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Solving an ammunition distribution network design problem using multi-objective mathematical modeling, combined AHP-TOPSIS, and GIS

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ABSTRACT

We study a strategic-level ammunution distribution network design problem (ADNDP) where the purpose is to determine the locations and the service assignments of main, regional, and local depots in order to meet the ammunition needs of military units considering several factors, e.g., stock levels at the depots, costs, and risk levels of depot locations. ADNDP is a real-world and large-scale problem for which scientific decision making methods do not exist. We propose a methodology that uses multi-objective mathematical modeling, Analytic Hierarchy Process (AHP), The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Geographic Information System (GIS) to solve the problem. The multi-objective mathematical model determines the locations and the service assignments of depots considering two objectives, namely, to minimize transportation costs and to minimize risk scores of main depot locations. The risk score of a depot location indicates how vulnerable the location is to disruptions and is determined by a combined AHP-TOPSIS analysis where TOPSIS is used to compute the risk scores and AHP is used to compute the weights needed by TOPSIS for the identified risk attributes. The GIS analysis is conducted to determine the potential depot locations using map layers based on spatial criteria.

We have applied the proposed methodology in designing and evaluating a real ammunition distribution network under different scenarios in collaboration and cooperation with the area experts. We have employed the weighted-sum method to find non-dominated solutions for each scenario and discussed their tradeoffs with the area experts. The purpose of this paper is to present the proposed methodology, findings, and insights.

1. Introduction

Law enforcement in Turkey is essentially carried out by two organizations: the General Directorate of Security (Police) and the General Command of the Gendarmerie (GCG). The Police is responsible for law enforcement in provinces and in some exceptional locations such as airports while GCG is responsible in the areas that fall outside the jurisdiction of the Police. Its area of jurisdiction is mostly rural areas where population and population density are low and crime rates are high. GCG is tasked to maintain public order as well as to assure internal security and general border control. In this respect, GCG actively engages in counter-terrorist operations throughout Turkey as well.

GCG is a law enforcement force of military nature and about the size of the Army. It is composed of the headquarters, internal security units, border units, schools and training units, logistics support units, aviation units, special forces, and other units established in accordance with the characteristics of a specific duty (e.g. criminal units, special public order command) (FIEP, 2017). It has about 1000 units of different sizes distributed in 81 provinces of Turkey. The units within the boundary of a province are under the command of provincial regimen command (PRC) in the province.

GCG units use light and heavy weapons, e.g., handguns, rifles, machine guns, rocket and grenade launchers, and mortars, in conducting their duties. Supplying ammunitions (henceforth called ammo) for these weapon systems at the right time, at the right place, and in the right quantity is of critical importance for the forces. This requires a streamlined ammo distribution system (ADS) that will be effective in the sustainment of the forces at all times.

In the current ADS, all ammo is supplied to the units through 81 depots, (one main depot (MD), three regional depots (RDs), and 77 local depots (LDs)), each of which is located in a different province. Only one type of depot is located in a province and all units within the boundary of a province are supplied from that depot. An LD is supplied by an RD or MD and RDs are supplied by MD. The number and locations

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of MDs, RDs, and LDs were determined about 50 years ago. Over the years, there has been intensive construction in the vicinity of MD and hence the population living close to MD has increased significantly. Moreover, the locations and structures of units in the provinces supported by RDs have changed over the years. These issues combined with the fact that MD and RDs are still used after the end of their economic lives have made it vital for GCG to redesign the current ADS. Specifically, GCG is to determine the number and locations of MDs, RDs, and LDs as well as the assignments of LDs to MDs and RDs by taking into account several factors such as stock levels at the depots and units, costs, and risk scores/levels (e.g., the possibility of disruption of a depot). We refer to the problem of GCG as the *Ammunition Distribution Network Design Problem* (ADNDP).

GCG does not have a system that will provide scientific decision support in solving ADNDP. Actually, there are no standards or methods for designing ADS in either national or international (e.g., United Nations and NATO) documents; related standards focus on storage conditions, maintenance, and security of ammo. In this regard, we propose a methodology that consists of the use of multi-objective mathematical modeling, Analytic Hierarchy Process (AHP), The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and geographic information system (GIS). We develop the multi-objective optimization model in order to determine the optimal locations and assignments of MDs and RDs where the total transportation cost and the risk scores of MD locations are minimized. We use the GIS analysis to determine the potential MD locations and the combined AHP-TOPSIS analysis to compute the risk levels of the potential MD locations needed in the optimization model. In the AHP-TOPSIS analysis, TOPSIS is used to compute the risk scores of MD locations while AHP is used to determine the weights needed by TOPSIS for the identified risk attributes.

The methodology has been applied in designing and evaluating the ADS of GCG in collaboration and cooperation with the experts from GCG. Our main contribution is to develop a manageable and applicable methodology for a large-scale, real-world, and original problem for which no analytical methodologies exist and to provide solution alternatives as well as insights to the decision makers. The methodology consists of the usage of four different methods, which is rare in the literature; most studies combine two methods, e.g., AHP and TOPSIS, AHP and mathematical modeling, GIS and mathematical modeling. Moreover, ADNDP is different from the distribution network design problems in the literature in several aspects (see Section 4) and hence the proposed optimization model is new and has several differentiating features. Even though our methodology has been developed for ADNDP, it can be applied to different problem contexts by adapting the specifics of the methodology as necessary.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the problem and summarizes the steps of the proposed solution methodology. Section 4 develops the mathematical model. Section 5 and Section 6 describe the application of GIS analysis and the application of AHP and TOPSIS, respectively. Section 7 defines the scenarios used for analysis and discusses the results in detail. Section 8 concludes the paper.

2. Literature review

We will give the literature related to (1) distribution network design focusing on ADNDP and (2) multi-criteria decision making concentrating on AHP, TOPSIS, and multi-objective mathematical modeling.

2.1. Ammunition distribution network design problem

Since the Second World War, researchers characterize logistics as business (civilian) and military logistics (Hauk, 1964; Kent & Flint, 1997). Rutner, Aviles, and Cox (2012) compare the military and business supply chains considering the US military logistics system. They state that the business SCM (supply chain management) has surpassed the military SCM at some point with respect to efficiency and effectiveness even though it was the military SCM leading the logistics field since its origination. Even though there are serious attempts to adopt the recent developments in the business SCM to improve the military SCM, the differences in the vision, mission, regulations, organizational structures, cultures, and attitudes are considered to prevent the the military SCM from adapting easily. This finding is essentially true for military logistics systems in other countries including Turkey as well.

The military logistics systems have historically been mass-based where large amounts of supplies are stockpiled at different echelons to avoid shortages and to provide flexibility for unforeseen requirements or changing missions. There has been significant shift in this approach for some supply items (e.g., food) but a mass-based system is still the practice for critical supply items such as ammo. GCG's distribution system is no exception. On the other hand, from a military perspective, the distribution management is divided into *strategic* and *tactical* segments. The former includes distribution management activities that move materials to a combatant commander while the latter includes distribution management activities in a theater of war and is the responsibility of the combatant commander. The locations of entities (e.g., depots and demand points) in different echelons are mostly fixed in strategic segment; however, the locations may change in the tactical segment depending on the course of the war.

GCG considers the distribution of ammo to the provinces as *strategic distribution* and the distribution of ammo to the units within the boundary of a province as *tactical distribution*. Tactical distribution (distribution of ammo from MDs, RDs, and LDs to the units in the provinces) is a pull system and conducted at the request of the units via their own transportation assets. On the other hand, strategic distribution is a push system; GCG Headquarters annually determines ammo needs of the units and the depots (MD, RDs, and LDs) considering several factors, develops the replenishment plan of the depots, and implements the plan. ADNDP addresses the strategic distribution and requires determining the provinces where MDs, RDs, and LDs are to be located and the assignments of LDs to MDs and RDs.

Distribution Network Design (DND) generally includes decisions about the type (e.g., warehouse, plant, etc.), number, and capacities of facilities, and the flow of materials through the network. DND is considered as a stragetic component of SCM that has a strong impact on the performance of the supply chain (Ballou, 2001; Mangiaracina, Marchet, Perotti, & Tumino, 2015). It sets constraints on tactical and operational decisions and hence directly affects the costs and customer service levels. Due to the recent developments in technology, business environment, and customer service requirements, DND has become more important (Melo, Nickel, & Saldanha-Da-Gama, 2009). As a result, a lot of research has been conducted about DND or related fields (e.g., facility location (Klose & Drexl, 2005; Revelle, Eiselt, & Daskin, 2008), location-allocation (Melo et al., 2009; Owen & Daskin, 1998), location-routing (Laporte, Nobert, & Taillefer, 1988; Melo et al., 2009), and location-allocation-routing (Toyoglu, Karasan, & Kara, 2011). Please see, for example, Mangiaracina et al. (2015), Melo et al. (2009), and Klose and Drexl (2005) for some recent surveys.

Melo et al. (2009) classify the studies in the literature with respect to the number of commodities, planning horizon, and type of data. According to this classification scheme, we can classify ADNDP as a strategic-level, single-period, multi-product, and multi-echelon system with two location layers. Some studies with similar properties carried out in the context of business SCM are Pirkul and Jayaraman (1998), Karabakal, Günal, and Ritchie (2000), Jayaraman and Pirkul (2001), Amiri (2006), and Cordeau, Pasin, and Solomon (2006).

In the context of military SCM, the studies that deal with strategic distribution of ammo are too limited. Cagrici (2007) studies the problem of locating ammo depots for multiple-launch rocket systems where the objective is to minimize total installation and transportation costs. He defines the problem on a two-layer network with the first and second layers representing the possible depot locations and the customers (units), respectively. He develops a mathematical model and genetic algorithm to solve the problem. Sabuncuoglu and Utku (2002) analyze the performance of the current corps artillery ammunition supply system via simulation and suggest a new system that eliminates the deficiencies of the current system. In the simulation study, they consider how the location of the depots changes the performance of the system as well. These two studies are too restricted in scope and complexity when compared to ADNDP addressed in this paper.

There are several studies that address the tactical distribution of ammo. Because the purpose of tactical distribution is to support a battle over time, these studies consider several aspects that are related to the dynamic and operational characteristics of a battle, e.g., mobilized depots whose locations change during the course of the battle (Bell, 2003; Cain, 1988; Gue, 2003; Toyoglu et al., 2011), time windows during which the demands must be met (Bell, 2003; Cain, 1988; Clark, Barnhart, & Kolitz, 2004; Gue, 2003; Lenhardt, 2006; Toyoglu et al., 2011), vehicle routing (Cain, 1988; Clark et al., 2004; Lenhardt, 2006; Sahin, 2006; Toyoglu et al., 2011), vehicle capacities (Cain, 1988; Clark et al., 2004; Powell, 2004; Sahin, 2006; Toyoglu et al., 2011), and inventory planning (Cain, 1988; Gue, 2003; Hehnen, 1970; Powell, 2004; Toyoglu et al., 2011). These aspects are generally not considered at the strategic level.

In most of the aforementioned studies, the nodes in each layer of the network represent a certain entity type, e.g., suppliers, plants, regional depots, customers, etc. Thus, the flow between the layers is allowed through nodes selected as locations for the associated entity type. In ADNDP, however, nodes in the location layers may assume an additional role. Specifically, nodes not selected as MD (RD) locations need to be treated as LD or nodes selected as MD (RD) need to be treated as both MD and LD (RD and LD). This requires that the flow be allowed from a node in RD layer to a node in MD layer or between nodes in MD and RD layers as necessary. This and other problem-specific properties of ADNDP differentiate it from most DND problems in the literature.

2.2. Multi-criteria decision making

Multi-criteria decision making (MCDM) is a field of operations research that aims at developing and implementing decision support tools and methodologies to tackle with complex decision problems involving multiple criteria, goals, or objectives of conflicting nature (Zopounidis & Doumpos, 2002). The literature about MCDM is so rich that there are even survey papers for different application areas and specific methods of MCDM. In this regard, we will touch upon the main points and refer the interested reader to mostly survey papers in the related subjects.

Hwang and Yoon (1981) categorize MCDM problems as *Multi-Attribute Decision Making* (MADM) and *Multi-Objective Decision Making* (MODM) problems. MADM problems involve the evaluation of a predetermined, limited number of alternatives over a predefined set of criteria or attributes. MODM problems, on the other hand, involve the situations where the alternatives are defined over a feasible region within a mathematical programming framework with two or more objectives rather than a single objective. Solving an MADM problem is a *selection* process while solving an MODM problem is a *design* process. MADM and MODM problems are referred to as *discrete* and *continuous* decision problems as well, respectively (Tzeng & Huang, 2011; Zopounidis & Doumpos, 2002; Zopounidis & Pardalos, 2010).

MCDM problems are also categorized depending on the quality and amount of information (knowledge) available for the decision situation. If the information is perfect (precise), the decision is made under certainty (deterministic decision making). If the information is not precise, the decision is made under uncertainty, which may be probabilistic or fuzzy (imprecise). Accordingly, MCDM problems are classified as *deterministic*, *stochastic*, and *fuzzy MADM/MODM problems* (Malczewski, 2006). In ADNDP, the information is assumed to be known with certainty and hence deterministic MADM/MODM methods are used.

MCDM problems are different in nature. In this regard, several methods have been developed to solve MCDM problems. Multi-Attribute Utility Theory-MAUT (Keeney & Raiffa, 1976), TOPSIS (Hwang & Yoon, 1981), Preference Ranking Organization Method for Enrichment Evaluation-PROMETHEE (Brans & Mareschal, 1992), Elimination and Choice Expressing Reality-ELECTRE (Roy & Mousseau, 1996), Analytic Network Process-ANP and AHP (Saaty & Vargas, 2006; Saaty, 1980, 2003), Step-Wise Weight Assessment Ratio Analysis-SWARA (Keršuliene, Zavadskas, & Turskis, 2010); Decision Making Trial and Evaluation Laboratory-DEMATEL (Gabus & Fontela, 1972); Simple Additive Weighting-SAW (Churchman & Ackoff, 1954), and VlseKriterijumska Optimizacija I Kompromisno Resenje-VIKOR (Zeleny, 1982) are some examples of MADM methods. These and other MCDM methods have been applied in many areas. See, for example, survey papers by Romero and Rehman (1987) for natural resource management, Steuer and Na (2003) for financial decision-making, Huang, Kuo, and Lo (2011) for environmental sciences, Wang and Poh (2014) and Kumar et al. (2017) for energy and environmental modeling, Mahase, Musingwini, and Nhleko (2016) for mine planning, and Danesh, Ryan, and Abbasi (2017) for project portfolio management. There are also survey papers that focus on specific methods. See, for example, Wallenius et al. (2008) for MAUT, Behzadian, Khanmohammadi Otaghsara, Yazdani, and Ignatius (2012) for TOPSIS, Behzadian, Kazemzadeh, Albadvi, and Aghdasi (2010) for PROMETHEE, Govindan and Jepsen (2016) for ELECTRE, and Ho (2008) for AHP. Marttunen, Lienert, and Belton (2017) review the combinations of problem structuring and MCDM methods. In these surveys, deterministic, stochastic, and fuzzy modifications of MCDM methods, e.g., fuzzy AHP and TOPSIS, are included as well. Mardani, Jusoh, MD Nor, et al. (2015) and Kahraman, Onar, and Oztaysi (2015) survey specifically fuzzy MCDM methods. For detailed descriptions of the methods, we refer the reader to, e.g., Belton and Stewart (2002), French, Maule, and Papamichail (2009), Eisenführ, Weber, and Langer (2010), and Zopounidis and Pardalos (2010). In this paper, we will describe AHP and TOPSIS methods in Section 6.

MODM extends the single-objective optimization (mathematical programming) toward the consideration of multiple (conflicting) objectives and goals. In this regard, MODM problems (and the corresponding solution methods) can be categorized similar to the single-objective optimization problems, e.g., linear, non-linear, integer, stochastic, and fuzzy MODM problems. There are several survey papers regarding MODM. We refer the reader to, e.g., Cho, Wang, Chen, Chan, and Swami (2017) for a comprehensive survey on modeling techniques (e.g., cooperative game theory or auction theory) and solutions approaches (e.g., scalarization-based, metaheuristics, hybrid metaheuristics, and trust-based approaches); Marler and Arora (2004) for continuous nonlinear multi-objective optimization; Shin and Ravindran (1991) and Miettinen, Ruiz, and Wierzbicki (2008) for interactive methods; Ulungu and Teghem (1994) for multi-objective combinatorial optimization; Coello (2000, 2006), Coello, Lamont, and Van Veldhuizen (2007), Deb (2014), Konak, Coit, and Smith (2006), Tan, Lee, and Khor (2002), Van Veldhuizen and Lamont (2000), and Zhou et al. (2011) for evolutionary algorithms; Reyes-Sierra and Coello (2006) and Donoso and Fabregat (2016) for bio-inspired algorithms; Gutjahr and Pichler (2016) for stochastic multi-objective optimization; and Lootsma (1997) for fuzzy multi-objective optimization. Zopounidis and Pardalos (2010) and Ehrgott and Gandibleux (2002) also provide good state-of-the art surveys about MODM.

The concept of optimal solution in single-objective optimization problems is replaced with the concept of non-dominated (efficient) solutions (feasible solutions for which no improvement in any objective function is possible without sacrifice at least in one of the other objective functions) in multi-objective optimization models. Non-dominated solutions can be found using several techniques, e.g., scalarization and metaheuristics (e.g., evolutionary algorithms, ant colony optimization, particle swarm optimization, and simulated annealing). For a summary of solution techniques, please see, for example, Cho et al. (2017) and Marler and Arora (2004). In scalarization techniques, a single objective is formulated to capture multiple objectives. Weighted sum, ε-constraint, goal programming, min-max, and Benson's methods are examples of scalarization techniques. In this study, we use the weigthed sum method (e.g., Coello, 2000; Ritzel, Eheart, & Ranjithan, 1994; Saad, Han, Debbah, Hjørungnes, & Basar, 2009; Saad, Han, Basar, Debbah, & Hjorungnes, 2011; Steuer, 1986) where to-be-optimized single-objective function is obtained by taking the non-negative weighted sum of multiple objectives. The multi-objective mathematical program that we develop in the paper aims at determining the optimal locations of the depots and service assignments such that the total transportation cost and the risk levels of the located depots are minimized. The risk levels of the potential depot locations are computed using AHP and TOPSIS with AHP providing the weights needed by TOPSIS. Potential depot locations are determined by GIS analysis.

TOPSIS, developed by Hwang and Yoon (1981), is an approach to identify an alternative which is closest to the ideal solution and farthest to the negative ideal solution in a multi-dimensional computing space (Qin, Huang, Chakma, Nie, & Lin, 2008). *TOPSIS requires the decision maker's cardinal preferences of attributes,* e.g., *the weights for the attributes, as an input* (Hwang & Yoon, 1981). Behzadian et al. (2012) provide a state-of the-art literature survey on TOPSIS applications and methodologies since 2000. They state that TOPSIS has been applied in several areas, e.g., logistics, energy management, design, engineering, and manufacturing systems, water resources management, and health and safety management. They also state that *the recent trend of TOPSIS studies has been shifting towards combining TOPSIS with one or more methods*, e.g., AHP (e.g., Önüt & Soner, 2008), ANP (e.g., Shyur, 2006), mathematical programming (e.g., Shidpour, Shahrokhi, & Bernard, 2013), fuzzy set approach (e.g., Awasthi, Chauhan, Omrani, & Panahi, 2011; Kahraman, Cevik, Ates, & Gulbay, 2007), and group decision making (e.g., Li, Huang, & Chen, 2010), *rather than stand-alone usage of TOPSIS*. An analysis of the papers indicates that TOPSIS has been combined with AHP in about 25% of the papers where AHP has been used in determining the attribute weights and with mathematical programming in about 10% of the papers.

AHP, developed by Saaty (1980), enables the decision maker to structure a complex problem in the form of a simple hierarchy and to evaluate a large number of quantitative and qualitative factors in a systematic manner under conflicting multiple attributes (Badri, 1999). The major characteristic of AHP is the use of pair-wise comparisons based on the judgements of experts to derive priority scales, which are used both *to compare the alternatives with respect to the various attributes* and *to estimate attribute weights* (Loken, 2007). AHP has been extensively applied in many areas, e.g., finance, education, engineering, government, industry, sports, and manufacturing. See, for example, Steuer and Na (2003) and Vaidya and Kumar (2006) for *stand-alone* applications of AHP in many different areas. AHP has also been used in combination with other methods. Ho (2008) reviews the applications of AHP integrated with mathematical programming, QFD (Quality Function Deployment), meta-heuristics, SWOT analysis, and DEA (Data Envelopment Analysis). Wang and Poh (2014) and Zhou, Ang, and Poh (2006) find out that AHP is the most popular method to be used with other methods, e.g., MODM, MAUT, and ELECTRE. TOPSIS is another method widely used with AHP. See, for example, Önüt and Soner (2008); Maheshwarkar and Sohani (2013), Dağdeviren, Yavuz, and Kılınç (2009), Guzel, Erdal, and Acar (2015), Sirisawat and Kiatcharoenpol (2018), Kasirian and Yusuff (2013), Khorshidi and Hassani (2013), and Kuo, Yang, Cho, and Tseng (2008) for some examples of integrated usage of AHP and TOPSIS. We refer the interested reader to review papers, e.g., Kumar et al. (2017), Mardani, Jusoh, MD Nor, et al. (2015), Mardani, Jusoh, and Zavadskas (2015), Kahraman et al. (2015), and Subramanian and Ramanathan (2012) for other examples of integrated usage of MCDM methods including AHP and TOPSIS.

Attribute weights can be determined subjectively as in the AHP method or objectively as in the entropy method (Deng, Yeh, & Willis, 2000). Barron and Barrett (1996), Hobbs (1980), and Schoemaker and Waid (1982) provide surveys about subjective weighting methods. The results of these studies indicate that no method can guarantee a more accurate result because decision makers are not always consistent with their judgements in different weighting methods (Velasquez & Hester, 2013). In this study, we prefer to use AHP as the weighting method because (1) the problem context requires multiple decision makers to state their preferences with regard to attributes and the method has an accepted method to combine the preferences of the decision makers to achieve consistency, (2) the method is easy to apply and explain to the decision makers, (3) the (sub-)attributes can be structured within a hierarchy, (4) there are no dependence and feedback between the (sub-) attributes, i.e., they are independent, (5) the method provides an inconsistency measure regarding the pairwise comparisons of the decision makers, and (6) the number of (sub-)attributes abides by the 7 ± 2 rule (Saaty & Ozdemir, 2003; Miller, 1956). 7 ± 2 rule states that, in making preference judgements on pairs of elements in a group, the number of elements in the group should be limited to seven plus or minus two because of our capacity to process information on simultaneously interacting elements with accuracy and validity. When the number of elements is seven or less (more), the inconsistency measurement is relatively large (small) with respect to the number of elements. In the former, it is easy to determine the most inconsistent judgement and improve consistency. In the latter, on the other hand, it is difficult because improving inconsistency requires small perturbations in judgements, which is hard to justify for a valid outcome. Even though it is possible to use AHP in assigning (risk) scores to the alternatives in order to rank them, we prefer not to use AHP because otherwise we would violate the 7 ± 2 rule (there are 13 potential MD locations). We use TOPSIS in assigning final (weighted) scores to potential MD locations because (1) it is simple to apply and program and requires the same number of steps regardless of the problem size (Ic, 2012); (2) the problem structure satisfies the requirements that attribute values must be numeric, monotonically increasing or decreasing, and have commensurable units to apply the technique (Behzadian et al., 2012); (3) there is a need to obtain scores between zero (0) and one (1) as they are used in the mathematical model, and (4) the literature indicates that the combined usage of AHP and TOPSIS has been successfully applied in many different problem contexts.

In determining the locations of MDs, we use GIS query and analysis. Malczewski (2006) surveys the GIS-based MCDM approaches from 1990 to 2004 and classifies the articles considering several criteria. He classifies the papers into four categories with respect to the extent of integration of GIS and MCDM: (1) no integration, (2) loose coupling, (3) tight coupling, and (4) full integration. In (2), GIS and MCDM approach exchange files such that one uses data from the other system as the input data. In (3), a single data model and a common interface is used. In (4), user-specified routines are specified and added to the routines of GIS package. In our study, the results of spatial query and analysis conducted using GIS are fed to the MCDM approach, i.e., GIS and MCDM are loosely coupled.

In the following sections, we give the problem description and detail the MCDM and GIS approaches.

3. Problem description and solution methodology

The ADS of GCG consists of five entities: (1) supply points, (2) MD (s), (3) RDs, (4) LDs, and (5) units. The flow of ammo between the entities in the current ADS is depicted in Fig. 1. Ammo procured from national or international suppliers is moved to MD. After undergoing processes such as parsing, classification, and grouping at MD, ammo is transported to RDs and to LDs assigned to MD. Similarly, ammo is sent

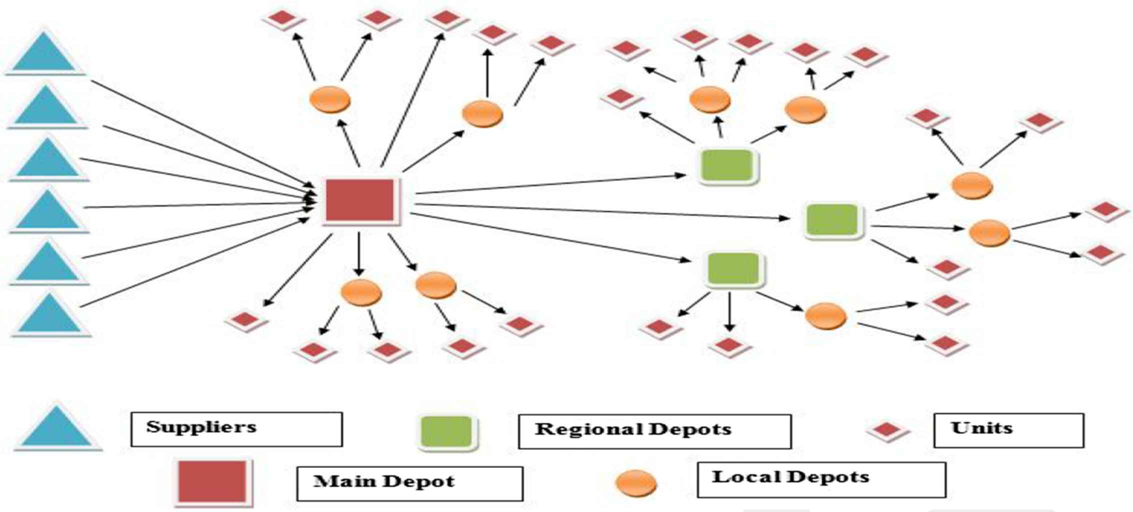

Fig. 1. The schematic representation of the flow of ammo between the entities in the current ADS.

from RDs to LDs assigned to them. Finally, ammo is transported from LDs to the units. MD and RDs directly supply the units in the provinces where they are located and hence LDs are not used in those provinces. In the remaining provinces, LDs supply the units. That is, in each province, either MD, one of RDs, or LD in the province is responsible for supplying ammo to the units within the boundary of the province. Transportation between all entities is carried out using trucks.

The current stocking policy of GCG requires MD, RDs, LDs, and units to keep a certain amount of inventory. A unit carries only *on-unit inventory* (inventory of ammo that will be sufficient for the unit just to operate for a few days) that may change depending on the structure and type of the unit. An LD keeps an inventory of ammo that is equivalent to the sum of the on-unit inventories and the inventory to meet the needs of all units assigned to it for the current year. An RD holds stock to meet the needs of all LDs and units under its responsibility for one year (after the needs for the current year are satisfied), i.e., the quantity of ammo to be transported to an RD is twice the total needs of LDs and units allocated to it. MD holds stock to meet the needs of all units in 81 provinces for three years (after the needs of RDs and units under its responsibility for the current year are met). So, the inventory of MD and RDs change depending on the LDs and units assigned to them and inventory transfer between RDs and LDs is not allowed. GCG prefers to use the same stocking policy in the new system but may change it if the analysis results confirm. In this regard, there is a need to try different stocking policies in the analysis.

Ammo may be sourced from national and international suppliers. Suppliers are grouped into six different supply points considering their locations. Of these six locations, four correspond to the locations of domestic manufacturers and two correspond to domestic ports of entry for international suppliers. Suppliers can source certain types of ammo within their capacity limits. Even though there are thousands of ammo types, they are classified into four groups considering their properties with regard to transportability and storage: (1) small arms ammo, (2) heavy weapons ammo, (3) explosives, and (4) pyrotecnic goods.

In the current system, there is a single MD and three RDs. The new system may have one or more MDs. If the current province is selected as an MD location, its current location in the province needs to be changed due to security, safety, and some other reasons. The new MDs may be located in any province satisfying *certain spatial criteria and risk attributes*. However, the spatial criteria and the risk attributes to be considered and how much the provinces satisfy these are not known. (The purpose in the design of ADS at this step is to determine the provinces where MDs will be located because deciding the exact location requires the consent of several other parties, e.g., municipality, ministries, etc.) The new system may or may not have RDs. If there occurs a need, however, they are allowed only in their current locations because there are not enough security units in other provinces and significant changes in unit formations are not desired. So, a decision is to be made about whether RDs should be closed or kept open. Finally, depending on the new locations of MDs and RDs, LDs are to be assigned to one MD or one RD to get service.

In differentiating between alternative designs, two criteria are considered as important: (1) total transportation cost and (2) risk levels of provinces where MD is to be located. Fixed costs, e.g., the cost of constructing an MD or RD, and the procurement costs of ammo are not taken into account because they do not change based on the locations of MD and RDs. Considering risk is important to ensure that provinces with better properties are selected and hence a reliable distribution system is established. For example, it is not desired to locate an MD in a province where disaster risk is high.

To summarize, GCG faces the problem of determining (1) the number and locations of MDs and RDs and (2) the assignment of RDs (LDs) to MDs (MDs or one of RDs) such that total transportation cost and risk levels are minimized.

There is no model, methodology, or guidance that GCG can use to design the new ADS. In this regard, we develop a methodology whose basic steps are given in Fig. 2. In the first step, we conduct interviews with the experts from GCG and analyze the current ADS in order to describe the problem. We finally come up with the planning issues discussed above (Section 3). Having described the problem, we develop a multi-objective optimization model in order to determine the optimal locations and assignments of MDs and RDs where the total transportation cost and the *risk levels of MD locations* are minimized (Section 4). We collect data with regard to demands, capacities, costs, etc. needed in the optimization model from experts and several documents. However, data regarding potential MD locations and their associated risk levels are not readily available. In this regard, we conduct analyses in order to determine (1) the potential MD locations and (2) the risk levels of potential MD locations. In (1), we identify *spatial criteria* and apply them using GIS analysis for filtering potential MD locations (Section 5). In (2), we compute the risk levels of the potential MD locations determined in (1) using combined AHP-TOPSIS analysis where TOPSIS is used to compute the risk levels (scores) of potential MD locations while AHP is used to determine the weights needed by TOPSIS for the identified risk attributes (Section 6). After verifying and validating the model, we solve the multi-objective model using several scenarios designed with the aid of the experts and analyze the the results of the scenarios. We present the resulting efficient solutions to the decision

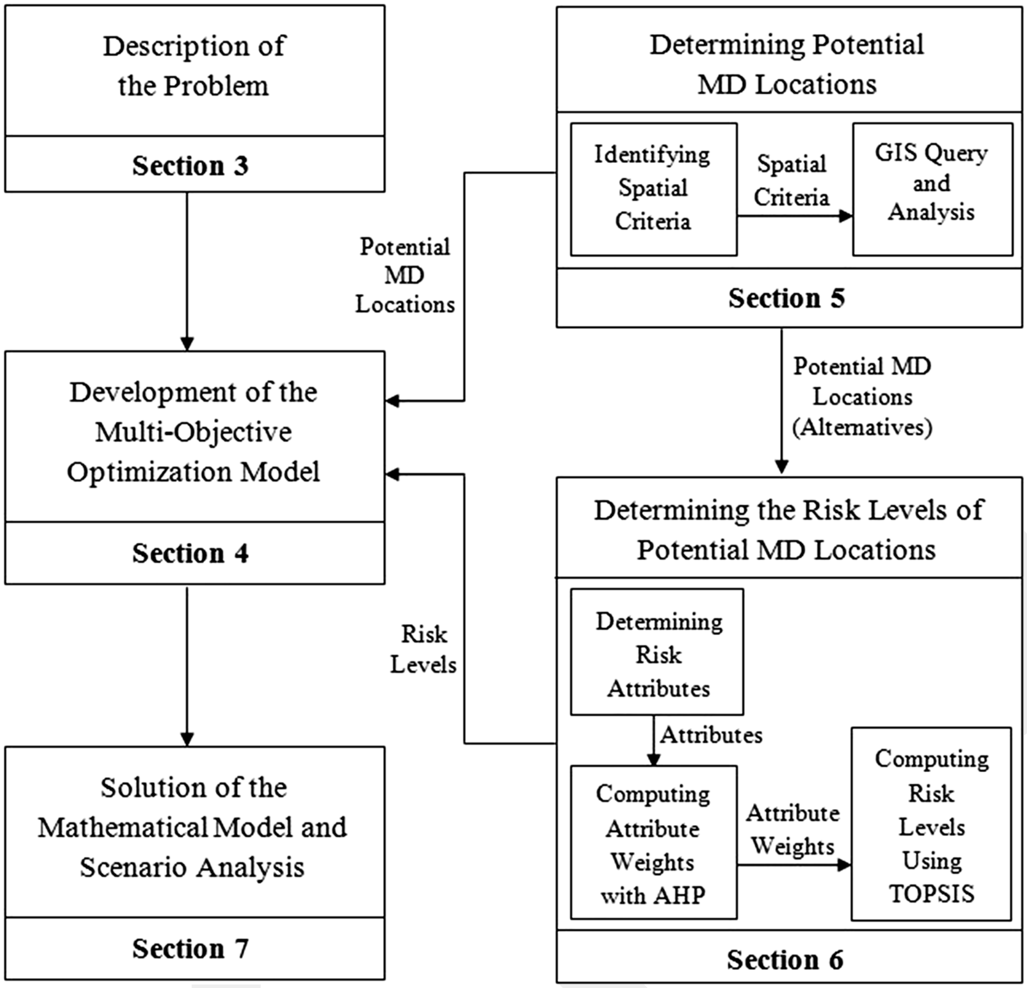

Fig. 2. Schematic representation of the proposed methodology.

makers.

In the following sections, we detail the steps of the methodology. For confidentiality purposes, the names of the provinces are represented as PX where X is a number randomly assigned.

Even though our methodology has been developed specifically for ADNDP, it can be applied in many different problem contexts by changing the specifics of each step as necessary. For example, the spatial criteria used for determining the potential locations and the attributes for determining the (dis)utilities of the alternative locations may be changed. As long as the attributes are independent, AHP and TOPSIS may be used for determining the (dis)utilities. If the attributes are not independent, other MADM methods, e.g., ANP, may be used for computing the (dis)utilities. The details of the mathematical model may be changed as well; however, as long as there is a tradeoff between the (dis)utilities of the alternative locations and some other objectives, the multi-objective model may be used to determine the final locations.

4. Development of the multi-objective optimization model

In ADNDP, we consider each province as a *demand point*. For ease of representation, we can think of these demand points as LDs in the provinces where there are no MDs or RDs. A province where an MD (RD) is located acts both as an LD and as an MD (RD). Thus, each province is assigned either a single role (LD) or a double role (LD + MD or LD + RD). This property of ADNDP differentiates it from most DND problems in the literature where the entities in each layer play a single role (e.g., plant, depot, etc.). Note that this also allows flows between the entities in each layer, e.g., if a potential MD node in the MD layer is not selected as MD, it should be supplied by another node (RD or MD).

We model ADNDP on a directed and connected network $G = (I, A)$ with node set I and arc set A. I consists of four types of nodes: (1) supply points I_k, (2) potential MD nodes I_a, (3) RD nodes I_t, and (4) LD nodes I_{bb} with $I_{bb} \cap I_a = \varnothing$ and . Thus, $I = I_k \cup I_a \cup I_t \cup I_{bb}$. Let $I_b = I_a \cup I_t \cup I_{bb}$ be the set of all demand points (provinces). We define the arc set A considering possible flows between the nodes. Flows occur (1) from a node in I_k to a node in I_a, (2) from a node in I_a to a node in I_t and I_{bb}, (3) from a node in I_t to a node in I_{bb}, (4) between nodes in I_a (when a node $i \in I_a$ is not selected as MD, it may be supplied from $j \in I_a$ selected as MD), (5) between nodes in I_t (when a node $i \in I_t$ is not selected as RD, it may be supplied from $j \in I_t$ selected as RD), and (6) from a node in I_t to a node in I_a that is not selected as an MD. The last three flows are allowed to correctly model single (LD) and dual (LD + MD or LD + RD) role of a node in I_a and I_t. Note that, given these requirements, flows in ADNDP cannot be modeled by only standard flow-balance constraints.

The annual capacity of a supply point $i \in I_k$ for a specific ammo type $m \in M$ is $capm_i^m$. The annual demand for ammo type $m \in M$ at demand node $i \in I_b$ is defined as D_i^m and may change depending on the structure and mission of the units at node i. The required inventory level for a specific ammo type m at MD and RD nodes is determined based on current regulations discussed above. MDs and RDs have prespecified capacities of cap_i and $capt_i$, respectively.

c_{trans} is defined as the average transportation cost per one ton of ammo per kilometer (km) and determined considering fuel, salary, maintenance and amortization costs. c_{ij} is defined as the distance in kms. For each potential MD location $i \in I_a$, a risk score (level)

Table 1
The parameters and the decision variables used in the model.

Sets	
I:	Set of all nodes $I = I_k \cup I_a \cup I_t \cup I_{bb}$
I_k:	Set of supplier nodes $I_k \subset I$
I_a:	Set of potential MD nodes $I_a \subset I$
I_t:	Set of RD nodes $I_t \subset I$
I_{bb}:	Set of LD nodes such that $I_{bb} \cap I_a = \varnothing$ and $I_{bb} \cap I_t = \varnothing$
I_b:	Set of all demand points (provinces) $I_b = I_a \cup I_t \cup I_{bb}$
M:	Set of ammo types $m \in M$
Parameters	
$capm_i^m$:	The annual capacity of a supply point $i \in I_k$ for a specific ammo type m
cap_i:	Capacity of MD node i
$capt_i$:	Capacity of RD node i
c_{ij}:	Distance between nodes i and j
c_{trans}:	Average transportation cost per one ton of ammo per kilometer
D_i^m:	The annual demand for ammo type m at demand node $i \in I_b$
p:	Number of MDs to be located
δ:	Weighting coefficient
w_i:	Risk score of potential MD node i with $w_i \in (0, 1)$
Decision variables	
S_i^m:	Amount of inventory of type m ammo at node i
x_{ij}^m:	Amount of flow of type m ammo from node i to node j
A_i:	1, if MD is located at node i; 0, otherwise
y_{ij}:	1, if node i is served by a facility at node j; 0, otherwise

$w_i \in (0, 1)$ is computed using combined AHP-TOPSIS analysis (Section 6). w_i shows how sensitive node i is against several risks. The objectives in the model are to minimize the total transportation cost and the average risk level of MD locations and hence the resulting model is multi-objective. However, we convert the multi-objective model into a single-objective model using the weighting method and find efficient solutions by changing the weight δ for the second objective.

We define four decision variables: (1) S_i^m is the amount of inventory of type m ammo at node i, (2) x_{ij}^m is the amount of flow of type m ammo from node i to node j, (3) A_i takes the value of 1 if MD is located at node i and 0 otherwise, and (4) y_{ij} takes the value of 1 if node i is served by a facility at node j. Because the locations of RDs are fixed and we need to decide whether they should be closed or not, we do not define location variables for them but consider all alternatives under different scenarios. The parameters and the decision variables used in the model are given in Table 1.

We next give the model for ADNDP.

Model ADNDM: Ammunition Distribution Network Design Model

Objective function:

$$\text{Min} \quad z = z_1 + \delta z_2 \tag{1}$$

$$z_1 = \sum_{i\in I_k}\sum_{j\in I_a}\sum_{m\in M} c_{trans}\cdot c_{ij}\cdot x_{ij}^m + \sum_{i\in I_a}\sum_{j\in I_b}\sum_{m\in M} c_{trans}\cdot c_{ij}\cdot x_{ij}^m + \sum_{i\in I_t}\sum_{j\in I_b}\sum_{m\in M} c_{trans}\cdot c_{ij}\cdot x_{ij}^m \tag{2}$$

$$z_2 = \sum_{i\in I_a} w_i\cdot A_i \tag{3}$$

Constraints:

$$\sum_{j\in(I_a\cup I_t)} x_{ji}^m = D_i^m \qquad \forall\ i \in I_b, \quad \forall\ m \in M \tag{4}$$

$$\sum_{j\in I_b} x_{ij}^m - \sum_{j\in I_k} x_{ji}^m = -S_i^m \qquad \forall\ i \in I_a, \quad \forall\ m \in M \tag{5}$$

$$3\cdot \sum_{j\in I_b} D_j^m\cdot A_i = S_i^m \qquad \forall\ i \in I_a, \quad \forall\ m \in M \tag{6}$$

$$\sum_{j\in I_b} x_{ij}^m + D_i^m = S_i^m \qquad \forall\ i \in I_t, \quad \forall\ m \in M \tag{7}$$

$$S_i^m + \sum_{j\in I_b} x_{ij}^m - \sum_{j\in I_a} x_{ji}^m = 0 \qquad \forall\ i \in I_t, \forall\ m \in M \tag{8}$$

$$\sum_{j\in I_k}\sum_{m\in M} x_{ji}^m \le cap_i.\ A_i \qquad \forall\ i \in I_a \tag{9}$$

$$x_{ij}^m \le capm_i^m\cdot A_j \qquad \forall\ i \in I_k, \forall\ j \in I_a, \forall\ m \in M \tag{10}$$

$$x_{ij}^m \le capt_i\cdot A_j \qquad \forall\ i \in I_a, \forall\ j \in I_t, \forall\ m \in M \tag{11}$$

$$x_{ij}^m \le D_j^m\cdot y_{ij} \qquad \forall\ i \in (I_a \cup I_t), \forall\ j \in (I_a \cup I_{bb}), \forall\ m \in M \tag{12}$$

$$x_{ij}^m \le \sum_{i\in I_b}\sum_{m\in M} D_j^m\cdot y_{ij} \qquad \forall\ i \in (I_a \cup I_t), \forall\ j \in I_t, \forall\ m \in M \tag{13}$$

$$\sum_{i\in(I_a\cup I_t)} y_{ij} = 1 \qquad \forall\ j \in I_{bb} \tag{14}$$

$$\sum_{i\in(I_a\cup I_t)} y_{ij} = 1 \qquad \forall\ j \in I_t \tag{15}$$

$$\sum_{\substack{i\in(I_a\cup I_t)\\(i\neq j)}} y_{ij} + A_j = 1 \qquad \forall\ j \in I_a \tag{16}$$

$$\sum_{i\in I_a} A_i = p \tag{17}$$

$$A_i, y_{ij} \in \{0, 1\} \qquad \forall\ i, j \in I \tag{18}$$

$$S_i^m, x_{ij}^m \ge 0 \qquad \forall\ i, j \in I, m \in M \tag{19}$$

Objective functions (2) and (3) represent the total transportation cost and the total risk of selected MDs, respectively. Objective function (1) is obtained by taking the nonnegative weighted sum of objective functions (2) and (3) and then normalizing the resulting weighted objective function by the weight of objective function (2). An efficient solution is found when ADNDM is solved with objective function (1) for a given value of δ. Constraints (4) are demand satisfaction constraints; the flow from the nodes in $I_a \cup I_t$ to a demand point should be equal to the demand of the node. Constraints (5) are flow-balance constraints for potential MD nodes. Constraints (6) and (7) set the inventory level at a potential MD and RD node to the required quantity (three times the total demand and one-year demand of assigned demand points) for each ammo type, respectively. Constraints (8) are flow-balance constraints for RD nodes. Constraints (9) allow flows from supply points to a potential MD node when it is selected as an MD location. Constraints (10) and (11) are capacity constraints for supply points and potential MD nodes, respectively. Constraints (12) and (13) ensure that flows from node j to node i are not allowed unless node i is served by node j. Constraints (14) requires each demand point (all provinces) to be assigned to only one MD or RD. Constraints (15) ensure that each potential RD location is assigned to one MD or one RD location (If assigned to an RD, it is treated as an LD). Constraints (16) assign a potential MD node either as an MD or as a demand point. Constraints (16) and (17) handle single and dual roles of RD and MD nodes. Constraints (17) require p facilities to be selected. Constraints (18) and (19) define the decision variables.

5. Determining the potential MD locations: GIS spatial query and analysis

We determine potential MD locations (provinces) through spatial query and analysis. Our goal is to eliminate provinces that are not appropriate for being used as MD locations at all through a set of *spatial* criteria. The spatial criteria we consider are (1) the proximity to the border (border layer), (2) the frequency of terror events (terror layer), and (3) the magnitude and probability of disasters (earthquake, flood, snowslide, and landslide layers). We collect non-graphical and graphical data for these criteria and build a database for GIS query and

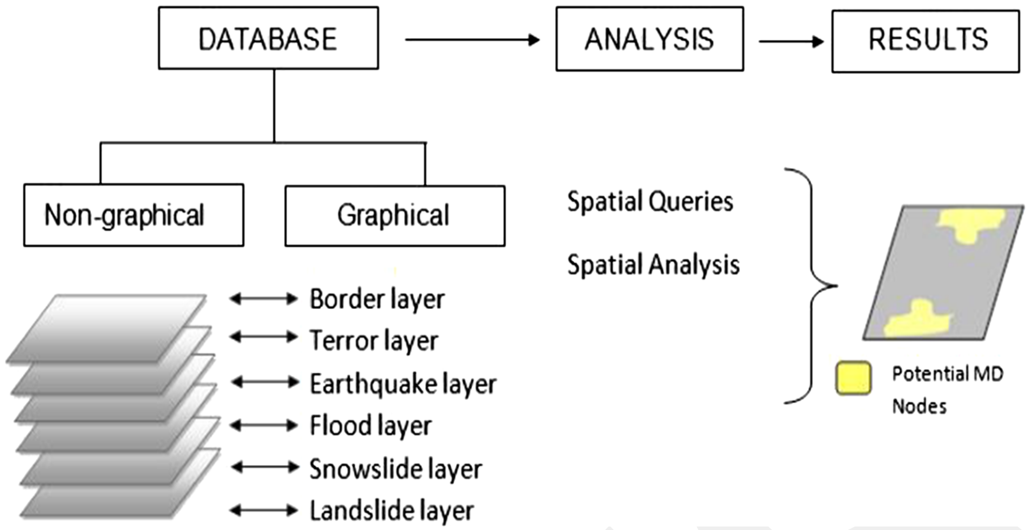

Fig. 3. Schematic representation of the GIS analysis.

analysis. We, then, use graphical and non-graphical data together with raster and vector map layers to conduct the analysis. In the conduct of the analysis, we use the ArcGIS 10.0 software that provides us with the opportunity to open the prepared layer with road network data to analyze accessibility to potential MD locations. Fig. 3 shows the steps and the spatial criteria used in the analysis.

The main steps of the analysis are: (1) Gather and digitize the raster disaster hazard maps obtained from the official website of AFAD (Disaster and Emergency Management Presidency in Turkey) (AFAD, 2017); (2) Correct the topological errors and georeference all data to UTM (Universal Transform Mercator) projection system and WGS-84 datum, (3) Add terror data to the attribute table of the terror layer with "join&relates" feature, (4) Prepare disaster layers by using "selection" feature to determine the first-degree disaster risk zones and the riskiest terror zones, (5) Open the vector map of AFAD consisting of line shapefile and the vector map of the world consisting of poligon shapefile and prepare the border layer using "select by location" feature with buffer zone analysis, (6) Perform the overlay analysis and merge all layers in a single layer, and (7) Complete the analysis and obtain the final map. As a result of the analysis, 13 provinces are selected as the potential MD locations. We represent these provinces with P03, P06, P18, P26, P38, P42, P50, P51, P58, P66, P68, P70, and P71 in the rest of the analysis.

6. Determining the risk levels of potential MD locations

To determine the risk levels of the provinces selected as potential MD locations, we use AHP and TOPSIS in combination. We summarize the steps of the combined approach in Fig. 4. The steps on the left and right define the steps of AHP and TOPSIS, respectively. Note that AHP is used to compute the weights needed by TOPSIS while TOPSIS is used to compute the risk levels of MD locations. In the following, we explain the AHP and TOPSIS methodologies and show their application to our problem.

6.1. The AHP method

(1) *Identify the risk attributes and design the attribute hierarchy*: Attributes to be used in the evaluation of the potential MD locations with respect to their risk levels are determined and structured in a tree-like hierarchy by 21 experts from GCG as shown in Fig. 5. Attribute hierarchy consists of the goal of the study (first level), the main attributes (the second level), and the sub-attributes under each main attribute if defined (the third level). (C1a through C1d, C2a through C2d, C3a and C3b, and C4a through C4c in the third level).

(2) *Do pairwise comparison of the (sub)attributes*: Let $C1$, $C2$, $\cdots$, Cn denote the set of attributes to be compared and a_{im} represent a quantified judgment on a pair of attributes, C_i and C_m. The degree of preference of one attribute over another is expressed using a 1–9 scale where the verbal judgments can be expressed as follows: 1 if equally preferred, 3 if moderately preferred, 5 if strongly preferred, 7 if very strongly preferred, and 9 if extremely preferred; 2, 4, 6, and 8 are used for compromise between the above values. In this regard, a pairwise comparison matrix is constructed by assigning $1/a_{im}$ for the pair (C_m, C_i) if a value of a_{im} is assigned for the pair (C_i, C_m). As an example, if C_i is very strongly preferred to C_m, then $a_{im} = 7$ and $a_{mi} = 1/7$. The values on the diagonal are 1. The structure of a pairwise comparison matrix is given in (20).

$$A = [a_{im}] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{21}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \qquad i,\, m = 1,\, 2,\, \cdots, n \tag{20}$$

In our problem, pairwise comparisons are conducted for (1) main attributes (C1 through C6) and (2) sub-atrributes (C1a through C1d, C2a through C2d, C3a and C3b, and C4a through C4c) under main attributes C1 through C4 by 21 experts as defined above. That is, each expert composes five pairwise comparison matrices.

(3) *Check consistency of the pairwise comparisons*: The relative weights of the attributes for a pairwise comparison matrix are obtained by the right eigenvector (w) that correspons to the largest eigenvalue (λ_{max}) as in (21).

$$Aw = \lambda_{max} w \tag{21}$$

Before using the weights, the quality of the pairwise comparisons should be checked. If the pairwise comparisons are completely consistent, $\lambda_{max} = n$. The consistency of a pairwise comparison matrix is dependent on the relation between the entries of A: $a_{ij} a_{jk} = a_{ik}$. The consistency index (CI) is

$$CI = (\lambda_{max} - n)/(n - 1) \tag{22}$$

The consistency ratio (CR) indicates whether the comparisons are sufficiently consistent and computed as the ratio of the CI and the random index (RI) as in (23). The RI for the number of attributes compared in a matrix is given in Table 2 (Saaty, 1980).

$$CR = CI/RI \tag{23}$$

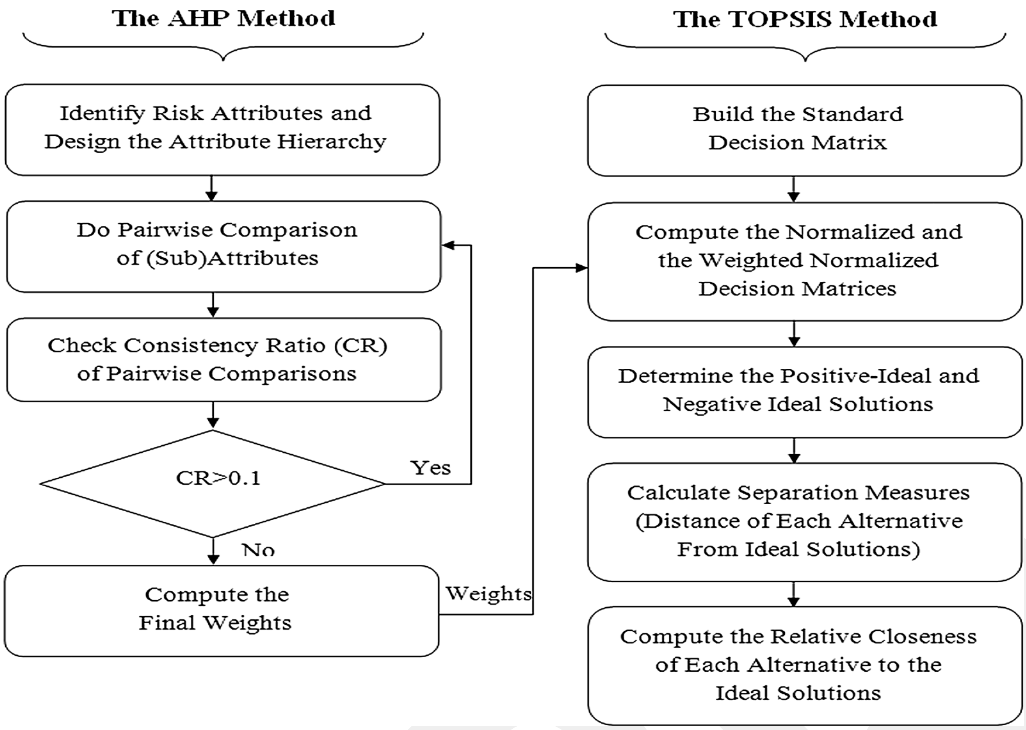

Fig. 4. The steps of the combined AHP-TOPSIS analysis.

If CR is less than 0.1, the judgments are considered to be consistent and the resulting weights can be used. Otherwise, the evaluation procedure is repeated to improve the consistency of the judgments.

In our problem, we compute the eigenvalues and consistency ratios for each pairwise comparison matrix constructed by each expert using Expert Choice software. For all matrices, a CR value less than 0.1 is obtained, i.e, the experts are consistent in their evaluations.

(4) *Compute the final weights*: If there are multiple evaluators as in our problem, their evaluations must be combined to obtain a single pairwise comparison matrix for each evalution. The evaluations are combined computing the geometric mean of the values assigned by the experts. Given that there are r experts, to find a single pairwise comparison value for the pair (C_i, C_m), $\sqrt[r]{\prod_{l=1}^{l=r} a_{iml}}$ with a_{iml} representing the judgement of the expert l is used.

Table 2
The random index.

Number of attributes	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

In our case, we obtain five combined pairwise comparison matrices and compute the local weights, i.e., for each pairwise comparison matrix, and the consistency ratios. To determine the final weights for the subattributes in the third level, local weights are multiplied considering the hierarchy. For example, to obtain the global weight of C1a, we need to multiply the local weight of C1 with that of C1a, i.e.,

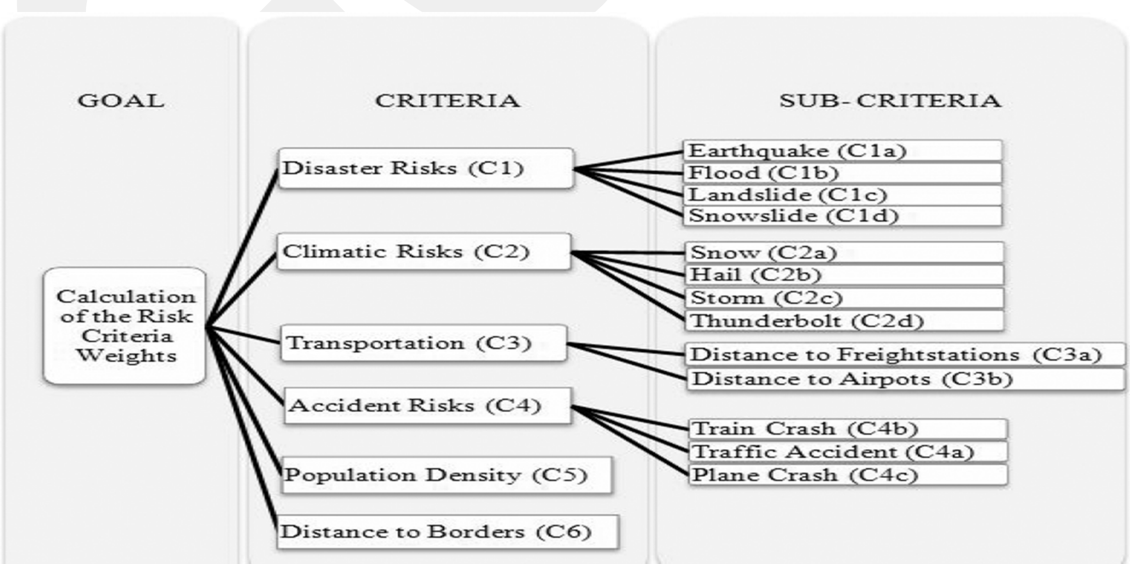

Fig. 5. AHP hierarchy.

Table 3
Weights computed using AHP.

Risk attributes	C1	C1a	C1b	C1c	C1d	C2	C2a	C2b	C2c	C2d
Local weights	0.425	0.587	0.218	0.123	0.072	0.042	0.175	0.045	0.494	0.285
Global weights	0.425	0.249	0.093	0.052	0.031	0.042	0.007	0.002	0.021	0.012

Risk attributes	C3	C3a	C3b	C4	C4a	C4b	C4c	C5	C6
Local weights	0.105	0.75	0.25	0.099	0.528	0.333	0.14	0.056	0.274
Global weights	0.105	0.078	0.026	0.099	0.052	0.033	0.014	0.056	0.274

Table 4
Consistency ratios.

	Goal	C1	C2	C3	C4	Overall consistency
CR	0.0124	0.0072	0.0162	0.0000	0.0000	0.0762

$0.425 \times 0.587 = 0.249$. The local and global weigths and consistency ratios are given in Tables 3 and 4. The results indicate that C1 (disaster risks) and C6 (distance to borders) are the two most important risk attributes while C2 is the least important attribute. Among C1 subattributes, C1a (earthquake risk) is the most important one.

6.2. The TOPSIS method

(1) *Build the standard decision matrix*: A decision matrix of the form as in (24) is constructed where A_j denotes the alternatives $j = 1, 2, \cdots, J$; F_i represents the *ith* attribute, $i = 1, 2, \cdots, n$,; and f_{ij} is a crisp value indicating the performance rating of each alternative A_i with respect to each attribute F_j.

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_J \end{array} \begin{array}{c} \begin{array}{cccccc} F_1 & F_2 & \cdots & F_j & \cdots & F_n \end{array} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1j} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2j} & \cdots & f_{2n} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{i1} & f_{i2} & \cdots & f_{ij} & \cdots & f_{in} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{J1} & f_{J2} & \cdots & f_{Jj} & \cdots & f_{Jn} \end{bmatrix} \end{array} \tag{24}$$

We obtain data for C5, C6, and each subattribute in the third level. All data used in TOPSIS calculations are quantitative and real. Data for C1a, C1b, C1c, C1d, C2a, C2b, C2c, C2d, C4a, C4b, and C4c are obtained from the official website of the AFAD (2017) by polling the National Disaster Archive of Turkey. AFAD includes a disaster event in the archive if one or more of the following criteria holds: (1) at least 10 dead people, (2) at least 50 injured people, (3) at least 100 people suffering from the disaster, and (4) affects the normal life in the disaster area. Data of C3a and C3b are obtained using the “get directions” feature of Google Maps and the distances for C6 are measured using ArcGIS 10.0. Finally, data for C5 are withdrawn from the address-based population registration system of the Turkish Statistical Institute (TUIK) (2017). Collected data and weights for the criteria are given in Table 5.

(2) *Compute the normalized and the weighted normalized decision matrices*: The normalized decision matrix consists of entries r_{ij} obtained using (25) and the weighted normalized decision matrix consists of entries V_{ij} obtained using (26) where w_i represents the weight of the i^{th} attribute. Table 6 presents the weighted normalized decision matrix.

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{n} f_{ij}^2}} = 1, 2, \cdots, J; \quad i = 1, 2, \cdots, n \tag{25}$$

$$V_{ij} = w_i x r_{ij}, \; j = 1, 2, \cdots, J; \quad i = 1, 2, \cdots, n \tag{26}$$

(3) *Determine the positive-ideal and negative-ideal solutions*: The positive-ideal and negative-ideal solutions are determined using (27) and (28) where I' and I'' are associated with the benefit and cost attributes, respectively.

$$A^* = \{(\max_j v_{ij} | i \in I'), (\min_j v_{ij} | i \in I'')\}, \quad A^* = \{v_1^*, v_2^*, \cdots, v_i^*\} \tag{27}$$

$$A^- = \{(\min_j v_{ij} | i \in I'), (\max_j v_{ij} | j \in I'')\}, \quad A^- = \{v_1^-, v_2^-, \cdots, v_i^-\} \tag{28}$$

(4) *Calculate separation measures (distance of each alternative from the ideal solutions)*: The separation of each alternative from the positive-ideal (negative-ideal) solution, D_j^* (D_j^-), is computed as in (29) and (30).

$$D_j^* = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^*)^2} \quad j = 1, 2, \cdots, J \tag{29}$$

$$D_j^- = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^-)^2} \quad j = 1, 2, \cdots, J \tag{30}$$

(5) *Compute the relative closeness of each alternative to the ideal solution (Risk Score)*: The relative closeness of alternative A_j can be expressed as in (31) where the index value (*risk score*) CC_j^* lies between 0 and 1. The smaller the index value means the better the performance of the alternatives for our problem.

$$CC_j^* = \frac{D_j^-}{D_j^* + D_j^-} \quad j = 1, 2, \cdots, J \tag{31}$$

Table 7 presents the final ranking of potential MD locations with the weights incorporated. The results indicate that P71 has the minimum risk scores with a CC_j value of 0.1359 and P58 has the highest risk coefficient with a CC_j value of 0.6162.

In order to check whether the ranking of the alternatives changes depending on the MADM methodologies used, we have used SWARA and DEMATEL for computing the weights and SAW and VIKOR for ranking the alternatives. The results indicate that the ranking of the alternatives does not change but the relative differences between risk levels of the alternatives change. Because the relative differences of the risk levels are sharper with the AHP-TOPSIS approach, we have decided to use this approach.

We remark that if there occurs a need to add a new risk attribute, all pairwise comparisons in the AHP analysis need to be conducted from scratch. The new attribute may change the weights and their relative differences as well as their ranking significantly. The new attribute may violate the independence assumption of the attributes and using another method, e.g., ANP, may be required. We have not been able to conduct exhaustive tests to determine whether the results (weights and risk levels) change or not if other methods are used; not only the relative differences of the risk levels and the weights but also their ordering may change with some other methods even if the same attribute set is used because the decision makers are not consistent in their

Table 5
The decision matrix (input values) of the TOPSIS analysis.

Weight	0.249 C1a	0.093 C1b	0.052 C1c	0.031 C1d	0.007 C2a	0.002 C2b	0.021 C2c	0.012 C2d	0.078 C3a	0.026 C3b	0.052 C4a	0.033 C4b	0.014 C4c	0.056 C5	0.274 C6
P03	6	3	3	0	1	6	18	0	2.3	5.2	0	0	0	703,948	207
P06	4	8	17	0	0	15	29	1	3.6	17.1	3	4	5	4,965,542	188
P18	5	1	7	0	0	1	10	0	0.85	149	2	0	0	184,406	153
P26	2	0	0	0	0	5	0	1	1.7	6	1	1	0	789,750	148
P38	4	3	9	0	1	1	9	0	0.11	6.8	0	0	0	1,274,968	205
P42	3	1	3	1	2	18	18	1	0.75	17.5	4	0	0	2,052,281	152
P50	0	0	0	0	8	29	52	2	60.8	87.6	0	0	0	285,190	201
P51	1	0	0	2	0	1	1	0	0.35	133	1	1	0	340,270	129
P58	5	12	35	2	6	12	14	0	2.3	203	2	0	0	623,535	149
P66	3	3	4	0	3	2	4	0	44.3	173	2	0	0	453,211	208
P68	0	2	2	0	0	1	6	0	118	142	1	0	0	379,915	181
P70	0	0	5	0	0	5	4	0	113	129	0	0	0	235,424	114
P71	0	4	6	0	0	0	25	0	2.8	89.5	1	0	0	274,727	222

evaluations when different methods are used.

7. Solution of the proposed model ADNDM and scenario analysis

To assess and gain insight about the results of ADNDM, we define and solve a set of scenarios. The scenarios are defined on the network structure described in Section 3. The distances between the nodes in the network are taken from the distance table prepared by the General Directorate of Highways in Turkey. Cost values are obtained from the experts working in the GCG Headquarters. Risk levels of potential MD locations are as given in Table 7.

ADNDM is coded with GAMS 22.3 and solved with the solver CPLEX 12.1. All computations are conducted on a laptop with 2.60 GHz CPU, 4 GB RAM, and Windows 8 operating system. The solutions are obtained in a matter of seconds for all scenarios.

7.1. Scenarios

We develop 10 scenarios in addition to the current scenario (S0) by changing the locations, assignments, and stocking policies of MD and RDs. We solve ADNDM for each scenario with $p = 1, 2,$ and 3, and obtain efficient solutions by changing the value of δ in the objective function (1) by increments of 50 as necessary. Table 8 summarizes the constructed scenarios detailed below.

Scenario 0 (S0) represents the current system. The location and service assignment decisions of MD and RDs are fixed in the model. MR and RDs keep a stock equal to three-year demand of all units and one-year demand of units assigned to them, respectively. This scenario allows us to compute the cost and risk level of the current system by setting $\delta = 0$.

Table 7
The risk scores and the ranking of potential MD locations.

	Separation measures		Relative closeness	Final ranking
	D_i^*	D_i^-	CC_j	
P03	0.1214	0.1263	0.5100	11
P06	0.0945	0.1155	0.5501	12
P18	0.1192	0.1091	0.4778	10
P26	0.1469	0.0517	0.2602	3
P38	0.1249	0.0865	0.4092	9
P42	0.1260	0.0780	0.3824	8
P50	0.1734	0.0362	0.1729	2
P51	0.1566	0.0552	0.2604	4
P58	0.0870	0.1396	0.6162	13
P66	0.1266	0.0714	0.3607	7
P68	0.1636	0.0621	0.2752	5
P70	0.1639	0.0776	0.3213	6
P71	0.1722	0.0271	0.1359	1

Scenario 1 (S1) is used to see how the location of MDs changes when risk factor is considered in the current situation. S1 is the same as S0 except that the model is allowed to determine the location of MDs while keeping the set of provinces served by MDs and RDs as fixed. Thus, when $p > 1$, the provinces served by MDs do not change but they are shared among MDs and each MD uses the same stocking policy as in S0 (three-year demands of all units).

Scenario 2 (S2) allows the model to determine the locations and service assignments of MDs as well as the service assignments of RDs if they are used as RD. Both MDs and RDs use the current stocking policy.

Scenario 3 (S3) is the same as S2 except that MDs keep a stock

Table 6
The weighted normalized decision matrix of the TOPSIS analysis.

	C1a	C1b	C1c	C1d	C2a	C2b	C2c	C2d	C3a	C3b	C4a	C4b	C4c	C5	C6
P03	0.1248	0.0172	0.0037	0.0000	0.0007	0.0003	0.0052	0.0000	0.0011	0.0004	0.0000	0.0000	0.0000	0.0069	0.0597
P06	0.0832	0.0459	0.0212	0.0000	0.0000	0.0007	0.0084	0.0045	0.0018	0.0013	0.0225	0.0130	0.0283	0.0486	0.0657
P18	0.1040	0.0057	0.0087	0.0000	0.0000	0.0000	0.0029	0.0000	0.0004	0.0110	0.0150	0.0000	0.0000	0.0018	0.0808
P26	0.0416	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0045	0.0008	0.0004	0.0075	0.0000	0.0071	0.0077	0.0835
P38	0.0832	0.0172	0.0112	0.0000	0.0007	0.0000	0.0026	0.0000	0.0001	0.0005	0.0000	0.0000	0.0000	0.0125	0.0603
P42	0.0624	0.0057	0.0037	0.0100	0.0013	0.0009	0.0052	0.0045	0.0004	0.0013	0.0300	0.0000	0.0000	0.0201	0.0813
P50	0.0000	0.0000	0.0000	0.0000	0.0052	0.0014	0.0151	0.0091	0.0301	0.0065	0.0000	0.0000	0.0000	0.0028	0.0615
P51	0.0208	0.0000	0.0000	0.0200	0.0000	0.0000	0.0003	0.0000	0.0002	0.0098	0.0075	0.0000	0.0071	0.0033	0.0958
P58	0.1040	0.0689	0.0436	0.0200	0.0039	0.0006	0.0041	0.0000	0.0011	0.0150	0.0150	0.0000	0.0000	0.0061	0.0830
P66	0.0624	0.0172	0.0050	0.0000	0.0020	0.0001	0.0012	0.0000	0.0219	0.0128	0.0150	0.0000	0.0000	0.0044	0.0594
P68	0.0000	0.0115	0.0025	0.0000	0.0000	0.0000	0.0017	0.0000	0.0584	0.0105	0.0075	0.0000	0.0000	0.0037	0.0683
P70	0.0000	0.0000	0.0062	0.0000	0.0000	0.0002	0.0012	0.0000	0.0559	0.0095	0.0000	0.0000	0.0000	0.0023	0.1084
P71	0.0000	0.0230	0.0075	0.0000	0.0000	0.0000	0.0072	0.0000	0.0014	0.0066	0.0075	0.0000	0.0000	0.0027	0.0557
A^*	0.1248	0.0459	0.0212	0.0200	0.0052	0.0014	0.0151	0.0091	0.0301	0.0110	0.0300	0.0130	0.0283	0.0486	0.0958
A^-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0004	0.0000	0.0000	0.0000	0.0018	0.0597

Table 8
Summary of the constructed scenarios.

		S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
MD locations	a	✓										
	b		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MD assignments	a	✓	✓									
	b			✓	✓	✓	✓	✓	✓	✓	✓	✓
RD locations	a	✓	✓				✓	✓	✓	✓	✓	✓
	b			✓	✓	✓						
RD assignments	a	✓	✓				✓	✓	✓	✓	✓	✓
	b			✓	✓	✓				✓	✓	✓
Stocking policy	c	✓	✓	✓			✓	✓	✓	✓	✓	✓
	d				✓							
	e					✓						

Explanation:
a. Fixed.
b. Not fixed (the model determines).
c. MD(s) holds a stock equal to the three-year demands of all units and RDs hold a stock equal to one-year demand of the units assigned to them after the demand for the current year is met.
d. MD(s) and RDs hold a stock equal to the three-year demands and one-year demand of the units assigned to them after the demand for the current year is met, respectively.
e. MD(s) holds a stock equal to one-year demand of the assigned units and RDs do not hold any stock.

equal to three-year demands of units assigned to them (not all units). This requirement is modeled by replacing constraints (6) with $3.\sum_{j\in I_b} x_{ij}^m = S_i^m, \forall\, i \in I_a, \forall\, m \in M$. S3 is designed because the cost resulting from the stocking policy in S2 is too high.

Scenario 4 (S4) is similar to S2 and S3 with respect to location and service assignments of MDs and RDs but different with respect to the stocking policy. In S4, MDs hold a stock equal to one-year demand of the assigned units and RDs do not hold stock. However, RDs may be used as a cross-docking point. This is achieved by replacing constraints (6) with $3.\sum_{j\in I_b} x_{ij}^m = S_i^m, \forall\, i \in I_a, \forall\, m \in M$ and removing constraints (7) from the constraint set. The purpose of this scenario is to observe the effect of the stocking policy on location and allocations decisions.

Scenarios 5 through 10 (S5-S10) are designed to determine whether using current RDs is advantageous or not. For this purpose, we allow one- and two-element combinations of RDs to be active at their current locations (P44, P56, and P65) in the scenarios. Specifically, RDs located at P44 (P56-P65), P56 (P44-P65), P65 (P44-P56), P44-P56 (P65), P44-P65 (P56), and P56-P65 (P44) are assumed to be active (inactive) in Scenarios 5–10, respectively. When an RD is active, the provinces currently served by that RD are assigned to it. For the provinces already served by deactivated RDs, the model determines the allocations. For example, In Scenario 8, RDs located at P44 and P56 are assumed to be active while RD located at P65 is deactivated. Thus, the provinces currently served by P44 and P56 continue to serve the same provinces (i.e., the assignments of these provinces are fixed) while the provinces currently served by P65 are reallocated by the model (to either P44 or P56 or the MD location). The model also determines the locations and the assignments of MDs considering the current stocking policies at MDs and RDs.

7.2. Scenario results

In analyzing the results of the scenarios, we try to determine how the locations of MDs change and whether using RDs is preferable or not. Figs. 6 through 8 indicate the solutions (MD locations) and the corresponding objective function values in different scenarios for different p values. The risk values and the cost values for each solution are shown in the lower and upper parts of the y-axis, respectively. Each distinct solution is labeled as an alternative solution. If the same solution appears in different scenarios, it is represented with the same label. For example, A1 represents the solution with MD location P06 while A2 represents the solution with MD location P71. The objective function values for each solution are also given in the tables below and above the graphs. Table 9 indicates the number of units assigned to each MD and RD in the solutions.

In the current situation (S0), MD is located at P06 (A1) and RDs are located at P44, P56, and P65. MD serves 68 provinces while P44, P56, and P65 serve 7, 5, and 4 provinces (including themselves), respectively. RDs serve a small number of provinces; however, the total quantity of ammo needed by the provinces served by RDs is significantly higher than the provinces served by MD.

In S1 that can be run only for $p = 1$, the current location of MD is selected when the risk is not taken into account. However, as the value of δ is increased sufficiently (risk is considered), the location of MD moves to P71 (A2). So, there is a need to change the location of MD

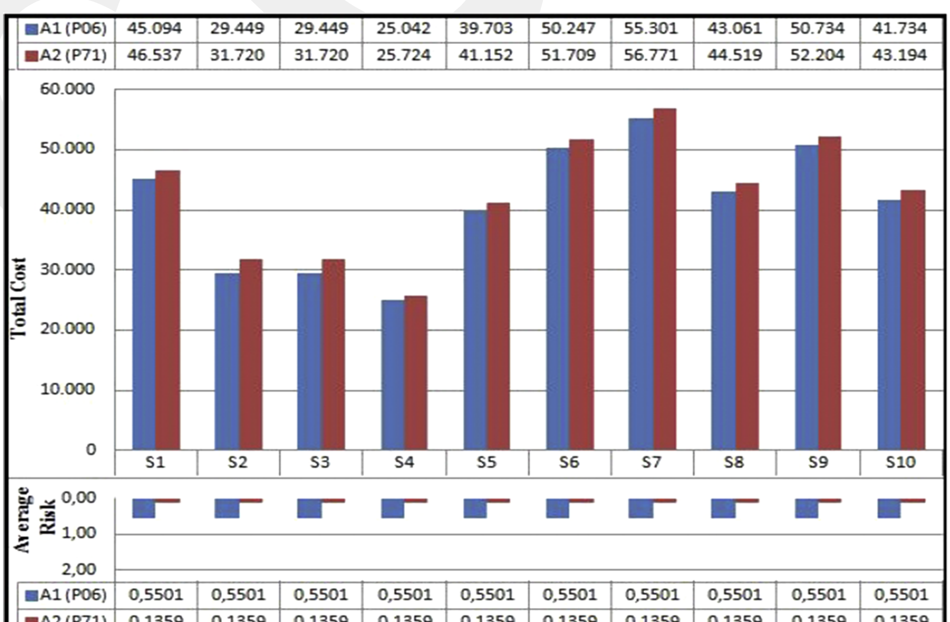

Fig. 6. Computational results of scenarios for $p = 1$.

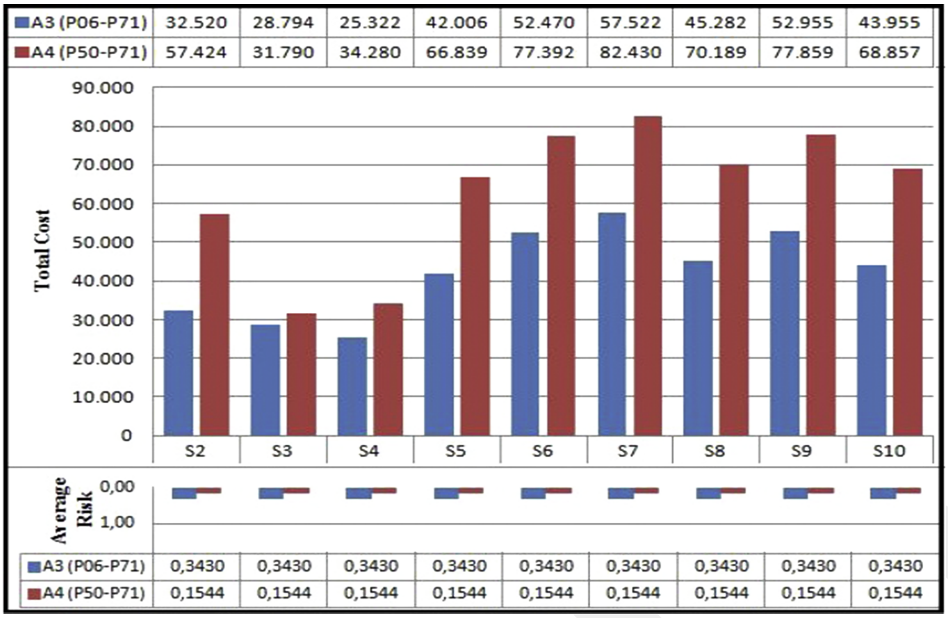

Fig. 7. Computational results of scenarios for p = 2.

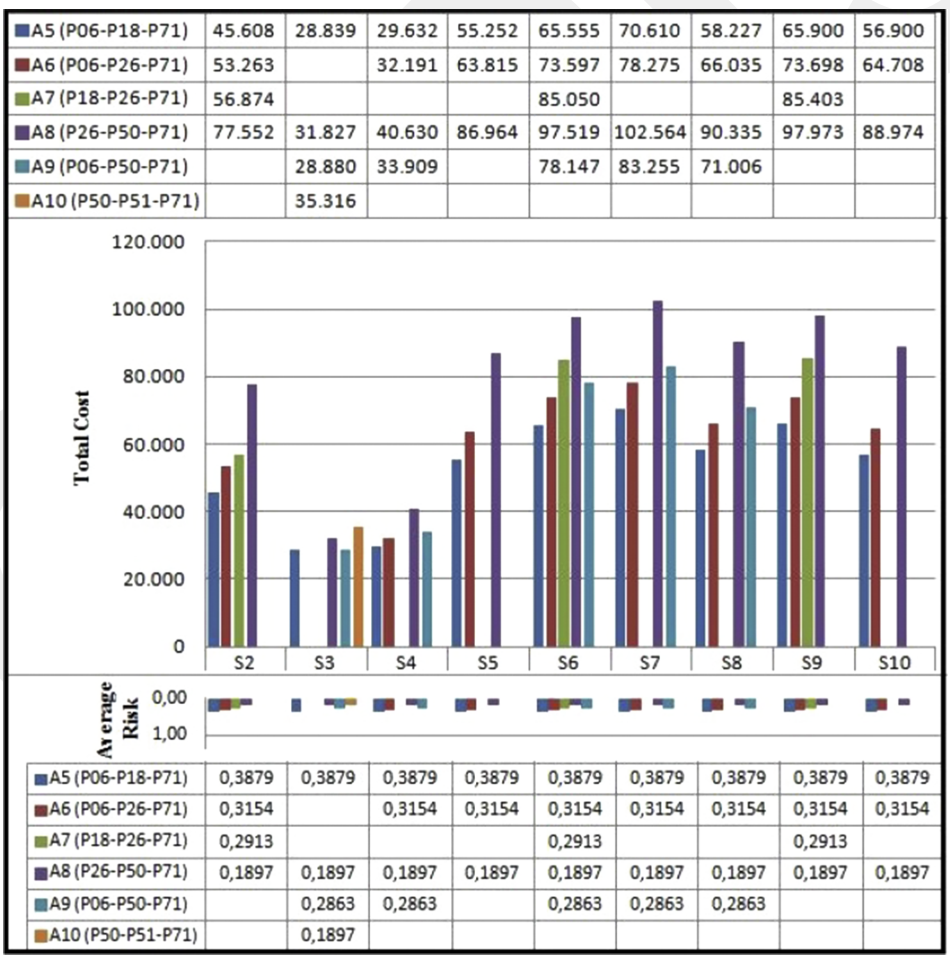

Fig. 8. Computational results of scenarios for p = 3.

even with the current assignments of MD and RDs.

In S2, our main observation is that none of the solutions uses RDs. This causes a decrease of about 35% in total cost compared to the current situation. This result is obtained due to shorter travel distances and the decrease in total flow quantity through the system (there is no need to send flow from MDs to RDs for stocking). In this scenario, different combinations of five locations (P06, P18, P26, P50, and P71) appear in eight solutions. It occurs that P71 and P06 are included in

Table 9
The number of demand points assigned to MDs and RDs.

p	A	Type	Nu.	S0–S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
$p = 1$	*A1*	MD1	P06	68	81	81	72	68	68	68	68	68	68
		RD1	P44	7	–	–	8	14	–	–	10	–	11
		RD2	P56	5	–	–	2	–	14	–	5	11	–
		RD3	P65	4	–	–	2	–	–	14	–	4	4
	A2	MD1	P71	68	81	81	77	68	68	68	68	68	68
		RD1	P44	7	–	–	3	14	–	–	10	–	11
		RD2	P56	5	–	–	2	–	14	–	5	11	–
		RD3	P65	4	–	–	2	–	–	14	–	4	4
$p = 2$	*A3*	MD1	P06		39	63	40	40	39	39	39	40	39
		MD2	P71		42	18	32	28	29	29	29	28	29
		RD1	P44		–	–	7	14	–	–	10	–	11
		RD2	P56		–	–	4	–	14	–	5	11	–
		RD3	P65		–	–	–	–	–	14	–	4	4
	A4	MD1	P50		2	1	2	2	2	2	2	2	2
		MD2	P71		79	80	76	66	66	66	66	66	66
		RD1	P44		–	–	2	14	–	–	10	–	11
		RD2	P56		–	–	2	–	14	–	5	11	–
		RD3	P65		–	–	2	–	–	14	–	4	4
$p = 3$	*A5*	MD1	P06		36	62	36	36	36	36	36	36	36
		MD2	P18		4	1	3	5	4	4	3	3	3
		MD3	P71		41	18	34	27	28	28	29	29	29
		RD1	P44		–	–	7	14	–	–	10	–	11
		RD2	P56		–	–	2	–	14	–	5	11	–
		RD3	P65		–	–	2	–	–	14	–	4	4
	A6	MD1	P06		39		34	32	32	32	32	32	32
		MD2	P26		7		7	9	8	7	7	7	7
		MD3	P71		35		32	27	28	29	29	29	29
		RD1	P44		–		7	14	–	–	10	–	11
		RD2	P56		–		2	–	14	–	5	11	–
		RD3	P65		–		2	–	–	14	–	4	4
	A7	MD1	P18		5				5			4	
		MD2	P26		25				21			22	
		MD3	P71		51				42			42	
		RD1	P44		–				–			–	
		RD2	P56		–				14			11	
		RD3	P65		–				–			4	
	A8	MD1	P26		23	1	23	23			23	23	23
		MD2	P50		2	1	2	2			2	2	2
		MD3	P71		56	79	48	43			43	43	43
		RD1	P44		–	–	7	14			10	–	11
		RD2	P56		–	–	2	–			5	11	–
		RD3	P65		–	–	2	–			–	4	4
	A9	MD1	P06			63	39		39	39	39		
		MD2	P50			1	2		2	3	2		
		MD3	P71			17	32		27	26	27		
		RD1	P44			–	7		–	–	10		
		RD2	P56			–	2		14	–	5		
		RD3	P65			–	2		–	14	–		
	A10	MD1	P50			1			23	23			
		MD2	P51			4			2	2			
		MD3	P71			76			43	43			
		RD1	P44			–			–	–			
		RD2	P56			–			14	–			
		RD3	P65			–			–	14			

most solutions with P71 appearing in all solutions. In S3, we make the same observation as in S2. All solutions except one (P51 appears in one solution) are combinations of the same five locations in S2. In this case, costs are lower due to the decreased flow quantity through the system resulting from the change in stocking policy.

In S4, where RDs do not hold stock and MDs hold just one-year stock of assigned units, solutions are combinations of the same five locations in S2. All solutions except one use all three RDs. This is expected because RDs are mostly on the way to the provinces they are currently serving and the flow quantity from MDs to RDs decreases. The results imply that using RDs may be preferable depending on the stocking policy. RDs may be advantageous for ease of command and control especially in areas where the usage of ammo is high.

In S5-S10, we observe that the units assigned to RDs change; most of the units already served by deactivated RDs are assigned to RDs whose locations are fixed. For example, the number of units assigned to P44 is 14 in S5 while it is 7 in the current situation. Actually, in S5-S7, the number of units assigned to each RD is 14. We obtain a similar result for S8-S10. The results in the previous scenarios indicate that using RDs is not preferred. The results in S5-S10 imply that the allocation of the units needs to be changed if any one- or two-element combination of RDs is open. MD locations in these scenarios are combinations of 5 locations (P06, P18, P26, P50, and P71) as in the previous scenarios.

The results in all scenarios indicate that seven candidate locations (P42, P58, P66, P68, P38, P03, and P70) do not appear in any solution. Table 10 indicates the number of times each MD location appears in the solutions (and hence the critical locations). On the other hand, even though P06 and P18 are critical, they have the second and fourth highest risk scores, respectively. In this regard, we present the results on the objective space where the axes represent the total transportation cost and average risk values. The resulting graph is given in Fig. 9. There are 73 points in Fig. 9; however, they actually correspond to 10 distinct solutions in different scenarios shown in Figs. 6–8.

Fig. 9 indicates that there are 27 points that dominate the current solution. Dominating solutions are obtained under S2, S3, S4, S5, and S8, and S10 with all solutions obtained in S3 and S4 dominating the current solution. The results imply that RDs should not be used or if they are to be used, they should keep a minimum of stock or no stock at all. 27 points dominating the current solution in Fig. 9 correspond to 8 distinct solutions (A1-A5, A8-A10). When all solutions are considered, the single *pareto-optimal* point is obtained in S4 for $p = 1$, which corresponds to the MD location P71 (A2). Pareto-optimal MD locations are P50 and P71 (A4) for $p = 2$ and P26, P50, and P71 (A8) for $p = 3$. Both solutions are obtained in S3.

All alternatives and tradeoffs have been discussed with the experts from GCG. GCG has finally made changes in the location of MDs, the usage of RDs, and the stocking policies at MD and RDs.

The following managerial insights can be drawn for GCG from the results of the scenarios:

- It is possible to obtain solutions better than the current solution with respect to risk and cost values.

Table 10
Number of times each MD location appears in a solution.

MD	S0-S1			S2			S3			S4			S5			S6			S7			S8			S9			S10			Total
	P			P			P			P			P			P			P			P			P			P			
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	
P71	1			1	2	4	1	2	4	1	2	4	1	2	3	1	2	5	1	2	4	1	2	4	1	2	4	1	2	3	**63**
P06	1			1	1	3	1	1	3	1	1	3	1	1	3	1	1	3	1	1	3	1	1	3	1	1	3	1	1	3	**46**
P50					1	1		1	3		1	2		1	1		1	2		1	2		1	2		1	1		1	1	**24**
P26						3			1			2			2			3			2			2			3			2	**20**
P18						2			1			1			1			2			1			1			2			1	**12**
P51									1																						**1**

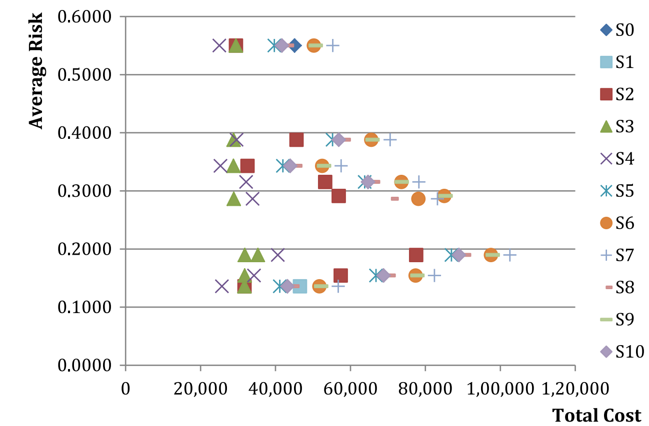

Fig. 9. The objective space of different solutions under different scenarios.

- The solutions change with the consideration of risk; the average risk value decreases as the cost value increases or vice versa.
- RDs should not be used or if they are used, they should keep a minimum of stock or no stock at all (i.e., RDs can be used as cross-docking points).
- If RDs are used, the allocation of the units (provinces) need to be changed.
- Considering the number of times each MD location appears in the solutions, 5 MD locations (P71, P06, P50, P26, and P18) turn out to be critical. Of these 5 locations, P06 and P18 have the second and fourth highest risk scores. In the pareto optimal solutions, MD locations are P71 for $p = 1$, P71 and P50 for $p = 2$, and P26, P50, and P71 for $p = 3$. That is, the critical MD locations turn out to be P26, P50, and P71.
- Changing the inventory policies at the MDs and RDs affect the results considerably. It is better to keep stock at an MD or RD location for only the units assigned to it.
- Instead of using one or more MDs, using one or more MDs with the role of an RD may be considered, i.e., a central depot is not used and the flow is directly from supply points to the MDs.

8. Conclusion

In this paper, we have studied the strategic-level ammunition distribution network design problem of GCG where the purpose is to determine the number and locations of depots and the service assignments considering several factors. We have proposed a scientific methodology that consists of the use of mathematical modeling, multi-attribute decision making methods AHP and TOPSIS, and GIS. The approach has allowed us to incorporate both subjective and objective factors into the decision-making process systematically. Specifically, we have used the multi-objective optimization model to determine the optimal locations of depots and service assignments such that the total cost and the average risk levels are minimized. We have computed the risk levels of potential depot locations using combined AHP-TOPSIS analysis that has allowed us take into account the preferences of the decision makers and several risk attributes. We have automated the determination of potential depot locations using map layers based on spatial criteria through GIS analysis. The methodology has been applied in designing and evaluating the ammunition distribution network of GCG under different scenarios in collaboration and cooperation with the experts from GCG. The results indicate the importance of addressing the problem from a scientific perspective.

It may be possible to extend the study in several directions. One direction may be to conduct exhaustive tests with other methods (e.g., DEMATEL and the entrophy method) to observe whether the results change or not. Another direction may be to develop a stochastic model incorporating the real ammunition consumption instead of organizational policy requirements when sufficient data is available. We think that we can contribute to determine better inventory policies and differentiate inventory policies for the units depending on their consumption rates. We can predict the cosumption rates of the units utilizing machine learning algorithms and automate the decision making process for the strategic- and tactical-level commanders.

9. Declarations of interest

None.

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References

Amiri, A. (2006). Designing a distribution network in a supply chain system: Formulation and efficient solution procedure. *European Journal of Operational Research, 171*(2), 567–576.
Awasthi, A., Chauhan, S. S., Omrani, H., & Panahi, A. (2011). A hybrid approach based on SERVQUAL and fuzzy TOPSIS for evaluating transportation service quality. *Computers & Industrial Engineering, 61*, 637–646.
Badri, M. A. (1999). Combining the analytic hierarchy process and goal programming for global facility location-allocation problem. *International Journal of Production Economics, 62*(3), 237–248.
Ballou, R. H. (2001). Unresolved issues in supply chain network design. *Information Systems Frontiers, 3*(4), 417–426.
Barron, F. H., & Barrett, B. E. (1996). Decision quality using ranked attribute weights. *Management Science, 42*(11), 1515–1523.
Behzadian, M., Kazemzadeh, R. B., Albadvi, A., & Aghdasi, M. (2010). PROMETHEE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research, 200*, 198–215.
Behzadian, M., Khanmohammadi Otaghsara, S., Yazdani, M., & Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications, 39*, 13051–13069.
Bell, J. E. (2003). *A simulated annealing approach for the composite facility location and resource allocation problem: A study of strategic positioning of US Air Force munitions (No. C102-927)*[Master Thesis]. California: Naval Postgraduate School Monterey.
Belton, V., & Stewart, T. J. (2002). *Multiple criteria decision analysis – An integrated approach.* Boston: Kluwer.
Brans, J. P., & Mareschal, B. (1992). PROMETHEE V: MCDM problems with segmentation constraints. *INFOR: Information Systems and Operational Research, 30*(2), 85–96.
Cagrici, H. (2007). *Determining the optimal locations of munitions' warehouse of the multiple launch rocket systems with genetic algoritms*[Master Thesis]. Ankara, Turkey: Turkish Army Military Academy.
Cain, M. J. (1988). *A GAMS-based model of the U.S. army wartime ammunition distribution system for the corps level*[Master Thesis]. California, USA: Naval Postgraduate School Monterey.
Cho, J. H., Wang, Y., Chen, R., Chan, K. S., & Swami, A. (2017). A survey on modeling and optimizing multi-objective systems. *IEEE Communications Surveys & Tutorials, 19*(3), 1867–1901.
Churchman, C. W., & Ackoff, R. L. (1954). An approximate measure of value. *Journal of the Operations Research Society of America, 2*(2), 172–187.
Clark, S. J., Barnhart, C., & Kolitz, S. E. (2004). Large-scale optimization planning methods for the distribution of United States army munitions. *Mathematical & Computer Modelling, 39*(6–8), 697–714.
Coello, C. A. C. (2000). An updated survey of GA-based multiobjective optimization techniques. *ACM Computing Surveys (CSUR), 32*(2), 109–143.
Coello, C. A. C. (2006). Evolutionary multi-objective optimization: A historical view of the field. *IEEE Computational Intelligence Magazine, 1*(1), 28–36.
Coello, C. A. C., Lamont, G. B., & Van Veldhuizen, D. A. (2007). *Evolutionary algorithms for solving multi-objective problems, Vol. 5.* New York: Springer.
Cordeau, J. F., Pasin, F., & Solomon, M. M. (2006). An integrated model for logistics network design. *Annals of Operations Research, 144*(1), 59–82.
Dağdeviren, M., Yavuz, S., & Kılınç, N. (2009). Weapon selection using the AHP and TOPSIS methods under fuzzy environment. *Expert Systems with Applications, 36*(4), 8143–8151.
Danesh, D., Ryan, M. J., & Abbasi, A. (2017). Multi-criteria decision-making methods for project portfolio management: A literature review. *International Journal of Management & Decision Making, 17*(1), 75–94.
Deb, K. (2014). *Multi-objective optimization. In Search methodologies.* Boston: Springer403–449.
AFAD, The official website of the Prime Ministry Disaster&Emergency Management

Presidency, Available from https://www.afad.gov.tr/EN/Index.aspx/ [Accessed on January 22, 2017].
Deng, H., Yeh, C.-H., & Willis, R. J. (2000). Inter-company comparison using modified TOPSIS with objective weights. *Computers & Operations Research, 27*(10), 963–973.
Donoso, Y., & Fabregat, R. (2016). *Multi-objective optimization in computer networks using metaheuristics.* Auerbach Publications.
Ehrgott, M., & Gandibleux, X. (2002). *Multiple criteria optimization-state of the art annotated bibliographic surveys Vol. 52 of Kluwers's International Series in Operations Research and Management Science.* Boston: Kluwer Academic Publishers.
Eisenführ, F., Weber, M., & Langer, T. (2010). *Rational decision making.* Berlin: Springer.
Association of the European and Mediterranean Police Forces and Gendarmeries with Military Status (FIEP), Turkish Gendarmerie. Available from http://www.fiep.org/member-forces/turkish-gendarmerie/ [Accessed on January 10, 2017].
French, S., Maule, J., & Papamichail, N. (2009). *Decision behaviour, analysis and support.* New York: Cambridge University Press.
Gabus, A., & Fontela, E. (1972). *World problems, an invitation to further thought within the framework of DEMATEL.* Geneva, Switzerland: Battelle Geneva Research Center1–8.
Govindan, K., & Jepsen, M. B. (2016). ELECTRE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research, 250*(1), 1–29.
Gue, K. R. (2003). A dynamic distribution model for combat logistics. *Computers & Operations Research, 30*(3), 367–381.
Gutjahr, W. J., & Pichler, A. (2016). Stochastic multi-objective optimization: A survey on non-scalarizing methods. *Annals of Operations Research, 236*(2), 475–499.
Guzel, D., Erdal, H., & Acar, E. (2015). A model proposal for increasing the effectiveness of law enforcement service: An integrated model of vehicle assignment. *The Journal of Academic Social Science Studies, 40*, 463–483.
Hauk, J. G. (1964). Logistics and physical distribution management in the military. *Transportation Journal, 4*(2), 12–19.
Hehnen, M. T. (1970). *An aproximate goal constraint model for ammunition inventory* [Master Thesis]. California, USA: Naval Postgraduate School Monterey.
Ho, W. (2008). Integrated analytic hierarchy process and its applications – A literature review. *European Journal of Operational Research, 186*, 211–228.
Hobbs, B. F. (1980). A comparison of weighting methods in power plant siting. *Decision Sciences, 11*(4), 725–737.
Huang, H. F., Kuo, J., & Lo, S. L. (2011). Review of PSR framework and development of a DPSIR model to assess greenhouse effect in Taiwan. *Environmental Monitoring and Assessment, 177*, 623–635.
Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications: A state-of-the-art survey*, *Vol. 186*. New York: Springer.
Ic, Y. (2012). An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies. *Robotics & Computer-Integrated Manufacturing, 28*(2), 245–256.
Jayaraman, V., & Pirkul, H. (2001). Planning and coordination of production and distribution facilities for multiple commodities. *European Journal of Operational Research, 133*(2), 394–408.
Kahraman, C., Cevik, S., Ates, N. Y., & Gulbay, M. (2007). Fuzzy multi-criteria evaluation of industrial robotic systems. *Computers & Industrial Engineering, 52*, 414–433.
Kahraman, C., Onar, S. C., & Oztaysi, B. (2015). Fuzzy multicriteria decision-making: A literature review. *International Journal of Computational Intelligence Systems, 8*(4), 637–666.
Karabakal, N., Günal, A., & Ritchie, W. (2000). Supply-chain analysis at Volkswagen of America. *Interfaces, 30*(4), 46–55.
Kasirian, M., & Yusuff, R. (2013). An integration of a hybrid modified TOPSIS with a PGP model for the supplier selection with interdependent criteria. *International Journal of Production Research, 51*, 1037–1054.
Keeney, R. L., & Raiffa, H. (1976). *Decisions with multiple objectives.* New York: John Wiley & Sons.
Kent, J. L., Jr., & Flint, D. J. (1997). Perspectives on the evolution of logistics thought. *Journal of Business Logistics, 18*(2), 15–29.
Keršuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *Journal of Business Economics & Management, 11*(2), 243–258.
Khorshidi, R., & Hassani, A. (2013). Comparative analysis between TOPSIS and PSI methods of materials selection to achieve a desirable combination of strength and workability in Al/SiC composite. *Materials & Design, 52*, 999–1010.
Klose, A., & Drexl, A. (2005). Facility location models for distribution system design. *European Journal of Operational Research, 162*(1), 4–29.
Konak, A., Coit, D. W., & Smith, A. E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety, 91*(9), 992–1007.
Kumar, A., Sah, B., Singh, A. T., Deng, Y., He, X., Kumar, P., & Bansal, R. C. (2017). A review of multi-criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews, 69*, 596–609.
Kuo, Y., Yang, T., Cho, C., & Tseng, Y.-C. (2008). Using simulation and multi-criteria methods to provide robust solutions to dispatching problems in a flow shop with multiple processors. *Mathematics & Computers in Simulation, 78*, 40–56.
Laporte, G., Nobert, Y., & Taillefer, S. (1988). Solving a family of multi-depot vehicle routing and location-routing problems. *Transportation Science, 22*(3), 161–172.
Lenhardt, T. A. (2006). Evaluation of a USMC combat service support logistics concept. *Mathematical & Computer Modelling, 44*(3), 368–376.
Li, D. F., Huang, Z. G., & Chen, G. H. (2010). A systematic approach to heterogeneous multi attributes group decision making. *Computers & Industrial Engineering, 59*, 561–572.
Loken, E. (2007). Use of multi-criteria decision analysis methods for energy planning problems. *Renewable & Sustainable Energy Reviews, 11*(7), 1584–1595.
Lootsma, F. A. (1997). Fuzzy multi-objective optimization. *Fuzzy logic for planning and decision making. Applied optimization, Vol. 8*.
Mahase, M. J., Musingwini, C., & Nhleko, A. S. (2016). A survey of applications of multicriteria decision analysis methods in mine planning and related case studies. *The Journal of the Southern African Institute of Mining and Metallurgy, 116*, 1051–1056.
Maheshwarkar, M., & Sohani, N. (2013). Combined AHP-TOPSIS based approach for the evaluation of knowledge sharing capabilities of supply chain partners. *Management Science & Engineering, 7*(3), 27–32.
Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. *International Journal of Geographical Information Science, 20*(7), 703–726.
Mangiaracina, R., Marchet, G., Perotti, S., & Tumino, A. (2015). A review of the environmental implications of B2C e-commerce: A logistics perspective. *International Journal of Physical Distribution & Logistics Management, 45*(6), 565–591.
Mardani, A., Jusoh, A., MD Nor, K., Khalifah, Z., Zakwan, N., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications-a review of the literature from 2000 to 2014. *Economic Research-Ekonomska Istraživanja, 28*(1), 516–571.
Mardani, A., Jusoh, A., & Zavadskas, E. K. (2015). Fuzzy multiple criteria decision-making techniques and applications – Two decades review from 1994 to 2014. *Expert Systems with Applications, 42*, 4126–4148.
Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural & Multidisciplinary Optimization, 26*(6), 369–395.
Marttunen, M., Lienert, J., & Belton, V. (2017). Structuring problems for multi-criteria decision analysis in practice: A literature review of method combinations. *European Journal of Operational Research, 263*, 1–17.
Melo, M. T., Nickel, S., & Saldanha-Da-Gama, F. (2009). Facility location and supply chain management-A review. *European Journal of Operational Research, 196*(2), 401–412.
Miettinen, K., Ruiz, F., & Wierzbicki, A. P. (2008). Introduction to multiobjective optimization: Interactive approaches. In J. Branke, K. Deb, K. Miettinen, & R. Słowiński (Vol. Eds.), *Multiobjective optimization. Lecture notes in computer science: Vol. 5252*. Berlin: Springer.
Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Pschological Review, 101*(2), 343–352.
Önüt, S., & Soner, S. (2008). Transshipment site selection using the AHP and TOPSIS approaches under fuzzy environment. *Waste Management, 28*, 1552–1559.
Owen, S. H., & Daskin, M. S. (1998). Strategic facility location: A review. *European Journal of Operational Research, 111*(3), 423–447.
Pirkul, H., & Jayaraman, V. (1998). A multi-commodity, multi-plant, capacitated facility location problem: Formulation and efficient heuristic solution. *Computers & Operations Research, 25*(10), 869–878.
Powell, D. S. (2004). *An optimization model for sea-based logistics supply system for the Navy and Marine Corps*[Master Thesis]. California, USA: Naval Postgraduate School Monterey.
Qin, X., Huang, G., Chakma, A., Nie, X., & Lin, Q. (2008). A MCDM-based expert system for climate-change impact assessment and adaptation planning – A case study for the Georgia Basin, Canada. *Expert Systems with Applications, 34*(3), 2164–2179.
Revelle, C. S., Eiselt, H. A., & Daskin, M. S. (2008). A bibliography for some fundamental problem categories in discrete location science. *European Journal of Operational Research, 184*(3), 817–848.
Reyes-Sierra, M., & Coello, C. C. (2006). Multi-objective particle swarm optimizers: A survey of the state-of-the-art. *International Journal of Computational Intelligence Research, 2*(3), 287–308.
Ritzel, B. J., Eheart, J. W., & Ranjithan, S. (1994). Using genetic algorithms to solve a multiple objective groundwater pollution containment problem. *Water Resources Research, 30*(5), 1589–1603.
Romero, C., & Rehman, T. (1987). Natural resource management and the use of multiple criteria decision-making techniques: A review. *European Review of Agricultural Economics, 14*, 61–89.
Roy, B., & Mousseau, V. (1996). A theoretical framework for analysing the notion of relative importance of criteria. *Journal of Multi-Criteria Decision Analysis, 5*(2), 145–159.
Rutner, S. M., Aviles, M., & Cox, S. (2012). Logistics evolution: A comparison of military and commercial logistics thought. *The International Journal of Logistics Management, 23*(1), 96–118.
Saad, W., Han, Z., Basar, T., Debbah, M., & Hjorungnes, A. (2011). Hedonic coalition formation for distributed task allocation among wireless agents. *IEEE Transactions on Mobile Computing, 10*(9), 1327–1344.
Saad, W., Han, Z., Debbah, M., Hjørungnes, A., & Basar, T. (2009). Coalitional game theory for communication networks: A tutorial. *IEEE Signal Processing Magazine, 26*(5), 77–97.
Saaty, T. L. (1980). *Multicriteria decision making: The analytic hierarchy process.* New York: McGraw-Hill.
Saaty, T. L. (2003). Decision-making with the AHP: Why is the principal eigenvector necessary. *European Journal of Operational Research, 145*(1), 85–91.
Saaty, T. L., & Ozdemir, M. S. (2003). Why the magic number seven plus or minus two. *Mathematical & Computer Modelling, 38*(3–4), 233–244.
Saaty, T. L., & Vargas, L. G. (2006). The analytic hierarchy process: Wash criteria should not be ignored. *International Journal of Management & Decision Making, 7*(2–3), 180–188.
Sabuncuoglu, I., & Utku, D. H. (2002). Logistics 2: Evaluation of army corps artillery ammunition supply systems via simulation. *Proceedings of the 34th conference on Winter simulation: Exploring new frontiers. Winter Simulation Conference* (pp. 917–920). .
Sahin, S. (2006). *A routing model for ammunition transportation and its application*[Master Thesis]. Ankara, Turkey: Turkish Army Military Academy.
Schoemaker, P. J., & Waid, C. C. (1982). An experimental comparison of different approaches to determining weights in additive utility models. *Management Science,*

28(2), 182–196.
Shidpour, H., Shahrokhi, M., & Bernard, A. (2013). A multi-objective programming approach, integrated into the TOPSIS method, in order to optimize product design; in three-dimensional concurrent engineering. *Computers & Industrial Engineering, 64*, 875–885.
Shin, W. S., & Ravindran, A. (1991). Interactive multiple objective optimization: Survey I-Continuous case. *Computers & Operations Research, 18*(1), 97–114.
Shyur, H. J. (2006). COTS evaluation using modified TOPSIS and ANP. *Applied Mathematics and Computation, 177*, 251–259.
Sirisawat, P., & Kiatcharoenpol, T. (2018). Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers. *Computers & Industrial Engineering, 117*, 303–318.
Steuer, R. E. (1986). *Multiple criteria optimization, theory, computation and applications.* New York: Willey.
Steuer, R. E., & Na, P. (2003). Multiple criteria decision making combined with finance: A categorized bibliographic study. *European Journal of Operational Research, 150*(3), 496–515.
Subramanian, N., & Ramanathan, R. (2012). A review of applications of analytic hierarchy process in operations management. *International Journal of Production Economics, 138*(2), 215–241.
Tan, K. C., Lee, T. H., & Khor, E. F. (2002). Evolutionary algorithms for multi-objective optimization: Performance assessments and comparisons. *Artificial Intelligence Review, 17*(4), 251–290.
Toyoglu, H., Karasan, O. E., & Kara, B. Y. (2011). Distribution network design on the battlefield. *Naval Research Logistics (NRL), 58*(3), 188–209.
Turkish Statistical Institute (TUIK), Population Statistics, Population of Provinces by Years, Available from http://www.turkstat.gov.tr/PreIstatistikTablo.do?istab_id=1590/ [Accessed on January 25, 2017].
Tzeng, G., & Huang, J. (2011). *Multiple attribute decision making methods and applications.* CRC Press, Taylor & Francis Group.
Ulungu, E. L., & Teghem, J. (1994). Multi-objective combinatorial optimization problems: A survey. *Journal of Multi-Criteria Decision Analysis, 3*(2), 83–104.
Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research, 169*(1), 1–29.
Van Veldhuizen, D. A., & Lamont, G. B. (2000). Multiobjective evolutionary algorithms: Analyzing the state-of-the-art. *Evolutionary Computation, 8*(2), 125–147.
Velasquez, M., & Hester, P. T. (2013). An analysis of multi-criteria decision making methods. *International Journal of Operations Research, 10*(2), 56–66.
Wallenius, J., Dyer, J. S., Fishburn, P. C., Steuer, R. E., Zionts, S., & Deb, K. (2008). Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead. *Management Science, 54*, 1336–1349.
Wang, Q., & Poh, K. L. (2014). A survey of integrated decision analysis in energy and environmental modeling. *Energy, 77*, 691–702.
Zeleny, M. (1982). *Multiple criteria decision making.* New York: Mc Graw-Hill.
Zhou, P., Ang, B. W., & Poh, K. L. (2006). Decision analysis in energy and environmental modeling: An update. *Energy, 31*(14), 2604–2622.
Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P. N., & Zhang, Q. (2011). Multiobjective evolutionary algorithms: A survey of the state of the art. *Swarm & Evolutionary Computation, 1*(1), 32–49.
Zopounidis, C., & Doumpos, M. (2002). *Multicriteria decision aid classification methods, Vol. 73*. New York: Springer.
Zopounidis, C., & Pardalos, P. M. (2010). *Handbook of multicriteria analysis.* Berlin Heidelberg: Springer-Verlag.