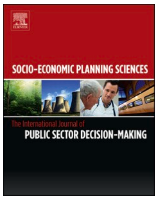
Socio-Economic Planning Sciences 72 (2020) 100919

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

journal homepage: http://www.elsevier.com/locate/seps



A multimodal, multicommodity, and multiperiod planning problem for coal distribution to poor families

İbrahim Akgün [a,*], Altan Özkil [b], Selçuk Gören [a]

[a] Abdullah Gul University, Department of Industrial Engineering, Kayseri, Turkey
[b] Atılım University, Department of Aviation Management, Ankara, Turkey

ARTICLE INFO

Keywords:
Freight transportation
Public sector operations research
UN sustainable development goals
Network optimization
Multimodal,
Multicommodity,
Multiperiod planning

ABSTRACT

Tackling poverty has been one of the greatest global challenges and a prerequisite to sustainable development of countries. Countries implement *nationally appropriate social protection systems and measures* to address poverty. This paper addresses an aid system adopted by the government in Turkey where significant amounts of coal is distributed to poor families each year. The objective of the *coal aid system* is to complete the delivery of coal to poor families by the start of winter. However, an analysis of the data from previous years indicates that the distribution to many families cannot be completed on time. This results from the fact that planning is done manually and by trial-and-error as there is no system that can be used for distribution planning. This paper describes the planning problem encountered and develops a mathematical model to solve it. The proposed model is a multimodal, multicommodity, and multiperiod linear programming (LP) model. The model can be used to develop and update a distribution plan as well as to answer several what-if questions with regard to capacities, time constraints, and so forth. The model is solved using CPLEX for several problem instances obtained under different scenarios using data for the year 2012. The results show that at least 9% cost savings and about 40% decrease in distribution completion time can be achieved when the model is used. We analyze scenario results qualitatively and quantitatively and provide several insights to the decision makers. As a part of quantitative analysis, we develop regression models to predict optimal costs based on several factors. Our main contribution is to provide an efficient and effective tool to handle a large-scale real-world problem. The model has also helped to prove that the organization responsible for distribution planning may move from the current planning practice to an all-encompassing top-down approach.

1. Introduction

Tackling *poverty* has been one of the greatest global challenges and a prerequisite to sustainable development of countries. Accordingly, "to eradicate extreme poverty and hunger" was set as the first goal of the eight Millennium Development Goals (MDGs), which were put into effect in 2000 and completed in 2015 by the United Nations (UN) [1]. Having realized significant achievements in all MDGs, the UN built upon them and put seventeen Sustainable Development Goals (SDGs) into effect in 2016. The first goal of the seventeen SDGs is again about poverty eradication and aims "to end poverty in all its forms everywhere." The first of the seventeen SDGs is again about poverty eradication and aims "to end poverty in all its forms everywhere." Among seven targets of the first goal, one aims to reduce at least by half the proportion of men, women and children of all ages living in poverty and *implement nationally appropriate social protection systems and measures* for all [2].

Poverty is broadly defined as income and material deprivation. In this regard, it is not only about restrictions imposed by lack of income but is also about other elements of deprivation such as lack of access to basic resources like food, housing, clothing, drinking water, and so forth (e.g., Ref. [3]). Measures and criteria about the income dimension of poverty may significantly change among nations, national and/or international institutions, and researchers. Nonetheless, it is frequently used to reflect the standards with regard to material deprivation.

In Turkey, surveys conducted by the governmental Turkish Statistical Institute (TSI) indicate that the population at the risk of poverty is about 13.29% (21.2%) when poverty threshold is set to 50% (60%) of the median income [4]. The survey also points out that Equation (1) 39.6% of the population has problems with regard heating the dwelling

---

* Corresponding author.
E-mail addresses: ibrahim.akgun@agu.edu.tr (İ. Akgün), altan.ozkil@atilim.edu.tr (A. Özkil), selcuk.goren@agu.edu.tr (S. Gören).

https://doi.org/10.1016/j.seps.2020.100919
Received 4 November 2019; Received in revised form 7 July 2020; Accepted 9 July 2020

and (2) 26.7% of the population has severe material deprivation (e.g., inability to pay rent and utility bills; inability to have a telephone, a washing machine, or a car; and inability to heat home adequately warm). When the survey results for previous years are considered, similar figures are observed even though there are improvements over the years. These statistics clearly indicate that it is necessary to approach the poverty issue systematically and to develop strategies to solve high-priority problems related to poverty in Turkey.

In Turkey, the General Directorate of Social Assistance (GDSA) operating under the Ministry of Family and Social Policies (MFSP) is responsible for dealing with poverty issues. The GDSA implements its social assistance activities through 975 local Social Assistance and Solidarity Foundations (SASFs) established in each district of Turkey. The decision body for a SASF is the Board of Trustees headed by the district governor. The SASFs are especially helpful in determining the needy people and ensuring that aids reach them.

One assistance program that has been adopted by the GDSA since 2003 is *to distribute free coal to poor families* including refugee families in order to tackle with the problem of *heating the dwelling*. Even though natural gas is used for heating in most urban areas, coal is still the primary resource in suburban and rural areas. According to Administrative Activity Report of the MFSP for 2015, the total amount of coal distributed to poor families between 2003 and 2015 was about 22 million tons while the amount of coal distributed to more than 2 million families was about 2.6 million tons in 2015 [5]. It is expected that this aid program will continue with increasing amounts because (1) it will take time to decrease poverty and (2) government has decided to increase coal production besides investments in clean energy alternatives.

The *coal aid system* is a complex system that includes several governmental and non-governmental organizations such as ministries, foundations, private mining and transportation companies, state-owned coal enterprises, Turkish State Railways, and governorates. The aid process starts with a decree of the Council of Ministers to initiate the process at the beginning of each year and finishes when required quantities of coal are delivered to needy families and necessary financial transactions are made. The main objective in the system is to complete the delivery of coal to poor families by the start of winter in the planning year, which may change from October to December depending on the region. An analysis of data from previous years indicates that a significant portion of delivery is completed by the end of December. However, it also indicates that a nonnegligible portion of the delivery does not finish until March in the subsequent planning year. For example, in 2012, about 90% of coal was delivered by the end of December. On the other hand, the amount delivered in the November–March period was about 30%–40% of the total. Unfortunately, most of the provinces with late delivery also happened to have cold climate. That is, the assistance program does not serve its purpose as many families are left with no (or insufficient) means of heating when they need it.

There are several problems in the system that contribute to this undesired result. However, the state-owned General Directorate of Turkish Coal Enterprises (TCE) is mostly held responsible for the result. The reason is that the TCE is the main planner and coordinator of almost all activities related to the supply and physical distribution of coal to 975 districts. The distribution within a district is the responsibility of the SASF in the district. In this context, the TCE is expected to develop a distribution plan taking into account several factors, e.g., capacities with regard to coal production and transportation. However, the TCE currently does not have a system and capability to develop such a plan; the planning is done manually and by trial-and-error. As a result, the final plan is mostly a rough plan and not applicable.

This paper describes the *Coal Distribution Planning Problem (CDPP)* that the TCE faces and develops a mathematical model to solve it. The proposed model is a multimodal, multicommodity, and multiperiod linear programming (LP) model. The model can be used to develop and update a distribution plan and to answer several what-if questions with regard to capacities, time constraints, and so forth. The model is solved using CPLEX for several problem instances obtained under different scenarios using data for the year 2012. The results show that at least 9% cost savings and about 40% decrease in distribution time can be achieved when the model is used. Our main contribution is to provide an efficient and effective tool to handle a large-scale real-world problem. The model has helped to prove that the TCE can implement an all-encompassing top-down approach instead of the current planning practice.

The rest of the paper is organized as follows: We review the literature in Section 2. We describe the problem and formulate it mathematically in Sections 3 and 4, respectively. We define scenarios, solve the mathematical model under these scenarios, and interpret their results in Section 5. We analyze the results of scenarios to determine the parameters that are statistically important on the distribution cost and time in Section 6. Finally, we conclude the paper in Section 7.

2. Literature review

The typical steps in coal production and distribution process include (1) the production of coal with different quality specifications and at different rates in the mines or the import of coal from different suppliers, (2) the shipment of coal to the silos where it undergoes a beneficiation process that improves the economic value of the ore by removing the valueless and undesirable minerals, (3) the blending of different grades of coal at silo facilities to obtain the desired quality specifications, and (4) the transportation of coal from mines or suppliers to the customers, e.g., power plants and subsidiaries. There are many studies in the literature that address several issues in the aforementioned process. We refer the reader to Ref. [6,7] for production scheduling in the mines; to Ref. 8–11 for coal blending optimization; to Ref. [12–14] for coal supply chain planning issues; to Ref. [15–17] for coal import planning; and to Ref. [18–22] for coal distribution.

Studies regarding coal distribution are mostly integrated with other problems in the coal industry. [18,19] study the coal blending and shipping problem and develop strategic and tactical level LP models that determine schedules for coal shipment to silos, cleaning and blending operations at the silos, and the subsequent shipment of coal to customers over a multi-period time horizon such that total operational cost is minimized. [20] similarly address the coal blending and shipping problem with additional considerations (e.g., the supply, quality, and price from each overseas contract; the demand, quality requirement, and limit on supply sources; seaport capacity utilization restrictions) and develop a mixed-integer programming model. [21] study a problem where coal is transported to a port by trains and then to the four subsidiaries by river vessels. They develop a Markov decision model that integrates ordering and delivery decisions. [22] develops a linear model to find the set of suppliers, coal products satisfying certain physical and chemical properties, and transportation routes that will minimize the purchase and transportation cost of the coal for the power plants. Even though the distribution of coal is considered in these studies, our problem context is completely different from theirs. Moreover, the problem characteristics are different. CDPP is a *multimodal*, *multicommodity*, and *multiperiod* transportation problem. [18,19] study a single-commodity, multiperiod problem while [20] study only a single-commodity problem. [21] address a multimodal problem. [22] considers multiple commodities but does not take the time factor into account.

In the following, we will shortly focus on the freight transportation planning literature that is related to the problem characteristics of CDPP.

A review of papers on multimodal freight transportation including the models and solution methodologies can be found in Ref. [23–26]. The first three studies cover the literature up to 2005 while the last one covers the papers from 2005 to 2014. The review papers categorize the multimodal freight transportation problems as *strategic*, *tactical*, and *operational* planning problems depending on the planning horizon of the problems.

Strategic planning problems focus on decisions regarding the existing or new infrastructures, e.g., determining the network topologies and the location of the terminals and hubs. Tactical planning problems deal with decisions related to optimally utilizing the given infrastructure, e.g., choosing the services and modes, allocating their capacities to meet demands, selecting vehicle fleet size and mix as well as routes and frequency on which the services are offered. Operational planning problems address the real-time planning problems that occur in the conduct of plans in a dynamic environment, e.g., routing and scheduling of vehicles, scheduling of crew, distribution of empty vehicles, and allocation of resources. The main difference between the tactical and operational planning is that time factor is explicitly considered in operational planning problems, e.g., the arrival and departure times of each vehicle. CDPP is mainly a tactical planning problem with an operational point of view.

There are two groups of models in tactical planning, namely, Network Flow Planning (NFP) and Service Network Design (SND) [26]. In NFP, the aim is to move the commodities throughout the network [27–33]. In SND, the purpose is to choose the transportation services and modes, e.g., origin, destination, intermediate terminals, route, capacity and price, with the goal of building regular services at a minimized cost [34–41]. SND is decomposed into static and deterministic dynamic problems with the main difference being the inclusion of time component in the deterministic dynamic SND.

In the formulation of NFP and SND models, continuous variables are used to represent the flow of commodities through the network. In SND models, in addition to continuous variables, binary variables are used to represent the selection of services [26]. Most SND models are in the form of deterministic, fixed cost, capacitated, multicommodity network design formulations [23]. Even though the same problems, e.g., the frequency of the service, the capacity allocation, and the routing and flow of commodities, are solved in both groups, deterministic dynamic SND problems have a time dimension in the formulation and result in a discrete multiperiod model defined on a time-space network. See Ref. [42] for a survey of dynamic SND problems.

[26] classify the NFP and static SND models into arc-based, path-based, and stochastic programming and the dynamic SND models into arc-based, path-based, cycle-based, and stochastic programming. The flow of commodities is represented on the arcs in the arc-based models and on the paths in the path-based models. Cycle-based formulations are used to model vehicle rotations.

In modeling the CDPP, arc-based continuous flow variables are used to represent the flows. Even though the flow variables represent the flow of vehicles, they indirectly represent the flow of commodities. An operational point of view is taken by including the time component in the model. The resulting model is a multiperiod model as in deterministic dynamic SND. However, it is not an SND model because we do not select regular services to be offered to the customers by using the binary variables. Unlike the previous studies, we do not use binary variables to select the modes (road and rail) either. We construct an artificial network to represent alternative routes consisting of different modes from the origins to the demand points. Accordingly, we determine how to route multiple commodities through this artificial network by utilizing available resources, e.g., the network and vehicles, to meet the demands, which is in accordance with the requirements of tactical planning. We can consider the CDPP as an NFP problem with the time component and problem-specific properties incorporated. To our knowledge, NFP models in the literature are static. Moreover, most models are single-mode [28–30,32]. With the aforementioned characteristics, CDPP is a multimodal, multicommodity, and multiperiod freight transportation planning problem with unique properties.

Finally, the CDPP is a public sector problem. The use of Operations Research/Management Science (OR/MS) in the public sector is termed as the Public Sector OR (PSOR) or Community OR (COR) [43]. define PSOR as "OR/MS applications that address 'provision of goods and services, or prescribe social policy actions, for which stakeholders are defined, in a spatial or social sense, as localized, or who are considered disadvantaged or underserved, or for which issues of equity or social influence are important considerations', as examples of community-based operations research". However, there is no agreed-upon definition of PSOR. We refer the reader to Ref. [44–48] for further discussion on PSOR.

3. Problem definition

Major coal producers in Turkey are General Directorate of Turkish Coal Enterprises (TCE), the Electricity Generation Company (EGC), and the Turkish Hard Coal Enterprises (THCE), which are all state-owned. In addition to state-owned companies, there are private companies that work under different mechanisms.

The *coal aid to poor families* is annually planned with the cooperation and collaboration of several organizations, e.g., the ministries, the SASFs, and the Governorates. After a governmental decree is issued to initiate the planning process, the TCE becomes the main coordinator and responsible for planning how to supply needed coal and monitoring the implementation of the plan.

As a first step for planning, the TCE requests the lists of needy families and delivery quantities along with other necessary information from the governorates. The governorates collect necessary data with the help of the SASFs and send the data to the TCE, which may take quite a long time. In the meantime, the TCE signs a protocol with the Turkish State Railways (TSR) to be able to use railways for coal transportation. The protocol specifies the total capacity assigned to the TCE, which accounts for about 15–20% of the total demand (about 400,000 tons in 2015). According to the protocol, the TSR provides trains when requested by the TCE.

The distribution of coal from mines to poor families is conducted in two phases. In the first phase, coal is transported *from mines to delivery locations in the districts* that are determined by the SASFs. In this phase, road transport or a combination of rail and road transport may be used. In the former, coal is loaded onto trucks at the mines and moved to the delivery locations in the districts by trucks. In the latter, coal is loaded onto railcars at the mines and moved to a destination station by train. At the destination station, coal is unloaded from railcars and loaded onto trucks for further transportation to delivery locations in the districts. In the second phase, coal is moved *from delivery locations to families within districts* by trucks. The TCE is responsible for the first phase while the SASF in each district is responsible for the second phase. However, the TCE may also request the support of the foundations when needed in the first phase, e.g., for arranging regional or local distribution.

Data analysis indicates that there are several problems in both phases of the distribution. For example, sometimes there are not sufficient number of trucks to carry the coal unloaded from railcars to the districts because the responsible foundation is not informed about the delivery time in advance to allow it to prepare for local or regional delivery. The preparation process for local or regional delivery takes time because the foundation need to go out to a tender, which may take several weeks, to determine the transportation company to carry coal. A similar problem may occur at the delivery locations in the districts. Such problems may require coal to be stored at the stations or delivery locations in the districts for some time. Even though coal can be stored under appropriate conditions in open or closed areas for short periods of time, some negative developments may be observed in various characteristics of coal, especially if stored in open areas. For example, caloric value may diminish, coal may be fragmented, and self-oxidation may cause fires. Because of such problems, the TCE would like to ensure that coal is not stored at the stations and at the delivery locations for a long time. In our model, we allow temporary inventory only at the rail stations.

The TCE governs about 40% of lignite production and operates 32 opencast and nine underground mines through its subsidiaries or private companies under subcontracts. Some of these mines produce coal only for industrial purposes, e.g., power generation and steel production, while some produce coal for heating dwellings and for industrial purposes. The TCE has to provide contracted amounts of coal to its dealers and customers in a given year. For this reason, it generally plans to meet about half of the total demand for the aid system from its own subsidiaries and the remaining from private subcontractors operating the TCE's mines. Selected mines assign a certain portion of their total throughput to poor families. The throughput of a mine is determined by loading capacities for each transportation mode, available transportation capacities, e.g., the number of trucks and trains, and the capacities of railcars and trucks allocated to poor families.

In addition to the above issues, the pollution level of each district is to be taken into account in planning to abide by the environmental regulations. The pollution level of a district determines what quality of coal can be used for heating purposes in the district. A district can receive coal with a quality level equal to or better than the corresponding pollution level. This requirement affects from which mines a district can be served because the quality of produced coal changes depending on the coal beds. Coal of different qualities may be produced in the same mine.

As being responsible for the first phase of coal distribution, the TCE is expected to develop a distribution plan that considers the movement of the coal from the supply points (subsidiaries or subcontractor companies) to the districts. Specifically, the TCE is to develop a distribution plan that includes from where (private- or state-operated mines), at what time(s), and by what transportation mode(s) each district is to be supplied. The plan should be developed taking the cost and other constraints into account, e.g., time and capacity constraints with regard to the coal production and transportation. Developing such a plan and making it public is of critical importance for both the TCE and other stakeholders in the process for control and coordination purposes. For example, it would be more desirable for the foundations to know the distribution schedule for their districts in advance so that they can make necessary preparations for distribution within the district. In the current situation, the plan essentially includes an allocation of supply points to districts on a monthly basis. It is left to the subsidiaries and subcontractors to coordinate with the foundations in the districts to determine specific distribution times. Nevertheless, this in turn allows supply points to take control of the process depending on their own priorities (e.g., different customers) even though there are regulations or procedures. The result is that the completion times of delivery for even two neighboring districts can be drastically different.

In the current practice of planning, the TCE does not use any system and develops a distribution plan manually. The TCE first assigns supply points under its control to meet the demand of some districts. This assignment is mainly based on the previous year's realized plan. The TCE then goes out to tender to meet the demand of the uncovered districts. Depending on the results of the tenders, which are essentially based on the bid prices by the subcontractors, the TCE determines the companies to serve the districts. The plan is finalized with the assignment of private subcontractors to the uncovered districts. This assignment is also based essentially on the previous year's realized plan.

Because of the adopted approach to develop the plan, most factors including cost are not exactly taken into account and alternative plans are not developed and evaluated. This is a disadvantage for the TCE because it misses the opportunity to come up with a plan with a high probability of success (in terms of delivery times) and lower cost. During a planning year, the TCE finances the program and then requests reimbursement from the Treasury. The Treasury makes payments depending on only the quantity of distributed coal and not on the distribution expenses. Thus, the cost of transportation becomes very critical for the TCE especially when private companies are used for transportation. The cost of transportation needs to be computed accurately and incorporated into per unit cost of the coal. The TCE has a cost analysis model, NAKMAL [49], developed exactly for that purpose. Nevertheless, the model computes point-to-point costs based on average values for different transportation modes considering several factors. It is especially used to evaluate offers during tenders with the purpose of keeping cost under the estimated amount. It is useful for the TCE but does not help to develop and consider alternative plans.

That the cost of the aid program reached about $400 million in 2013 [50] and that the program will continue for the coming years make it necessary for the TCE to have a system capable of developing alternative distribution plans such that the cost is minimized and the delivery schedules are met.

This paper describes a mathematical model that is developed to address all aforementioned issues and analyzes the results of the model through a set of scenarios. The results indicate that the model can be used to meet the needs of the TCE.

4. Formulation of the problem

The explanations for the sets, indices, parameters, and decision variables used in the formulation of the problem are presented in Table 1.

We formulate the problem on a network $G = (N, A)$ constructed to represent the alternative routes from the origins (the mines) to the demand points (the districts). The network consists of three echelons where the nodes in the first, second (middle), and third levels represent N^S, N^{TR}, and N^D, respectively. N^{TR} is comprised of N^{Rail}, where transport mode changes from rail to road, and $N^{\bar{S}}$ that act as *dummy* transfer points. That is, $N = N^S \cup N^{TR} \cup N^D$ with $N^{TR} = N^{\text{Rail}} \cup N^{\bar{S}}$. The nodes in two consecutive echelons are connected via directed arcs (i, j) that represent possible transportation movements as well as the shortest paths from mines to rail stations and from rail stations to districts. Fig. 1 gives a schematic representation of the constructed network where dashed lines represent the rail transportation while solid lines represent the road transportation. We remind that the network structure given in Fig. 1 is a constructed network and does not represent the real physical

Table 1
Sets, indices, parameters, and decision variables of the proposed model.

Sets, Indices, and Parameters	
$i, j \in N$	Nodes in the network $G = (N, A)$, $N = N^S \cup N^{TR} \cup N^D$
$k, \bar{k} \in K$	Coal types, $K = \{1, 2\}$
$m \in M$	Transportation modes, $M = \{road, rail\}$
$t \in T$	Time periods (weeks), $T = \{1, 2, \ldots, \lvert T\rvert\}$, $\lvert T\rvert = 20, 25, 30, 35, 40$
N^S	Set of origin nodes (mines)
$N^{\bar{S}}$	Set of copies of origin nodes
N^{Rail}	Set of nodes representing railway stations
N^{TR}	Set of transshipment nodes, $N^{TR} = N^{\text{Rail}} \cup N^{\bar{S}}$
N^D	Set of nodes representing demand points (districts)
N_k^S	Set of mines that produce type k coal
N_k^D	Set of demand points that require type k coal
dem_{ik}	Demand of coal type k at demand node i
c_{ijkm}	Cost of sending one ton of coal type k from node i to node j using transportation mode m
vcap_m	Vehicle capacity for transportation mode m
pcap_{ik}	Production capacity of coal type k at mine i
lcap_{im}	Loading capacity for transportation mode m at mine i
mcap_m	Maximum allowable capacity of transportation mode m
availveh_{im}	Available number of vehicles of transportation mode m at node $i \in (N^{\text{Rail}} \cup N^S$
arrveh_{im}	Max number of loaded vehicles of transportation mode $m = rail$ allowed to arrive at node $i \in N^{\text{Rail}}$
Decision Variables	
X_{ijkmt}	the number of vehicles of transportation mode m that carry type k coal from node i to node j in period t

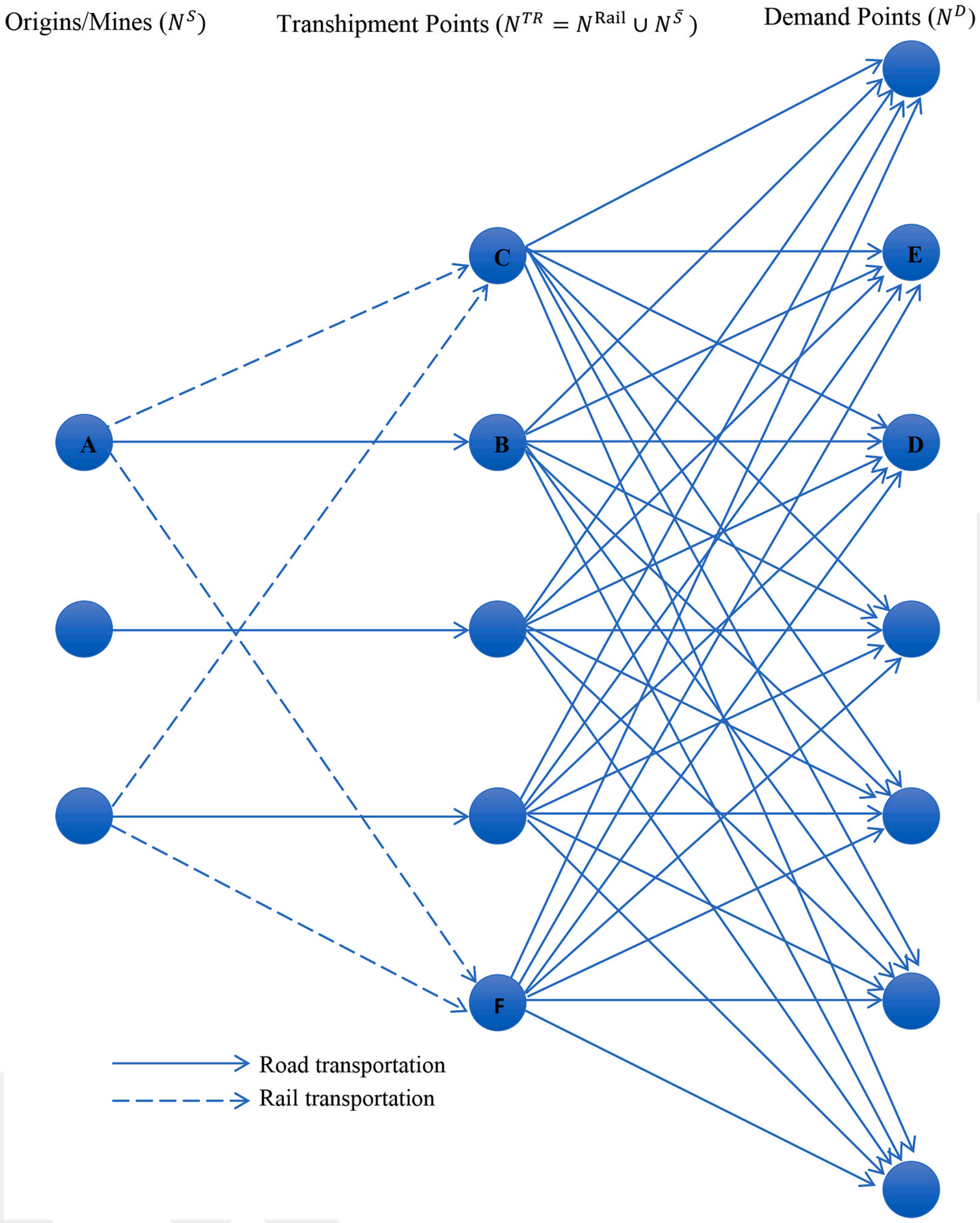


Fig. 1. Schematic representation of the constructed network.

network. The shortest path from a mine to a rail station, e.g., C, on the real physical network may consist of other rail stations, e.g., F, as intermediate nodes of the shortest paths. In this case, transportation of coal between transshipment points is possible; however, coal is not transferred to other trains at these intermediate transshipment points and they are used just as transit points. A similar situation occurs in the second level of the network. A truck moving from a rail station or a mine to a district, e.g., D, may go through other districts, e.g., E. However, coal is not transferred to other trucks at the districts.

There are two options to transport coal from $i \in N^S$ to $l \in N^D$: (1) by trucks and (2) by a combination of trains and trucks. If trucks are to be used, trucks move from $i \in N^S$ to $j \in N^{\bar{S}}$ and then from j to demand point l. For example, in Fig. 1, the route from A to E using trucks is $A- B- E$ with B acting as a *dummy* transfer point. If a combination of trains and trucks are to be used, the flow is via trains from $i \in N^S$ to $n \in N^{\text{Rail}}$ and then from n to l via trucks. At the railway station n, coal is unloaded from railcars and loaded onto trucks destined to the districts. For example, in Fig. 1, there are two routes from A to E that use both transport modes: $A - C - E$ and $A - F - E$. The transportation from A to C (F) is by train and the transportation from C (F) to E is by trucks. In constructing the network, we assume that, if there is a mine in a district, the demand of that district will be met from the mine in the district. Moreover, we do not allow links from an origin node to the copy of another origin node in the second level because it is not reasonable to send coal from a mine to another mine.

The decision about which routes to use from origins to demand points is based on the total *purchasing and transportation cost*. To incorporate the costs appropriately, we associate a cost c_{ijkm} with each arc (i, j) that changes depending on coal type $k \in K$, transportation mode $m \in M$, and the role of the arc in the constructed network (e.g., whether it connects a source node and a transfer node or a transfer node and a destination node). The cost c_{ijkm} associated with arc (i,j) for $i \in N^S$, $j \in N^{\text{Rail}}$, and $m = \text{rail}$ represents the *purchasing and transportation cost* per ton of type k coal using *rail* transportation, e.g., the cost on the arc (A, C) in Fig. 1, while the cost c_{jlkm} associated with arc (j, l) for $j \in N^{\text{Rail}}$, $l \in N^D$, and $m = \text{road}$ represents the *transportation cost* per one ton of type k coal using *road* transportation, e.g., the cost for (C, D) in Fig. 1. The cost c_{nlkm} for arc (n, l) with $n \in N^{\bar{S}}$, $l \in N^D$, and $m = \text{road}$ represents the *purchasing and transportation cost* per one ton of type k coal using *road* transportation (e.g., the cost for (B, E) in Fig. 1). The cost for an arc connecting an origin node to its copy is zero, e.g., $c_{ijkm} = 0$ for $(i, j) = (A, B)$ in Fig. 1.

We additionally define the parameters pcap_{ik}, lcap_{im}, dem_{lk}, mcap_m, and vcap_m and the sets N_k^S and N_k^D. In our representation, $k = 2$ is of lower quality than $k = 1$. We assume that a single type of vehicle with a maximum capacity is used for each transportation mode. Specifically, a truck is assumed to have a maximum capacity of 25 tons while a train is assumed to have a maximum capacity of 500 tons. The capacity of a train between two points, e.g., a mine and railway station, is actually determined by the number of railroad cars assigned by the TSR at the request of the TCE.

Even though not considered in the current planning practice, the number of available vehicles at the mines and railway stations to carry coal may be limited. Moreover, the number of arriving trains that can be handled at the railway stations may be restricted. These capacity constraints may result from contractor capacity or infrastructural limitations. To incorporate capacity constraints into the model, we define availveh_{im} and arrveh_{im}.

We formulate the problem as a multimodal, multi-commodity, and multiperiod network flow model. The length of a period t is one week. We assume that sufficient number of vehicles are available at the required locations in each week; trucking companies make new trucks available or ensure that trucks reaching demand points come back to their departure points and the TSR assigns capacity on scheduled trains. To formulate the problem, we define the decision variable X_{ijkmt} as the number of vehicles of transportation mode m that carry type k coal from node i to node j in period t.

Model CDPM: Coal Distribution Planning Model

$$z^* = \min_X z = \sum_{i,j,k,m,t} c_{ijkm} \text{vcap}_m X_{ijkmt} \tag{1}$$

$$s.t. \quad \sum_{i \in N^{TR}, \bar{k} \le k, m=\text{road}, t} \text{vcap}_m X_{ij\bar{k}mt} = \text{dem}_{jk} \qquad j \in N_k^D, k \tag{2}$$

$$\sum_{j \in N^{TR}, m, t} \text{vcap}_m X_{ijkmt} \le \text{pcap}_{ik} \qquad i \in N_k^S, k \tag{3}$$

$$\sum_{j \in N^{TR}, k} \text{vcap}_m X_{ijkmt} \le \text{lcap}_{im} \qquad i \in N^S, m, t \tag{4}$$

$$\sum_{i \in N^S, j \in N^{TR}, k, t} \text{vcap}_m X_{ijkmt} \le \text{mcap}_m \qquad m \tag{5}$$

$$\sum_{j \in N_k^D, m=\text{road}} \text{vcap}_m X_{ijkmt} - \sum_{j \in N_k^S, m=\text{rail}} \text{vcap}_m X_{jikm,t-1} = 0 \qquad i \in N^{\text{Rail}}, k, t \tag{6}$$

$$\sum_{j \in N_k^D, m=\text{road}} \text{vcap}_m X_{ijkmt} - \sum_{j \in N_k^S, m = \text{road}} \text{vcap}_m X_{jikmt} = 0 \qquad i \in N^{\bar{S}}, k, t \tag{7}$$

$$\sum_{j \in N^{TR}, k} X_{ijkmt} \le \text{availveh}_{im} \qquad i \in N^S, m, t \tag{8}$$

$$\sum_{j \in N_k^D, k} X_{ijkmt} \le \text{availveh}_{im} \qquad i \in N^{\text{Rail}}, m = \text{road}, t \tag{9}$$

$$\sum_{j \in N^S, k} X_{jikmt} \le \text{arrveh}_{im} \qquad i \in N^{\text{Rail}}, m = \text{rail}, t \tag{10}$$

$$X_{ijkmt} \ge 0 \quad i, j, k, m, t \tag{11}$$

Objective function (1) minimizes the total purchasing and transportation cost that depends on the quantity of coal transported by the vehicles. Constraints (2) are demand satisfaction constraints. The constraints ensure that each district receives the required or better-quality coal throughout the planning period. If data are available, we can ensure that coal is distributed to the districts within the specified time windows by restricting the summation over time index in Constraints (2) to time windows of the districts. Constraints (3) and (4) require that production and loading capacities at the mines be satisfied, respectively. Constraints (5) restrict the total amount of coal that can be transported by each transport mode. Constraints (6) and (7) are flow-balance constraints for transshipment nodes, i.e., dummy transfer nodes and rail stations. We assume that coal sent from a mine by trucks will reach the demand points in one week while coal sent from a mine to a rail station will reach the demand points by trucks in two weeks. That is, we allow temporary inventory at the stations for one week if needed. Constraints (8) restrict the number of trucks and trains that can be sent from mines while constraints (9) restrict the number of trucks that can be sent from rail stations in one week. Constraints (10) limit the number of trains that can arrive at rail stations. We remark that the capacity constraints indirectly distribute the transportation load across the planning period. Constraints (11) define the decision variables.

CDPM does not track which mines supply which districts explicitly. However, this information can be extracted from the solution by tracking the incoming flow to a district backwards to the origins. The difficulty may arise when multiple mines send a specific type of coal to a railway station and when the railway station sends that specific type of coal to multiple districts in a period. For example, in Fig. 1, railway station C may receive coal from both mines and then send it to D and E. Such a solution is highly unlikely. There are three mines with the infrastructure supporting rail transportation and 201 railway stations. A district mostly receives coal from the nearest railway station, which also receives coal mostly from a single mine as long as the capacities are sufficient because of the cost minimization objective. However, if such a solution occurs, we can assign districts receiving coal to the mines sending coal at a specific time period by taking into account the flow quantities arbitrarily because which mines serve which districts does not affect the total cost and distribution time. In this case, what is important for a mine is to know which railway station to send coal in a specific time period and not the district it is to supply because coal from different mines is consolidated at the railway station and then distributed to the districts. The Social Assistance and Solidarity Foundation in the region is responsible for organizing this.

In CDPM, we define x_{ijkmt} as a continuous variable. We have made this decision after having discussions with the experts from the TCE and ensuring that the usage of continuous variables is valid in the context of the problem. The results of scenarios also confirm the validity of the continuous variables. When the decision variables take on fractional values, they can be rounded up or down because the total amount of coal sent by the TCE changes in practice as well for several reasons. For example, new families may be added to the distribution list in a district or slight changes may be made in the amount of coal distributed to families in a district. As a result, the TCE may prefer to use full truck load instead of less than truckload shipment for a district or prefer not to send less than truckload shipment to a district. Moreover, the decision variables take on high values and rounding up or down has a meaning in reality. To explain, consider the year of 2012 when about 2 million tons of coal was distributed. Given the total transportation mode capacities (400,000 tons by train and 1,600,000 by truck) and vehicle capacities (500 tons for trains and 25 tons for trucks), this implies that 800 trains and 64,000 trucks are needed in total. If we assume that the vehicles are evenly distributed over the planning period, 20 trains and 1,600 (One thousand and six hundred) trucks are needed in each week for a 40-week planning period. If we assume that trucks (trains) are evenly distributed among 15 (3) mines, the number of trains and trucks leaving from each mine are 8.33 and 106.7, respectively. The number of wagons for each train is at least 8 based on the capacity of the wagons. Thus, if the number of trains to be sent from a mine is 8.33, it means that the TCE should request 67 or 66 ($8.33 \times 8 = 66.6$) wagons from the Turkish State Railways. Please note that the Turkish State Railways does not dedicate trains to the TCE to carry coal but assigns a capacity on certain scheduled trains. The TCE needs to determine the capacity to request from the Turkish State Railways, which can be done rounding up or down the resulting solution value. Similarly, the value of 106.7 can be rounded up or down.

5. Solution of the model and scenario analysis

5.1. Scenarios

To gain insights about the problem and to test the performance of CDPM, we construct and solve a set of scenarios that are based on real data for the year 2012. The total demand for 975 districts is about 2 million tons. The number of mines that produce coal for heating dwellings is 15 and only three of them has the infrastructure to support rail transportation. The number of railway stations is 201. The constructed network consists of 1206 nodes (15, 216, and 975 nodes in three consecutive layers, respectively) and 211,218 arcs (618 arcs connecting the first and second layers and 210,600 arcs connecting the second and third layers).

We define scenarios using different data sets for production capacities (pcap_{ik}), loading capacities (lcap_{im}), transportation mode capacities (mcap_{m}), the number of available vehicles (trucks and trains) at the mines and railway stations ($\mathrm{availveh}_{im}$), and the number of trains allowed to reach the rail stations (arrveh_{im}). The data sets for the aforementioned parameters are given in Table 2 through 5, respectively. In all tables, the first data set represents the actual situation while other data sets represent possible cases. Data set 1 in Table 2 represents the actual production capacities of the mines used in 2012. Data set 2 in Table 2 is designed to allow more flexibility to the model to determine the mines that will supply coal for the aid system. The production capacities in data set 2 are close to each other and hence more balanced. The values change from 15000 to 300000 in data set 1 and from 200000 to 250000 in data set 2. If the changes were not that significant, we would not be able to determine which mines are better to supply from and the assignments would be mostly similar to the current practice. Data sets 2 and 3 in Table 3 are determined assuming that the capacities allocated to the aid system are increased by 25% and 50%. Similarly, data sets 2 and 3 in Table 4 are specified considering possible cases. Data sets 2, 3, and 4 in Table 5 are determined after analyzing the results of the scenarios that do not take into account vehicle capacities. We remark that the values in the tables represent the capacities that can be used for the aid system and not the overall (production, loading, etc.) capacities.

We define scenarios using different combinations of data sets in Tables 2–5. We construct three categories of scenarios. The first category **S1** represents the real situation in 2012, i.e., the first data sets in Tables 2–5 are used. The second category **S2** consists of scenarios obtained by using different data sets for the first three parameters, i.e., pcap_{ik}, lcap_{im}, and mcap_{m}. In this category, we set the values of $\mathrm{availveh}_{im}$ and arrveh_{im} to infinity, i.e., they are not restrictive. The third category **S3** consists of the scenarios obtained by adding restrictive values regarding $\mathrm{availveh}_{im}$ and arrveh_{im} to scenarios in **S2**. We have defined data sets in **S3** after analyzing the solutions of **S1** and **S2**. In **S3,** the number of trains available at a mine i and the number of trains arriving at a station j, i.e., $\mathrm{availveh}_{i,rail}$ and $\mathrm{arrveh}_{j,rail}$ are set to the same value. The number of trains available at a station j, $\mathrm{availveh}_{j,rail}$, are set to zero. In all scenarios, we use the same demand (dem_{ik}) and cost (c_{ijkm})

Table 2
Data regarding production capacities at the mines (tons/week).

Mines	Data Sets for pcap_{ik}			
	1		2	
	Coal Type 1	Coal Type 2	Coal Type 1	Coal Type 2
A	80000		200000	
B	20000		200000	
C	250000		250000	
D		65000		200000
E	50000		200000	
F	250000	250000	250000	250000
G	250000	250000	250000	250000
H		65000		200000
I	20000		200000	200000
J	80000		200000	
K		80000		200000
L	80000		200000	
M		15000		200000
N		300000		200000
O		15000		200000

Table 3
Data regarding loading capacities at the mines (tons/week).

Mines	Data Sets for lcap_{im}					
	1		2		3	
	Road	Rail	Road	Rail	Road	Rail
A	10000		12500		15000	
B	10000		12500		15000	
C	10000		12500		15000	
D		10000		12500		15000
E	10000		12500		15000	
F	10000	10000	12500	12500	15000	15000
G	10000	10000	12500	12500	15000	15000
H		10000		12500		15000
I	10000		12500		15000	
J	10000		12500		15000	
K		10000		12500		15000
L	10000		12500		15000	
M		10000		12500		15000
N		10000		12500		15000
O		10000		12500		15000

Table 4
Data regarding total transportation mode capacities (in tons).

Transportation Mode	Data Sets for mcap_{m}		
	1	2	3
Road	1650000	1650000	2000000
Rail	400000	800000	800000

Table 5
Data regarding restrictions on the number of vehicles allowed to enter and leave the nodes (per week) (inf: infinity).

Node Types	Data Sets for $\mathrm{availveh}_{im}$and arrveh_{im}							
	1		2		3		4	
	Road	Rail	Road	Rail	Road	Rail	Road	Rail
Mines ($\mathrm{availveh}_{im}$)	inf	inf	400	40	300	30	200	20
Railway stations ($\mathrm{availveh}_{im}$)	inf	0	400	0	300	0	200	0
Railway stations (arrveh_{im})	0	inf	0	40	0	30	0	20

Table 6
Scenarios **S1** and **S2** and their results.

Scenarios	$\|T\|$	pcap_{ik}	lcap_{im}	mcap_{m}	veh_{im}	Imp
1	20	1	1	1	1	Infeasible
2	25	1	1	1	1	9.18
3	30	1	1	1	1	9.37
4	35	1	1	1	1	9.52
5	40	1	1	1	1	9.64
6	20	1	1	2	1	Infeasible
7	25	1	1	2	1	10.73
8	30	1	1	2	1	11.94
9	35	1	1	2	1	12.87
10	40	1	1	2	1	13.33
11	20	1	1	3	1	Infeasible
12	25	1	1	3	1	10.73
13	30	1	1	3	1	11.94
14	35	1	1	3	1	12.87
15	40	1	1	3	1	13.33
16	20	1	2	1	1	9.18
17	25	1	2	1	1	9.41
18	30	1	2	1	1	9.58
19	35	1	2	1	1	9.69
20	40	1	2	1	1	9.69
21	20	1	3	1	1	9.37
22	25	1	3	1	1	9.58
23	30	1	3	1	1	9.69
24	35	1	3	1	1	9.69
25	40	1	3	1	1	9.69
26	20	1	2	2	1	10.66
27	25	1	2	2	1	12.14
28	30	1	2	2	1	13.15
29	35	1	2	2	1	13.37
30	40	1	2	2	1	13.37
31	20	1	2	3	1	10.66
32	25	1	2	3	1	12.14
33	30	1	2	3	1	13.15
34	35	1	2	3	1	13.37
35	40	1	2	3	1	13.37
36	20	1	3	2	1	11.83
37	25	1	3	2	1	13.12
38	30	1	3	2	1	13.37
39	35	1	3	2	1	13.37
40	40	1	3	2	1	13.37
41	20	1	3	3	1	11.83
42	25	1	3	3	1	13.12
43	30	1	3	3	1	13.37
44	35	1	3	3	1	13.37
45	40	1	3	3	1	13.37
46	20	2	1	1	1	22.60
47	25	2	1	1	1	22.64
48	30	2	1	1	1	22.65
49	35	2	1	1	1	22.65
50	40	2	1	1	1	22.65
51	20	2	1	2	1	23.91
52	25	2	1	2	1	24.22
53	30	2	1	2	1	24.36
54	35	2	1	2	1	24.42
55	40	2	1	2	1	24.48
56	20	2	1	3	1	23.91
57	25	2	1	3	1	24.22
58	30	2	1	3	1	24.36
59	35	2	1	3	1	24.42
60	40	2	1	3	1	24.48
61	20	2	2	1	1	22.64
62	25	2	2	1	1	22.65
63	30	2	2	1	1	22.65
64	35	2	2	1	1	22.65
65	40	2	2	1	1	22.65
66	20	2	3	1	1	22.65
67	25	2	3	1	1	22.65
68	30	2	3	1	1	22.65
69	35	2	3	1	1	22.65
70	40	2	3	1	1	22.65
71	20	2	2	2	1	24.21
72	25	2	2	2	1	24.38
73	30	2	2	2	1	24.45
74	35	2	2	2	1	24.52
75	40	2	2	2	1	24.59
76	20	2	2	3	1	24.21
77	25	2	2	3	1	24.38
78	30	2	2	3	1	24.45
79	35	2	2	3	1	24.52
80	40	2	2	3	1	24.59
81	20	2	3	2	1	24.35
82	25	2	3	2	1	24.44
83	30	2	3	2	1	24.53
84	35	2	3	2	1	24.60
85	40	2	3	2	1	24.60
86	20	2	3	3	1	24.35
87	25	2	3	3	1	24.44
88	30	2	3	3	1	24.53
89	35	2	3	3	1	24.60
90	40	2	3	3	1	24.60

data. We have encountered problems especially in determining costs from mines to railway stations, from railway stations to districts, and from mines to districts. The TCE has provided us with cost data only for the realized distributions in the past between certain locations. For the remaining point-to-point cost data, we have made educated guesses in coordination with the representatives from the TCE. We have not been able to use NAKMAL, the cost analysis model of the TCE, because it does not have necessary data in its database to do analysis for new point-to-point distributions.

We give all scenarios in **S1** (1–5) and **S2** (6–90) in Table 6 and all scenarios in **S3** (91–210) in Table 7. We compare the optimal objective function values z^* for each scenario with the realized cost value z_c in 2012 and give how much improvement ($\textbf{Imp} = 100 \times (z_c - z^*)/z^*$) is achieved in Tables 6 and 7. Even though the distribution period is about *40 weeks in 2012*, we find solutions for $|T| = 20, 25, 30, 35,$ and 40 to see whether distribution is possible in less-than 40-week period.

We have coded CDPM with GAMS 26.1 [51] and solved it with the solver CPLEX 12.3 using default settings [52]. We have conducted all computations on a PC with 2.50 Intel Core i7-4710HQ processor and 16 GB of RAM. Optimal solutions for about 90% of scenarios are obtained within less than 1 h while the solution times increase up to 2 h for the remaining 10%.

5.2. Scenario results

5.2.1. The results for S1 (Scenarios 1–5)

The results for **S1** indicate that both the completion time of distribution and the cost realized in 2012 can be reduced when the model is used. Specifically, a completion time of 25 weeks with a cost reduction of 9.18% can be achieved. However, it is not possible to complete the distribution in less than 25 weeks. When the completion time is set to 40 weeks, the cost reduction increases to 9.64%, which corresponds to about $40 million in 2012 dollars [53]. This reduction results from the changes in the assignments of mines to districts, in the routes used, and in the usage of transportation modes.

5.2.2. The results for S2

5.2.2.1. The effect of transportation mode capacities (scenarios 6–15). In **S1**, the whole rail capacity is used because rail transportation is cheaper than road transportation. When the transportation mode capacities are increased, the distribution time cannot be decreased below 25 weeks. That is, transportation mode capacities are not the limiting factor for

Table 7
Scenarios **S3** and their results.

Scenarios	$\|T\|$	pcap$_{ik}$	lcap$_{im}$	mcap$_{m}$	veh$_{im}$	Imp	Imp (Table 6)
91	20	1	1	1	2	**Infeasible**	Infeasible
92	25	1	1	1	2	**Infeasible**	9.18
93	30	1	1	1	2	9.37	9.37
94	35	1	1	1	2	9.52	9.52
95	40	1	1	1	2	9.64	9.64
96	20	1	1	1	3	**Infeasible**	Infeasible
97	25	1	1	1	3	**Infeasible**	9.18
98	30	1	1	1	3	**Infeasible**	9.37
99	35	1	1	1	3	8.74	9.52
100	40	1	1	1	3	9.37	9.64
101	20	1	1	2	2	**Infeasible**	Infeasible
102	25	1	1	2	2	10.18	10.73
103	30	1	1	2	2	11.94	11.94
104	35	1	1	2	2	12.87	12.87
105	40	1	1	2	2	13.33	13.33
106	20	1	1	2	3	**Infeasible**	Infeasible
107	25	1	1	2	3	**Infeasible**	10.73
108	30	1	1	2	3	10.92	11.94
109	35	1	1	2	3	12.65	12.87
110	40	1	1	2	3	13.33	13.33
111	20	1	2	1	2	**Infeasible**	9.18
112	25	1	2	1	2	**Infeasible**	9.41
113	30	1	2	1	2	9.37	9.58
114	35	1	2	1	2	9.52	9.69
115	40	1	2	1	2	9.64	9.69
116	20	1	2	1	3	**Infeasible**	9.18
117	25	1	2	1	3	**Infeasible**	9.41
118	30	1	2	1	3	**Infeasible**	9.58
119	35	1	2	1	3	8.74	9.69
120	40	1	2	1	3	9.37	9.69
121	20	1	3	1	2	**Infeasible**	9.37
122	25	1	3	1	2	**Infeasible**	9.58
123	30	1	3	1	2	9.37	9.69
124	35	1	3	1	2	9.52	9.69
125	40	1	3	1	2	9.64	9.69
126	20	1	3	1	3	**Infeasible**	9.37
127	25	1	3	1	3	**Infeasible**	9.58
128	30	1	3	1	3	**Infeasible**	9.69
129	35	1	3	1	3	8.74	9.69
130	40	1	3	1	3	9.37	9.69
131	20	1	2	2	2	**Infeasible**	10.66
132	25	1	2	2	2	11.71	12.14
133	30	1	2	2	2	13.15	13.15
134	35	1	2	2	2	13.37	13.37
135	40	1	2	2	2	13.37	13.37
136	20	1	2	2	3	**Infeasible**	10.66
137	25	1	2	2	3	**Infeasible**	12.14
138	30	1	2	2	3	12.55	13.15
139	35	1	2	2	3	13.36	13.37
140	40	1	2	2	3	13.37	13.37
141	20	1	3	2	2	**Infeasible**	11.83
142	25	1	3	2	2	12.93	13.12
143	30	1	3	2	2	13.37	13.37
144	35	1	3	2	2	13.37	13.37
145	40	1	3	2	2	13.37	13.37
146	20	1	3	2	3	**Infeasible**	11.83
147	25	1	3	2	3	**Infeasible**	13.12
148	30	1	3	2	3	13.10	13.37
149	35	1	3	2	3	13.36	13.37
150	40	1	3	2	3	13.37	13.37
151	20	2	1	1	3	19.23	22.60
152	25	2	1	1	3	21.91	22.64
153	30	2	1	1	3	22.66	22.65
154	35	2	1	1	3	22.66	22.65
155	40	2	1	1	3	22.66	22.65
156	20	2	1	1	4	**Infeasible**	22.60
157	25	2	1	1	4	16.53	22.64
158	30	2	1	1	4	19.34	22.65
159	35	2	1	1	4	21.18	22.65

(*continued on next page*)

Table 7 (*continued*)

Scenarios	$\lvert T\rvert$	$pcap_{ik}$	$lcap_{im}$	$mcap_m$	veh_{im}	Imp	Imp (Table 6)
160	40	2	1	1	4	22.66	22.65
161	20	2	1	2	3	21.18	23.91
162	25	2	1	2	3	23.83	24.22
163	30	2	1	2	3	24.36	24.36
164	35	2	1	2	3	24.42	24.42
165	40	2	1	2	3	24.48	24.48
166	20	2	1	2	4	12.38	23.91
167	25	2	1	2	4	20.24	24.22
168	30	2	1	2	4	22.49	24.36
169	35	2	1	2	4	23.67	24.42
170	40	2	1	2	4	24.48	24.48
171	20	2	2	1	3	19.28	22.64
172	25	2	2	1	3	21.92	22.65
173	30	2	2	1	3	22.66	22.65
174	35	2	2	1	3	22.66	22.65
175	40	2	2	1	3	22.66	22.65
176	20	2	2	1	4	**Infeasible**	22.64
177	25	2	2	1	4	16.53	22.65
178	30	2	2	1	4	19.34	22.65
179	35	2	2	1	4	21.18	22.65
180	40	2	2	1	4	22.66	22.65
181	20	2	3	1	3	19.33	22.65
182	25	2	3	1	3	21.92	22.65
183	30	2	3	1	3	22.65	22.65
184	35	2	3	1	3	22.65	22.65
185	40	2	3	1	3	22.65	22.65
186	20	2	3	1	4	Infeasible	22.65
187	25	2	3	1	4	16.53	22.65
188	30	2	3	1	4	19.34	22.65
189	35	2	3	1	4	21.18	22.65
190	40	2	3	1	4	22.66	22.65
Scenarios	$\lvert T\rvert$	$pcap_{ik}$	$lcap_{im}$	$mcap_m$	veh_{im}	Imp	Imp (Table 6)
191	20	2	2	2	3	21.94	24.21
192	25	2	2	2	3	24.02	24.38
193	30	2	2	2	3	24.45	24.45
194	35	2	2	2	3	24.52	24.52
195	40	2	2	2	3	24.59	24.59
196	20	2	2	2	4	12.38	24.21
197	25	2	2	2	4	20.24	24.38
198	30	2	2	2	4	22.49	24.45
199	35	2	2	2	4	23.67	24.52
200	40	2	2	2	4	24.48	24.59
201	20	2	3	2	3	22.44	24.35
202	25	2	3	2	3	24.09	24.44
203	30	2	3	2	3	24.53	24.53
204	35	2	3	2	3	24.60	24.60
205	40	2	3	2	3	24.60	24.60
206	20	2	3	2	4	12.38	24.35
207	25	2	3	2	4	20.24	24.44
208	30	2	3	2	4	22.49	24.53
209	35	2	3	2	4	23.67	24.60
210	40	2	3	2	4	24.48	24.60

decreasing the completion time. On the other hand, increasing mode capacities results in more cost reductions (between 1.55% and 3.69%) than those in **S1**. When $|T| = 25\,(40)$, a cost reduction of 10.73% (13.33%) can be achieved. That the same results are obtained when only rail capacity and both rail and road capacities are increased (data sets 2 and 3 in Table 4) indicates that cost improvement results from the increase in the rail transportation capacity.

5.2.2.2. The effect of loading capacities (scenarios 16–25). Increasing the loading capacities at the mines by 25% and more allows the distribution time to be completed in 20 weeks. Moreover, slightly better cost reductions than the ones in **S1** are obtained. However, additional cost reduction cannot be obtained when $|T| \geq 35\,(30)$with 25% (50%) increase (The maximum cost reduction is 9.69%). That is, increasing the loading capacity has a limited effect on the cost reduction. If the loading capacities are increased more, the same cost reduction with a lower distribution time can be achieved. Because 25% increase allows the distribution time to be decreased to 20 weeks and additional cost improvement obtained with 50% over 25% increase is minimal, 25% increase may be considered sufficient as well.

5.2.2.3. The effect of transportation mode and loading capacities (scenarios 26–45). The previous scenarios indicate that increasing the mode capacities reduces the cost much more than increasing the loading capacities (in comparison to **S1**) while increasing the loading capacities decreases the distribution time. When both changes are applied simultaneously, the distribution can be completed in 20 weeks as a result of the increased loading capacity. Moreover, better cost improvements than those obtained with increasing only the mode capacities are attained for the same planning horizon. However, the cost improvements decrease and almost vanishes as the planning horizon increases, e.g., the cost improvement is 1.41% (2.39%) for $|T| = 20$ while it is 0.04%

(0.04%) for $|T| = 40$ with 25% (50%) increase in the loading capacity. Considering that cost improvement with 50% is higher than that with 25%, we can conclude that 50% increase in the loading capacity is useful when the mode capacity is increased as well.

5.2.2.4. The effect of production capacity (scenarios 46–50). When only the production capacity is increased, a cost improvement of about 23% with a distribution time of 20 weeks can be achieved. With these figures, the production capacity has the most significant impact on the results. For $|T| \geq 25$, the cost improvement remains the same.

5.2.2.5. The effect of production and mode capacities (scenarios 51–60). Increasing the production and mode capacities simultaneously improves the cost reductions obtained by only increasing the production capacities (Scenarios 46–50) by 1.31–1.83%. These figures indicate that increasing the mode capacity contributes less to improve the cost reduction in the existence of increased production capacity. As observed before, additional cost reductions over the Scenarios 46–50 result from increasing the rail capacity.

5.2.2.6. The effect of the production and loading capacities (scenarios 61–70). Increasing the loading capacities does not have an effect on the cost reductions obtained with only increasing the production capacities (Scenarios 46–50) except a slight change in one instance (Scenario 61). That is, increasing only the production capacities is sufficient to achieve the desired cost reduction and distribution time.

5.2.2.7. The effect of production, loading, and mode capacities (71–90). When the loading capacities are increased in the existence of increased production capacities, the loading capacities do not have an effect on the cost reductions. However, when mode capacities are increased as well, cost reductions are improved slightly (by 0.3–0.1%) over the ones obtained with increasing both production and mode capacities (Scenarios 51–60). We consider these improvements to be negligible and conclude that increasing the loading capacity is not necessary in the existence of increased production capacities. Note that the contribution of 50% increase in the loading capacity over 25% increase to decrease the cost is negligible as well.

5.2.3. *The results for S3*

In this section, we discuss the effect of constraints regarding vehicles in Table 5 on the results of previous scenarios in **S1** and **S2**. Note that there are 120 scenarios instead of 180 in **S3** in Table 7 because we do not include some scenarios in Table 6. Specifically, because we obtain the same results with data sets 2 and 3 in Table 4 regarding mode capacities (mcap$_m$) when all other data sets are the same, we give only the results for data set 2. We do not give the results for the scenarios with data set 4 in Table 5 regarding vehicle constraints (availveh$_{im}$ and arrveh$_{im}$) and data set 1 in Table 2 regarding production capacities (pcap$_{ik}$) because we cannot obtain feasible solutions no matter what the other data sets (mcap$_{ik}$ and lcap$_{im}$) are. Moreover, we do not present the results for the scenarios with data set 2 in Table 5 and data set 2 in Table 2 because we obtain the same results for the scenarios with data set 1 in Table 5 and data set 2 in Table 2 no matter what the other data sets are. To summarize, we do not give results for the scenarios that are infeasible or that give the same results as other scenarios. Specifically, we do not give the results for the scenarios where the data sets are set to (*,*,3,*), (1,*,*,4), and (2,*,*,2) with the * indicating any data regarding the corresponding parameter. However, we consider their effects on the results in Section 6.2. For ease of comparison, we have added the improvements of the scenarios in Table 6 as the last column in Table 7 corresponding to the scenarios whose data sets for pcap$_{\text{ik}}$, lcap$_{\text{im}}$, and mcap$_{\text{m}}$ are the same as those in Table 6.

5.2.3.1. The effect of vehicle constraints on S1 (scenarios 91–100). When vehicle constraints are added, the distribution time increases as expected. Specifically, when data set 2 (3) is used, the distribution is completed in 30 (35) weeks (compare to 25 weeks in Scenarios 1–5). This may have several implications for planning coal distribution that has not been considered before. For example, if truck transportation is to be outsourced, the trucking company should be able to allocate sufficient number of trucks for coal distribution weekly.

The results indicate that as the vehicle constraints become more restrictive, cost reductions may worsen for the same planning horizon up to a certain value of $|T|$. However, when $|T|$ is sufficiently large, the same reductions can be obtained. For data set 2, the cost reductions are the same as those in **S1** (Scenarios 1–5) when $|T|$ is sufficiently large to have a solution. For data set 3, however, the cost reductions are worse than those in **S1**.

5.2.3.2. The combined effect of mode capacities and vehicle constraints (scenarios 101–110). When data set 2 is used, we obtain the same results in **S2** (Scenarios 6–15) except that the cost improvement for $|T| = 25$ is slightly worse. However, when data set 3 is used, the distribution time increases to 30 weeks with a cost reduction less than that in Scenario 8 (10.92% compared to 11.94%). When $|T| = 40$, the same cost reduction in Scenario 10 is obtained. The results imply that the advantage of increased mode capacities diminishes as the vehicle constraints are more restrictive.

5.2.3.3. The effect of loading capacities and vehicle constraints (scenarios 111–130). Increasing the loading capacities (Scenarios 16–25) has contributed to decrease distribution time. However, adding vehicle constraints eliminates this advantage because the results for Scenarios 111–130 are the same as those in Scenarios 91–100. That is, vehicle constraints are more restrictive than the loading capacities and hence determine the distribution time and cost reduction. The implication of this is that the loading capacities are sufficient to support the distribution system with the given vehicle constraints.

5.2.3.4. The effect of mode capacities, loading capacities, and vehicle constraints (scenarios 131–150). We observe the same pattern in Scenarios 101–110 indicating that transportation mode capacities rather than the loading capacities are the dominant factor. The distribution completion time is extended to 25 and 30 weeks with data sets 2 and 3 in Table 5, respectively. However, cost reductions are slightly better than those in Scenarios 101–110 and the same as those in Scenarios 26–45 for $|T| \geq 30$ (35) with data set 2 (3). That is, even though increased loading capacities do not have an impact on the results in the existence of vehicle constraints, they contribute to improve the total cost when used with increased mode capacities.

This can be explained as follows: In the existence of vehicle constraints, the distribution is time-phased increasing the distribution completion time compared to that in S1. When mode capacities are increased, more loading capacity (specifically rail capacity) can be used, which decreases the distribution time and improves the cost reductions. When loading capacities are increased, they do not affect the results because the vehicle constraints rather than the loading capacities are binding. When both loading and mode capacities are increased, more loading capacity can be used due to the increased mode capacity, which improves the cost reductions.

5.2.3.5. The effect of production capacity and vehicle constraints (scenarios 151–160). The vehicle constraints worsen the results in the Scenarios 46–50. However, the degree of worsening is low because we can still obtain significant cost reductions even with data set 4 in Table 5. For data set 4, the distribution cannot be completed in 20 weeks and the cost reductions are worse than those in the Scenarios 46–50 for the same planning horizon except for $|T| = 40$. The results for data set 3 are much better and cost reductions of about 20% and more can be obtained.

The results indicate that the vehicle constraints have limited effect on the results when the production capacities are increased. This can be explained as follows. The production capacities at some mines are not sufficient to consume the whole capacity of the vehicles. That is, if 300 trucks are available at a mine each week, these 300 trucks can be used until the total production at the mine reaches the production capacity. From that point on, the vehicle capacity at that mine is not used. When the production capacities are increased, it becomes possible to use the unused vehicle capacities, which significantly improves the cost.

5.2.3.6. The effect of production capacities, mode capacities, and vehicle constraints (scenarios 161–170). Increasing the mode capacities in addition to production capacities alleviates the negative effect of vehicle constraints observed in the Scenarios 151–160. We can obtain feasible solutions for $|T| = 20$ even with data set 4. The resulting cost reduction is almost half of the original value but, for $|T| \geq 35$, we obtain the same cost reductions in the Scenarios 51–60. For data set 3, all cost reductions are more than 21% and equal to those in the Scenarios 51–60 for $|T| \geq 25$. To sum up, vehicle constraints worsen the results slightly in the Scenarios 51–60 for $|T| \geq 25$.

5.2.3.7. The effect of production capacities, loading capacities, and vehicle constraints (scenarios 171–190). The results are the same as those in the Scenarios 151–160 where we observe the effect of vehicle constraints on the increased production capacities. This is expected because the cost improvements with increased production capacities (Scenarios 46–50) are the same as those obtained with increased production and loading capacities (Scenarios 61–70).

5.2.3.8. The effect of production capacities, mode capacities, loading capacities, and vehicle constraints (scenarios 191–210). The cost improvements with data set 4 are the same as those obtained in the Scenarios 166–170 where the effect of vehicle constraints with increased production capacities is observed. Thus, increasing the loading capacities by even 50% does not have an effect on the costs in the existence of tight vehicle constraints (data set 4). With data set 3, loading capacities increased by 25% and 50% have almost the same effect on the cost reductions. Moreover, increasing the loading capacity slightly improves the cost reductions obtained in the Scenarios 161–165. The results are actually consistent with the results obtained in the Scenarios 71–90.

To sum up, adding vehicle constraints increases the completion time of the distribution for most scenarios with the first data set for production capacities. In this regard, feasible solutions are not obtained in some scenarios for $|T| \leq 25$ and even for $|T| = 30$. Accordingly, cost improvements are reduced for certain values of $|T|$ but when $|T|$ is set to a sufficiently large value, e.g., $|T| = 35, 40$, the same or slightly worse cost reductions for the corresponding scenarios in **S1** and **S2** can be obtained. Increasing the production capacities significantly alleviate the effect of vehicle constraints.

6. Statistical analysis

CDPM formulation uses $|T|$, pcap_{ik}, lcap_{im}, mcap_m, availveh_{im}, and $\text{arrveh}_{\text{im}}$ as parameters to come up with a minimum-cost distribution plan. However, if we look at the overall decision-making problem the TCE tackles, these factors are under the control of the TCE's to some extent. In case the TCE is not content with the distribution plan proposed by an optimal solution to the *CDPM*, the TCE needs to know its options to derive the *CDPM* solution to a more agreeable distribution plan, and implement the necessary changes, e.g., tender specifications, to achieve that distribution plan while making preparations for the upcoming year. Hence, it is important for the TCE to quantify the effects of these parameters on the minimum possible cost. In this regard, to be able to better analyze the scenario results and quantify the effects of different factors and their interactions on optimal costs and also to provide the TCE with a model to predict optimal costs that can be achieved especially for different $|T|$ choices that we do not include in our scenarios, we develop two multiple linear regression models. We remark that these regression models enable us to analyze the effects of different factors and their interactions (i.e., pcap_{ik}, lcap_{im}, mcap_m, availveh_{im}, and $\text{arrveh}_{\text{im}}$) in a more thorough manner than before: In Section 5.2, we deduce the effects of these parameters by taking some scenarios as the basis and comparing their optimal costs to those of some other scenarios in a *ceteris paribus* manner. The regression models, however, enable us to assess the effects by considering the scenarios altogether and hence give us a better idea about how optimal cost changes when we change these parameters within the boundaries of the considered parameter space.

6.1. Regression without vehicle limits

We propose the first model for **S1** and **S2**, where the number of vehicles are not limited. The regressor (independent) variables are encoded as shown in Table 8.

In Table 8, we have five independent variables that are used to explain the total cost. The first variable is the length of the planning horizon, $|T|$. The variable Prod is used to encode production capacities pcap_{ik}: $\text{Prod} = -1$ and $\text{Prod} = +1$ refer to the data sets 1 and 2 in Table 2, respectively. The variable Load represents loading capacities lcap_{im}: $\text{Load} = -1$, $\text{Load} = 0$, and $\text{Load} = +1$ refer to the data sets 1, 2, and 3 in Table 3, respectively. The transportation load capacities (i.e., mcap_m) is encoded with two factors: Road and Rail. The first, second, and third data sets in Table 4 correspond to the cases $\text{Road} = -1$, $\text{Rail} = -1$; $\text{Road} = -1$, $\text{Rail} = +1$; and $\text{Road} = +1$, $\text{Rail} = +1$, respectively.

After excluding the infeasible factor combinations in Table 6, with the remaining 87 observations, we first carry out a model selection analysis. The largest possible model includes all five main effects of the factors as well as their 2-, 3-, 4-, and 5-way interactions. Thus, the largest model has 32 terms, including the intercept. We look for the best possible subset of these 32 terms to include in the final model. We have carried out an exhaustive search and found out that the model (12) is the best in terms of the minimum Schwartz's Bayesian Information Criterion (BIC) value. The model keeps 13 terms (including the intercept) and excludes the remaining 19 effects. The most striking exclusions are the main effect Roadand *all* interaction effects involving Road as well as some interactions involving Rail. This result corroborates the discussion on the effect of transportation mode capacities in Section 5.2.2 (Scenarios 6–15), which highlights that the cost improvement mainly results from the increase in the rail capacity as opposed to road capacity. Since the values of R^2, adjusted R^2, and Mallows' C_p criteria for this model is very close to their respective bests, we are settled with it to include as few parameters as possible. The selected model is

Table 8
Regressor variables for the first multiple linear regression model.

Factor	Levels
T	Numeric, ranging from 20to 40
Prod	− 1: Low, + 1: High
Load	− 1: Low, 0: Medium, + 1: High
Road	− 1: Low, + 1: High
Rail	− 1: Low, + 1: High

$$\begin{aligned}\text{Cost} = {} & 598749517.02 - 232153.23T - 37664364.83\text{Prod} - 4746186.15\text{Load} \\ & - 1936578.92\text{Rail} + 196270.72T \times \text{Prod} + 118350.38T \times \text{Load} \\ & - 142312.33T \times \text{Rail} + 3806761.35\text{Prod} \times \text{Load} - 671152.99\text{Load} \times \text{Rail} \\ & - 95887.70T \times \text{Prod} \times \text{Load} + 75385.01T \times \text{Prod} \times \text{Rail} \\ & + 431759.09\text{Prod} \times \text{Load} \times \text{Rail}\end{aligned} \tag{12}$$

The overall test for significance and partial t tests can be seen in Fig. 2. Extra sum of squares ANOVA results are given in Fig. 3.

The results in Figs. 2 and 3 indicate that the overall regression model as well as all the included main and interaction effects are strongly significant. The adjusted R^2 is greater than 99.8%, the mean absolute percentage error (MAPE) is 0.1373%, and the maximum absolute percentage error is 0.6144%. That is, the model fits the data very well.

Examining Fig. 2 enables us to expand our previous *ceteris paribus* analysis in Section 5.2.2. The regression model not only confirms all our previous findings but it also enables us to gain more insights. We first remark that the most important main effect is Prod, which agrees with our previous discussion regarding Scenarios 46–50 in Section 5.2.2. In the discussion of the effect of loading capacities (Section 5.2.2, Scenarios 16–25), we point out that increasing the mode capacities reduces the cost much more than increasing the loading capacities. Examining the regression model (12), we can further say that this is *not* due to the main effects (the main effect of Load is greater than the main effect of Rail) but rather as a result of the interactions in addition to the main effects. Specifically, we note that the interaction Prod × Load has a very significant contribution to the total cost *in the opposite direction* of separate main effects Prod and Load (i.e., the interaction increases the cost rather than decrease). This observation helps explain why Railis more effective in reducing costs despite the greater main effect of Load: even though the main effect of Load is negative and significant, its interaction with Prod drastically deteriorates the contribution and eventually, the effect of Rail outweighs. Moreover, the deterioration due to the positive and significant Prod × Load interaction (and positive Prod × Load × Rail interaction as well) also corroborates our repeated previous observations about the limited effect of the loading capacities on the cost reduction (Section 5.2.2, Scenarios 16–25, 26–45, 61–70, and 71–90).

6.2. *Regression with vehicle limits*

The second model is for **S3** where we have upper bounds on the number of vehicles arriving and leaving certain nodes in the network. In addition to the factors that we consider in the previous regression model (12), we also introduce Veh to encode the available number of vehicles as high (+ 1), medium (0), and low (− 1) in the presence of vehicle limitations. These values correspond to the data sets 2, 3, and 4 in Table 5, respectively.

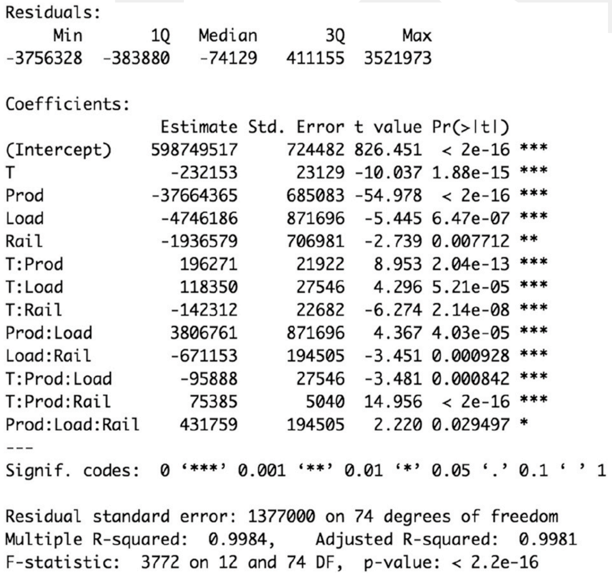
To construct the sample to fit a regression model, we first exclude the infeasible factor combinations in Table 7. Recall that, as explained in Section 5.2.3., there are fewer scenarios reported in Table 7 than possible because we omit data set 3 in Table 4 regarding mcap_m since the results are the same as the results with data set 2. The combinations of mcap_m in data set 3 in Table 4 with other factors and their respective optimal cost values, however, are relevant and valid when fitting a regression model. We therefore include these combinations in our sample here, resulting in a sample size of 189 observations. We again first carry out a model selection analysis. The largest possible model includes all six main effects of the factors as well as their 2-, 3-, 4-, 5-, and 6-way interactions. Thus, the largest model has 64 terms, including the intercept. We look for the best possible subset of these 64 terms to include in the final model. We have carried out an exhaustive search (allowing at most 4-way interactions, since higher order interactions in practice are almost never statistically significant) and found out that the model given in (13) is the best in terms of the Schwartz's BIC. Moreover, in terms of Mallows' C_p, R^2, and adjusted R^2 criteria, the selected model performs nearly the same as the respective best models. As a result, we prefer the model in (13), which includes fewer parameters:

$$\begin{aligned}\text{Cost} = {} & 629280208.03 - 1024276.37T - 31570019.10\text{Prod} \\ & - 42086778.82\text{Veh} - 216027.83T \times \text{Rail} + 1115444.42T \times \text{Veh} \\ & + 80089.22T \times \text{Prod} \times \text{Rail}\end{aligned} \tag{13}$$

The overall test for significance and partial t tests can be seen in Fig. 4. Extra sum of squares ANOVA results are given in Fig. 5.

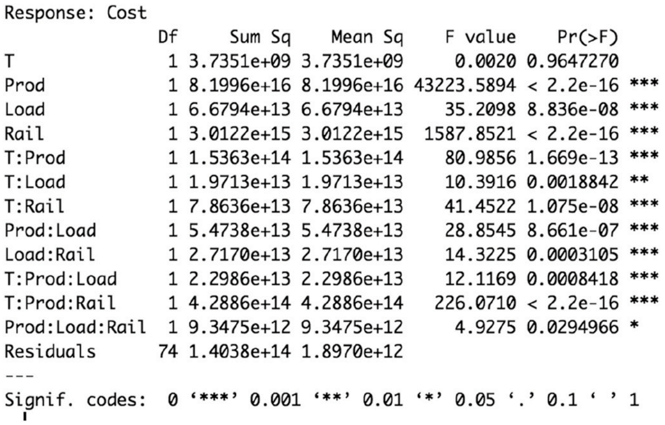
The results in Figs. 4 and 5 indicate that the overall regression model as well as all the included main and interaction effects are strongly significant. The adjusted R^2 is greater than 95%, the mean absolute percentage error (MAPE) is 0.7042% and the maximum absolute percentage error is 3.5735%, i.e., the model fits the data very well.

The results in Fig. 4 show that the presence of vehicle limitation affects the total cost considerably, even more than the production capacity. As a further insight, we note that in the presence of vehicle limitation, the effects of transportation mode and loading capacities vanish; they are not significant any more even though Rail has some statistically significant (but minor) interaction effects with the length of the distribution period $|T|$. Finally, we remark the sizeable positive effect of $|T|$ × Veh interaction consistent with our previous observations in Section 5.2.3, where we note that if vehicle constraints are added, the distribution time increases.



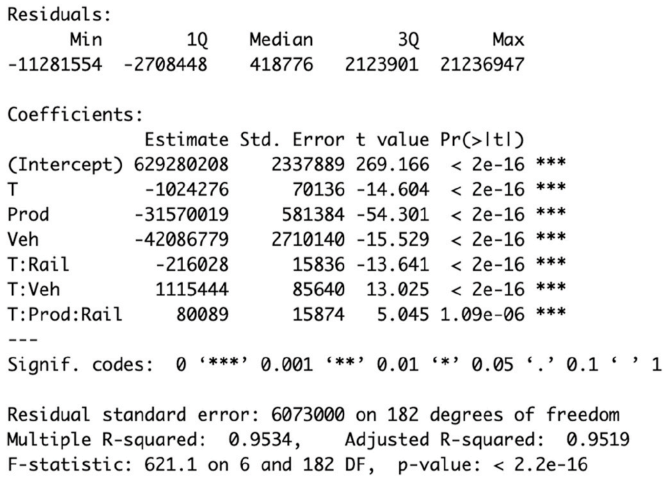
```
Residuals:
     Min       1Q   Median       3Q      Max
-3756328  -383880   -74129   411155  3521973

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    598749517     724482 826.451  < 2e-16 ***
T                -232153      23129 -10.037 1.88e-15 ***
Prod           -37664365     685083 -54.978  < 2e-16 ***
Load            -4746186     871696  -5.445 6.47e-07 ***
Rail            -1936579     706981  -2.739 0.007712 **
T:Prod            196271      21922   8.953 2.04e-13 ***
T:Load            118350      27546   4.296 5.21e-05 ***
T:Rail           -142312      22682  -6.274 2.14e-08 ***
Prod:Load        3806761     871696   4.367 4.03e-05 ***
Load:Rail        -671153     194505  -3.451 0.000928 ***
T:Prod:Load       -95888      27546  -3.481 0.000842 ***
T:Prod:Rail        75385       5040  14.956  < 2e-16 ***
Prod:Load:Rail    431759     194505   2.220 0.029497 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1377000 on 74 degrees of freedom
Multiple R-squared:  0.9984,	Adjusted R-squared:  0.9981
F-statistic:  3772 on 12 and 74 DF,  p-value: < 2.2e-16
```

Fig. 2. Summary of the first regression model.



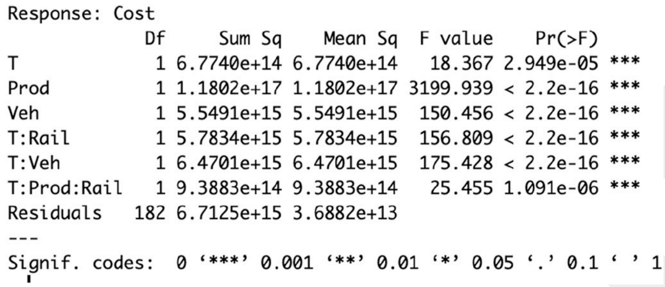
```
Response: Cost
               Df     Sum Sq    Mean Sq    F value    Pr(>F)
T               1 3.7351e+09 3.7351e+09     0.0020 0.9647270
Prod            1 8.1996e+16 8.1996e+16 43223.5894 < 2.2e-16 ***
Load            1 6.6794e+13 6.6794e+13    35.2098 8.836e-08 ***
Rail            1 3.0122e+15 3.0122e+15  1587.8521 < 2.2e-16 ***
T:Prod          1 1.5363e+14 1.5363e+14    80.9856 1.669e-13 ***
T:Load          1 1.9713e+13 1.9713e+13    10.3916 0.0018842 **
T:Rail          1 7.8636e+13 7.8636e+13    41.4522 1.075e-08 ***
Prod:Load       1 5.4738e+13 5.4738e+13    28.8545 8.661e-07 ***
Load:Rail       1 2.7170e+13 2.7170e+13    14.3225 0.0003105 ***
T:Prod:Load     1 2.2986e+13 2.2986e+13    12.1169 0.0008418 ***
T:Prod:Rail     1 4.2886e+14 4.2886e+14   226.0710 < 2.2e-16 ***
Prod:Load:Rail  1 9.3475e+12 9.3475e+12     4.9275 0.0294966 *
Residuals      74 1.4038e+14 1.8970e+12
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 3. Extra sum of squares F tests for the first regression model.



```
Residuals:
      Min        1Q    Median        3Q       Max
-11281554  -2708448    418776   2123901  21236947

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 629280208    2337889 269.166  < 2e-16 ***
T            -1024276      70136 -14.604  < 2e-16 ***
Prod        -31570019     581384 -54.301  < 2e-16 ***
Veh         -42086779    2710140 -15.529  < 2e-16 ***
T:Rail        -216028      15836 -13.641  < 2e-16 ***
T:Veh         1115444      85640  13.025  < 2e-16 ***
T:Prod:Rail     80089      15874   5.045 1.09e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6073000 on 182 degrees of freedom
Multiple R-squared:  0.9534,	Adjusted R-squared:  0.9519
F-statistic: 621.1 on 6 and 182 DF,  p-value: < 2.2e-16
```

Fig. 4. Summary of the second regression model.



```
Response: Cost
             Df     Sum Sq    Mean Sq  F value    Pr(>F)
T             1 6.7740e+14 6.7740e+14   18.367 2.949e-05 ***
Prod          1 1.1802e+17 1.1802e+17 3199.939 < 2.2e-16 ***
Veh           1 5.5491e+15 5.5491e+15  150.456 < 2.2e-16 ***
T:Rail        1 5.7834e+15 5.7834e+15  156.809 < 2.2e-16 ***
T:Veh         1 6.4701e+15 6.4701e+15  175.428 < 2.2e-16 ***
T:Prod:Rail   1 9.3883e+14 9.3883e+14   25.455 1.091e-06 ***
Residuals   182 6.7125e+15 3.6882e+13
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 5. Extra sum of squares F tests for the second regression model.

7. Conclusion

In this paper, we study the problem of coal distribution to poor families as a part of an aid system to tackle poverty, which is one of the greatest global challenges and a prerequisite to sustainable development of countries. We define the problem and develop a multimodal, multicommodity, and multiperiod LP model. We use the model to solve several scenarios constructed using different combinations of real data sets for different parameters and time periods and analyze the results qualitatively and quantitatively. As a part of quantitative analysis, we develop regression models to predict optimal costs that can be achieved for different time periods that we do not include in our scenarios. The main results and insights gained through the analysis of scenarios using the data in 2012 are as follows:

- Using mathematical modeling allows us to find better solutions and to gain more insights regarding the problem and the solutions.
- Under the conditions in 2012, the distribution could be achieved with about 9% cost savings and 15 weeks less than the current distribution time (25 weeks compared to current distribution time of 40 weeks).
- The cost reduction resulting from the increase in transportation mode capacities are mainly due to the increase in the rail transportation capacity.
- Increasing only the loading capacity has limited effect on the cost but a 25% increase allows to decrease the current distribution time to 20 weeks.
- Increasing the transportation mode and loading capacities simultaneously improves both the cost and the distribution time (20 weeks) but their combined effect is limited.
- The increase in the production capacity has the most significant effect on the results with a 23% decrease in cost and a 20-week distribution time.
- In the existence of increased production capacities, increasing only the rail transportation mode capacity is sufficient to achieve the desired results.
- Considering the vehicle constraints in distribution planning produces more realistic solutions and provides valuable insights to the planners.
- As vehicle constraints become more restrictive, the distribution time and cost reductions may worsen significantly.
- The loading capacities are sufficient to support the distribution system with the given vehicle constraints (vehicle constraints are more restrictive than loading constraints).
- As vehicle constraints become more restrictive, the advantage of increased mode and loading capacities diminishes.
- The vehicle constraints have limited effect on the results when the production capacities are increased.
- Increasing the production and rail mode capacities is critical with and without the vehicle constraints.
- Regardless of the existence of restrictive availability of vehicles, the most important factor on the optimal cost is the production capacity.
- When the availability of vehicles is not an issue, TCE had better increase the rail transportation mode capacity.

Our main contribution in this study has been to provide an efficient and effective tool to handle a large-scale real-world problem. The model has also helped to prove that the TCE, the organization responsible for coal distribution planning to poor families, may move from the current planning practice to an all-encompassing top-down approach. The TCE can use the model develop and update a distribution plan and to provide answers to several what-if questions with regard to production, loading, and transportation mode capacities as well as time constraints.

This study has been conducted as a part of the project to analyze and design the coal aid system. In the context of the project, several statistical and process analyses have been conducted and a comprehensive decision support system that integrates all stakeholders has been proposed. The proposed optimization model and regression model will be used as a part of the model base in the decision support system. As more data become available through the decision support system, the proposed optimization model may be extended to include coal distribution within districts for an end-to-end planning. Moreover, predictive models may be integrated into the decision support system to determine potential problems in the system.

Acknowledgements

This research has been supported by the TCE. The authors are grateful to anonymous referees for providing constructive feedback that has helped improve in major ways the presentation of the material in the paper.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.seps.2020.100919.

References

[1] United Nations. The millennium development goals Report 2015. 2015. New York. (Accessed on October 25, 2019 at, https://www.un.org/millenniumgoals/reports.shtml.

[2] United Nations. Transforming our world: the 2030 agenda for sustainable development. 2015. New York. (Accessed on October 25, 2019 at, https://sustainabledevelopment.un.org/post2015/transformingourworld.

[3] Saatci E, Akpinar E. Assessing poverty and related factors in Turkey. Croat Med J 2007;48(5):628–35.

[4] Turkish Statistical Institute (TSI). Income and living conditions survey 2015. 2019 (Accessed on March 7, 2020 at, http://www.turkstat.gov.tr/PreHaberBultenleri.do?id=30755.

[5] Ministry of Family and Social Policies (MFSP). Administrative activity Report for 2015. 2016 (Accessed on March 7, 2020 at, http://sp.gov.tr/upload/xSPRapor/files/rVONs+aile.pdf.

[6] Pendharkar PC. A fuzzy linear programming model for production planning in coal mines. Comput Oper Res 1997;24(12):1141–9.

[7] Sarin SC, West-Hansen J. The long-term mine production scheduling problem. IIE Trans 2005;37(2):109–21.

[8] Shih J-S, Christopher Frey H. Coal blending optimization under uncertainty. Eur J Oper Res 1995;83:452–65.

[9] Chakraborty M, Chandra MK. Multicriteria decision making for optimal blending for beneficiation of coal: a fuzzy programming approach. Int Jf Manag Sci OMEGA 2005;33:413–8.

[10] Lyu J, Gunesekaran A, Chen CY, Kao C. A goal programming model for the coal blending problem. Comput Ind Eng 1995;28(4):861–8.

[11] Yin C, Luo Z, Zhou J, Cen K. A novel non-linear programming-based coal blending technology for power plants. Trans IChemE 2000;78(A):118–24.

[12] Peng H, Zhou M, Liu M, Zhang Y, Huang Y. A dynamic optimization model of an integrated coal supply chain system and its application. Min Sci Technol 2009;19: 842–6.

[13] Zhou R-J, Li L-J. Joint capacity planning and distribution network optimization of coal supply chains under uncertainty. Am Instit Chem Eng AIChE J 2018;64(4): 1246–61.

[14] Yang H, Sun F, Chen J, Chen B. Financing decisions in a supply chain with a capital-constrained manufacturer as new entrant. Int J Prod Econ 2019;216: 321–32.

[15] Shih L-H. Planning of fuel coal imports using a mixed integer programming method. Int J Prod Econ 1997;51:243–9.

[16] Lai J-W, Chen C-Y. A cost minimization model for coal import strategy. Energy Pol 1996;24:1111–7.

[17] Wu T-H, Huang K-I, Chen W. Optimal scheduling plan for a coal shipment problem: an efficient approach. Comput Ind Eng 1995;29(1– 4):489–93.

[18] Sherali HD, Puri R. Models for a coal blending and distribution problem. Int Jf Manag Sci OMEGA 1993;21(2):235–43.

[19] Sherali Hf, Saifee QJ. In: Du D-Z, Pardalos PM, editors. Strategic and tactical models and algorithms for the coal industry under the 1990 clean air act. Network optimization problems: algorithms, applications and complexity, series on applied mathematics, vol. 2. World Scientific Publishing Company; 1993. p. 233–62.

[20] Liu C-M, Sherali HD. A coal shipping and blending problem for an electric utility company. Int Jf Manag Sci OMEGA 2000;28:433–44.

[21] Zhao QH, Chen S, Leung SCH, Lai KK. Integration of inventory and transportation decision in a logistic system. Transport Res Part E 2010;46:913–25.

[22] Yucekaya A. Cost minimizing coal logistics for power plants considering transportation constraints. J Traffic Logist Eng 2013;1(2):122–7.

[23] Crainic TG, Kim KH. Intermodal transportation. In: Barnhart C, Laporte G, editors. Handbook in operations research and management science, vol. 14; 2007. p. 467–537.

[24] Christiansen M, Fagerholt K, Nygreen B, Ronen D. Maritime transportation. In: Barnhart C, Laporte G, editors. Handbooks in operations research and management science, vol. 14; 2007. p. 189–284.

[25] Bektas T, Crainic T. A brief overview of intermodal transportation. In: Taylor G, editor. Logistics engineering handbook; 2008. p. 1–16.

[26] SteadieSeifi M, Dellaert NP, Nuijten W, Van Woensel T, Raoufi T. Multimodal freight transportation planning: a literature review. Eur J Oper Res 2014;233:1–15.

[27] Cohn A, Davey M, Schkade L, Siegel A, Wong C. Network design and flow problems with cross-arc costs. Eur J Oper Res 2008;189:890–901.

[28] Verma M, Verter V. A lead-time based approach for planning railtruck intermodal transportation of dangerous goods. Eur J Oper Res 2010;202:696–706.

[29] Verma M, Verter V, Zufferey N. A bi-objective model for planning and managing rail-truck intermodal transportation of hazardous materials. Transport Res Part E 2012;48:132–49.

[30] Meng Q, Wang S. Liner shipping service network design with empty container repositioning. Transport Res Part E 2011;47:695–708.

[31] Chen L, Miller-Hooks E. Resilience: an indicator of recovery capability in intermodal freight transport. Transport Sci 2012;46:109–23.

[32] Meng Q, Wang T, Wang S. Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand. Eur J Oper Res 2012; 223:96–105.

[33] Miller-Hooks E, Zhang X, Faturechi R. Measuring and maximizing resilience of freight transportation networks. Comput Oper Res 2012;39:1633–43.

[34] Ayar B, Yaman H. An intermodal multicommodity routing problem with scheduled services. Comput Optim Appl 2012;53:131–53.

[35] Minh V, Crainic T, Toulouse M. A three-stage metaheuristic for the capacitated multi-commodity fixed-cost network design with design-balance constraints. CIRRELT; 2012. Technical report 21.

[36] Caris A, Macharis C, Janssens G. Corridor network design in hinterland transportation systems. Flex Serv Manuf J 2012;24:294–319.

[37] Crainic TG. Service network design in freight transportation. Eur J Oper Res 2000; 122:272–88.

[38] Crainic T, Li Y, Toulouse M. A first multilevel cooperative algorithm for capacitated multicommodity network design. Comput Oper Res 2006;33:2602–22.

[39] Andersen J, Christiansen M. Designing new European rail freight services. J Oper Res Soc 2009;60:348–60.

[40] Bai R, Kendall G, Qu R, Atkin J. Tabu assisted guided local search approaches for freight service network design. Inf Sci 2012;189:266–81.

[41] Teypaz N, Schrenk S, Cung V. A decomposition scheme for large-scale service network design with asset management. Transport Res Part E 2010;46:156–70.

[42] Wieberneit N. Service network design for freight transportation: a review. Spectrum 2008;30:77–112.

[43] Michael P, Johnson Jr. Community-based operations research: introduction, theory and applications. In: Johnson Michael P, editor. Community-based operations research: decision modeling for local impact and diverse populations. first ed. New York: Springer; 2011. p. 3–36.

[44] Pollock SM, Maltz MD. Operations research in the public sector: an introduction and brief history. In: Pollock SM, Rothkopf MH, Barnett A, editors. In operations research and the public sector: handbooks in operations research and management science, vol. 6. Amsterdam: Elsevier Science. B.V; 1994. p. 1–22.

[45] Fox KJ. Efficiency in the public sector. Series: studies in productivity and efficiency, vol. 1. Kluwer Boston; 2002.

[46] Larson RC. Public sector operations research: a personal journey. Oper Res 2002;50 (1):135–45.

[47] Sinuany-Stern Z, Sherman HD. Operations research in the public sector and non-profit organizations. Ann Oper Res 2014;221:1–8.

[48] Midgley G, Johnson MP, Chichirau G. What is community operational research? Eur J Oper Res 2018;268:771–83.

[49] Demir E, Karpuz C, Demirel N. Design and implementation of a multimodal transportation cost analysis model for domestic lignite supply in Turkey. J S Afr Inst Min Metall 2012;112:993–8.

[50] Sahin U, Asici A, Acar S, Bal-Gedikkaya P, Karababa AO, Kurnaz L. Coal Report: Turkey's coal policies related to climate change, economy, and health. Technical Report prepared for Istanbul Policy Center; 2016.

[51] GAMS Development Corporation. GAMS-Documentation. 2019 (Accessed April 6, 2019 at, https://www.gams.com/latest/docs/gams.pdf.

[52] IBM ILOG. IBM ILOG CPLEX V12.3. User's Manual for CPLEX; 2009.

[53] Oil Change International. Turkey's coal subsidies and public finance. 2014. Technical Report. (Accessed on April 1, 2020 at, http://priceofoil.org/content/uploads/2014/07/Turkey-Coal-Subsidies-Full-07.28.14.pdf.