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Article

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Operations Research Perspectives

Provided in Cooperation with:

Elsevier

Suggested Citation: Pudasaini, Pramesh (2021) : Integrated planning of downstream petroleum supply chain: A multi-objective stochastic approach, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 8, pp. 1-15, <https://doi.org/10.1016/j.orp.2021.100189>

This Version is available at:

<https://hdl.handle.net/10419/246447>

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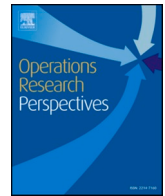
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Integrated planning of downstream petroleum supply chain: a multi-objective stochastic approach

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ARTICLE INFO

Keywords:

Uncertainty modeling
Multi-objective optimization
Multimodal transportation
Integrated planning
Petroleum supply chain

ABSTRACT

In studying petroleum supply chain networks, past studies have largely segregated three critical decision-making aspects: integrated planning, uncertainties, and multi-objective setting. This study focuses on consolidating these aspects and proposes a stochastic, multi-objective, mixed-integer linear programming model for strategic and tactical planning of downstream petroleum supply chain (DPSC) networks. Demand, considered the uncertain parameter, is modeled using a two-stage stochastic approach based on scenarios. The model—designed for multiple supply centers, distribution centers, products, and transportation modes—also considers transshipment between the centers. The objective functions consider simultaneous minimization of transportation cost and product loss cost that is incurred during transportation between the centers. The application of the proposed model is demonstrated with a case study of a real-world DPSC network undergoing construction of new pipelines and expansion of storage facilities. The augmented ϵ -constraint method is used to solve the model. Interesting trade-offs in the case study are analyzed, aiding the decision-makers in exploiting the model as a decision-support tool to better understand the complexity, flexibility, and risk of integrated decision-making under uncertainty.

1. Introduction

Petroleum industries supply the necessary oil and gas products to sustain global energy demand and play a prominent role in global economy [48]. Owing to their broad logistic network, these industries have one of the most comprehensive and complex supply chains with a vertically integrated structure. Typically, a petroleum supply chain (PSC) is segmented into three: upstream, midstream, and downstream [4,16,31,41]. The upstream incorporates exploration of crude oil, production tasks, and transportation to refineries. The midstream activities include transformation and production through refineries. Finally, the downstream follows up with transportation from refineries, storage of refined products, and subsequent distribution to consumer markets. This last segment of the PSC network thus encompasses a number of entities including refineries or supply centers, storage depots or distribution centers, consumer markets, and different transportation modes.

The ever-increasing demand for refined petroleum products—for instance, 6.3% per year in China [23]—has made it indispensable for decision-makers to consider multiple aspects such as integrated decisions, uncertainty features, and multi-objective setting while planning optimal PSC networks [31]. In the past two decades, a rather extensive

literature has addressed different segments of PSC planning, with several methodologies proposed and numerous case studies analyzed. As indicated by a handful of review studies, however, most of the research on the downstream petroleum supply chain (DPSC) have focused on formulating network design models and determining product flow allocations [4,31,41] without a consolidated assessment of the aforesaid critical aspects. The subsequent subsections, with a specific focus on the downstream segment, discuss and contextualize the consideration of integrated decision levels, uncertainties, and multi-objective setting in prior PSC planning studies and the proposed study.

1.1. Decision levels in PSC

A hierarchy of decisions are imposed in a DPSC network in order to effectively coordinate logistic operations and sustain satisfaction of product demands [9,38]. Strategic decisions include long-term infrastructural setup; tactical decisions focus on product flow allocations for a medium-term (monthly or quarterly); operational decisions involve day-to-day logistics. Interestingly, Al-Qahtani and Elkamel [2] underscore the restrictions imposed by strategic decisions on tactical planning, the effect of which in turn is realized at the operational level. This,

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thus, emphasizes the importance of mutual integration, optimization, and analysis in addressing real-world PSC planning problems.

The integration of multiple decisions at different segments of PSC networks has been explored by numerous studies. Kim et al. [27] proposed a deterministic collaboration-based integrated model, where production planning and distribution scheduling were implemented using mixed-integer nonlinear programming (MINLP) and mixed-integer linear programming (MILP) approaches, respectively. They argue that relocation of distribution centers and reconfiguration of their linkages to various markets could significantly reduce distribution costs in the supply chain. Guajardo et al. [21] formulated a deterministic optimization model using MINLP approach to integrate pricing and production decisions in a divergent specialty PSC network. Andersen et al. [5] proposed a multi-period MILP investment planning model for strategic planning of ethanol's optimal network and the product's integration with gasoline supply chains. The MILP model by Fiorencio et al. [15] considered investment in logistics infrastructures as strategic decisions, while that in inventory management and distribution as tactical. Fernandes et al. [12,13] proposed MILP profit maximization models; Kazemi and Szmerekovsky [26] formulated a total cost minimization model; and Nasab and Amin-Naseri [34] implemented a multi-period MILP model for enterprise-wide profit maximization. These four PSC optimization models, besides integrating strategic and tactical decisions, were deterministic and characterized by—as in the proposed study—multi-entity, multi-echelon, multi-product, and multimodal transportation.

Neiro and Pinto [36] proposed a multi-period large-scale MINLP framework for integrating tactical and operational production planning with the objective of maximizing revenues in the Brazilian PSC network. Kuo and Chang [28] developed an MILP model to coordinate tactical decisions at corporate level and operational planning at plant level. (The proposed study integrates strategic decisions at central level and tactical planning at depot level.) Their model aimed at defining procurement scheme for crude oils, production scheduling for petrochemical products, and logistics involved in the processes. Guyonnet et al. [22] integrated tactical and operational planning for all PSC segments by incorporating unloading, production, and distribution processes. They concluded that, compared to the model segregated on individual segments, the integrated model achieved a significantly higher overall profit over the considered time horizon. Ghaithan et al. [18] proposed a multi-objective model for tactical planning of Saudi Arabian downstream sector with the objectives of minimizing total cost, maximizing total revenue, and maximizing service level. Similarly, Attia et al. [6] formulated a multi-objective model focused on sustainability and environmental aspects for tactical planning of upstream PSC. Their objectives considered minimization of total costs, maximization of total revenue, and minimization of depletion rate of oil and gas reserves.

The integration of strategic, tactical, and/or operational decisions is of a great practical interest to decision-makers during PSC planning. Therefore, the proposed study's scope encompasses both strategic and tactical decisions so as to integrate planning and facilitate operational decisions. Despite advancements in methodological complexity, a shortcoming of all the studies discussed in this subsection is their reliance on deterministic formulations. For real-world problems, these models cannot fully apprise decision-makers with the complexity of integrated decision-making under uncertainty.

1.2. Uncertainty in PSC planning

A fundamental aspect, engendering from the inherent nature of PSCs, is the plethora of commercial and technical uncertainties pertaining to the dynamic cost of crude oil, demand, supply, investment cost, and production rates, among others [30,31]. At the planning stage, such uncertainties and their impacts are typically beyond the control of decision-makers and cannot be captured by deterministic approaches. As highlighted by prior studies, a stochastic approach yields more

flexible supply chain network configuration [3], and unlike its deterministic counterpart, does not underestimate the value of Pareto optimal solutions in case of multi-objective problems [39]. Thus, a prudent consideration of uncertainties is crucial for better decision-making.

Govindan et al. [20] reviewed studies in the field of supply chain network (SCN) design and identified a number of approaches that deal with uncertainty in optimizing SCNs: continuous stochastic parameters [7]; chance-constrained programming [49]; scenario-based stochastic programming; robust optimization [43]; and fuzzy mathematical programming [45]. SCN optimization problems using scenario-based stochastic programming involve a set of discrete scenarios and known probabilities. Such problems are further categorized by Birge and Louveaux [8] into two groups: two-stage stochastic programs [17] and multi-stage stochastic programs [11]. Owing to the two-stage nature of decisions in most SCN planning—strategic decisions as the first stage and tactical/operational decisions as the second stage—two-stage stochastic programming is the most widely used approach [20].

Uncertainty has been addressed in the design and planning of PSC networks with different approaches. For optimizing a multi-period scheduling problem, Escudero et al. [10] implemented a two-stage scenario analysis approach, capturing uncertainties in product demand, spot supply cost, and spot selling price. Considering uncertainty in market demands and product prices, Dempster et al. [9] formulated a stochastic multi-period optimization problem for strategic and tactical planning of logistics operations. Lababidi et al. [29] developed an optimization model for a petrochemical supply chain based on two-stage stochastic linear programming approach, taking into account uncertainties in demands, raw material costs, production yields, and market prices. Similarly, Al-Othman et al. [1] proposed both deterministic and stochastic optimization models for a hypothetical supply chain network in an oil-producing country. They analyzed uncertainties in market demands and product prices, however, their stochastic model and cases assessed only three scenarios: above average (+20%), average, and below average (-20%). Ghatee and Hashemi [19] developed an optimization modeling framework for optimal transportation in the crude oil distribution system. They analyzed the adequate status of storage tanks to better satisfy network demand by capturing uncertainty in supply and demand with fuzzy parameters. Extending upon their earlier works, Fernandes et al. [14] formulated a collaborative stochastic, multi-objective MILP model for Portuguese DPSC network considering market demand uncertainty represented by a scenario tree. Pudasaini [39] proposed a two-stage stochastic, multi-objective model for tactical planning of the transportation subsystem of a DPSC under demand uncertainty. Comparing the stochastic optimization results with that from a deterministic model, the study spotlights the effects of not considering uncertainty in petroleum transportation network design problems where the environment is actually uncertain. Wang et al. [47] formulated a single-objective, two-stage stochastic MILP model for planning new pipeline route and optimizing refined oil distribution, while minimizing costs of pipeline construction and transportation in DPSC networks.

The review by Govindan et al. [20] found over 80% of studies to have investigated demand as an uncertain parameter in SCN design problems. Results from both Lababidi et al. [29] and Al-Othman et al. [1] identified uncertainty in market demands as the most prominent factor influencing PSC network planning. Future uncertainties in demand can be explicitly captured by generating a scenario tree, where each scenario with its probability of occurrence exhibits a discrete future outcome [9,17,14,30,39]. Vanston Jr. et al. [46] and Schoemaker [42] explain the use of scenario planning techniques and the procedures for constructing appropriate scenarios.

1.3. Multi-objective approach

An important subsystem within the downstream segment that often seeks a multi-objective assessment of integrated planning is the product

transportation network comprising supply centers, distribution centers, and multimodal transportation routes. For a petroleum enterprise governing this network, the relative planning and optimization prioritizes vary for decision-makers at different organizational levels. The central level decision-maker, for instance, prioritizes strategic planning and seeks minimization of total costs of import, transportation, and storage. Quite the contrary, the decision-maker at a distribution center is more interested in tactical decisions and primarily targets minimization of product loss risks during transportation. For better decision-making, a multi-objective approach aids decision-makers at both levels assess the nature of such incompatibility by presenting them with interesting trade-offs and respective win-win situations.

Multi-objective assessment of DPSC networks is, however, quite rare in literature. Iakovou [25] formulated a multi-objective model analyzing trade-offs in transportation cost and oil spillage risk for strategic planning of maritime oil transportation. Subsequent to this study, different network-specific cost minimization and profit maximization objectives have been examined by Fernandes et al. [14], Ghaithan et al. [18], and Pudasaini [39]. Zhou et al. [50] proposed a deterministic, multi-objective MILP model that minimizes total economic costs and carbon emissions for optimal design of multi-product pipelines in Chinese DPSC.

In solving multi-objective mathematical programming (MOMP) problems, decision-makers can express their preferences in decision-making process in a few stages: a priori stage, interactive stage, and generation or a posteriori stage [24]. A priori methods—for instance, goal programming—require decision-makers to express their preference before the solution process. The solution process is iterative in interactive methods where decision-maker continually interacts with the method in finding the most-preferred solution. The generation methods, unlike previous approaches, first aim at generating all the Pareto optimal solutions, and only then the decision-maker participates in selection of the most-preferred solution.

Weighting method and ϵ -constraint method are the most popular generation methods. Amin and Zhang [3] implemented both approaches in analyzing uncertainties in demand and return of a closed-loop supply chain using scenario-based stochastic programming. Their test results revealed that the ϵ -constraint method, compared to weighting method, obtained more efficient solutions. Some apparent advantages of the ϵ -constraint method over the weighting method are also underscored by Mavrotas [32]: generation of only efficient extreme solutions; generation of unsupported efficient solutions in multi-objective integer programming (MOIP) and mixed integer programming (MIP) problems; unbiased from scaling effects; and better control over the number of generated efficient solutions. Mavrotas [32] developed a novel version of the conventional ϵ -constraint method as augmented ϵ -constraint (AUGMECON) algorithm for solving MOMP problems. AUGMECON2—an improved version of the original AUGMECON—proposed by Mavrotas and Florios [33], can generate the exact Pareto set in MOIP problems. For problems with two or three objectives, the augmented ϵ -constraint algorithm has been implemented by many DPSC studies to obtain the exact Pareto set [14,18,39,50]. Nikas et al. [37] proposed further improvements to the AUGMECON algorithms allowing robust and timely optimization as more objective functions are added to the problem.

1.4. Study rationale

This study proposes a multi-objective MILP model for an integrated planning of DPSC networks considering uncertainty in demand. The model, designed for a DPSC subsystem at cross-border locations, incorporates multiple supply centers, distribution centers, refined products, transportation modes, and transshipment between the centers. From strategic planning perspective, the goal is to know the optimal additional storage capacity of distribution centers to meet the total monthly network demand for each product. The tactical decisions

Table 1
Key characteristics of PSC planning studies.

Author	Decisions			Uncertainty		Obj	Entities		Case
	S	T	O	Det	St		MP	MM	
Dempster et al. (2000)	X	X	-	X	X	1	X	X	X
Iakovou (2001)	X	-	-	X	-	2	X	X	X
Neiro & Pinto (2004)	-	X	X	X	-	1	X	-	X
Al-Othman et al. (2008)	-	X	X	X	X	1	X	-	-
Kim et al. (2008)	X	X	X	X	-	1	X	-	X
Kuo & Chang (2008)	-	X	X	X	-	1	X	X	-
Ghatee & Hashemi (2009)	X	X	-	-	X	1	-	-	X
Guyonnet et al. (2009)	-	X	X	X	-	1	X	X	X
Andersen et al. (2013)	X	-	-	X	-	1	X	X	-
Fernandes et al. (2013)	X	X	-	X	-	1	X	X	X
Guajardo et al. (2013)	X	X	X	X	-	1	X	-	-
Fernandes et al. (2014)	X	X	-	X	-	1	X	X	X
Fernandes et al. (2015)	X	X	-	-	X	2	X	X	X
Fiorencio et al. (2015)	X	X	-	X	-	1	X	X	X
Kazemi & Szmerekovsky (2015)	X	X	-	X	-	1	X	X	X
Nasab & Amin-Naseri (2016)	X	X	-	X	-	1	X	X	X
Ghaithan et al. (2017)	-	X	X	X	-	3	X	-	X
Attia et al. (2019)	-	X	X	X	-	3	X	-	X
Pudasaini (2019)	-	X	-	X	X	2	X	-	X
Wang et al. (2019)	X	X	-	-	X	1	X	X	X
Zhou et al. (2020)	X	-	X	X	-	2	X	-	X
This study	X	X	-	-	X	2	X	X	X

S = Strategic; T = Tactical; O = Operational; Det = Deterministic; St = Stochastic; Obj = No. of objectives; MP = multi-product; MM = multi-mode

include the shipment volumes between supply centers and distribution centers along different transportation modes. The objective functions consider simultaneous minimization of transportation cost and product loss cost that is incurred during transportation or transshipment between the centers. Besides the incompatibility of the considered objectives from an operational perspective, their relative priority is different at the organizational levels at which decisions are taken. The study aims to test the applicability of this integrated, stochastic, multi-objective model with the case study of a real-world DPSC network undergoing construction of new pipeline routes, expansion of storage facilities, and relocation of existing depots.

DPSC network planning and management has been identified by Lima et al. [31] as a flourishing research domain that requires vertical integration of strategic and tactical planning decisions, multi-objective approaches, stochastic formulations, and new operational objective functions. Table 1 summarizes the key characteristics of prior PSC planning studies (discussed in the earlier subsections) and elucidates the focus areas of this study. It is evident that past studies have largely segregated three critical decision-making aspects: integrated planning, uncertainties, and multi-objective setting. Despite the due consideration of integrated planning in most DPSC studies, only a handful shed light on decision-making from the aspects of uncertainty [1,9,14,19,39,47] and multiple objectives [14,18,25,39,50]. To the best of the author’s knowledge, none of the studies till date have dealt with the integration of strategic and tactical decisions of DPSC subsystems under uncertainty in a multimodal and multi-objective setting. Given the shortcomings and gaps identified from the literature review, the MILP model proposed in this study is a novel multi-objective investigation that integrates

Table 2
Nomenclature of sets and subsets, parameters, and decision variables.

Notation	Description
Sets and subsets	
i	Index of all transshipment centers (supply nodes), where $i \in I$
j	Index of all transshipment centers (receipt nodes), where $j \in J : J \subset I$
m	Index of supply centers, where $m \in M : M \subset I$
n	Index of distribution centers, where $n \in N : N \subset J$
p	Index of products (diesel, petrol), where $p \in P$
r	Index of transportation modes (truck, pipeline), where $r \in R$
o	Index of pipeline transportation mode, where $o \in O : O \subset R$
s	Index of scenarios, where $s \in S$
t	Index of time periods, where $t \in T$
Parameters	
A_{pi}^t	Units of product p available at center i in time period t (KL/month)
D_{sp}^t	Units of product p demanded under scenario s in time period t (KL/month)
U_{pj}	Existing storage capacity of product p at center j (KL)
W_j	Permissible additional storage capacity at center j (KL)
H_{pij}	Hours of pipeline pumping for product p between center i and center j (hr/month)
F_{ij}	Flow rate in pipeline between center i and center j (KL/hr)
α_{pj}	Demand share of product p at center j (%)
β_{pj}	Minimum demand fulfilment of product p at center j (%)
γ_p	Share of flow of product p for storage (%)
ψ_{sp}	Probability of scenario s for product p
TC_{rij}	Transportation cost between center i and center j via mode r (Rs/KL)
LC_{prij}	Loss cost of product p between center i and center j via mode r (Rs/KL)
Decision variables	
V_{spj}^t	Additional storage capacity of product p at center j under scenario s in time period t (KL) (first-stage variables in the stochastic formulation)
X_{sprij}^t	Units of product p shipped between center i and center j via mode r under scenario s in time period t (KL/month) (second-stage variables in the stochastic formulation)

strategic and tactical decisions while taking into account demand uncertainty and multimodal transshipment in a DPSC configuration.

2. Mathematical formulation

The proposed integrated, stochastic, multi-objective MILP model is formulated for the transportation subsystem of a DPSC network. The considered components and activities of the network, followed by model development, are described in the following subsections.

2.1. Network description

The entities of the DPSC network under consideration include: refineries or supply centers, storage depots or distribution centers, refined products, and two types of transportation modes. The refineries and storage depots are located at the respective sides of cross-border locations. For such a network, refined oil products are produced in refineries and transported via trucks and/or pipelines from supply centers (first echelon) to distribution centers (second echelon), with allowance of simultaneous multimodal transportation of products within the centers at both echelons. In other words, each center acts as a transshipment node that can receive products from as well as supply products to any other center. Transportation from distribution centers to fuel retail outlets (third echelon) is not of a significant concern to decision-makers in this study's context, and is therefore not considered for model formulation.

In developing the model, a marginally simplified bi-echelon network of a real-world downstream segment is considered, and the following assumptions are made in the network configuration:

- Locations of supply and distribution centers are fixed.

- The time horizon considered in terms of supply, demand, and flow allocations is monthly.
- The available supply via different modes and the expected deterministic demand are known in advance to decision-makers.
- Existing storage capacity and permissible additional storage capacity of a distribution center are known in advance.
- Transportation of products takes place from one center to another without intermediate supply to fuel retail outlets.

The nomenclature of sets and subsets, parameters, and decision variables used in the formulation are introduced in Table 2.

2.2. Model constraints

For the network configuration aforesaid, the decision-makers need to take into account a number of strategic and tactical constraints engendered from the undergoing planning and construction of new pipeline routes, expansion of storage facilities, relocation of existing depots, and shipment of product volumes in optimal transportation routes. First, the decision-making complexity involved in the problem is addressed in a two-stage stochastic model with first- and second-stage decisions as follows:

- First-stage decisions are of strategic nature and include: planning of new pipeline routes to be constructed, relocation of existing depots, and expansion of storage facilities. The first two of these decisions are pre-determined by the decision-maker in this study's network.
- Second-stage decisions are of tactical nature and involve the optimal distribution of shipment volumes along different transportation modes and routes. These decisions are taken after analyzing the network design problem.

A set of linear constraints are introduced in order to determine the feasible region of the model. These constraints are categorized into four groups as discussed below.

Supply constraint: Eq. (1) ensures that for any time period, scenario, and product, the difference of the total amount shipped from and the total amount shipped to a supply node via all modes shall not exceed its available supply.

$$\sum_{r \in R} \sum_{\substack{j \in J \\ j \neq i}} (X_{sprij}^t - X_{sprji}^t) \leq A_{pi}^t \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall i \in M \quad (1)$$

Demand constraints: As represented by Eq. (2), for any time period, scenario, and product, the difference of the total amount received by and the total amount analogously shipped from a distribution node shall not be less than its demand. The demand of a distribution node is the total demand of the network factored by its share of demand. Similarly, Eq. (3) guarantees that for any time period, scenario, and product, the difference of the total amount received by and the total amount analogously shipped from a distribution mode shall not exceed the sum of its demand, existing storage capacity, and additional storage capacity. These constraints respectively define the lower and upper limits of shipment in the context of demand.

$$\sum_{r \in R} \sum_{\substack{i \in I \\ i \neq j}} (X_{sprij}^t - X_{sprji}^t) \geq \alpha_{pj} D_{sp}^t \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall j \in N \quad (2)$$

$$\sum_{r \in R} \sum_{\substack{i \in I \\ i \neq j}} (X_{sprij}^t - X_{sprji}^t) \leq \alpha_{pj} D_{sp}^t + U_{pj} + V_{spj}^t \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall j \in N \quad (3)$$

Pipeline capacity constraint: Eq. (4) ensures that in case of pipeline transportation, for any time period, scenario, and product, the total



Fig. 1. Existing network.

quantity transported from one node to another shall not exceed the pipeline capacity determined by pumping hours and flow rate.

$$X_{sprij}^t \leq H_{pij} F_{ij} \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall r \in O, \forall i \in I, \forall j \in J \quad (4)$$

Storage constraints: Eqs. (5) and (6) represent demand-imposed storage restrictions at distribution centers for any time period, product, and scenario. Eq. (5) ensures that the sum of existing and additional storage capacity of all distribution centers must meet the total monthly demand of the network. On a similar note, Eq. (6) guarantees that the sum of additional and existing storage capacity must be such as to cater the minimum monthly demand of that center. This minimum monthly demand is based on the strategic importance of a distribution center in the network and is determined by the product of its minimum demand fulfilment factor and its monthly demand (product of demand share and network demand).

$$\sum_{j \in N} (U_{pj} + V_{spj}^t) \geq D_{sp}^t \quad \forall t \in T, \forall s \in S, \forall p \in P \quad (5)$$

$$U_{pj} + V_{spj}^t \geq \beta_{pj} \alpha_{pj} D_{sp}^t \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall j \in N \quad (6)$$

Eq. (7) represents the storage restriction imposed by depot loading/unloading operations. For any time period, scenario, and product, the sum of existing and additional storage capacities of a distribution center must be such as to cater a portion of the total inflow from different modes and supply nodes. On the other hand, Eq. (8) represents the storage restriction imposed by land availability. For any time period and scenario, the total additional storage capacity of all products at a distribution center shall not exceed the permissible additional total storage capacity at that center.

$$U_{pj} + V_{spj}^t \geq \gamma_p \sum_{r \in R} \sum_{i \in I, i \neq j} X_{sprij}^t \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall j \in N \quad (7)$$

$$\sum_{p \in P} V_{spj}^t \leq W_j \quad \forall t \in T, \forall s \in S, \forall j \in N \quad (8)$$

Eqs. (9) and (10) represent the operational *non-negativity constraints* on the decision variables.

$$X_{sprij}^t \geq 0 \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall r \in R, \forall i \in I, \forall j \in J \quad (9)$$

$$V_{spj}^t \geq 0 \quad \forall t \in T, \forall s \in S, \forall p \in P, \forall j \in N \quad (10)$$

2.3. Model objective functions

The model has two objectives which are incompatible from the operational perspective as well as from the organizational levels at which decisions are taken. The first objective, stated in Eq. (11), is the minimization of total transportation cost from supply centers to distribution centers and between distribution centers. This objective is relatively a top priority to the decision-maker making decisions of supply, transshipment, and storage capacity utilization at the central level of a DPSC organization. Secondly, the objective denoted by Eq. (12) considers the minimization of product loss (quantified in terms of cost) that takes place during transportation from supply centers to distribution centers and between distribution centers. Owing to the monthly product loss targets imposed by the central office at different distribution centers, this objective is relatively more important to the decision-maker making decisions of transshipment and storage capacity utilization at the distribution center.

$$\min Z_1 = \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} \sum_{i \in I} \sum_{j \in J} \sum_{j \neq i} \psi_{sp} TC_{rij} X_{sprij}^t \quad (11)$$

$$\min Z_2 = \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} \sum_{i \in I} \sum_{j \in J} \sum_{j \neq i} \psi_{sp} LC_{rij} X_{sprij}^t \quad (12)$$

3. Illustrative case study

This section elucidates the utility of the proposed integrated,

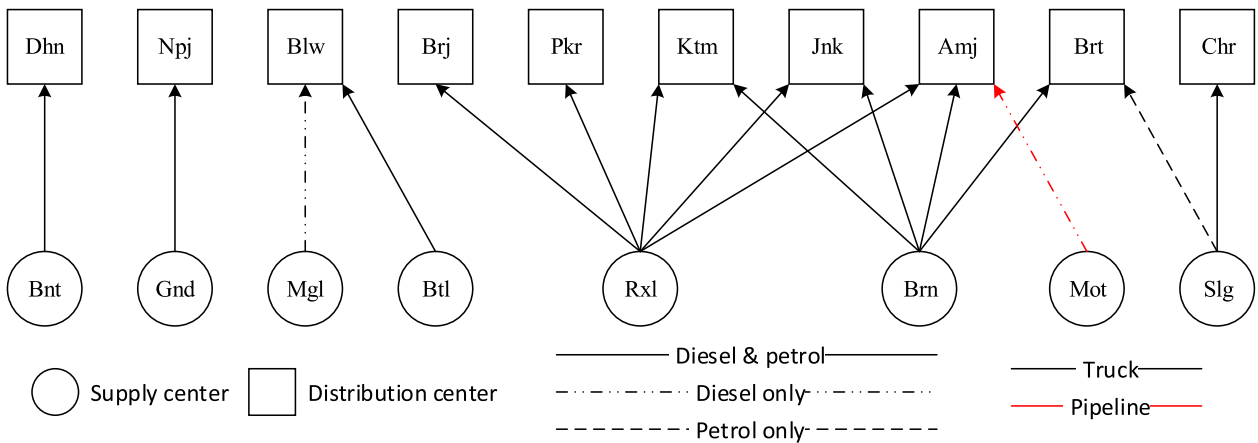


Fig. 2. Existing shipping pattern.

stochastic, multi-objective MILP model in the context of a real-world DPSC network in Nepal. First, existing and study networks are introduced, followed by discussions on the input parameters used in the model.

3.1. Existing network

The existing DPSC network consists of supply centers, distribution centers, road links, and a pipeline link, as shown in Fig. 1. The supply centers, governed by Indian Oil Corporation Limited (IOCL), are 8 in number: Siliguri (Slg), Barauni (Brn), Motihari (Mot), Raxaul (Rxl), Baitalpur (Btl), Mughalsarai (Mgl), Gonda (Gnd), and Banthara (Bnt). The distribution centers are under the jurisdiction of Nepal Oil Corporation Limited (NOCL), and are 10 in number: Charali (Chr), Biratnagar (Brt), Janakpur (Jnk), Birgunj (Brj), Amlekhgunj (Amj), Kathmandu

(Ktm), Pokhara (Pkr), Bhalwari (Blw), Nepalgunj (Npj), and Dhangadhi (Dhn). The shipping pattern in the network under normal condition is represented in Fig. 2. Diesel (die) and petrol (pet) are the only products considered for transportation in the context of this study. Most of the supply of these products to distribution centers takes place via trucks, except Amlekhgunj which additionally receives diesel from the pipeline connecting it from Motihari. Besides these direct shipping from supply centers to distribution centers, there's also occasional transshipment from one distribution center to another.

3.2. Study network

Compared to the monthly demand of both diesel and petrol, the respective storage capacities at the existing distribution centers are minimal, capable of meeting the demand for less than a week. Charali,

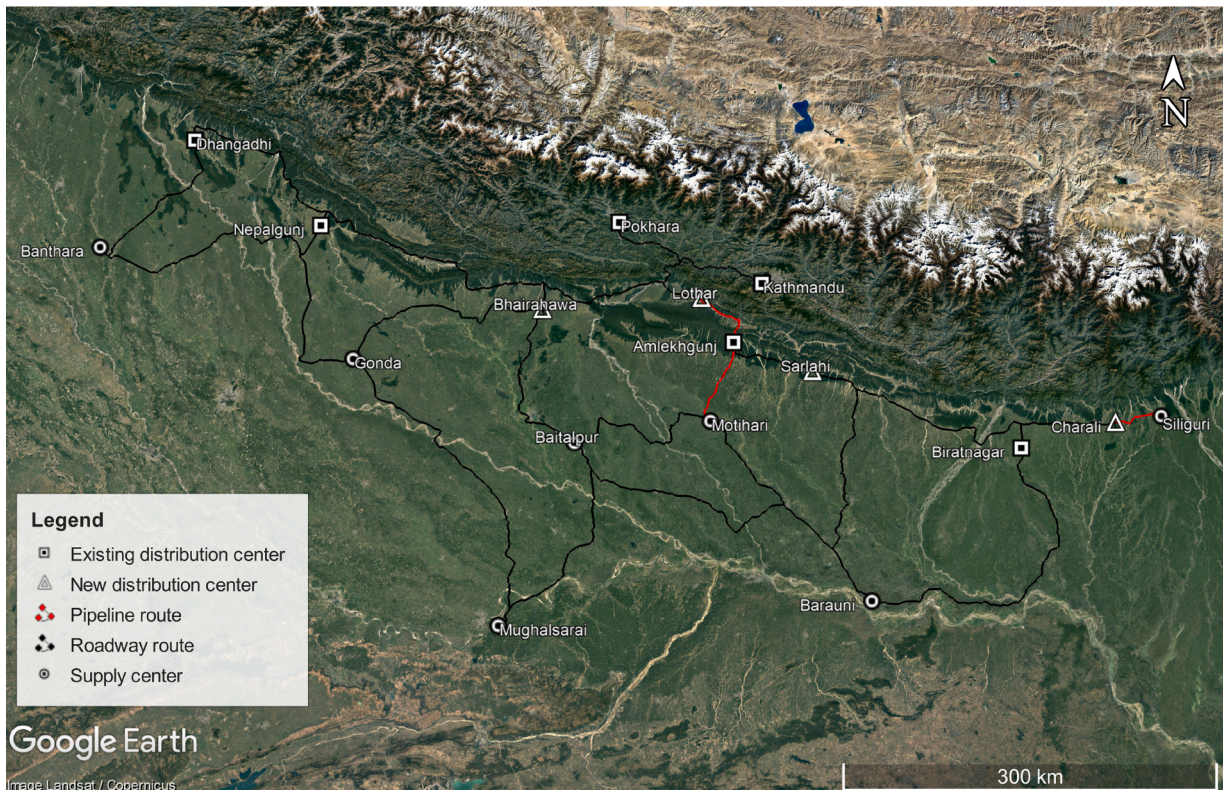


Fig. 3. Study network.

Table 3
Distance matrix of external routes (KM).

	Chr	Brt	Srl	Amj	Ctw	Ktm	Plkr	Bhw	Npj	Dhn
Slg	46	146.3	331.8	410	471.6	641.3	620.3	641.7	869.9	1024.5
Brn	387.3	287	249.3	280.2	341.8	511.5	490.5	476	740.1	894.7
Mot	420.4	358.7	134.6	73.2	134.8	304.5	283.5	304.9	533.1	687.7
Btl	556	494.3	270.2	208.8	270.4	423.4	402.4	155	424	578.6
Mgl	755	693.3	469.2	407.8	469.4	622.4	601.4	354	470	647.8
Gnd	789.7	728	503.9	425.7	364.1	462.4	441.4	194	170	347.8
Bnt	1062.9	1001.2	777.1	698.9	637.3	735.6	714.6	508	239	150

Table 4
Distance matrix of internal routes (KM).

	Chr	Brt	Srl	Amj	Ctw	Ktm	Plkr	Bhw	Npj	Dhn
Chr	0	100.3	285.8	364	425.6	595.3	574.3	595.7	823.9	978.5
Brt	100.3	0	224.1	302.3	363.9	533.6	512.6	534	762.2	916.8
Srl	285.8	224.1	0	78.2	139.8	309.5	288.5	309.9	538.1	692.7
Amj	364	302.3	78.2	0	61.6	231.3	210.3	231.7	459.9	614.5
Ctw	425.6	363.9	139.8	61.6	0	169.7	148.7	170.1	398.3	552.9
Ktm	595.3	533.6	309.5	231.3	169.7	0	247	268.4	496.6	651.2
Plkr	574.3	512.6	288.5	210.3	148.7	247	0	247.4	475.6	630.2
Bhw	595.7	534	309.9	231.7	170.1	268.4	247.4	0	269	423.6
Npj	823.9	762.2	538.1	459.9	398.3	496.6	475.6	269	0	177.8
Dhn	978.5	916.8	692.7	614.5	552.9	651.2	630.2	423.6	177.8	0

Birgunj, and Janakpur, in particular, have negligible storage capacity; these centers simply distribute products from the incoming truck fleet to fuel retail outlets whose demand they cater. Birgunj, Janakpur, Bhalwari, and Dhangadhi are located in areas with dense settlements and are in dire need of relocation. Amlekhgunj currently has the country’s largest storage capacity, and it along with Pokhara have projects ongoing for expansion of storage facilities. Similar addition of storage facilities is not feasible in Kathmandu, Nepalgunj, and Dhangadhi due to land restrictions. Owing to these limitations of storage capacity in the existing centers, NOCL has acquired land for the construction of new storage facilities in four different locations: Charali (near the existing Charali distribution center), Sarlahi (Srl), Lothar in Chitwan (Ctw), and Bhairahawa (Bhw). For the purpose of this study, the following first-stage decisions are considered to be made beforehand in the existing network: relocation of the existing Charali distribution center at the new Charali center; relocation of Janakpur at Sarlahi; relocation of Bhalwari at Bhairahawa; inclusion of Chitwan; and exclusion of Birgunj, thereby comprising 10 distribution centers in the study network.

In the supply side, this study considers three pipeline links: existing Motihari–Amlekhgunj pipeline (MAP), Siliguri–Charali pipeline (SCP), and Amlekhgunj–Chitwan pipeline (ACP). The latter two are pipeline projects under planning phase. Motihari is an under-construction terminal currently supplying only diesel via MAP. Based on the decision-maker’s feedback, analysis is sought considering the supply of both products via pipelines. In case of Raxaul, which is located in a densely settled area, IOCL has planned to completely relocate the depot therein to Motihari. Hence, with Raxaul relocated to Motihari, there’s a total of 7 supply centers. The resulting study network with supply centers, distribution centers, road links, and pipeline routes is presented in Fig. 3.

3.3. Transportation cost

NOCL’s freight costs between supply centers and distribution centers and between distribution centers and fuel retail outlets are based on round-trip kilometer (RTKM), which is simply twice the one-way distance between the centers. These RTKM figures in this study’s context, however, suffered from a drawback: the RTKM data were available for only the roadway links in the existing network. As a result, the transportation cost of all identified routes in the study network was computed utilizing both RTKM data as well as the distance data measured using Google Earth. First, the node to node distances were computed in Google

Earth to yield a distance matrix. Then, a conventional k-shortest path algorithm was implemented in MATLAB (R 2019a 9.6.0.1072779) to compute the shortest distance (d_{ij}) between all possible node pairs in the network. The computed distance between supply and distribution centers is presented in Table 3; that between distribution centers is presented in Table 4.

From NOCL’s pre-defined freight rates (Rs. per KL), a selection was made of the RTKM data and freight cost data for transportation routes that were geographically similar to the ones considered in the study network. A dataset of 83 such observations with transportation cost (TC_{ij}), distance (D_{ij}), and route type (RT_{ij}) were obtained. The conventional RTKM figures were converted into kilometer-based distances. Routes were categorized as external and internal: external routes link supply centers to distribution centers, whereas internal routes link distribution centers with one another and with fuel retail outlets. A regression was then carried out of transportation cost on independent variables distance and route type, with the freight rates of February 18, 2020 as the reference data. The regression equation represented in Eq. (13) yielded an R-squared value of 0.98 with a highly significant p-value and a residual standard error of 197.9. The reference category for the route type is “internal.” In computing the truck transportation cost for the study network, the distances obtained from the shortest path analysis were used in Eq. (13). The transportation cost in pipelines, upon consultation with the decision-maker, was assumed to be zero.

$$TC_{ij} = 512.4814 + 7.2793d_{ij} - 272.7279RT_{ij} \tag{13}$$

3.4. Product loss cost

Whether diesel or petrol, all liquid petroleum products undergo a wide variety of heat and mass transfer processes within the transportation chain. Stock losses can be categorized into two groups: true and apparent. True stock loss refers to a loss of mass and is primarily attributed to theft and spillage. Given their nature, these loss mechanisms are difficult to quantify and are hence beyond the scope of this study. Apparent stock loss, on the other hand, involves only a loss of volume in the transportation chain, and arises from two sources: errors in measurement and shrinkage, the former of which too is beyond the scope of this study. The major source of apparent product loss is shrinkage which is due to the changes in fuel density with respect to temperature. In case of liquid hydrocarbons, a relatively small change in

Table 5
Product loss cost for diesel (Rs. per KL).

	Chr	Brt	Srl	Amj	Lth	Ktm	Pkr	Bhw	Npj	Dhn
Slg	0	0	10	0	0	290	230	0	0	0
Brn	370	240	380	290	360	660	600	350	300	290
Mot	160	30	170	80	150	450	390	140	90	80
Btl	50	0	60	0	50	350	290	30	0	0
Mgl	80	0	80	0	70	370	310	50	10	0
Gnd	110	0	120	30	110	410	350	90	50	40
Bnt	280	150	290	200	270	570	510	260	210	200

Table 6
Product loss cost for petrol (Rs. per KL).

	Chr	Brt	Srl	Amj	Lth	Ktm	Pkr	Bhw	Npj	Dhn
Slg	0	0	120	0	90	540	550	20	0	180
Brn	320	290	430	300	410	850	860	340	230	490
Mot	90	70	210	80	190	630	640	120	10	270
Btl	50	20	160	40	140	580	600	70	0	220
Mgl	140	120	260	130	230	680	690	160	60	320
Gnd	210	190	330	200	300	750	760	230	130	390
Bnt	270	250	390	260	360	810	820	290	190	440

Table 7
Existing and permissible additional storage capacities of distribution centers (KL).

		Chr	Brt	Srl	Amj	Ctw	Ktm	Pkr	Bhw	Npj	Dhn
existing	die	0	7110	0	20,600	0	8400	2280	0	2280	1590
	pet	0	560	0	1930	0	5310	350	0	210	70
addition	both	40,000	5330	23,000	17,470	102,000	760	10,760	40,000	760	760

temperature will result in a significant change in volume. Diesel, in proximity of ambient temperature, expands or contracts by 0.08% for each °C, whereas petrol changes by 0.12% volume/°C [35]. The temperature shrinkage coefficients fixed by NOCL assume the expansion or contraction of diesel by 0.075% for each °C change in temperature, while that of petrol by 0.106% volume/°C [39].

The temperature loss via truck transportation for both diesel and petrol is worked out as follows. First, the mean monthly temperature of products supplied from all supply centers and products received at all distribution centers were computed, taking the data from the FY 2017/18 as the reference. (For the study network under consideration, the temperature of Motihari, Sarlahi, Chitwan, and Bhairahawa were approximated as that of Raxaul, Janakpur, Amlekhgunj, and Bhalwari, respectively from the existing network.) The mean of the monthly mean temperature was then computed for each center and the temperature loss was quantified in terms of the difference between supply and distribution centers. The loss was then weighted with NOCL’s shrinkage coefficients. Negative temperature loss indicate impractical product gains, which after consultation with the decision-maker were adjusted to zero values. The resultant matrix was the adjusted weighted temperature loss which was further converted to monetary terms assuming the price of diesel as Rs. 100 per liter and of petrol as Rs. 110 per liter. The final result was the product loss cost via trucks for both diesel and petrol as presented in Tables 5 and 6, respectively. Product loss in pipeline transportation was assumed to be zero.

3.5. Storage capacity

The storage capacities in most of the existing distribution centers are only nominal and constrained due to land restrictions. For these centers, the optimal storage capacity that can be utilized was assessed upon consultation with the decision-maker. For Amlekhgunj and Pokhara, where projects are ongoing for additional storage facilities, the planned additional capacities were taken into account. For new distribution centers, the optimum storage capacities were considered in line with

NOCL’s plan for constructing large-scale bulk storage of petroleum products at these locations. Therefore, based on the decision-maker’s understanding of the plans for future projects, the maximum permissible additional storage capacity were worked out. Table 7 presents the existing as well as maximum permissible additional storage capacities of diesel and petrol at all distribution centers in the study network.

3.6. Supply

The total monthly supply of a supply center is the cumulative of supply via trucks and pipeline. This total was computed considering a planning horizon of three time periods: t_1 , t_2 , and t_3 . These planning periods are indicative of subsequent fiscal years—2021/22, 2022/23, and 2023/24. FY 2020/21, the year at the time of this study, was considered the base time period t_0 . Perusing the statistics of the past three fiscal years (2016/17, 2017/18, and 2018/19), the data pertaining to monthly supply of both products via trucks from each supply center were obtained. The recorded maximum monthly supply of each product and supply center in the 36 months’ period was assumed to be the expected monthly supply via trucks for that particular product and supply center in the base time period t_0 . With Motihari expected to replace Raxaul within the planning period, it’s expected maximum monthly supply via trucks for the base time period t_0 was approximated as that of Raxaul.

In regard to the expected monthly supply via pipeline, there wasn’t sufficient data, given that the supply of diesel through MAP was commissioned only at the beginning of the FY 2019/20. Amlekhgunj currently doesn’t have the required excess storage capacity to handle the interface product of a multi-product pipeline transportation. Only with the completion of the ongoing projects for additional storage facilities at Amlekhgunj, it will be able to receive multiple products via pipeline as well. The case is similar for ACP and SCP as well, whose construction completion within the planning horizon will ensure multi-product pipeline transportation. In these contexts, for the base time period t_0 , NOCL expects monthly supply from MAP (and ACP) at an average flow

Table 8

Total monthly supply in time period t_3 (KL).

Product	Slg	Brn	Mot	Btl	Mgl	Gnd	Bnt
die	61,700	72,600	170,900	25,100	5700	21,600	11,000
pet	21,500	30,700	62,200	6700	2600	4800	2400

Table 9

Demand share (α) and minimum demand fulfilment factor (β).

		Chr	Brt	Srl	Amj	Ctw	Ktm	Pkr	Bhw	Npj	Dhn
α	die	5%	14%	5%	18%	12%	17%	4%	14%	6%	5%
	pet	6%	13%	5%	11%	11%	31%	6%	10%	4%	3%
β	die	30%	20%	30%	20%	50%	20%	10%	30%	10%	10%
	pet	30%	20%	30%	20%	50%	20%	10%	30%	10%	10%

rate of 250 kl/hr with operational periods of 15 full days per month for diesel and 6 full days per month for petrol. On a similar note, NOCL expects monthly supply from SCP at an average flow rate of 200 kl/hr with operational periods of 9 full days per month for diesel and 3 full days per month for petrol.

The monthly supply from truck and pipeline were summed to obtain the total monthly supply of each product from each supply center in the base time period t_0 . Then, for each of the three time periods, this monthly supply from the base period was increased at a constant rate of 5% per annum. All these assumptions and computations were carried out based on the decision-maker’s feedback. The resulting total monthly supply of each supply center and product for time period t_3 is presented in Table 8.

3.7. Demand

The total monthly demand of each distribution center was computed considering three aspects: a) observation of annual and monthly demand of each distribution center during the past seven fiscal years; b) demand projection used by NOCL for ACP and SCP projects; and c) decision-maker’s understanding of market share of product-specific demand at the end of three-year planning horizon. The former aspect revealed that

although the consumption or demand of both products had increased over the years, there wasn’t an observable trend in the growth rate, making it difficult to forecast demand using time series analysis. It was, however, noted that the annual demand share of each distribution center remained steady over the past years. In this context, based on the decision-maker’s feedback and in line with the observed average demand share, the expected demand share of each product and each distribution center in the study network was determined. Considerations were made to the change in demand share of existing distribution centers based on their historical share and owing to the addition of new distribution centers. The computed demand share along with the minimum demand fulfilment factor assigned by the decision-maker are presented in Table 9.

NOCL has predicted the annual demand growth rates of 6% and 8% respectively for diesel and petrol in its demand projection of pipeline projects. Based on this growth rate, and with the average monthly demand of the FY 2018/19 as the reference, the monthly network demand for the base time period t_0 was forecasted, resulting in demands of 151,484 kl for diesel and 51,015 kl for petrol.

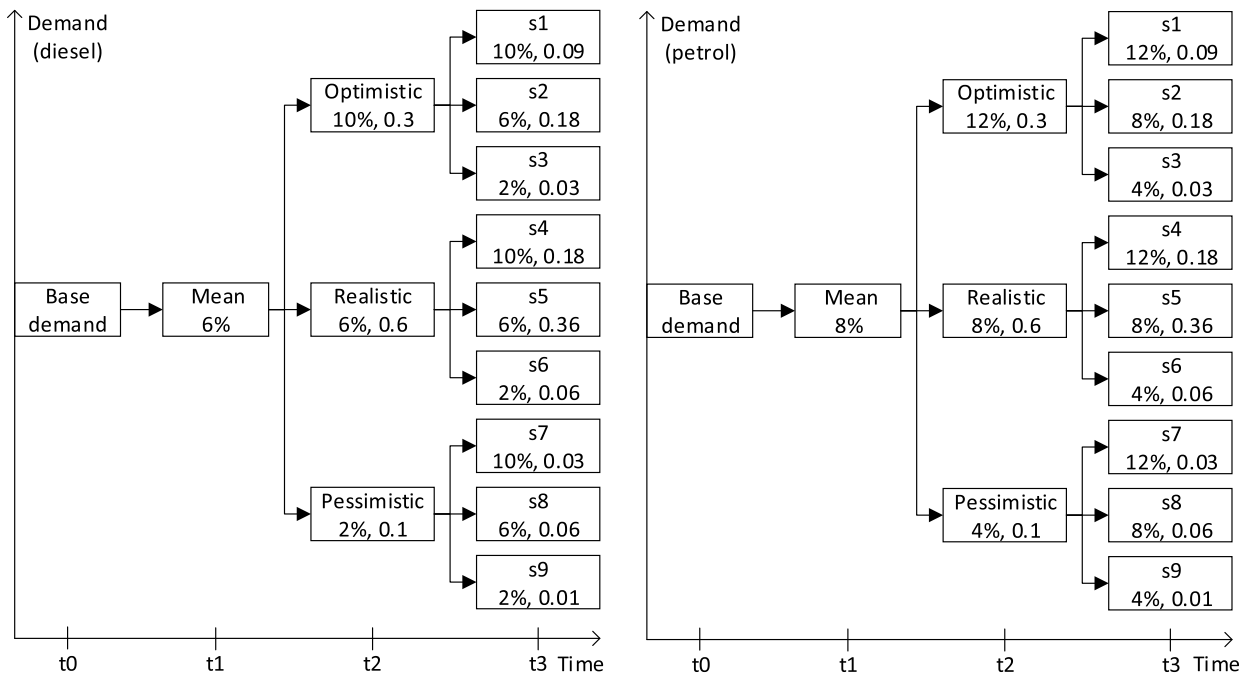


Fig. 4. Scenario trees.

Table 10
Scenario-based total monthly demand in time period t_3 (KL).

Product	s1	s2	s3	s4	s5	s6	s7	s8	s9
die	195,000	188,000	180,000	188,000	181,000	174,000	180,000	174,000	167,000
pet	69,000	66,000	63,000	66,000	64,000	61,000	63,000	61,000	59,000

Table 11
Model statistics.

Blocks of equations	13	Single equations	15,825
Blocks of variables	4	Single variables	10,335
Non zero elements	71,428		

Table 12
Payoff table.

	Transportation Cost (Rs.)	Product Loss Cost (Rs.)
min Transportation Cost (Z_1)	242,931,980.00	29,307,380.00
min Product Loss Cost (Z_2)	556,664,880.00	21,918,040.00

4. Analysis

This section first discusses the development of a scenario tree in dealing with demand uncertainty and follows up with numerical results and discussions.

4.1. Scenario tree

The conventional approach in handling uncertainty involved a sequence of making assumptions of probabilistic distribution, estimating the parameters based on historical data, and formulating a stochastic model. According to Escudero et al. [10], such approach may prove

unreliable particularly when the historical information available is limited and also in case the problem dictates requirement of considering information that is not reflected in the historical dataset. For this study, a two-stage scenario analysis is proposed and demand uncertainty is modeled via a set of scenarios (refer back to Section 1.2). A scenario tree is constructed for each product considering three factors: historical growth trend, average annual growth rates predicted by NOCL, and the decision-maker’s understanding of import trend of petroleum products in recent years. The trees, as shown in Fig. 4, are representative of a set of scenarios that considers optimistic, realistic, and pessimistic growth rates of demand for each product.

Each scenario is associated with a growth rate of demand and a probability assigned to it by the decision-maker. The mean demand from the time period t_0 is forecasted to the first planning period t_1 based on NOCL’s predicted growth rates. The scenario with mean demand from time period t_1 splits into three scenarios in time period t_2 . For diesel, optimistic scenario assumes a demand growth rate of 10% with a probability of 0.3, realistic scenario a growth rate of 6% with a probability of 0.6, and pessimistic scenario a growth rate of 2% with a probability of 0.1. For petrol, the respective growth rates in the three scenarios are 12%, 8%, and 4% respectively, with their respective probabilities the same as in diesel. From time period t_2 , the tree further breaks down into nine scenarios in time period t_3 , the analysis in which is of much interest to the decision-maker. Overall, the scenario tree handles product-specific uncertainty in time-varying demands for up to three time periods.

The scenario-based stochastic analysis is proposed for time period t_3

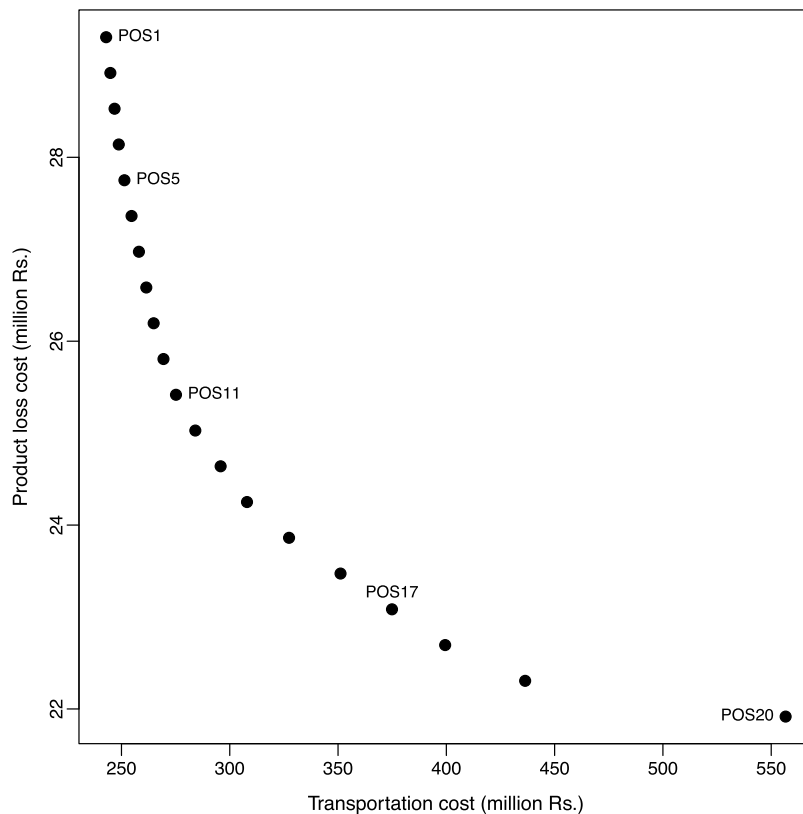


Fig. 5. Pareto optimal solutions.

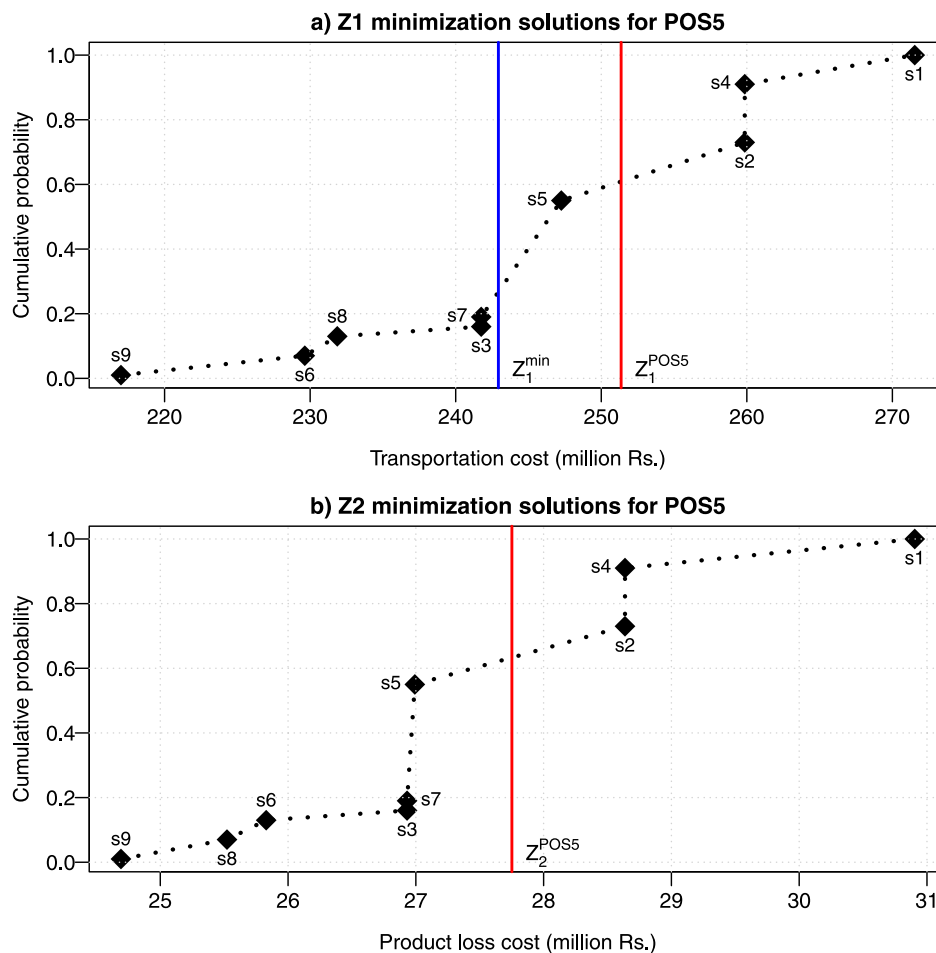


Fig. 6. Cumulative probability distribution of objective functions for POS5.

so as to aid the decision-makers in making both strategic and tactical decisions at the end of the planning horizon. The results from time periods t_1 and t_2 are left unexplored for two reasons: first, owing to their fewer raw scenarios, the analysis of these time periods aren't of much interest to the decision-maker; and second, the nine scenarios at the end of the planning horizon provide the decision-makers with unique scenario-specific DPSC network configurations, thus aiding in understanding the flexibility and complexity of making integrated decisions. Based on the demand at base time period t_0 , the total monthly demand of each product at time period t_3 is computed for each of the nine scenarios. The resulting scenario-specific demand is presented in Table 10.

4.2. Numerical results

The integrated, stochastic, multi-objective MILP model based on the parameters discussed was modeled for time period t_3 in GAMS 32.2.0 [40] and solved with commercial solver CPLEX 12.10.0.0. Table 11 summarizes the resulting model statistics.

For generating the efficient or Pareto optimal solutions (POS), the AUGMECON2 algorithm proposed by Mavrotas and Florios [33] was used (refer back to Section 1.3). The algorithm initially carries out a lexicographic optimization of each objective function in order to construct a payoff table that specifies the range of the POS of each function. The procedure is as follows: first, the model was optimized based on minimizing the objective function of higher priority (Z_1 in this case), thereby yielding a minimum Z_1 value of Rs. 242,931,980.00; the corresponding Z_2 value was Rs. 29,307,380.00. Then, the second objective function was minimized subject to Z_1 value as an equality constraint so as to retain the optimal solution of the first optimization.

The minimum Z_2 value obtained was Rs. 21,918,040.00, for which the corresponding Z_1 value was Rs. 556,664,880.00. (These figures are indicative of average values weighted by respective probabilities across the 9 scenarios considered.) Table 12 presents the payoff matrix from lexicographic optimization.

The second step in the algorithm is to generate a set of intermediate POS from the payoff matrix by dividing the range of Z_2 equidistantly into grid points. The number of grid points in the algorithm was set to 19, so that a total of 20 POS were obtained for further analysis. Moreover, in order to force the solver to minimize the slack and surplus variables of the constraints, the value of eps was chosen to be as high as 10^{-3} , given the range $eps \in [10^{-6}, 10^{-3}]$ [33]. The time elapsed in solving the model was 4.13 seconds. Fig. 5 presents the plot of the set of 20 POS obtained.

Following a similar approach—and for the purpose of this case study—the resulting POS of the stochastic analysis was compared with its deterministic counterpart as well. For deterministic analysis, instead of a scenario set of demands, the mean demand of refined products in time period t_3 was considered. The optimization results yielded Z_1 values between Rs. 237,646,000.00 and Rs. 534,993,000.00 and Z_2 values between Rs. 21,557,800.00 and Rs. 28,753,900.00, respectively. Compared to the stochastic set of POS, it was observed that the deterministic counterpart underestimated the optimal values of the objective functions. Hereinafter, further analysis of the decision variables are sought based on the results of stochastic analysis.

4.3. Discussions

Under the set of scenario-varying product demands in time period t_3 , each POS implies a DPSC network configuration with unique strategic

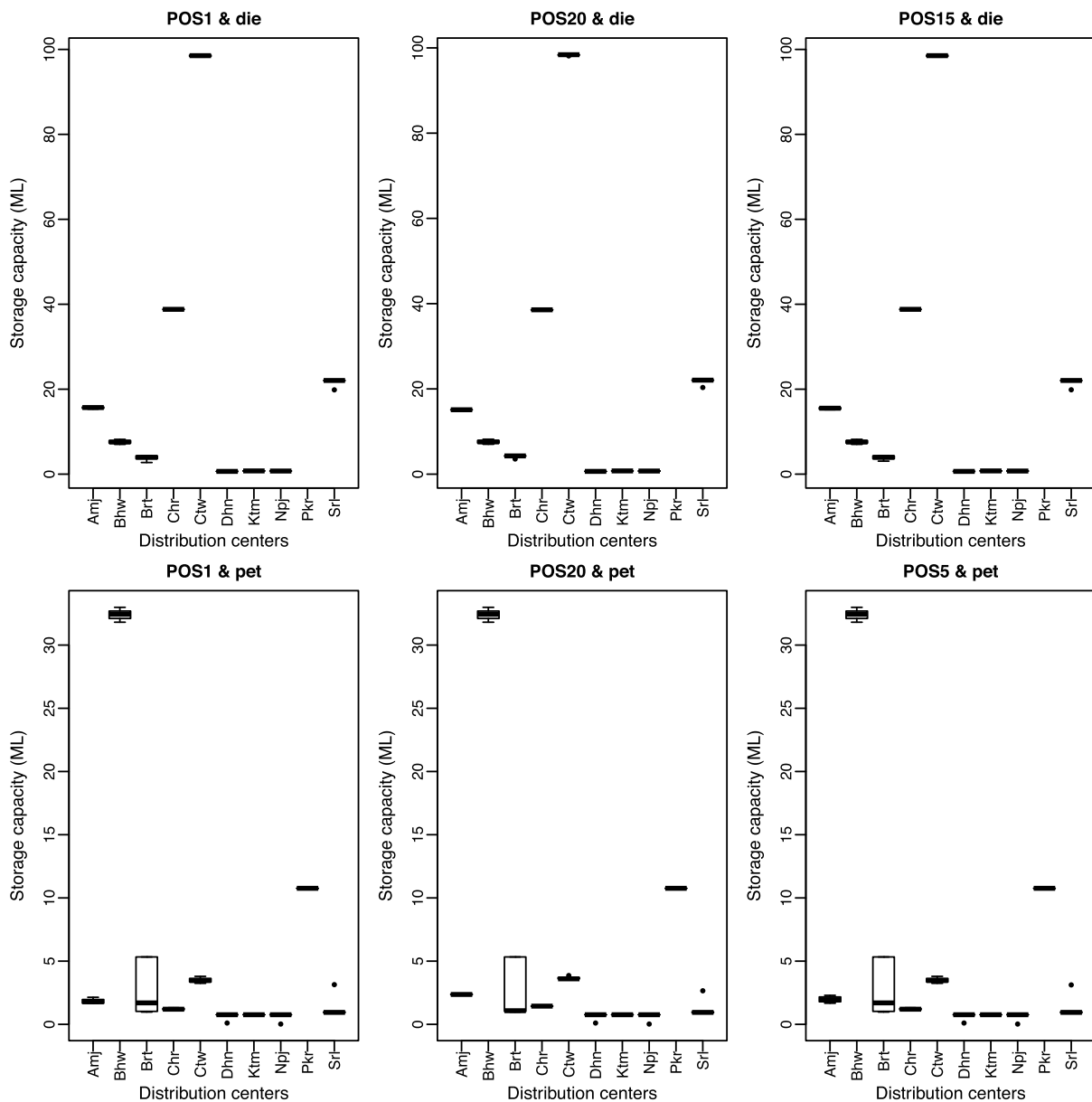


Fig. 7. Storage capacities of diesel and petrol for POS1, POS5 & POS20.

and tactical decisions. POS1 represents the DPSC network with the best possible minimization of transportation cost (Z_1^{min}), leaving product loss cost worse off. On the other hand, POS20 describes the network with the best possible minimization of product loss cost (Z_2^{min}), at the expense of a very high transportation cost. Given the range of the payoff table, minimization of about Rs. 313.7 million in transportation cost and Rs. 7.4 million in product loss cost can be obtained with POS1 and POS20, respectively. Every other intermediate solution indicates a trade-off between the two objectives, thereby yielding unique DPSC network configurations with simultaneous minimization of both the objective functions. POS5, for instance, yields minimization of 97% in Z_1 and 21% in Z_2 within the range of the payoff matrix. On a similar note, minimization of 90% in Z_1 and 53% in Z_2 can be obtained with POS11, 58% in Z_1 and 84% in Z_2 with POS17. These intermediate solutions, especially the ones between POS1 and POS11, are of much interest to the decision-makers as they make better compromise solutions in monetary terms.

For further analysis, let's consider a solution of particular interest to the decision-maker—POS5, yielding transportation cost (Z_1^{POS5}) of Rs. 251,363,620.00 and product loss cost (Z_2^{POS5}) of Rs. 27,751,729.00. With

this POS, the DPSC network configurations for the 9 scenarios considered generate transportation cost between Rs. 217,004,000.00 and Rs. 271,536,000.00. The cumulative probability distribution, as shown in Fig. 6, indicates that the network configurations obtained with this particular POS have 0.6087 probability of generating transportation cost lower than Z_1^{POS5} , 0.2672 probability of achieving the best minimum transportation cost Z_1^{min} , and 0.3415 probability of generating transportation cost between Z_1^{min} and Z_1^{POS5} . Similarly, with regard to the other objective, POS5 yields product loss cost between Rs. 24,692,400.00 and Rs. 30,904,400.00 with 0.6331 probability of generating product loss cost lower than Z_2^{POS5} .

An important aspect of multi-objective optimization, besides optimization itself, is decision support which assists the decision-makers in selecting their most-preferred solution from the set of POS generated. In order to make this selection in the context of this study, the decision-maker may implement the interactive approach proposed by Mavrotas [32]. The procedure follows a series of iterative decisions from the decision-maker in a search toward the most-preferred POS. After the POS are generated with the algorithm, the derived POS are filtered down

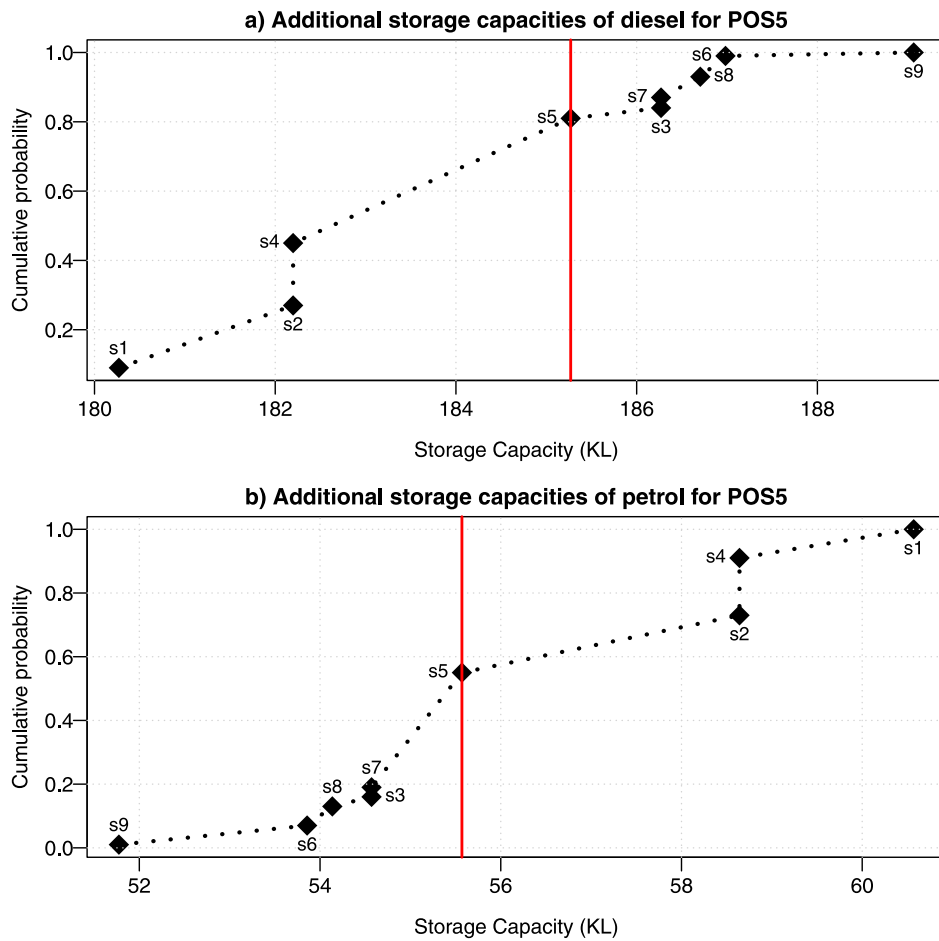


Fig. 8. Cumulative probability distribution of additional storage capacities for POS5.

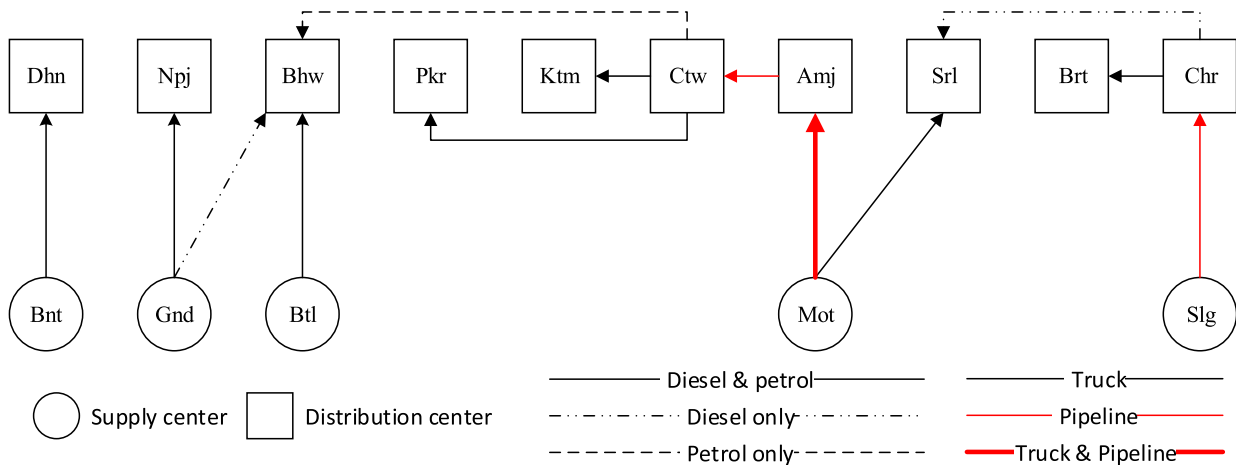


Fig. 9. Shipping pattern of POS5 under s1.

to 5 using a forward filtering process and presented to the decision-maker. The decision-maker then selects the most-preferred solutions from this representative set, and the search space is pruned around these selections to obtain more most-preferred solutions. The iterative process continues until the decision-maker is satisfied with a most-preferred POS.

The decision-makers at different organizational levels can select a solution through the procedure aforesaid and further assess the network configurations from strategic as well as tactical aspects. For strategic

decision-making, solutions depicting lower variability in first-stage variables under the set of scenarios considered are more preferable to the decision-makers as decision support tool. On the other hand, from tactical planning perspective, shipping pattern with a larger number of transportation links having low-quantity flow of products from one center to another may render a particular POS unreliable and unpragmatic.

Fig. 7 presents the product-specific box plots of additional storage capacities for all distribution centers. It is evident from the figures that

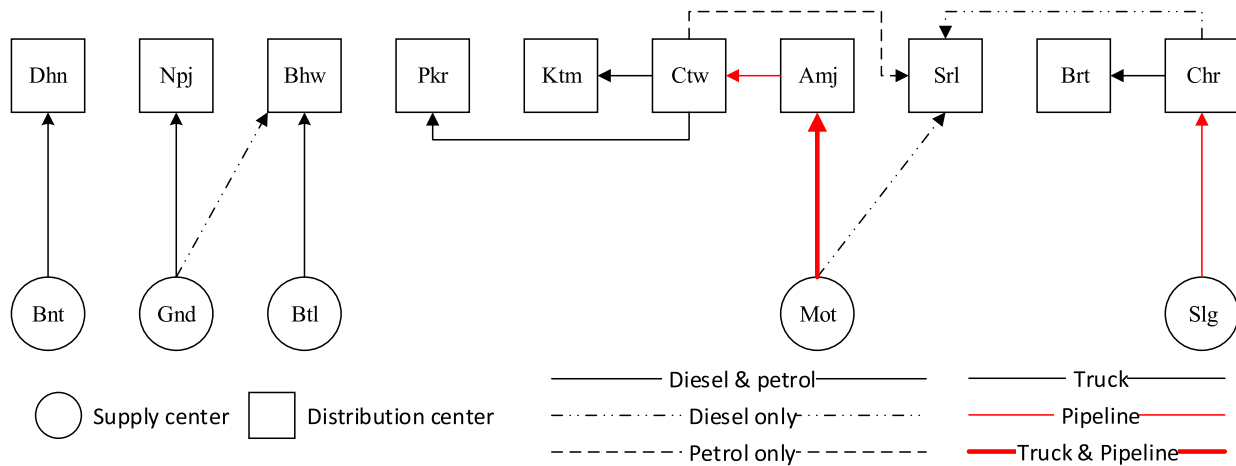


Fig. 10. Shipping pattern of POS5 under s5.

the variability of storage capacities to be expanded at each center with respect to POS1, POS5, and POS20 is nominal, thus reinforcing the decision-maker’s strategic decisions under all set of demand scenarios and with both the objectives considered. Furthermore, considering POS5 again, the DPSC network configurations under different scenarios yield additional total storage capacities between 180,270 KL and 189,066 KL for diesel and between 51,774 KL and 60,570 KL for petrol at the end of the planning horizon. Under s5—the most realistic scenario (owing to its higher probability weightage) in t_3 —POS5 indicates 0.81 probability of expanding storage capacity of diesel below 185,270 KL and 0.55 probability of expanding storage capacity of petrol below 55,570 KL, as shown in Fig. 8.

Examining POS5 at the tactical level, Figs. 9 and 10 present the optimal shipping patterns of the DPSC networks generated under scenarios s1 (most optimistic in t_3) and s5 (most realistic in t_3), respectively. In both network configurations, supply takes place from only 5 supply centers: Siliguri, Motihari, Baitalpur, Gonda, and Banthara (compared to 8 in the existing network). Quite interestingly, the distribution centers Charali, Amlekhgunj, and Chitwan—owing to their direct connection to supply centers via pipeline—act as transshipment hubs and cater the demand of other distribution centers, thereby reducing the exorbitant direct transportation cost between a supply center and a distribution center. Overall, such tactical decisions aid the decision-maker in visualizing the importance of multimodal transportation and transshipment in DPSC network configurations under time-varying demand scenarios.

Based on the results and in-depth analyses from this case study, the proposed model is found to be quite pragmatic, reliable, and tractable in its integrated assessment of multiple objectives, taking into account uncertainties and multimodal transshipment. This is an apparent advantage over much recent DPSC planning studies [14,18,26,34,39,47,50] that largely segregated these critical decision-making aspects and entities. Methodologically, the two-stage stochastic model implemented in this study, compared to the three-scenarios approach adopted by Al-Othman et al. [1], is found to be superior in terms of analyzing both decision variables and monetary trade-offs within a wide spectrum of possible scenarios. Another observable edge of the proposed stochastic approach over that by Ghatee and Hashemi [19] is the ease with which decision-makers can perceive these scenarios, thus bypassing the reliance on granular information for modeling uncertainty with fuzzy parameters. Given the complexity imposed by the model statistics presented in Table 11, the case analyzed in this study was found to be effectively solved using the ϵ -constraint method. For problems of larger scales, however, Tirkolae et al. [44] emphasize the use of heuristic and meta-heuristic algorithms for obtaining more efficient Pareto fronts.

5. Conclusion

This paper proposed a two-stage stochastic, multi-objective MILP model for an integrated planning of DPSC networks. A case study of a real-world DPSC network in Nepal demonstrated the applicability of the model as a decision-support tool. The formulated model and the analyzed case study attempted to address gaps identified in the review of PSC studies by Lima et al. [31]. The study’s novelty lies in dealing with integrated planning of a DPSC subsystem under uncertainty in a multi-objective setting, while also considering multiple products, multimodal transportation, and transshipment.

Consideration of stochasticity into the proposed model aided the decision-maker in assessing the impacts of demand uncertainty on different Pareto optimal network configurations, thus providing the foundation for a more flexible decision-making. The computational results demonstrated the rationality of adopting a set of scenarios to approximate the stochastic nature of a multi-objective optimization problem, where the objectives targeted simultaneous minimization of transportation cost and product loss risk cost incurred during transportation. Moreover, an in-depth analysis of interesting efficient solutions further aided in understanding the nature of decision variables in scenario-varying product demands and the overlying monetary trade-offs at different decision levels. At the strategic level, the model determined the required additional storage capacity at each distribution center to meet the overall network demand; at the tactical level, the amount of products to be transported or transshipped between the centers along different transportation modes were assessed. In developing countries like Nepal, where the downstream segment is fully reliant on the import of petroleum products from a neighboring country, the importance of these decisions are particularly realized at times of supply irregularities when the overall network demand has to be satisfied via the transshipment of stock available at various distribution centers.

For future research, the model can be extended by taking into account the spatio-temporal demand of consumer markets as well. Such an integrated model can further incorporate the balance of storage capacity between successive time periods in a multi-period setting. A higher complexity of the model can also be tested considering the nonlinear behavior of the operational aspects at distribution centers—for instance, stock loss from storage tanks and dynamic allocation of truck fleet for transshipment, among others. Moreover, new objectives concerning the maximization of profit or revenue and the minimization of other environmental risks can be assessed to better understand relatively understudied insights to decision-making in DPSC planning studies.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Pramesh Pudasaini: Conceptualization, Methodology, Investigation, Resources, Data curation, Software, Formal analysis, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

None.

Acknowledgement

The author is thankful to the editor and three anonymous referees for their valuable comments which helped in significantly improving the paper.

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