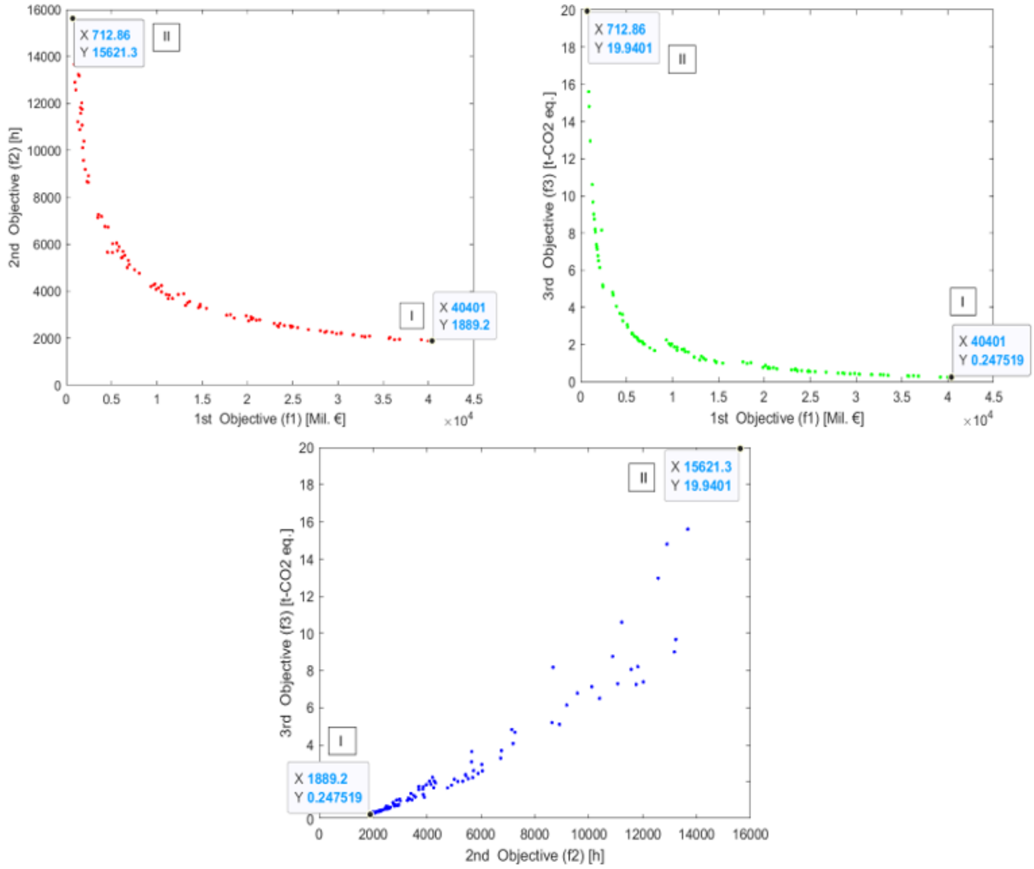

Figure 3. Base model Pareto solution diagrams

To be able to express effects of objective functions on each other numerically, two points, farthest from each other, which can be seen in the Figure 3 are selected from the solution set and a comparison is made. Table 12 indicates the comparison of these points in the base model solution set. Based on the outcomes, decreasing cost objective by 98.24% will lead to increase in the total time and emissions values in 87.91% and 98.76%, respectively. Also, Table 12 shows that increase in the value of time objective by 87.91% will result in 98.76% increase in the value of emissions objective. Thus, these numerical results denotes while objective function 1 has inverse relation with two other objectives, objectives 2 and 3 are quite positively related with each other.

Table 12. Comparison of two points in the base model solution set

	Solution Point I	Solution Point II	Change Percentage
Obj. 1 Value (€)	€ 40,401.00	€ 712.86	98.24%

Table 12. Cont'd

Obj. 2 Value (hour)	€ 1,889.20	€ 15,621.30	87.91%
Obj. 3 Value ($t-CO_2$)	€ 0.25	€ 19.94	98.76%

5.1.2. Risk 1 Activated Model Solution Set

Risk 1 is the environmental risk category, and it was explained in detail how risk 1 is converted into a constraint and integrated into the model, in Chapter 3. In this regard, risk 1 activated model is the model created by adding the constraint representing risk 1 to the base model and only one point is considered where risk 1 is active. After forming the risk 1 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 4.

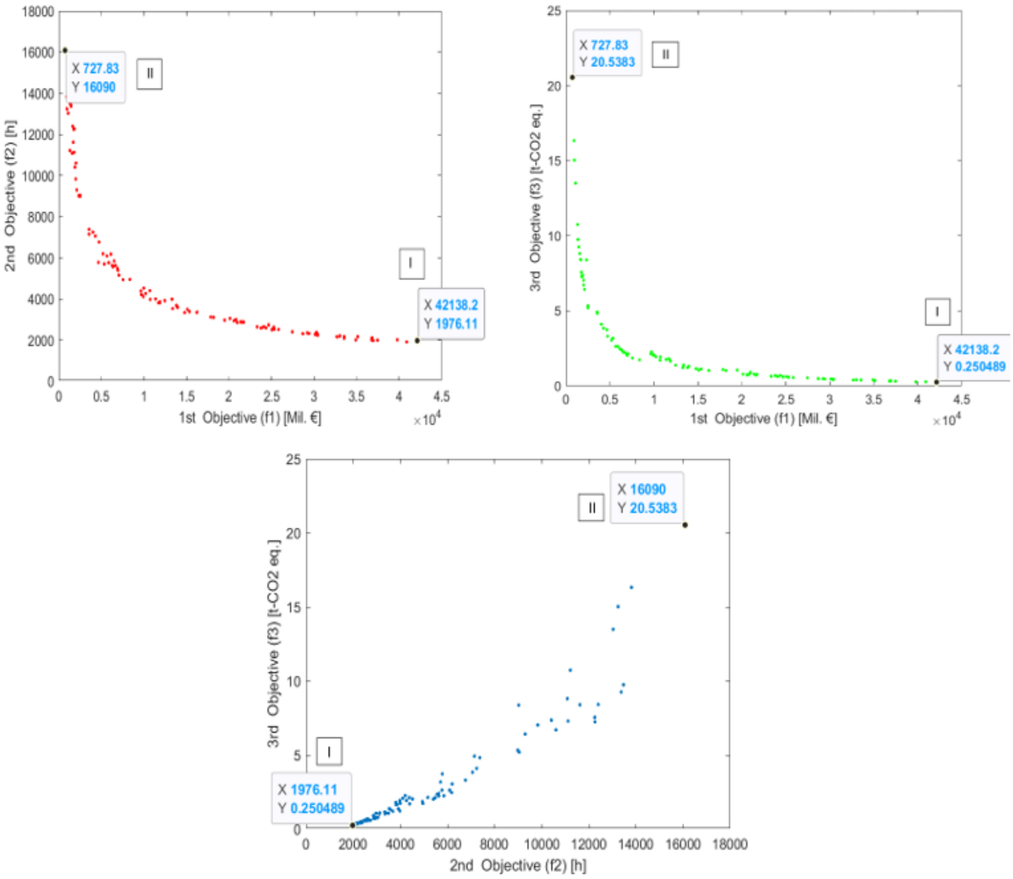

Figure 4. Risk 1 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 1 activated model to see impact of risk 1 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 1 activated model and two extreme points from the solution set of base model solution set are chosen. Point I and II in Figure 4 are the points used for risk 1 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 1 activated model is summarized in Table 13. According to Table 13, risk 1 leads to increase in cost by 4.3%, time by 4.60% and emissions by 1.20%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 1 causes increase in cost by 2.10%, time and emissions by 3% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 1 occurs in a point, cost, time, and emissions values which are the three objectives increases.

Table 13. Comparison of two points in base model and risk 1 activated model solution set

	Point I in Base Model Solution	Point I in Risk 1 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 1 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	42,138.20	4.30%	712.86	727.83	2.10%
Obj. 2 Value (hour)	1,889.20	1,976.11	4.60%	15,621.30	16,090.00	3.00%
Obj. 3 Value (t-CO_2)	0.248	0.250	1.20%	19.94	20.54	3.00%

5.1.3. Risk 2 Activated Model Solution Set

Risk 2 is the policy risk category, and it was explained in detail how risk 2 was converted into a constraint and integrated into the model, in Chapter 3. In this regard, risk 2 activated model is the model created by adding the constraint representing risk 2 to the base model and only one point is considered where risk 2 is active. After forming the risk 2 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 5.

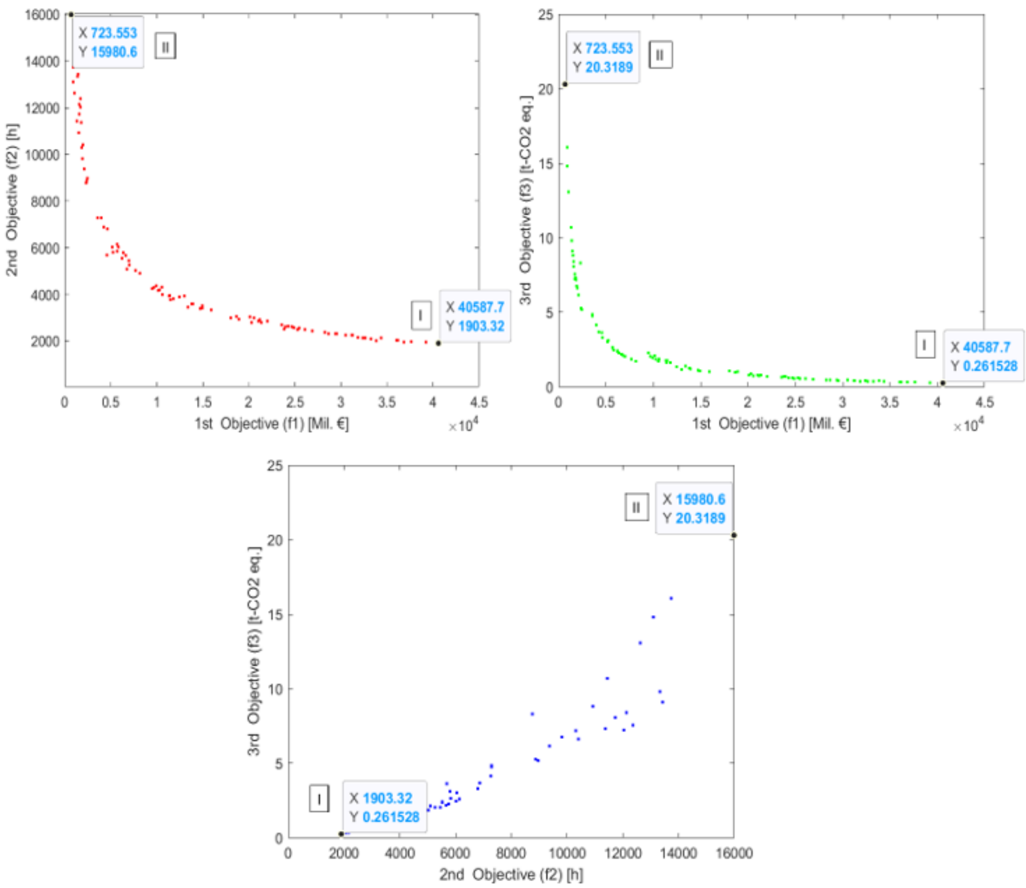

Figure 5. Risk 2 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 2 activated model to see impact of risk 2 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 2 activated model and two extreme points from the solution set of base model solution set were chosen. Point I and II in Figure 5 are the points used for risk 2 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 2 activated model is summarized in Table 14. According to table, we can claim that risk 1 leads to increase in cost by 0.46%, time by 0.75% and emissions by 5.04%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 1 causes increase in cost by 1.50%, time by 2.30% and emissions by 1.91% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 2 occurs in a point, cost, time, and emissions values which are the three objectives increases.

Table 14. Comparison of two points in base model and risk 2 activated model solution set

	Point I in Base Model Solution	Point I in Risk 2 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 2 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	40,587.70	0.46%	712.86	723.55	1.50%
Obj. 2 Value (hour)	1,889.20	1,903.32	0.75%	15,621.30	15,980.60	2.30%
Obj. 3 Value (t-CO_2)	0.248	0.260	5.04%	19.94	20.32	1.91%

5.1.4. Risk 3 Activated Model Solution Set

Risk 3 is the security risk category, and it was explained in detail how risk 3 was converted into a constraint and integrated into the model, in chapter 3. In this regard, risk 3 activated model is the model created by adding the constraint representing risk 3 to the base model and only one point is considered where risk 3 is active. After forming the risk 3 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 6.

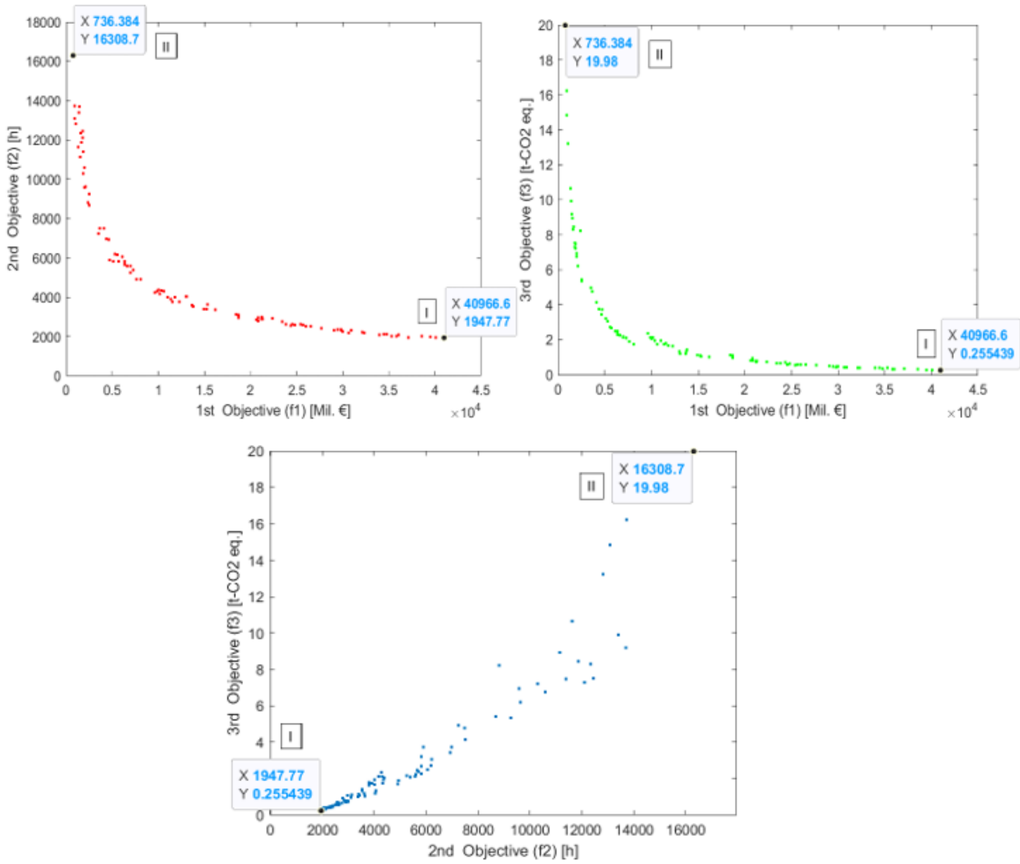

Figure 6. Risk 3 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 3 activated model to see impact of risk 3 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 3 activated model and two extreme points from the solution set of base model solution set were chosen. Point I and II in Figure 6 are the points used for risk 3 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 3 activated model is summarized in Table 15. According to table, we can claim that risk 3 leads to increase in cost by 1.40%, time by 3.10% and emissions by 3.18%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 3 causes increase in cost by 3.30%, time by 4.40% and emissions by 0.20% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 3 occurs in a point, cost, time, and emissions values which are the three objectives increases.

Table 15. Comparison of two points in base model and risk 3 activated model solution set

	Point I in Base Model Solution	Point I in Risk 3 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 3 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	40,966.60	1.40%	712.86	736.38	3.30%
Obj. 2 Value (hour)	1,889.20	1,947.77	3.10%	15,621.30	16,308.70	4.40%
Obj. 3 Value (t-CO_2)	0.25	0.26	3.18%	19.94	19.98	0.20%

5.1.5. Risk 4 Activated Model Solution Set

Risk 4 is the operational risk category, and it was explained in detail how risk 4 was converted into a constraint and integrated into the model, in Chapter 3. In this regard, risk 4 activated model is the model created by adding the constraint representing risk 4 to the base model and only one point is considered where risk 4 is active. After forming the risk 4 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 7.

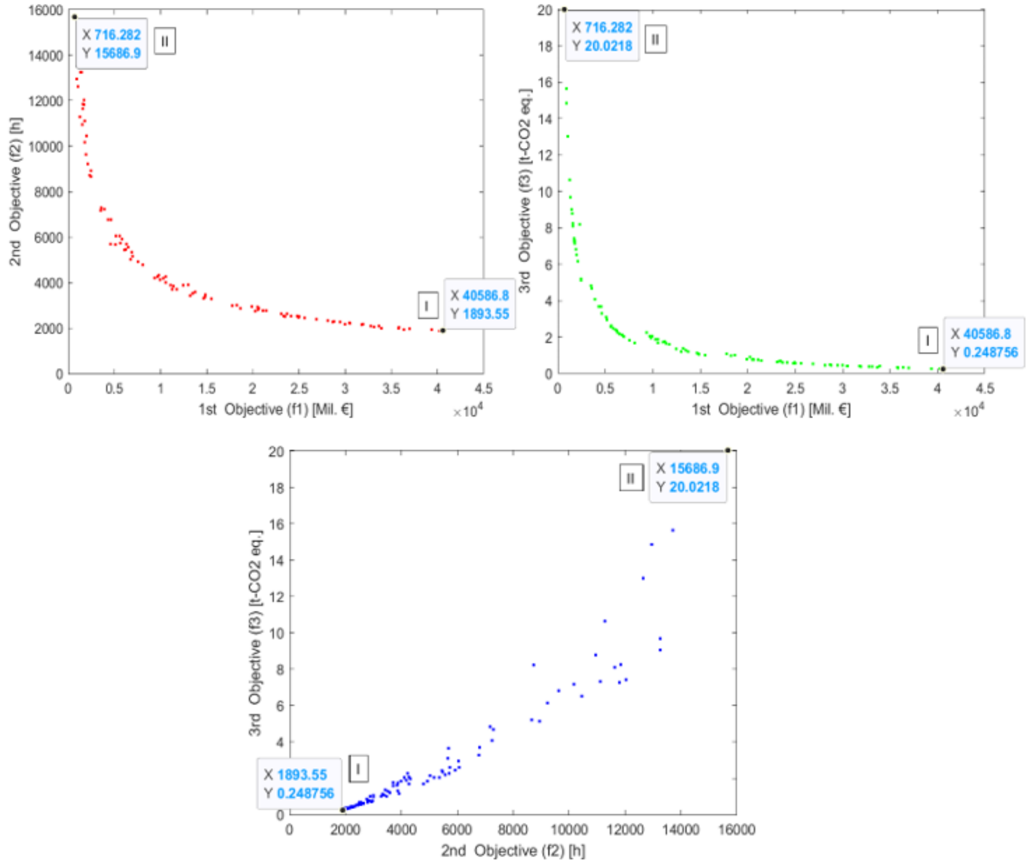

Figure 7. Risk 4 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 4 activated model to see impact of risk 4 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 4 activated model and two extreme points from the solution set of base model solution set were chosen. Point I and II in Figure 7 are the points used for risk 4 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 4 activated model is summarized in Table 16. According to table, we can claim that risk 4 leads to increase in cost by 0.46%, time by 0.23% and emissions by 0.50%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 4 causes increase in cost by 0.48%, time by 0.42% and emissions by 0.41% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 4 occurs in a point, cost, time, and emissions values which are the three objectives increases fairly.

Table 16. Comparison of two points in base model and risk 4 activated model solution set

	Point I in Base Model Solution	Point I in Risk 4 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 4 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	40,586.80	0.46%	712.86	716.28	0.48%
Obj. 2 Value (hour)	1,889.20	1,893.55	0.23%	15,621.30	15,686.90	0.42%
Obj. 3 Value (t-CO_2)	0.248	0.249	0.50%	19.94	20.02	0.41%

5.1.6. Risk 5 Activated Model Solution Set

Risk 5 is the supply risk category, and it was explained in detail how risk 5 was converted into a constraint and integrated into the model, in Chapter 3. In this regard, risk 5 activated model is the model created by adding the constraint representing risk 5 to the base model and only one point is considered where risk 5 is active. After forming the risk 5 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 8.

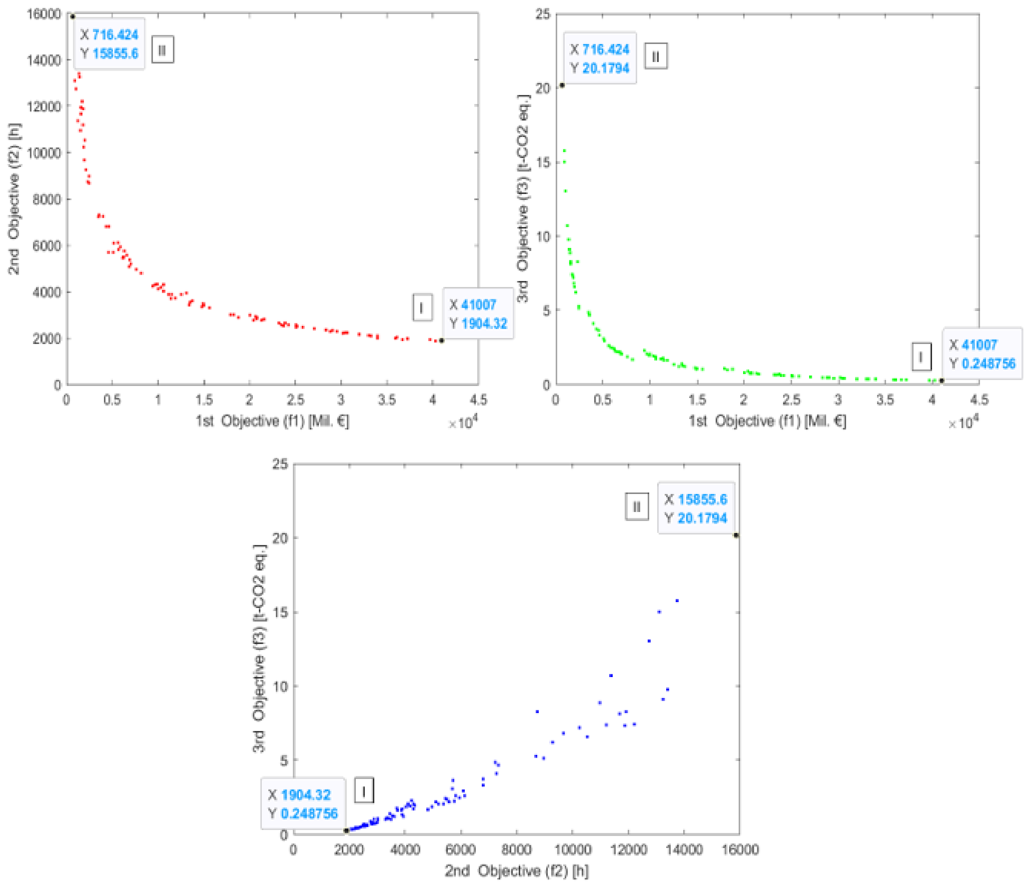

Figure 8. Risk 5 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 5 activated model to see impact of risk 5 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 5 activated model and two extreme points from the solution set of base model solution set were chosen. Point I and II in Figure 8 are the points used for risk 5 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 1 activated model is summarized in Table 17. According to table, we can claim that risk 5 leads to increase in cost by 1.50%, time by 0.80% and emissions by 0.50%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 1 causes increase in cost by 0.50%, time by 1.50% and emissions by 1.20% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 5 occurs in a point, cost, time, and emissions values which are the three objectives increases.

Table 17. Comparison of two points in base model and risk 5 activated model solution set

	Point I in Base Model Solution	Point I in Risk 5 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 5 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	41,007.00	1.50%	712.86	716.42	0.50%
Obj. 2 Value (hour)	1,889.20	1,904.32	0.80%	15,621.30	15,855.60	1.50%
Obj. 3 Value (t-CO_2)	0.248	0.249	0.50%	19.94	20.18	1.20%

5.1.7. Risk 6 Activated Model Solution Set

Risk 6 is the economic risk category, and it was explained in detail how risk 6 was converted into a constraint and integrated into the model, in Chapter 3. In this regard, risk 6 activated model is the model created by adding the constraint representing risk 6 to the base model and only one point is considered where risk 6 is active. After forming the risk 6 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 9.

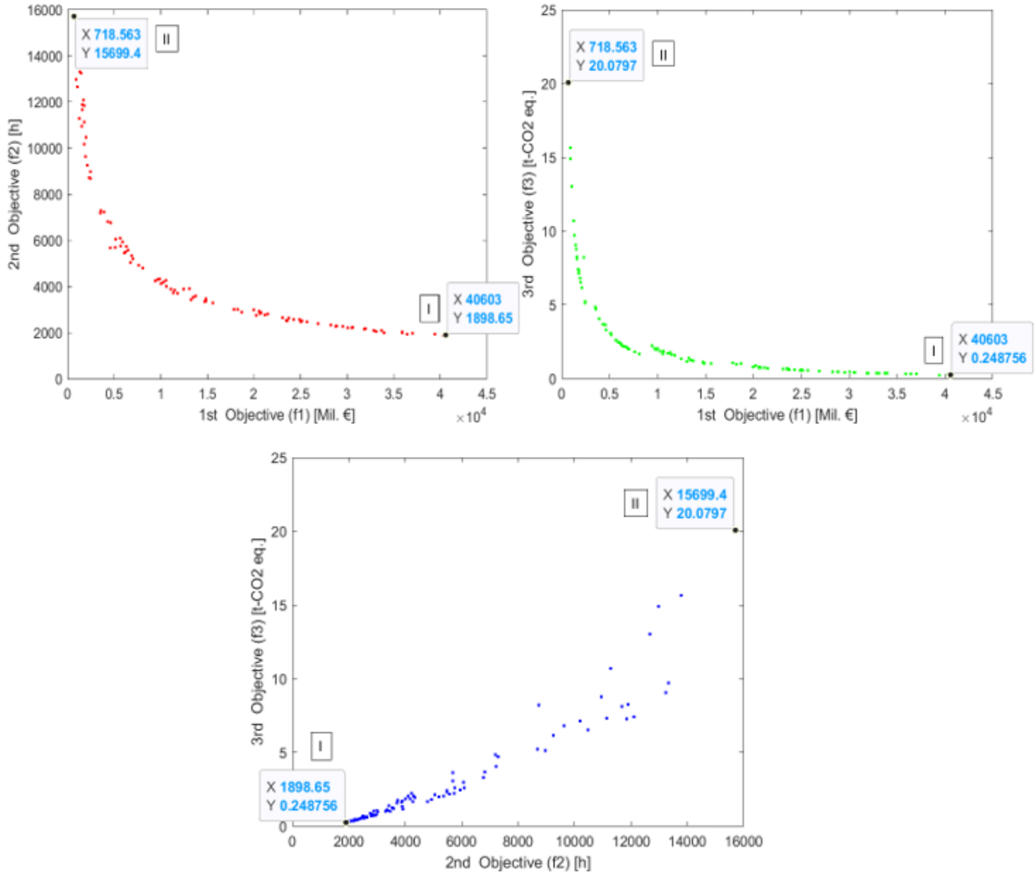

Figure 9. Risk 6 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 6 activated model to see impact of risk 6 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 6 activated model and two extreme points from the solution set of base model solution set were chosen. Point I and II in Figure 9 are the points used for risk 1 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 6 activated model is summarized in Table 18. According to table, we can claim that risk 6 leads to increase in cost by 0.50%, time by 0.50% and emissions by 0.50%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 6 causes increase in cost by 0.80%, time by 0.50 and emissions by 0.70% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 6 occurs in a point, cost, time, and emissions values which are the three objectives increase fairly.

Table 18. Comparison of two points in base model and risk 6 activated model solution set

	Point I in Base Model Solution	Point I in Risk 6 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 6 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	40,603.00	0.50%	712.86	718.56	0.80%
Obj. 2 Value (hour)	1,889.20	1,898.65	0.50%	15,621.30	15,699.40	0.50%
Obj. 3 Value (t-CO_2)	0.248	0.249	0.50%	19.94	20.08	0.70%

5.1.8. Risk 7 Activated Model Solution Set

Risk 7 is the technological risk category, and it was explained in detail how risk 1 was converted into a constraint and integrated into the model, in Chapter 3. In this regard, risk 7 activated model is the model created by adding the constraint representing risk 7 to the base model and only one point is considered where risk 7 is active. After forming the risk 7 activated model, model was run 100 times with different epsilon values yielding different results, as performed in the base model part. Resulted Pareto frontiers that shows non-dominated solution points are reflected in Figure 10.

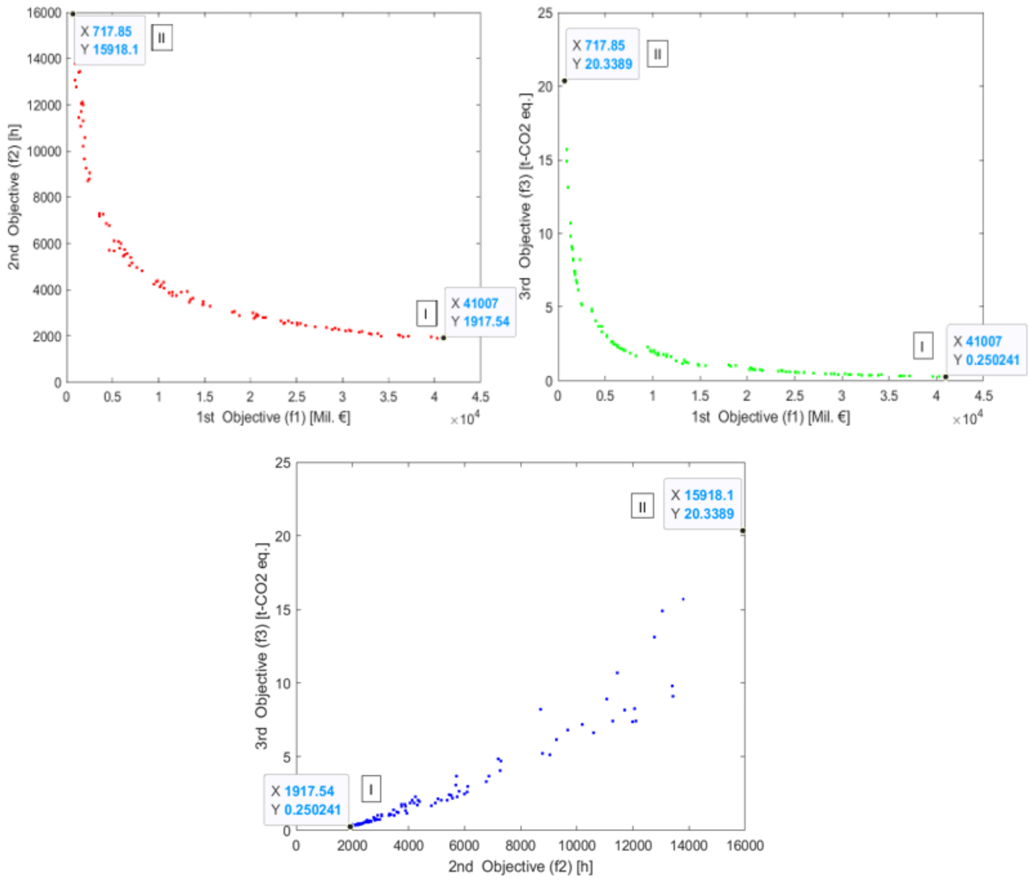

Figure 10. Risk 7 activated model Pareto solution diagrams

It is desired to make a comparison on the results of base model and risk 7 activated model to see impact of risk 7 on cost, time, and emissions. By this reason, two extreme points from the solution set of risk 7 activated model and two extreme points from the solution set of base model solution set were chosen. Point I and II in Figure 10 are the points used for risk 7 activated model and point I and II in Figure 3, where mentioned in the base model solution set part, are the points used for base model in this regard. Comparison between base model and risk 7 activated model is summarized in Table 19. According to table, we can claim that risk 7 leads to increase in cost by 1.50%, time by 1.50% and emissions by 1.10%, based on the comparison of point Is, where cost is the highest. Moreover, we can state that risk 7 causes increase in cost by 0.70%, time by 1.90% and emissions by 2.00% based on the comparison of point IIs, where cost is the lowest. We can conclude that when risk 7 occurs in a point, cost, time, and emissions values which are the three objectives increases.

Table 19. Comparison of two points in base model and risk 7 activated model solution set

	Point I in Base Model Solution	Point I in Risk 7 Activated Model Solution	Change Percentage	Point II in Base Model Solution	Point II in Risk 7 Activated Model Solution	Change Percentage
Obj. 1 Value (€)	40,401.00	41,007.00	1.50%	712.86	717.85	0.70%
Obj. 2 Value (hour)	1,889.20	1,917.54	1.50%	15,621.30	15,918.10	1.90%
Obj. 3 Value (t-CO_2)	0.248	0.250	1.10%	19.94	20.34	2.00%

5.2. t-Distributed Stochastic Neighbor Embedding Algorithm Application

It is explained that Pareto solution sets are obtained after running each afore mentioned model and corresponding Pareto solution diagrams are represented in previous parts. These Pareto solution sets include high amount of data that makes difficult to perform clustering algorithm due to the dimension of the data. Thus, it is determined to make dimension reduction on the solution sets. Performing a dimension reduction before clustering will enable to attain accurate results from clustering algorithm. Therefore, t-distributed stochastic neighbor embedding method is applied to the solution sets for reducing dimension to two and Python version 3.6.3 (Python Software Foundation, 2016) is utilized for the implementation of t-SNE. A computer with AMD Ryzen 5 3500U with Raedon Vega Mobile Gfx with 2.10 Ghz processor, and with 8.00 GB RAM is used. Additionally, parameter tuning is carried out and then t-SNE is performed with the tuned parameter. Application of t-SNE will be explained in sub-sections in detail.

5.2.1. Tuning of Perplexity Parameter

It was mentioned in Chapter 3 that t-SNE has several input parameters. van der Maaten, and Hinton (2008) who are the creator of this algorithm states in their study that change in the value of perplexity, which is defined as measure for effective number of neighbors, affects the performance of t-SNE and typical perplexity values are between 5 and 50. Based on this, it was decided to perform tuning operation for this parameter so different perplexity values was tried in t-SNE algorithm to make a comparison among them and to perform tuning. Below figures exhibit the t-SNE outputs of these perplexity values.

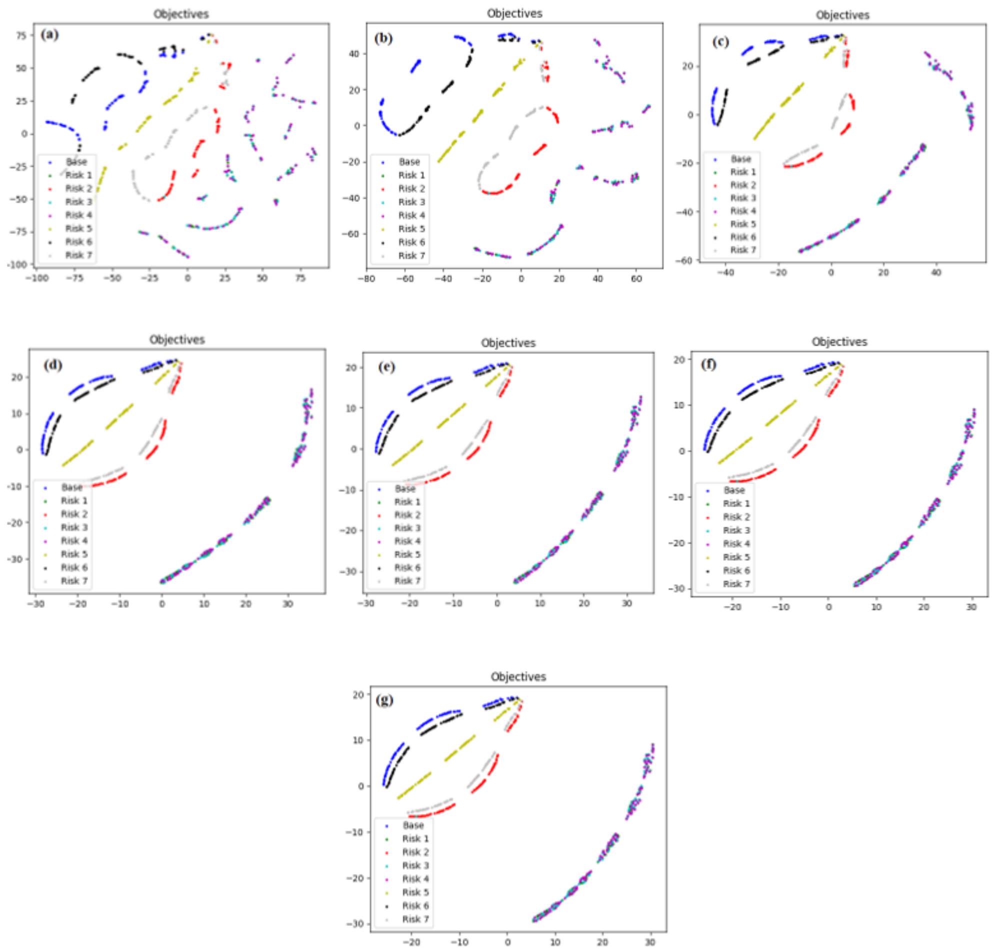

Figure 11. t-SNE outputs with different perplexity values (a) perplexity: 5 (b) perplexity: 10 (c) perplexity: 20 (d) perplexity: 30 (e) perplexity: 40 (f) perplexity: 45 (g) perplexity: 50

According to above graphs, graph (a), (b) and (c) in which perplexity is lower shows scattered visualization of the points whereas other graphs show that points are more centralized. Thus, it can be clearly seen that when perplexity value becomes higher, t-SNE algorithm will result in better quality outputs in our data set and for perplexity values greater than 30 in graph (d), (e), (f) and (g) t-SNE algorithm gives similar results. Therefore, t-SNE is also performed for the perplexity values higher than 50, and it is seen that t-SNE results has poor quality. Thus, it is determined to take perplexity value as 50.

5.2.2. t-SNE Algorithm Results

After tuning of perplexity parameter, t-SNE algorithm is applied to the obtained Pareto solution sets with tuned perplexity value. Table 20 shows the values of the parameters used in t-SNE algorithm. Parameter named '*n_components'* represent the resulting dimension of data set. Since it is desired to obtain two-dimensional data set, this parameter was taken as 2. Parameter '*init'* which stands for initialization of dimension reduction algorithm can be either *'random'* or *'pca'*. If random was chosen initialization of space embedding will be performed randomly whereas *'pca'* choice will start t-SNE by first applying principal component analysis (PCA) algorithm to the data set. Thus, '*init'* parameter is set to *'pca'* because it is thought that starting with PCA algorithm will enable to obtain better results from t-SNE algorithm. It was also mentioned previously how perplexity value is found. Lastly, default values are taken for '*n_iter'* which is maximum number of iterations and learning rate parameters (scikit-learn, 2020).

Table 20. Input parameters used in t-SNE algorithm

t-SNE Algorithm Parameters	Value
Perplexity	50
n_components	2
Learning rate	200
n_iter	1000
init	pca

Figure 12 visualizes the outputs of t-SNE algorithm. This algorithm found corresponding x and y points for each of the solution point in the Pareto solution sets in two-dimensional space. When graph is examined, one can realize that points representing solutions for risk factors 1, 3 and 4 are almost overlapped with each other. Effects of these risks were explained in detail in Chapter 3 and even if risk 1, 3 and 4 are different risk factors, their effect on the logistics activities are alike to each other. Thus, their resulting values in the Pareto solution sets are highly close. This is the main reason why t-SNE shows such output for risk factors 1, 3 and 4.

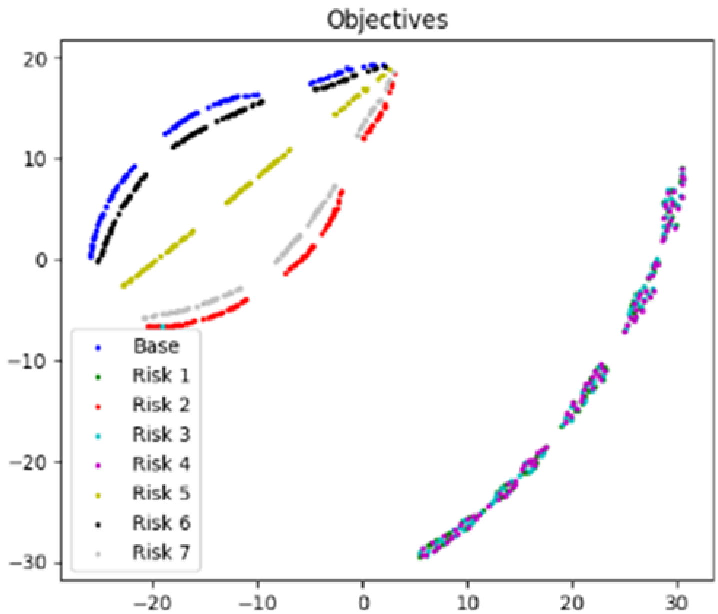

Figure 12. t-SNE algorithm results

5.3. k-Means Algorithm Application

Pareto solution sets that have high dimension is converted into 2-dimensional data after performing t-SNE algorithm. It is previously mentioned that this dimension reduction operation is applied for better clustering results. Thus, output of t-SNE is used as input to k-means algorithm and clustering is performed and Python version 3.6.3 (Python Software Foundation, 2016) is utilized for the implementation of k-means algorithm. A computer with AMD Ryzen 5 3500U with Raedon Vega Mobile Gfx with 2.10 Ghz processor, and with 8.00 GB RAM is used. Additionally, parameter tuning is carried out and then k-means is performed with the tuned parameter. Application of k-means will be explained in sub-sections in detail.

5.3.1. Tuning of k Parameter

It was mentioned in Chapter 3 that k-means algorithm uses several input parameters, according to Umargono, Suseno, and Gunawan (2020), this algorithm shows weaknesses on cluster number choice and algorithm results highly depends on the parameter for cluster number which we denote in this study as *'k'*. Thus, one of the popular optimization methods, the Elbow method, is applied to find optimal number of clusters. Since there are seven risk factors, while minimum possible cluster number is one, maximum number of clusters can be seven. Thus, algorithm is run with different k parameters that takes value from 1 to 7 in the Elbow method. Figure 13 shows the

Elbow method results. For each of the cluster value in x-axis, corresponding within-cluster sum of squared error value is denoted in y-axis. The Elbow method states that k-value must be set as the point where the last elbow shaped seen. When below figure is examined, it can be clearly seen that last elbow shaped is seen at point four in the x-axis. That means optimum number of clusters must be four in k-means algorithm.

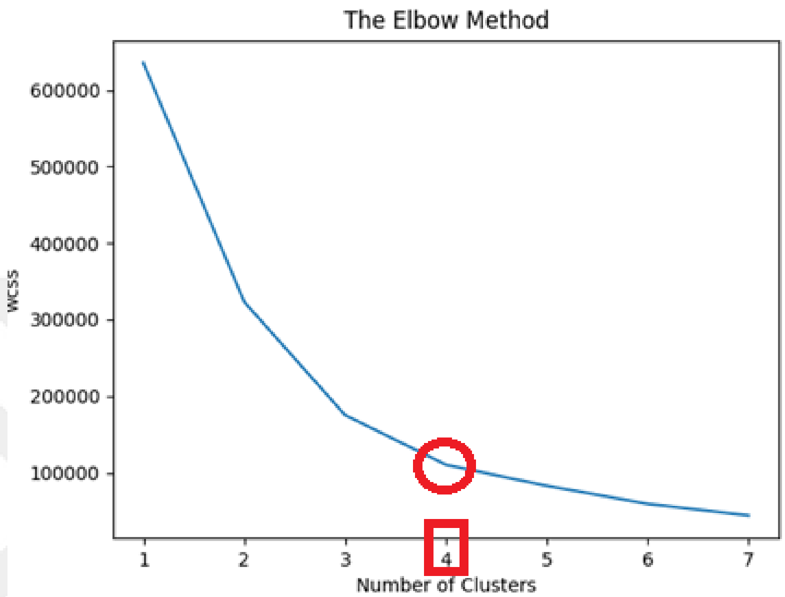

Figure 13. Elbow method result for tuning of parameter k

5.3.2. k-Means Algorithm Results

After completion of k parameter tuning, k-means algorithm is applied to the two-dimensional data set where was obtained from t-SNE algorithm. Table 21 shows the values of the parameters used in k-means algorithm. Parameter named '*init'* represent the selection for initialization of cluster centroids and can be either '*k-means++*' or *'random'*. If *'random'* is chosen, then initial centroids will be selected randomly whereas '*k-means++*' option will provide a selection of cluster which quickens the convergence of the k-means algorithm. Thus, '*k-means++*' option is set for the *init* parameter. Besides, parameter '*random_state*', which is used for performing random number generation for centroid initialization, is taken as 0 so that randomness will not be probabilistic. It was also mentioned previously how total number of clusters is found. Therefore, *'n_clusters'* which stands for number of clusters is set to 4. Lastly, *'n_init'*, which denotes how many times k-means uses different centroid seeds, and *'max_iter'* parameters are taken as default values 10 and 300, respectively (scikit-learn, 2020).

Table 21. Input parameters used in k-means algorithm

k-means Algorithm Parameters	Value
n_clusters	4
n_init	10
random_state	0
max_iter	300
init	k-means++

Below figures represent k-means algorithm results. In graph (a), four different colors denote only four clusters, but it does not show which risks fall into which cluster whereas in graph (b) coloring is applied based on which risks belong to which cluster with seven different colors. Besides, centroids of each cluster are pointed with black dots in each graph.

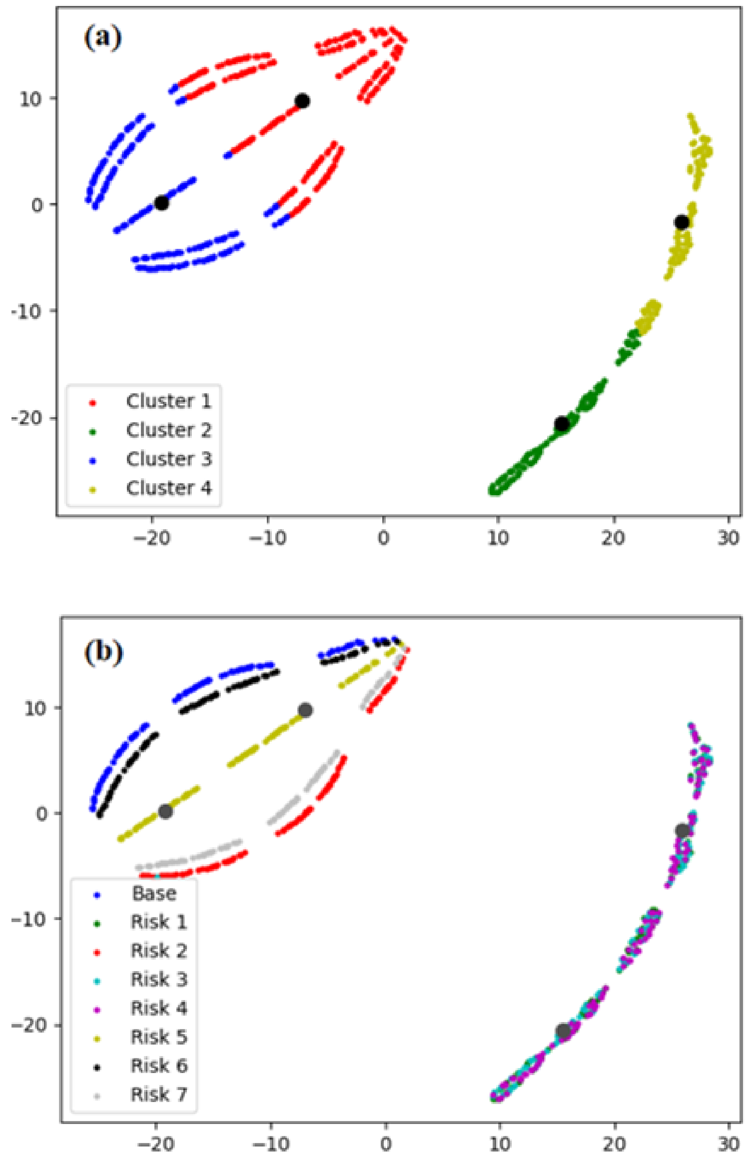

Figure 14. k-means algorithm results (a) cluster specified graph (b) risks specified in clusters graph

Results of the k-means algorithm are analyzed to understand properties of clusters in terms of cost, time, and emissions values. Below table represents these analyses and table also shows risk factors that takes place in each cluster. Based on the table, cluster 1 is a cost-oriented cluster which means that least costly solutions are assigned to this cluster. However, while solution set in this cluster is cost friendly, time and emissions values are above the average at the same time. Cluster 2 includes lowest emissions-valued solutions thus is an emissions-oriented cluster with high cost and low time values. Cluster 3 is the time-oriented cluster with high cost and low emissions values likewise the cluster 2. And the last cluster which is cluster 4 consists of the solutions which are low for cost and emissions but above the average for time.

Table 22. Risk factor assignment to clusters and cluster features

	Risk Factor	Cost	Time	Emissions
Cluster 1	2, 5, 6, 7	Lowest	Medium	Medium
Cluster 2	1, 3, 4	High	Low	Lowest
Cluster 3	2, 5, 6, 7	High	Lowest	Low
Cluster 4	1, 3, 4	Low	Medium	Low

When Table 22 is reviewed, it can be realized that risk factor 2, 5, 6 and 7 take places in both cluster 1 and 3, while risk factor 1, 3 and 4 falls within the clusters 2 and 4. In Chapter 3, Pareto solution sets for each of the model are given and it is shown that these solution sets include several solution points. Some of them reflect high result for one of the cost, time, and emissions objective, whereas some of them are low or medium valued for the objectives. Thus, each solution sets consists of not one type of solution but various types with mixture of high, medium, low results. That is the reason that solution points in risk factors fall into not only one cluster but two clusters.

When these results are shown to decision makers, they will be able to choose solutions based on their focus in the result set. For example, when a logistics company faces with risk 1, to be able to minimize the effect of this risk they must choose one of the solutions from the risk 1 activated solution set. This choice depends on decision makers' requirements or priorities in terms of cost, time, and emissions. For instance, if decision maker states that cost is the focus in their logistics activities, and they always prefer least costly solutions then solution sets of 4th cluster for this risk factor will be offered to decision maker. Even if the risk cannot be prevented beforehand, effects of it will be able to be minimized by this way.

CHAPTER 6: CONCLUSIONS & FUTURE RESEARCH DIRECTION

Supply chains have highly complex structures and technological improvements, increasing customer needs in today's world lead supply chains to globalize.

According to (Maslarić, Brnjac, and Bago, 2016, p. 12),

> *"Transportation is often presented as 'the glue which connects members of a supply chain' on the efficiency of which the effectiveness of the whole chain depends in the literature."*

Thus, any disruption in transportation network can result in devastating effects in whole supply chain operations. It is a fact that risk is inevitable in real-life operations and transportation activities are prone to disrupt due to various risk factors. Thus, risk management in these activities and constructing resilient transportation network under any risk occurrence is highly important. For this purpose, multimodal transportation which is an effective transportation way in the logistics compared to unimodal type is taken into account and risk management studies is performed in this matter. A multimodal transportation optimization model is proposed in this regard. Also, multi-objectivity consideration is added to the proposed model because not only cost but also time and environmental factors are the goals in logistics operations. Then, risk factors that transportation operations can face are categorized and integration of those risks into proposed model is performed to be able to measure the impact of several risks in terms of cost, time, and environmental considerations. After that, all obtained models with various risks involvement are implemented in GAMS (GAMS Development Corporation, 2019) and Pareto solution sets of each model where each risk is activated are analyzed and comparison of results with the base model in which any risk is not included is completed. Moreover, t-SNE algorithm is performed for reducing the dimension of obtained Pareto solution sets into 2-dimensions. In this way, clustering of same featured solution points could be made effectively by using k-means algorithm. Finally, results are shared with decision makers (logistic planner, logistic director, logistic operations manager) in one of the largest logistic firms in Turkey, who makes the decisions in managerial side for the transportation operations, so that they can select and implement any optimal solution based on their focus (least costly, timely or less emissions) for their transportation activities when one of the previously categorized risk is active. Since intent is setting forth a generic model that can be utilized by several logistics companies for their operations. Revisions for which transportation modes to be in action, scope of transportation network such as supply and demand points, unit container size and costs regarding to per container, capacities of transportation used can be revised based on decision makers' preferences.

In conclusion, this study enables to perform risk management in multimodal transportation activities and provides decision makers various solutions that they can select upon their preferences under any risk activation. By this way, severe impacts of risks could be reduced beforehand and risk resiliency and management in transportation networks can be achieved. As a future direction of this research, risk types can be extended, and some other alternative risks can be defined by making detailed research. Also, risks are considered to be effective for short period of time, but their impacts are much longer in real-life applications. Thus, risks can be converted into objectives as a utility function and their impact score can be aimed to minimize. By this way, their effect will be taken as continuous instead of limited time interval. In addition, while risks and their impacts have likelihood probabilities in real-life cases, this case is not considered in the scope of this study and all risk related parameters are assumed to be deterministic. Therefore, probabilistic cases regarding to risks such as risk occurrence probabilities, capacity coefficient factor can be implemented in this study as a future research direction. Moreover, load factor, traffic congestions, vehicle routing and capacity of vehicles in each transportation mode can be included to the proposed model and transportation network can be enlarged. Additionally, metaheuristics for the solution of developed model, some other machine learning and clustering algorithms can be implemented because of increase in complexity of the developed model in the future. Lastly, even though conducted study enables to narrow down the solution sets for the decision makers with the obtained risk clusters and solution points in each cluster, there is still multiple criteria and multiple solution points that can make difficult for decision makers to select an efficient solution. Thus, as a future research direction of this study, multi-criteria decision-making tools such as simple additive weighting (SAW) (MacCrimmon, 1968), analytic hierarchy process (AHP) (Saaty, 1980), technique for order of preference by similarity to ideal solution (TOPSIS) (Hwang, and Yoon, 1981), elimination and choice translating reality (ELECTRE) (Roy, 1968), preference ranking organization method for enrichment evaluations (PROMETHEE) (Mareschal, Brans, and Vincke, 1984) etc. can be implemented to the obtained risk clusters so that decision makers can make their final and most preferred decision from the multiple solution points from the created risk clusters.

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