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Comprehensive quantity discount model for dynamic green supplier selection and order allocation

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ABSTRACT

We model and solve a deterministic multi-period single-product green supplier selection and order allocation problem in which the considered suppliers' availability, cost, and green performance change from one period to another in the planning horizon. Moreover, the available suppliers may offer an all-unit or an incremental quantity discount (QD) scheme, resulting in three problem configurations. In one configuration, all suppliers offer all-unit QD. In the second, all suppliers offer incremental QD. In the third, some suppliers offer all-unit QD, and others offer incremental QD. The problem is modeled using a bi-objective integer linear programming formulation that maximizes the total green value of the purchased items from all the suppliers and minimizes their total corresponding cost, including the fixed cost, variable cost, inventory holding cost, and shortage cost. The proposed bi-objective model is scalarized and solved using the branch-and-cut algorithm and a population-based heuristic. A numerical analysis is conducted, which allows first to validate the heuristic approach using small-size instances by comparing its results with those of the exact approach. Moreover, an extensive comparison between the exact and heuristic solution approaches is carried out. The results reveal different findings. First, the economic and environmental solutions of an instance are different, and the environmental solution is independent of the suppliers' pricing schemes. Second, the maximum difference between the heuristic approach and the exact approach in terms of the bi-objective function value is 4.72%, which makes the proposed heuristic recommended for large-size instances due to its short computation time and good accuracy. Third, there is no difference in terms of the heuristic performance between the combined model and the models with a single type of discount. Fourth, the all-unit discount scheme seems to be generally better in terms of the trade-off between the green value of purchasing and cost.

1. Introduction

Recently, effective and efficient supply chain management (SCM) has become crucial especially for large and multi-national companies to keep improving their economic but also environmental performance in order to remain competitive in a changing global market. In addition, the importance of sustainability and environment protection has become essential for businesses and for the society in general. For instance, at least four out of the 17 Sustainable Development Goals that the United Nations has adopted are related to the management of companies' operations (United Nations, 2021): SDG-9, SDG-11, SDG-12, and SDG-13. This pressure has led many companies worldwide to adopt more environmental friendly operations and therefore to rely on green SCM. Moreover, in the particular context of the 2019 coronavirus pandemic, many companies could have regretted their reliance on a single supplier, which led some factories to close due to the shortage of supplies that resulted because of the lockdowns that happened in many countries. This fact confirms the necessity of increasing supply chain resilience by relying on more than one supply source especially for important items.

In this context, supplier selection is a tactical tool of SCM that organizations use to reduce their costs, minimize disruption risks, and improve the quality of their products (Alkahtani and Kaid, 2018). Choosing the best suppliers whether for manufacturing or service organizations has become a complex task that depends on multiple-criteria such as cost, quality, reliability, risk, social and environmental performance etc. On the other hand, due to awareness, governmental regulations, and globalization, organizations are considering more and

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more the environmental aspects in their supplier selection process. As mentioned earlier, international competition but also national regulations are constraining companies to achieve sustainability objectives in their operations.

Indeed, international competition has led companies to prioritize environmental factors in various SCM stages (Akman, 2015; Hafezalkotob, 2015; Zhang et al., 2014). As a result, the process of choosing the best supplier(s) to contract with from a panel of available suppliers while considering the environmental aspects is known as green supplier selection. Moreover, on a tactical level, in addition to choosing the best supplier(s), the decision of determining the quantities to be purchased from each selected supplier leads to a problem known as the supplier selection and order allocation (SSOA) problem. In the literature, it is formulated as an optimization problem (Kaviani et al., 2020). This problem is shown to be NP-hard and solved using heuristics approaches such as genetic algorithms (GA) in Basa et al. (2020) and Hashemzahi et al. (2020). Usually, the SSOA problem considers variable parameters, such as demand, capacity and cost, in a fixed planning horizon.

Suppliers usually offer to their customers, especially in a business-to-business environment, quantity discounts (QD) that can take different forms, such as the "all-unit" QD, "incremental" QD or other forms (Ayhan and Kilic, 2015). Most of the works in the literature (as it will be shown in the literature review section) have focused on one type of QD assuming that all suppliers offer the same policy while in reality, it may differ. Moreover, the QD problem formulations may not be solved optimally for large-size instances. Therefore, this paper attempts to bridge these gaps in the literature. Indeed, the contribution of this paper compared to the existing literature is threefold. First, this paper extends the green multiple-period and multiple-supplier SSOA problem by proposing a formulation that considers three QD policies: all-unit, incremental, and both (comprehensive or combined). This formulation integrates both discount schemes while considering the dynamic nature of the problem allowing, for example, the supplier availability to vary from one period to another in the planning horizon and therefore the available number of suppliers may vary from one period to another. Second, this work proposes a new population-based heuristic to solve large-size instances of the formulated problem and provides an extensive comparative analysis that shows the effectiveness of the proposed heuristic for large-size instances allowing to obtain good quality solutions in a reasonable time and with a good level of accuracy. Third, this paper proposes a decision support system that implements the mathematical formulation which helps procurement managers in the supplier selection and order allocation process in practice while allowing them to consider the practiced QD schemes and the green aspect. Therefore, the objectives of this study are as follows:

- To propose a new formulation of the multiple-period and multiple-supplier dynamic SSOA problem that considers the environmental performance of suppliers in addition to three QD schemes: all-unit, incremental, and both.
- To develop a heuristic solution approach to solve large-size instances of the formulated problem in a reasonable time and with a good level of accuracy.
- To develop a computer software that implements the proposed approach so that it can be used by decision-makers in the industry.

The rest of this paper proceeds as follows: In Section 2, we provide a literature review on the SSOA problem. In Section 3, we explain the mathematical formulation and the developed software. In addition, we present the bi-objective solution technique and the population-based heuristic used to solve large-sized instances and we illustrate the developed software in Section 4. In Section 5, we conduct a numerical study and discuss the results. Finally, Section 6 provides concluding remarks.

2. Literature review

The SSOA problem is a critical tactical tool in SCM. Indeed, for every organization, the accurate evaluation of the available suppliers to procure a good or a service and the selection process of the best one(s) to fulfill the organization needs and objectives is very important since it usually lasts for months and sometimes years. In this process, order allocation to the selected suppliers is often neglected, and considered as a supplementary part (Pasquale et al., 2020). However, SSOA is a core process in supply chain planning and with high complexity, because it should meet qualitative and quantitative criteria such as cost, quality, environmental aspects, etc. (Polat et al., 2017; Chen et al., 2016). Therefore, researchers have used multi-criteria decision-making (MCDM) models to address SSOA problem. SSOA problems have been widely investigated in the literature. The focus of this literature review is on studies related to SSOA, QD policies, and the use of green (environmental) criteria in SSOA. The scope of the literature review is mainly including the works published in the last two decades given that a very large number of related works has been published recently. The literature review comprises six sections: supplier selection, green supplier selection, SSOA, QD policies, datasets for the SSOA problem, and the research gap.

2.1. Supplier selection

Supplier selection has been studied for more than a decade utilizing various methods and criteria considerations. Researchers have employed integrated MCDM methods extensively in assessing suppliers and rating criteria in a variety of perspectives, including different working environments such as industry, small and medium businesses, and government. Thus, the supplier selection problem has been viewed and studied as an MCDM problem. Sorting, ranking, and selection, as well as determining criteria weight, are the key selection tasks addressed by these MCDM methods (Hashemi et al., 2015). For example, the analytic hierarchy process (AHP) has been used by Levary (2008) to rank and evaluate the available suppliers based on the risk criteria. Another well-known MCDM method, namely VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), has been used by Chen and Wang (2009) to evaluate suppliers and rank them to find the preferred suppliers. Kannan et al. (2014a) have used fuzzy axiomatic design. In addition, Saen (2010) and Rouyendegh et al. (2020) have used the technique for order of preference by similarity to ideal solution (TOPSIS) to rank and select the suppliers using real application data in a convenient way. Other researchers have used the analytic network process (ANP) to figure out the determinants in the supplier selection problem for a sustainable transportation case and to evaluate the transportation policies respectively (Sayyadi and Awasthi, 2018, 2016). Banaeian et al. (2018) presented a comparative study between fuzzy TOPSIS, fuzzy VIKOR, and fuzzy grey relational analysis (GRA) in the context of supplier selection. Sevkli (2010) has proposed the elimination choice translating reality and cross-industry standard process methods and compared them based on real data of three suppliers from a manufacturing company. Rahimi et al. (2021) introduced an intuitionistic fuzzy entropy measure, a novel fuzzy decision-making technique for selecting and ranking suppliers based on attributes. Finally, the decision-making trial and evaluation laboratory (DEMATEL) method has been used in Chang et al. (2011) to illustrate the factors and criteria that affect the supplier selection process.

Moreover, instead of using a single MCDM approach to assess and select the best suppliers, some researchers have used hybrid approaches, which consist of combinations of methods. An example is the combination of the weighted aggregated sum product assessment method and interval fuzzy sets (Ghorabaee et al., 2016). Other examples integrate composite indicators, data envelopment analysis, and common weights analysis (Dobos and Vörösmarty, 2014), ANP and improved GRA (Hashemi et al., 2015), Kano model and fuzzy

MCDM (Ghorbani et al., 2013), best worst method (BWM) and extended VIKOR (Wu et al., 2019), and BWM and fuzzy TOPSIS (Javad et al., 2020). Readers can refer to the work of Manucharyan (2021) for a recent review.

Recently, with the growth in the use of artificial intelligence algorithms, some researchers have utilized them in supplier evaluation and classification. For example, neural networks have been used for price forecasting and supplier evaluation (Lee et al., 2009), while grey system theory has been used in analyzing and evaluating suppliers' criteria (Li et al., 2007; Wu, 2009). Guo et al. (2009) have applied the support vector machine to classify suppliers with less computation time and high performance. GA has been used as a heuristic algorithm in the supplier selection problem to find the optimal solution, and as an example, Yeh and Chuang (2011) have developed a multi-objective model using GA that aims to minimize the cost and time while maximizing product quality and environmental criteria. While Jouida and Krichen (2020) designed a hybrid GA to assist each organization in making the best procurement policy decision possible. They considered two scenarios for the single objective model that aims to minimize the cost when dealing with different businesses and suppliers: first, allocating each firm to one supplier separately, and second, accumulating the amounts of the participating firms and then assigning each coalition to the proper provider.

Moreover, optimization techniques have been used in different contexts involving supplier selection. For instance, Amorim et al. (2016) have proposed a mixed-integer linear programming (MILP) model to maximize a food organization's profit and minimize the risk. The authors indicated that the proposed model improved the solutions in the supplier selection problem, especially in large instances. Furthermore, Yoon et al. (2018) have proposed a multi-objective MILP model to address the supplier selection problem in a multi-period framework. Some studies, such as Torabi et al. (2015), have used a bi-objective model with stochastic programming aiming to improve the organization's response while considering uncertainties and disruption risks in a supplier selection problem. They have used a real case study to show the applicability of their approach. Finally, goal programming has been used for different objectives, which are minimizing price, rejected items, lead-time, and to evaluate the risks and product life cycles in a supplier selection problem respectively (Jadidi et al., 2015; Kull and Talluri, 2008). In pharmaceutical industries and using fuzzy TOPSIS, Modibbo et al. (2022) proposed a MILP model to choose the best supplier. A numerical example was used to show the effectiveness of the presented model. The proposed model is simple, and it can be solved using readily available commercial software such as LINDO/LINGO and GAMS. Several supplier selection literature reviews have been published recently. These authors focused on sourcing strategy, decision scope, selection criteria, and solution methods as key elements in supplier selection and evaluation, see for instance Dutta et al. (2022) and Saputro et al. (2022).

2.2. Green supplier selection

In recent years, green criteria have been playing a major role in supplier selection, due to customer concerns and government rules. Therefore, many researchers have focused on the consideration of green criteria, such as the amount of recycled materials, mode of transportation, environmental certification, etc. in the evaluation of suppliers using different techniques. For instance, Yeh and Chuang (2011) have developed a multi-objective model to maximize product quality and environmental criteria in a supplier selection problem. Kannan et al. (2014b) have tried to consider green and capacity criteria while modeling the supplier selection problem. Moreover, Büyüközkan and Çifçi (2012) have applied fuzzy DEMATEL, fuzzy ANP, and fuzzy TOPSIS to evaluate and select suppliers based on environmental aspects. In addition, Darabi and Heydari (2016) have proposed an interval-valued hesitant fuzzy approach to rank the green suppliers. Furthermore, Galankashi et al. (2015) used the nominal group technique to measure the critical performance of the suppliers and select based on green criteria. Liao et al. (2016) have proposed new integrated fuzzy techniques and fuzzy additive ratio assessment with multi-segment goal programming model to evaluate and select the green suppliers. In the last two years, many studies have considered environmental criteria in the supplier selection process for different purposes and applications. We refer the reader to Ecer (2022), Gupta et al. (2019), Haeri and Rezaei (2019), Kilic and Yalcin (2020), Krishankumar et al. (2020), Javad et al. (2020), Rouyendegh et al. (2020), Watróbski (2019), Wu et al. (2019), nar et al. (2021), Tirkolaee et al. (2021) and Wei et al. (2021). Recently, many publications have done a comprehensive assessment of existing literature on supplier selection by highlighting the inclusion of green aspects into supplier selection, with the goal of presenting a summary of the developed models and approaches to support different industries in identifying the best green/sustainable suppliers such as Zhang et al. (2020) and Ograh et al. (2021). The two works studied and analyzed publications from 2009 to 2020.

2.3. Green SSOA

Supplier capacity is an important factor that determines whether a single supplier or multiple suppliers are required to fulfill the demand. While MCDM tools only rank suppliers based on multiple criteria, researchers have developed different optimization models that consider multiple factors and at the same time specific constraints that translate features of the systems. These models aim at selecting the optimal suppliers and allocating the orders to the selected suppliers while considering the supplier capacities. For example, Lin et al. (2011) have used a linear programming (LP) approach to allocate orders after the supplier is evaluated and selected, while non-linear programming is used in Hsu et al. (2010). In addition, order allocation is considered as a critical and complicated process especially within multi-product and multi-period frameworks. For that reason, there are some studies that have focused on the order allocation problem separately such as Basnet and Leung (2005) and Ruiz-Torres and Mahmoodi (2006). In addition, Xiang et al. (2014) have developed a mathematical model based on capacity and load equilibrium for multi-period and multi-suppliers that uses two order allocation strategies. Another proposed model clusters suppliers and evaluates order allocation strategies in a way that considers the market conditions and environmental criteria (Renna and Perrone, 2015). Recently, Gupta et al. (2018) have developed a multi-objective optimization model for order allocation using goal programming. The authors considered fuzzy demand and aimed to maximize the satisfaction of suppliers and customers. Zheng et al. (2021) studied the SSOA problem under stochastic demand and project life cycle using the scenario tree approach and used chaos optimization algorithm and maximum similarity method to solve the problem. Sun et al. (2022) considered a stochastic Poisson demand in a multi-echelon order-splitting optimization model for the SSOA problem.

However, given the dynamic nature of the market and the capacity limitations of the suppliers, it is very common to decide on a tactical level about the selection of the suppliers and the allocation of the orders in a SSOA context. Most of the studies on the SSOA problem use combined supplier evaluation approaches along with multiple objectives. In addition, with the recent development of green SCM, researchers have started to consider the green criteria in supplier evaluation as mentioned earlier, which led to some works focusing on green SSOA. For example, capacity limitations of suppliers have been considered by Kannan et al. (2014b) in a model that is based on fuzzy TOPSIS and fuzzy multi-objective optimization. Mafakheri et al. (2011) have introduced a SSOA model considering green criteria and using fuzzy AHP (FAHP) and bi-objective integer LP model. Hamdan and Jarndal (2017) have proposed a two-stage SSOA using GA. Sadeghi (2018) has introduced a multi-objective model using FAHP and fuzzy TOPSIS while considering green criteria instead of traditional criteria to address

SSOA. Aiming to generalize the SSOA problem, Mirzaee et al. (2018) have proposed a multi-objective model for multiple periods, multiple products, and multiple suppliers using fuzzy goal programming. Additionally, Lo et al. (2018) have developed a multi-objective LP model that integrates BWM, and modified fuzzy TOPSIS, to address SSOA with green criteria.

Recently, Torğul and Paksoy (2019) have introduced a multi-objective LP model integrating lean and green paradigms for SSOA using fuzzy TOPSIS. Moreover, Kilic and Yalcin (2020) and many other studies have tried to overcome the weaknesses of previous models by developing two-phase approaches using fuzzy goal programming with intuitionistic fuzzy TOPSIS to address multi-period, multi-supplier, and multi-product SSOA. In addition, by combining AHP, non-linear programming, and GA approaches, Hashemzahi et al. (2020) have developed a green SSOA model with multiple suppliers. Ali and Zhang (2023) introduced a holistic model for global green SSOA, which combines the international transportation risk criteria with economic and environmental aspects. They used fuzzy TOPSIS and multi-objective linear programming to solve and validate the problem through a real case study. Table 1 summarizes the SSOA-related studies and shows the used criteria and approaches of each study. In the topic of SSOA, several authors have written literature review papers, and Naqvi and Amin (2021) wrote the most recent one.

2.4. SSOA with QDs

Based on a win-win relationship that can provide benefits to suppliers and customers, the QD offered by suppliers to customers plays a determining role in product pricing and the size of orders placed by customers. Many researchers have considered different QD policies (linear, total business, all-unit, and incremental). Burke et al. (2008) studied three supplier pricing schemes (linear, all-unit, and incremental) while considering the supplier's capacities using three different models for one period. Ebrahim et al. (2009) developed an optimization model for SSOA considering three QD policies. Razmi and Maghool (2010) proposed a bi-objective multi-product multi-period fuzzy optimization model considering all-unit, total business, and incremental QD. The literature review revealed that total or all-unit QD stands out as the most popular form among other recently used policies. Some works, such as that by Kamali et al. (2011), have considered only one type of QD policies. Kamali et al. (2011) addressed the multi-objective SSOA problem using a MILP model considering all-unit QD. In addition, AHP and fuzzy compromise programming have been used to formulate a mathematical model considering all-unit QD (Wang and Yang, 2009). Ayhan and Kilic (2015) developed an integrated approach of fuzzy TOPSIS, AHP, and a multi-objective MILP model in a single period framework with one QD policy. Mirzaee et al. (2018) developed an MILP model using fuzzy goal programming considering incremental discount. Hammami et al. (2014) developed a stochastic model that considers all-unit QD and exchange rate uncertainties. Cheraghalipour and Farsad (2018) utilized the best worst method and revised multi-choice goal programming to solve the SSOA with QD. Hamdan and Cheaitou (2017b) also considered all-unit QD and varying suppliers in the green SSOA problem. Hamdan and Cheaitou (2017c) modified the model presented in Hamdan and Cheaitou (2017b) to consider incremental QD. Stadtler (2007) proposed a single-objective general QD model for the SSOA problem. The author used CPLEX with a time limit to obtain near-optimal solutions. On the other hand, total QD is another scheme similar to all-unit QD. In total QD, a discount is provided on all purchased quantities. Goossens et al. (2007) studied the total QD and demonstrated its NP-hardness. Goossens et al. (2007) presented a branch-and-bound approach based on a reformulation of the min-cost flow to solve the problem. Manerba and Mansini (2012) used a heuristic enhancement from LP, and Manerba and Mansini (2014) used an integer linear programming (ILP) refinement approach to solve the capacitated total QD problem. In Manerba et al. (2018), the authors extended the problem by utilizing a two-stage stochastic programming formulation with recourse, which helps in adaptation actions when product prices or product demand are stochastic. They considered uncertainty conditions and activation costs. Later, by using several scenarios with large numbers of up to 20 suppliers and 30 products, Manerba and Perboli (2019) successfully solved the same problem using Stochastic Programming with multiple versions of a Progressive Hedging-based heuristic technique, as well as the Benders algorithm, in the testing process. On the other hand, the all-unit QD policy can also be found in several routing or purchasing problems for inbound and outbound logistics that are not covered in the existing literature. Lee et al. (2013) and other scholars considered all-unit or incremental QD using MILP models with GA algorithms for multiple suppliers and in multiple-period environments. Pereira and Costa (2015), who covered the most relevant literature from 1995 to 2013, was one of the few articles that provided a literature review on models developed for the economic order quantity and the applicable QD policies. Readers can refer to Munson and Jackson (2014) for a literature review on QD policies, with an emphasis on the differences between theoretical concepts and actual applications and considering all QD scenarios.

2.5. Datasets for the SSOA problem

In order to verify and validate the developed model, we have thoroughly investigated real-world datasets or benchmark instances utilized in SSOA problems in the literature review. The available datasets are categorized into two categories: random designed data and real data. For instance, Goossens et al. (2007) provided some randomly generated benchmark instances for the non-capacitated total QD problem. Manerba et al. (2018) described how structured instances can be randomly generated for the SSOA problem with total QD. Other scholars used simple numerical examples to test their models, such as Abrishami et al. (2020), Baek and Kim (2020), Beauchamp et al. (2015), and Hamdan and Cheaitou (2017a). On the other hand, many researchers used real data to test their models, such as data from the plastic industry (Cheraghalipour and Farsad, 2018), electronic medical device industry (Ghadimi et al., 2018), packaging industry (Nourmohamadi Shalke et al., 2018), auto parts (Amin et al., 2011), and metal industry (Mohammed et al., 2019). Table 1 classifies articles based on data source and availability. Note that not all datasets can be used for testing, as either the models' structures and assumptions are incompatible (Mohammed et al., 2019; Torres-Ruiz and Ravindran, 2019; Hashemzahi et al., 2020), or the datasets are not completely available in the articles, requiring some assumptions to be useful in the testing process, such as Li et al. (2021).

2.6. Findings and research gap

Based on the literature review, Table 2 shows a comparison between the current study and the studies related to the SSOA problem ranked based on the year of publication for the last two decades. This comparison presents the research gap especially when our work is compared to the study (Kilic and Yalcin, 2020) which has introduced a multi-supplier, multi-period, and multi-item model but without considering any QD policy. Indeed, the contribution of this paper fills the gap illustrated in Table 1 by proposing a multi-objective MILP model with multiple periods and multiple suppliers that considers green criteria to address the SSOA problem with three QD policies, namely all-unit, incremental, and both (comprehensive or combined). It extends the works of the literature on green SSOA (Hamdan and Cheaitou, 2015, 2017b,d) by considering the QD policies and solving the resulting model using a GA based approach. In addition, Table 2 demonstrates that most works considered all-unit QD scheme in SSOA models, while fewer considered incremental QD. To summarize, our contribution is twofold. First, conceptual, since we model and solve a variant of SSOA problem in which a comprehensive QD policy is considered. Second, practical, with the easy-to-use software that allows managers to use the proposed approach.

Table 1
Datasets for SSOA models.

Authors	Data availability in the article	Data source
Stadtler (2007)	✓	Randomly designed datasets
Goossens et al. (2007)	✓	Randomly designed datasets
Demirtas and Üstün (2008)	✓	Real data from four different plastic molding firms working with a refrigerator plant are evaluated according to 14 criteria
Amin et al. (2011)	✓	Real data from company of auto parts (S.G. Company) in Iran
Shaw et al. (2012)	✓	Indian based garment manufacturing company
Kannan et al. (2013)	✓	Iranian automobile manufacturing company
Choudhary and Shankar (2014)	✓	Illustrative case
Beauchamp et al. (2015)	✓	Randomly designed datasets
Torabi et al. (2015)		Randomly designed datasets
Hamdan and Cheaitou (2017a)	✓	Randomly designed datasets
Manerba et al. (2018), Manerba and Mansini (2014)		Benchmark instances with a generation algorithm
Sabouhi et al. (2018)		Real data from pharmaceutical company (APC) in Iran
Vahidi et al. (2018)	✓	Randomly designed datasets
Lo et al. (2018)	✓	Actual data provided by an electronics company in Taiwan
Nourmohamadi Shalke et al. (2018)	✓	Real data from the protein materials packaging industry in Iran
Cheraghalipour and Farsad (2018)	✓	Real data from plastic industry in Iran
Mirzaee et al. (2018)	✓	Data from literature
Ghadimi et al. (2018)	✓	Real data from an industrial case study operating in the electronics sector in medical device industry in Ireland
Lamba and Singh (2019)	✓	Randomly generated datasets
Mohammed et al. (2019)		Real data from raw materials for a metal factory in Saudi Arabia
Torres-Ruiz and Ravindran (2019)	✓	Data obtained from an international auto parts manufacturer in Mexico
Abrishami et al. (2020)	✓	A designed numerical example based on manufacturer data
Baek and Kim (2020)	✓	Randomly designed datasets
Hashemzahi et al. (2020)	✓	Real data from steel baskets manufacturer in Malaysia
Suprasongsin et al. (2020)	✓	Randomly designed experiments
Rezaei et al. (2020)		Real data from car manufacturing case study in Iran
Jia et al. (2020)	✓	Real data from steel company in China
Feng and Gong (2020)	✓	Real data from automotive manufacturing enterprise in China
Sahebjamnia (2020)	✓	Real data from furniture company in Iran
Li et al. (2021)	✓	Real data from new energy vehicles industry
Beiki et al. (2021)	✓	Real data from automotive manufacturing company
Kaur and Singh (2021)	✓	Real data from automobile company in India
Khalili Nasr et al. (2021)	✓	Real data from suit production and distribution chain
Sun et al. (2022)	✓	Randomly designed experiment
Ahmad et al. (2022)	✓	Real data from major belt conveyor company in India

3. Model

The studied problem consists in selecting the best suppliers and determining the quantities to buy from them in order to satisfy the deterministic demand of a single product in every period of a fixed planning horizon. If the demand in a given period exceeds the available amount of items, then a shortage happens and a corresponding penalty shortage cost is incurred. On the other hand, if the available amount at the end of a period is positive, then it is carried out to the next period and an inventory holding cost is incurred. The selection of the suppliers is based on maximizing the total green value of the purchased products and at the same time minimizing the total cost. The green value of the products is based on an assessment of the suppliers green performance using fuzzy TOPSIS while the total cost includes the fixed and variable purchasing costs, the inventory holding cost and the shortage cost. The supplier's availability changes from period to period as well as the corresponding supply capacities, their fixed and variable costs, and their green performance. In addition, each supplier proposes a

Table 2
SSOA studies comparison and the research gap.

Authors	Criteria		Multiple		QD policy			Models and approaches
	Economic	Environmental	Periods	Suppliers	All unit	Incremental	Combined	
Stadtler (2007)	✓		✓	✓	✓	✓		MIP
Wang et al. (2008)	✓			✓				ILP
Demirtas and Üstün (2008)	✓			✓				ANP and MILP
Lee and Ou-Yang (2009)	✓	✓		✓				Neural networks
Ebrahim et al. (2009)	✓			✓	✓	✓		mathematical model
Wang and Yang (2009)	✓			✓	✓			AHP and MILP
Lin (2009)	✓			✓				Fuzzy ANP and LP
Razmi and Maghool (2010)	✓		✓	✓	✓	✓		meta-heuristic model
Fazlollahtabar et al. (2011)	✓		✓	✓				AHP and TOPSIS
Kamali et al. (2011)	✓			✓	✓			mixed-integer non-linear programming model
Mafakheri et al. (2011)	✓			✓				AHP and multiple criteria dynamic programming
Manerba and Mansini (2012)	✓			✓	✓[a]			Heuristic enhancement from LP
Büyüközkan and Çifçi (2012)	✓	✓		✓				ANP, TOPSIS and DEMATEL
Lee et al. (2013)	✓		✓	✓	✓	✓		MIP and GA
Kannan et al. (2014a)	✓	✓		✓				fuzzy axiomatic design
Manerba and Mansini (2014)	✓			✓	✓[a]			ILP refinement approach
Hammami et al. (2014)	✓			✓		✓		mixed integer scenario-based stochastic programming
Dobos and Vörösmarty (2014)	✓	✓		✓				composite indicators, data envelopment analysis and common weights analysis
Kazemi et al. (2014)	✓			✓	✓			fuzzy preference programming, interval based TOPSIS and LP
Singh (2014)	✓			✓				MILP and TOPSIS
Galankashi et al. (2015)	✓	✓		✓				nominal group technique and fuzzy ANP
Torabi et al. (2015)	✓			✓				stochastic programming
Hashemi et al. (2015)	✓	✓		✓				ANP and traditional GRA
Ayhan and Kilic (2015)	✓			✓	✓			FAHP and MILP
Tsai (2015)	✓			✓				mixed-integer non-linear programming
Moghaddam (2015)	✓			✓				Monte Carlo simulation integrated with fuzzy goal programming
Scott et al. (2015)	✓			✓				AHP and quality function deployment
Hamdan and Cheaitou (2015)	✓	✓	✓					Fuzzy TOPSIS, AHP and integer programming
Ghorabaee et al. (2016)		✓		✓				Type-2 fuzzy sets and weighted aggregated sum product assessment
Darabi and Heydari (2016)		✓		✓				interval-valued hesitant fuzzy ranking
Liao et al. (2016)	✓	✓		✓				FAHP, fuzzy additive ratio assessment and multi-segment goal programming
Meena and Sarmah (2016)	✓			✓	✓			Analytical model and solution procedure
Hamdan and Cheaitou (2017d)	✓	✓	✓	✓				fuzzy TOPSIS, AHP and integer programming
Hamdan and Cheaitou (2017b)	✓	✓	✓	✓	✓			fuzzy TOPSIS, and integer programming
Banaeian et al. (2018)		✓		✓				Fuzzy TOPSIS, VIKOR and GRA
Manerba et al. (2018)	✓			✓	✓[a]			two-stage stochastic programming formulation with recourse

(continued on next page)

Table 2 (*continued*).

Authors	Criteria		Multiple		QD policy			Models and approaches
	Economic	Environmental	Periods	Suppliers	All unit	Incremental	Combined	
Sadeghi (2018)	✓	✓		✓				FAHP and mathematical programming
Mirzaee et al. (2018)	✓		✓	✓		✓		MILP and fuzzy goal programming
Lo et al. (2018)	✓	✓		✓				BWM, fuzzy TOPSIS and LP
Nasiri et al. (2018)	✓	✓		✓				MILP
Torğul and Paksoy (2019)	✓	✓		✓				fuzzy TOPSIS
Alegoz and Yapicioglu (2019)	✓			✓		✓		fuzzy TOPSIS, trapezoidal type-2 FAHP and goal programming
Manerba and Perboli (2019)	✓			✓	✓[a]			Stochastic mathematical model using Progressive Hedging based heuristic and a Benders algorithm
Govindan et al. (2020)	✓	✓		✓				fuzzy ANP, fuzzy DEMATEL and MILP
Basa et al. (2020)	✓			✓	✓			mixed-integer non-linear program and GA
Hashemzahi et al. (2020)	✓	✓		✓				FAHP, non-linear LP and GA
Kaviani et al. (2020)	✓			✓				intuitionistic FAHP and fuzzy multi objective optimization
Wang et al. (2020)	✓	✓		✓				ANP and integer programming
Kilic and Yalcin (2020)	✓	✓	✓	✓				intuitionistic fuzzy TOPSIS and fuzzy goal programming
Qazvini et al. (2021)	✓	✓	✓	✓				FAHP and MILP
Rezaei et al. (2021)	✓	✓		✓				mixed-integer non-linear programming models, risk reduction strategies and grasshopper optimization algorithm
Esmaeili-Najafabadi et al. (2021)	✓			✓				mixed-integer non-linear programming and particle swarm optimization
Firouzi and Jadidi (2021)	✓			✓				fuzzy multi-objective model
Alejo-Reyes et al. (2021)	✓		✓	✓				particle swarm optimization and differential evolution
Kaur and Singh (2021)	✓		✓	✓				data envelopment analysis, FAHP-TOPSIS and MIP
Ecer (2022)	✓	✓		✓				Type 2 FAHP
Lakshmanpriya et al. (2022)	✓	✓	✓	✓				grey theory and updated MCDM with multi-objective mixed-integer non-linear program
Amin-Tahmasbi et al. (2023)	✓		✓	✓				multi-objective particle swarm optimization and multi-objective vibration damping optimization
Jadidi et al. (2022)	✓			✓				TOPSIS and optimization algorithm
This work	✓	✓	✓	✓	✓	✓	✓	Fuzzy TOPSIS and ILP, branch-and-cut algorithm and population-based heuristic

[a]Known as total QD since the policy considers the discount on the total purchased quantity of different products.

QD scheme that can be either of the type “all-unit” or “incremental”. A supplier offering “all-unit” QDs in one period cannot change to “incremental” QDs in the other periods and vice-versa. Thus, the QD scheme is used as an input to the mathematical model. A generalization of this model that optimizes the QD scheme selection is provided in the Appendix for interested readers. We model this problem using a bi-objective integer LP approach in which the total green value of the purchased items (TGVP) from all selected suppliers in all the periods is maximized while the total cost of purchasing (TCP) is minimized. The model considers the constraints of availability and capacity of the suppliers as well as the dynamic behavior of the system.

3.1. Model notations

3.1.1. Model parameters

- T: Number of discrete periods of same duration in the planning horizon.
- a_t and b_t : Set of suppliers offering all-unit QD in period t and increment QD in period t, respectively.
- n_t: Total number of available suppliers in period t. $n_t = |a_t| + |b_t|$; $t = 1, \dots, T$. Note that the elements in a_t and b_t are non-repeated integers from 1 to n_t representing the available suppliers who can either be in a_t or b_t.
- R_i: Number of QD interval ranges (all-unit or incremental) for supplier $i; i = 1, \dots, n_t$.
- GW_{it}: Green performance of supplier i in period t obtained using fuzzy TOPSIS with $i = 1, \dots, n_t$ and $t = 1, \dots, T$.
- vc_{itr}: Unit variable cost of supplier i, $i = 1, \dots, n_t$ in period t corresponding to the QD interval r, $r = 1, \dots, R_i$.
- FC_{it}: Fixed ordering cost per period incurred if a positive quantity is ordered from supplier i, $i = 1, \dots, n_t$ in period t; $t = 1, \dots, T$.
- H_t: Unit inventory storage cost in period t ; $t = 1, \dots, T$.
- S_t: Unit penalty shortage cost in period t; $t = 1, \dots, T$.
- l_{itr}, u_{itr}: Lower and upper limits of the QD interval (“all-unit” or “incremental”) r, $r = 1, \dots, R_i$ of supplier i, $i = 1, \dots, n_t$ in period t ; $t = 1, \dots, T$. Note that we define $u_{it0} = 0$ for modeling purposes.

Table 3
Criterion rating scale.

Linguistic variable	TFN
Little importance (LI)	(0.00, 0.00, 0.25)
Moderately important (MI)	(0.00, 0.25, 0.50)
Important (I)	(0.25, 0.50, 0.75)
Very important (VI)	(0.50, 0.75, 1.00)
Absolutely important (AI)	(0.75, 1.00, 1.00)

Table 4
Alternative rating scale.

Linguistic variable	TFN
Very low (VL)	(0.00, 0.00, 0.25)
Low (L)	(0.00, 0.25, 0.50)
Good (G)	(0.25, 0.50, 0.75)
High (H)	(0.50, 0.75, 1.00)
Very high (VH)	(0.75, 1.00, 1.00)

- D_t: Deterministic demand of the product to be fulfilled in period $t, t = 1, \dots, T$.
- M: A big positive number; it can be equal to a factor (larger than or equal to one) multiplied by the total demand.
- ϵ: A positive number less than one. We assume it equal to 0.5.

3.1.2. Decision variables

- Q_{itr}: Amount purchased from supplier i, $i = 1, \dots, n_t$ in period t, $t = 1, \dots, T$ within the QD interval range r, $r = 1, \dots, R_i$.
- Y_{itr}: A binary decision variables equals to 1 if a non-zero amount is purchased from supplier i, $i = 1, \dots, n_t$ in period $t, t = 1, \dots, T$ within the QD range r, $r = 1, \dots, R_i$ ($Y_{itr} = 1$) or not ($Y_{itr} = 0$).

3.1.3. State variables

- I_t^H : Inventory level available at the end of period t, $t = 1, \dots, T$. I_0 is the initial inventory level that is available at the beginning of the first period.
- I_t^S : Unsatisfied demand units (shortage) at the end of period t, $t = 1, \dots, T$.
- Y_t^H: A binary variable that is equal to one ($Y_t^H = 1$) if the inventory at the end of period t, $t = 1, \dots, T$ is positive and zero otherwise ($Y_t^H = 0$).
- Y_t^S: A binary variable that is equal to one ($Y_t^S = 1$) if the inventory at the end of period $t, t = 1, \dots, T$ is negative and zero otherwise ($Y_t^S = 0$).

3.2. Fuzzy TOPSIS

We use fuzzy TOPSIS in a way similar to the way that it was used by Hamdan and Cheaitou (2017d) in order to estimate the green performance of supplier i in period t, i.e. GW_{it}. In order to do so, we express the fuzziness in the decision-makers' assessment of the environmental performance of suppliers using the most widely used format of fuzzy numbers, i.e. triangular fuzzy numbers (TFNs). A TFN can be defined as a triplet ($\mathscr{L}$, $\mathscr{M}$, $\mathscr{U}$), with a membership function as defined in Hamdan and Cheaitou (2017d) where $\mathscr{L}$ is the minimum possible value, $\mathscr{M}$ is the most possible value, and $\mathscr{U}$ is the maximum possible value. Moreover, linguistic variables are used to account for the uncertainty in the decision-makers judgment since they are simple enough to be represented as fuzzy numbers. In this work, we use the five-point linguistic scale proposed by Lau et al. (2003) as shown in Tables 3 and 4. The decision makers assign a weight to every green criterion considered in the assessment of the green performance of the suppliers such as having an environmental management system, using recycled materials, using renewable energy, etc. Moreover, the decision makers also assign a weight to every supplier with respect to each criterion. The assignment of the weights to the criteria is based on the available knowledge and expertise of the decision makers as well as the relative importance of each criterion to the company. The assignment of weights to the suppliers with respect to the criteria can be done using available historical data, the capability studies on the suppliers, and the laboratory testing and analysis of the product to be purchased.

Fuzzy TOPSIS calculations are then done in five steps.

Step 1: In every period $t, t = 1, \dots, T$ of the planning horizon, each decision maker $\mathrm{DM}_k, k = 1, \dots, K$, uses the linguistic variables defined in Table 3 to assign a weight transformed into TFN, w_c^k, to each criterion $c, c = 1, \dots, C$. The decision makers use also the linguistic variables defined in Table 4 to assign a linguistic weight transformed into TFN, x_{cit}^k, to each supplier $i = 1, \dots, n_t$ available in period t with respect to each criterion c. The weights are then aggregated according to the following equations:

$$\overline{w}_c = \left(\overline{\mathscr{L}}_c, \overline{\mathscr{M}}_c, \overline{\mathscr{U}}_c\right) = \frac{1}{K}\left(w_c^1 + w_c^2 + \cdots + w_c^K\right), \tag{1}$$

$$\overline{x}_{cit} = \left(\overline{\mathscr{L}}_{cit}, \overline{\mathscr{M}}_{cit}, \overline{\mathscr{U}}_{cit}\right) = \frac{1}{K}\left(x_{cit}^1 + x_{cit}^2 + \cdots + x_{cit}^K\right), \tag{2}$$

where $w_c^k = (\mathscr{L}_i^k, \mathscr{M}_i^k, \mathscr{U}_i^k)$, a fuzzy number, is the weight of criterion c given by decision maker DM_k, and $x_{cit}^k = (\mathscr{L}_{cit}^k, \mathscr{M}_{cit}^k, \mathscr{U}_{cit}^k)$, a fuzzy number, is the weight of supplier i available in period t with respect to criterion c given by decision maker DM_k.

Step 2: A normalization approach is then used to eliminate the different units of measurement of the weights $\overline{x}_{cit}$ as follows:

$$\mathscr{R}_{cit} = \left(\frac{\overline{\mathscr{L}}_{cit}}{\mathscr{U}_{it}}, \frac{\overline{\mathscr{M}}_{cit}}{\mathscr{U}_{it}}, \frac{\overline{\mathscr{U}}_{cit}}{\mathscr{U}_{it}}\right), \tag{3}$$

for every benefit criterion c, and

$$\mathscr{R}_{cit} = \left(\frac{\mathscr{L}_{it}}{\overline{\mathscr{U}}_{cit}}, \frac{\mathscr{L}_{it}}{\overline{\mathscr{M}}_{cit}}, \frac{\mathscr{L}_{it}}{\overline{\mathscr{L}}_{cit}}\right), \tag{4}$$

for every cost criterion, c, where $\mathscr{R}_{cit}$ is the normalized value of $\overline{x}_{cit}$ and $\mathscr{U}_{it} = max_c \mathscr{U}_{cit}$ and $\mathscr{L}_{it} = min_c \mathscr{L}_{cit}$. We then combine the matrix $[\mathscr{R}_{cit}]_{(C\times n_t)}$ with the vector $[\overline{w}_c]_{(1\times C)}$ to form the decision matrix.

Step 3: In this step, the weight of each supplier in each period is multiplied by the weight of each criterion to obtain the weighted normalized fuzzy decision matrix as in the following equation:

$$V = [v_{cit}]_{(C\times n_t)}, \text{ where } v_{cit} = \mathscr{R}_{cit} \otimes w_c. \tag{5}$$

Indeed, V is the result of the multiplication of the last row in the decision matrix obtained in Step 2, $\overline{w}_c$, by each row of that matrix.

Step 4: The fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS) are then identified. Given that normalized values of v_{cit} are from 0 to 1, the FPIS is defined as (1,1,1), while the FNIS is defined as (0,0,0). These values are then used to determine the distance from the positive ideal (dist_{it}^+) and the negative ideal (dist_{it}^-) solutions for each supplier i in each period t as follows:

$$\mathrm{dist}_{it}^+ = \sum_c \mathrm{dist}(v_{cit}, \mathrm{FPIS}), \tag{6}$$

$$\mathrm{dist}_{it}^- = \sum_c \mathrm{dist}(v_{cit}, \mathrm{FNIS}). \tag{7}$$

The distances dist_{it}^+ and dist_{it}^- are estimated using following the equation that calculates the distance between the two fuzzy numbers $A = (\mathscr{L}_A, \mathscr{M}_A, \mathscr{U}_A)$ and $B = (\mathscr{L}_B, \mathscr{M}_B, \mathscr{U}_B)$:

$$\mathrm{dist}(A, B) = \sqrt{\frac{1}{3}\left[(\mathscr{L}_A - \mathscr{L}_B)^2 + (\mathscr{M}_A - \mathscr{M}_B)^2 + (\mathscr{U}_A - \mathscr{U}_B)^2\right]}. \tag{8}$$

Step 5: Finally, the closeness coefficient, i.e. the green weight of each supplier i available in each period t, GW_{it}, is calculated as follows:

$$GW_{it} = \frac{\mathrm{dist}_{it}^-}{\mathrm{dist}_{it}^- + \mathrm{dist}_{it}^+}. \tag{9}$$

3.3. Mathematical model

The bi-objective integer LP model is defined as follows:

$$\max \mathrm{TGVP} = \sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{r=1}^{R_i} GW_{it} \times Q_{itr}, \tag{10}$$

$$\min \mathrm{TCP} = \sum_{t=1}^{T}\sum_{i=1}^{n_t}\left(V\left(Q_{it}\right) + \sum_{r=1}^{R_i} Y_{itr} \times FC_{it}\right) + \sum_{t=1}^{T}\left(H_t \times I_t^H + S_t \times I_t^S\right), \tag{11}$$

where

$$V\left(Q_{it}\right) = \begin{cases} \sum_{r=1}^{R_i} vc_{itr} Q_{itr}, & \text{for } i \in a_t \\ \sum_{r=1}^{R_i}\left(vc_{itr}\left(Q_{itr} - u_{it(r-1)}Y_{itr}\right) + \left(Y_{itr}\sum_{k=1}^{r-1} vc_{itk}\left(u_{itk} - u_{it(k-1)}\right)\right)\right), & \text{for } i \in b_t \end{cases} \tag{12}$$

Subject to

$$\sum_{r=1}^{R_i} Y_{itr} \le 1, \qquad \forall i = 1,\dots,n_t,\ t = 1,\dots,T, \tag{13}$$

$$Y_{itr} l_{itr} \le Q_{itr} \le Y_{itr} u_{itr} \qquad \forall i = 1,\dots,n_t,\ t = 1,\dots,T,\ r = 1,\dots,R_i, \tag{14}$$

$$I_{t-1}^H - I_{t-1}^S + \sum_{i=1}^{n_t}\sum_{r=1}^{R_i} Q_{itr} - I_t^H + I_t^S = D_t, \tag{15}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{r=1}^{R_i} Q_{itr} + I_0 = \sum_{t=1}^{T} D_t, \tag{16}$$

$$\epsilon Y_t^S \le I_t^S \le MY_t^S, \qquad \forall t = 1,\dots,T, \tag{17}$$

$$\epsilon Y_t^H \le I_t^H \le MY_t^H, \qquad \forall t = 1,\dots,T, \tag{18}$$

$$Y_t^H + Y_t^S \le 1, \qquad \forall t = 1,\dots,T, \tag{19}$$

$$Q_{itr} \in \mathbb{N},\ Y_{itr} \in \{0,1\}, \qquad \forall i = 1,\dots,n_t,\ t = 1,\dots,T,\ r = 1,\dots,R_i, \tag{20}$$

$$I_t^H \in \mathbb{N},\ I_t^S \in \mathbb{N},\ Y_t^H \in \{0,1\},\ Y_t^S \in \{0,1\}, \qquad \forall t = 1,\dots,T. \tag{21}$$

Although the model proposed in this paper considers two QD policies allowing some suppliers to provide the “all-unit” policy and some others to provide the “incremental” policy, it can also be used as a pure “all-unit” or pure “incremental” QD model. The choice implementation of one of the three possible configurations of the model can simply be achieved by changing the set of suppliers offering the two types of discounts and the number of suppliers in these sets, i.e. a_t and b_t.

The model maximizes the TGVP (Eq. (10)) and minimizes the TCP (Eq. (11)) of the products purchased from all suppliers in all periods. Eq. (10) is a weighted sum of the purchased amounts in which the quantities are multiplied by the green performance levels of the corresponding suppliers. The first part of Eq. (11) represents the total variable and fixed costs of the purchased items, while the second part represents the inventory holding and shortage costs. Moreover, Eq. (12) represents the total variable cost as function of the QD policy. The first part of Eq. (12) represents the variable cost for the planning horizon and all suppliers offering an “all-unit” QD scheme while the second part applies on suppliers offering “incremental” QDs.

Constraint (13) ensures that only one QD interval range, at most, is chosen for every supplier in each period. In addition, constraint (14) ensures that the quantity from every selected supplier lies within the corresponding chosen QD interval range. Constraint (15) controls the dynamic behavior of the inventory levels in the periods of the planning horizon, while constraint (16) guarantees that, at the end of the planning horizon, all the deterministic demand is fulfilled either using the initial inventory or the ordered quantities from the suppliers during the planning horizon periods.

Constraints (17) and (18) ensure respectively that Y_t^S and Y_t^H are equal to one if I_t^S and I_t^H are positive. Constraint (19) ensures that at most one of the two binary variables representing the status of the inventory at the end of each period (positive inventory or shortage) may equal to one. Finally, Constraints (20) and (21) ensure that the decision variables Q_{itr}, I_t^H and I_t^S are non-negative integers, and Y_{itr}, Y_t^H and Y_t^S are binary.

Moreover, although the proposed model considers the backlog case, the lost sales case can be also considered by incorporating few changes into the model. Indeed, removing I_{t-1}^S from the left-hand side of constraint (15) and ignoring constraint (16) will result in a lost sales model.

Remark 1. The model presented in this section can be extended to optimize the QD scheme (as shown in Appendix). This extension is achieved by introducing another index j to the decision variables Q_{itr} and Y_{itr}. This index accounts for the different QD schemes. For instance, $j = 1$ represents an all-unit QD scheme, and $j = 2$ represents an incremental QD scheme. Then, Constraint (13) in Appendix can be modified to ensure that at most one range and one scheme is chosen. To obtain meaningful results, the buyer-oriented objective function must be replaced to consider both the buyer’s and the suppliers’ interests. This aspect is beyond the scope of this paper.

3.4. Bi-objective solution

In order to determine the Pareto front and the corresponding Pareto solutions of the model defined in Eqs. (10)–(21), we use a scalarization technique called the weighted comprehensive criterion method (WCCM) (Kamali et al., 2011; Hamdan and Cheaitou, 2017b; Abdallah et al., 2021; Alsyouf et al., 2021). This method requires solving the model in three steps.

Step 1:
The model that maximizes the TGVP only is solved, i.e. Eq. (10), subject to constraints (13)–(21). This step gives the optimal value $\mathrm{TGVP}_{\max}$.

Step 2:
The model that minimizes the TCP only is solved, i.e. Eqs. (11) and (12), subject to constraints (13)–(21). This step results in the optimal value $\mathrm{TCP}_{\min}$.

Step 3:
Steps 1 and 2 focus on single objective formulation to obtain the two ideal values $\mathrm{TGVP}_{\max}$ and $\mathrm{TCP}_{\min}$. These two values will be used in defining a new objective function that solves the cost and the value simultaneously by combining them. Since the two objective functions have different order of magnitudes and units, their optimal values ($\mathrm{TGVP}_{\max}$ and $\mathrm{TCP}_{\min}$) are used to normalize the objective functions. These normalize functions are:

$$f_{\mathrm{TGVP}} = \frac{\mathrm{TGVP}_{\max} - \mathrm{TGVP}}{\mathrm{TGVP}_{\max}}, \tag{22}$$

$$f_{\mathrm{TCP}} = \frac{\mathrm{TCP} - \mathrm{TCP}_{\min}}{\mathrm{TCP}_{\min}}, \tag{23}$$

Eq. (22) calculates the relative difference between the ideal green value ($\mathrm{TGVP}_{\max}$) obtained from Step 1 and the TGVP calculated using Eq. (10). Similarly, Eq. (23) calculates the relative difference between the TCP calculated using Eq. (11) and ideal cost ($\mathrm{TCP}_{\min}$) obtained from Step 2. Eqs. (22) and (23) target to bring objective functions (10) and (11) when combined together close to their optimal values after eliminating the effect of the units. Thus, a model consisting of a weighted combination of Eqs. (22) and (23), as given in Eq. (24) and

	Period 1				Period T			
	Supplier 1	Supplier 2	...	Supplier n_1	Supplier 1	Supplier 2	...	Supplier n_T
Individual 1	50	100	...	320	124	123	...	0
Individual 2	214	245	...	59	74	0	...	0
Individual 3	145	312	...	54	41	21	...	35
⋮	⋮	⋮	⋱	⋮	⋮	⋮	⋱	⋮
Individual N	41	210	...	21	78	78	...	78

Fig. 1. The quantity chromosome with the rows for the individuals and columns for the suppliers and periods. The cells contain the quantity value Q_{itr}.

	Period 1	Period 2	...	Period T
Inventory (I_t^H)				
Individual 1	12	0	...	32
Individual 2	0	45	...	5
Individual 3	15	32	...	4
⋮	⋮	⋮	⋱	⋮
Individual N	1	0	...	0
Unsatisfied demand (I_t^S)				
Individual 1	0	10	...	0
Individual 2	14	0	...	0
Individual 3	0	0	...	0
⋮	⋮	⋮	⋱	⋮
Individual N	0	21	...	0

Fig. 2. The inventory chromosome with the rows for the individuals and columns for the periods. The cells contain the inventory levels (positive inventory, I_t^H, and unsatisfied demand, I_t^S).

the same constraints defined in Eqs. (13)–(21) is solved. The solution of this model gives the bi-objective optimal solution.

$$\min f = \alpha_1 f_{\mathrm{TGVP}} + \alpha_2 f_{\mathrm{TCP}}. \quad (24)$$

α_1 and α_2 are two weights between 0 and 1 with $\alpha_1+\alpha_2 = 1$. Varying the values of α_1 and α_2 and solving (24) subject to (13)–(21) results in different Pareto solutions that help identify the problem Pareto front.

3.5. Solution approach

We propose a population-based heuristic to solve large-sized instances within a reasonable computation time as shown in Algorithm 1. This heuristic starts by generating Ψ individuals (Ψ is a multiple of eight), each of which ($\psi = 1,\ldots,\Psi$) consisting of a random feasible solution (i.e., selected suppliers, quantities to be ordered and inventory levels) for each period t ($t = 1,\ldots,T$). The design of the used chromosomes is given in Figs. 1 and 2. Note that the inventory chromosome is created based on the quantity chromosome for each individual. For each individual ψ, a list of suppliers and periods (ω_ψ) is randomly generated, such that the selected suppliers and periods are enough to fulfill the demand (Constraint (16)). Then, a quantity is randomly assigned for each period and supplier in the list while not exceeding the capacity of supplier i in period t (u_{itR_i}). That is, constraint (14) is respected. A feasible solution is ensured by randomly modifying the assigned quantities such that constraint (16) is satisfied. After that the inventory level chromosome in each period t is created using $\sum_{i=1}^{n_t}\sum_{r=1}^{R_i} Q_{itr} - D_t$, which results in the decision variables I_t^H and I_t^S in Constraint (15).

The algorithm then sets the ideal TGVP (TGVP$_{\max}$), the ideal TCP (TCP$_{\min}$), and the global total variation (f_G) to $-\infty$, $+\infty$ and $+\infty$, respectively. In each iteration δ, $\delta = 1,\ldots,\Delta$, the heuristic performs the following steps:

1. It computes the TGVP for each individual (TCP$_\psi$) using Eq. (10).
2. It identifies the best TGVP among the individuals in the iteration as $\max_{\psi=1,\ldots,\Psi}$ TGVP$_\psi$ and saves its value in TGVP$_B$.
3. It computes the TCP for each individual (TCP$_\psi$) using Eq. (11).
4. It identifies the best TCP among the individuals in the iteration as $\min_{\psi=1,\ldots,\Psi}$ TCP$_\psi$ and saves its value in TCP$_B$.
5. It then compares TGVP$_B$ and TCP$_B$ with the current ideal values (TGVP$_{\max}$, TCP$_{\min}$) and updates the ideal values if better values are found and recalculates $f_{\min}$.
6. Next, it computes the total variation for each individual (f_ψ) using Eq. (24).
7. Finally, it selects the best total variation (f_B) as $\min_{\psi=1,\ldots,\Psi} f_\psi$ and updates the ideal total variation $f_{\min}$.

If the best total variation f_B in any iteration is better than the global total variation $f_{\min}$, then the algorithm updates $f_{\min}$ and resets the counter τ to zero. When $f_{\min}$ is not updated, then the counter τ is increased by one. The counter τ stores the consecutive number of iterations without improvement in $f_{\min}$. This technique allows escaping local optimum solutions and enhances the solution diversity.

To explore other potential solutions, the heuristic in each iteration splits the Ψ individuals into subgroups, each of eight individuals. It then performs the following steps on each subgroup:

1. It selects the best individual based on f_ψ
2. It performs eight operations on best individual to create eight new individuals.
3. It replaces the individuals with the new ones.

The eight operations used to create new individuals are:

1. Do nothing, that is keep the best.
2. Change quantity Q_{itr} between two locations (suppliers and periods) on the quantity chromosome.
3. Change quantity Q_{itr} between two suppliers in the same period t.

4. Change quantity Q_{itr} between two periods from the same supplier i.
5. Increase the capacity utilization of supplier i.
6. Decrease the shortage in a randomly selected period.
7. Decrease the amount of inventory holding in a randomly selected period.
8. Switch the quantities for a randomly selected supplier between different periods.

If τ reaches the maximum predefined number of iterations allowed without change ($\tau_{\max}$), then all individuals are removed and new individuals are generated randomly.

Moreover, in order to guarantee a stable heuristic solution and to reduce the randomness impact when comparing it with the exact approach, the heuristic is solved a certain number of times for each instance and the average objective value of the solutions is considered and compared with the corresponding exact objective value.

4. Implementation software

In order to facilitate the implementation of the proposed mathematical model and the solution approach in practice for decision-makers and users in the industry, a MATLAB-based software has been developed. The software has a graphical user interface that was designed using the "App Designer" package available in MATLAB 2021a. Fig. 3 shows the fuzzy TOPSIS tab in the developed software. The software requires the user to input the fuzzy TOPSIS scale and the evaluations in Excel format ".xlsx". It returns the green (and non-green) weights.

Fig. 4 illustrates the optimization tab in the software. The user must upload inventory data (holding and shortage costs), demand data and suppliers' data (green weights, fixed costs, variable costs for each QD interval range, capacity details, QD type, and availability) as Excel files ".xlsx". The user also needs to specify the weight of the TCP objective function, and consequently, the importance of the TGVP objective function will be automatically calculated. The user needs to identify whether the QD scheme is uniform for all suppliers or mixed and to select the desired optimization method. The software returns the chosen supplier selection and the order allocation decisions for every period as shown in Fig. 4.

5. Numerical study

In Section 5.1, we construct an illustrative example using the case study data presented in Choudhary and Shankar (2014). We show the impact of different QD schemes on the selected suppliers, inventory levels, TCP value, and TGVP value using this illustrative example. In addition, we generate the Pareto frontier and illustrate the trade-offs between TCP and TGVP under different QD schemes. Then, in Section 5.2, we generate large-sized instances to test the developed model and the solution approaches. The instance generation technique is similar to the one discussed in Manerba et al. (2018) and adapted for our problem. Table 5 provides details on the parameter generation rules used to generate the parameter values used in this section. For each instance, three QD scenarios have been considered:

- Scenario 1: all suppliers offer "all-unit" QDs.
- Scenario 2: all the suppliers offer "incremental" QDs.
- Scenario 3: some suppliers offer "all-unit" QD while others offer "incremental" QDs.

We use the notation P$N-T-\lambda-\mathcal{S}$ to represent different instance configurations and problem sizes, where N represents the maximum number of suppliers in the instance, T is the number of periods, λ represents the level of the number of suppliers required to fulfill the demand. The values of λ are defined as follows: "L" for low, "M" for medium and "H" (see Table 5). The last letter in the notation, $\mathcal{S}$, represents the studied scenario, with "A" for Scenario 1, "I" for Scenario 2 and "C" for Scenario 3. The asterisk (*) indicates that the exact solution is not optimal as the solver reached the maximum time limit without providing the optimal solution (three hours in this work). For example,

Algorithm 1: Population-based heuristic.

input : Sets and parameters defined in the Section 3.1.1
output : Selected suppliers and corresponding orders and inventory levels

set $\text{TGVP}_{\max}=-\infty$, $\text{TCP}_{\min}=\infty$, $f_{\min}=\infty$, $\tau=0$, $\tau_{\max}=2000$ and $\Delta=200,000$;
initialize Ψ individuals;
for $\psi \leftarrow 1$ *to* Ψ **do**
  generate a random list of suppliers and periods (ω_ψ);
  assign random Q_{itr} for suppliers and periods in ω_ψ;
  calculate I_t^H and I_t^S for each $t=1,\dots,T$;
  check and fix violations in Constraints (14)–(16)
end
for $\delta \leftarrow 1$ *to* Δ **do**
  for $\psi \leftarrow 1$ *to* Ψ **do**
    calculate TGVP_ψ and TCP_ψ using Eqs. (10) and (11)–(12), respectively;
  end
  set $\text{TGVP}_B=\max_{\psi=1,\dots,\Psi}\text{TGVP}_\psi$;
  set $\text{TCP}_B=\min_{\psi=1,\dots,\Psi}\text{TCP}_\psi$;
  if $TGVP_B > TGVP_{max}$ **then**
    set $\text{TGVP}_{\max}=\text{TGVP}_B$;
    if $\delta \neq 1$ **then**
      recalculate $f_{\min}$ using the updated $\text{TGVP}_{\max}$;
    end
  end
  if $TCP_B < TCP_{min}$ **then**
    set $\text{TCP}_{\min}=\text{TCP}_B$;
    if $\delta \neq 1$ **then**
      recalculate $f_{\min}$ using the updated $\text{TCP}_{\min}$;
    end
  end
  foreach $\psi \leftarrow 1$ *to* Ψ **do**
    calculate f_ψ using Eq. (24);
  end
  set $f_B=\min_{\psi=1,\dots,\Psi} f_\psi$;
  if $f_B < f_{min}$ **then**
    set $f_{\min}=f_B$;
    store the best individual as the global best;
    set $\tau=0$
  else
    set $\tau=\tau+1$
  end
  for $k \leftarrow 1$ *to* $\Psi/8$ **do**
    select randomly eight individuals with their corresponding TCP_ψ, TGVP_ψ, and f_ψ;
    identify best individual in the subgroup based on f_ψ;
    perform the eight operations listed in Section 3.5;
    replace the individuals in the subgroup with the newly created ones;
  end
  if $\tau \geq \tau_{\max}$ **then**
    discard all individuals and create new ones;
  end
end
return the global best solution.

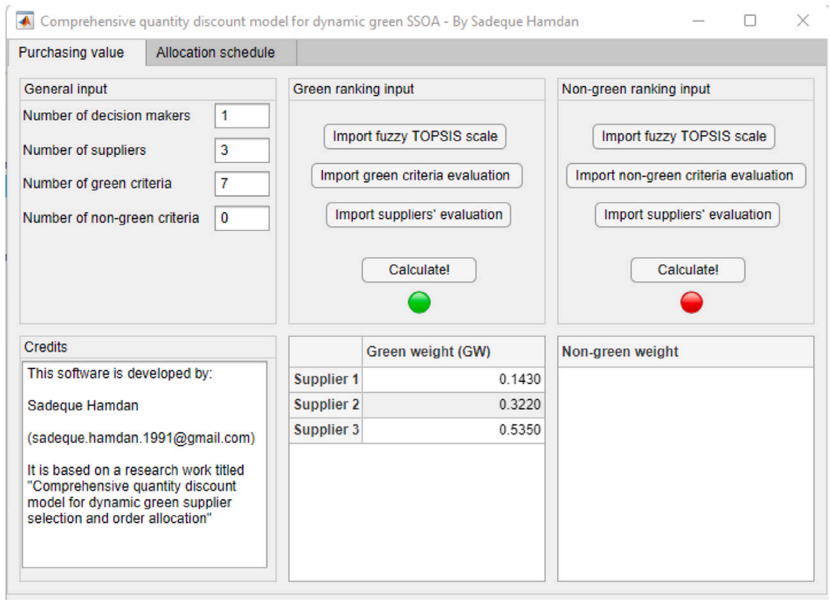

Fig. 3. Fuzzy TOPSIS tab in the developed decision-making software.

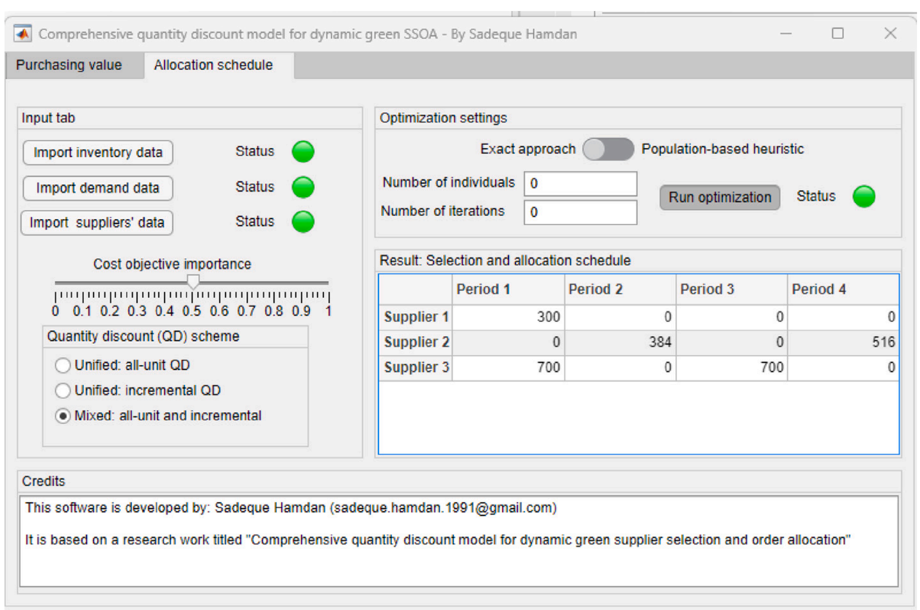

Fig. 4. Optimization tab in the developed decision-making software.

P10-40-L-I* is an instance with ten suppliers using only incremental QDs (Scenario 2), forty periods and low number of suppliers required to fulfill the demand. The solver did not reach the optimal solution for this instance due to the time limit. All instances have been solved using the exact approach and the proposed population-based heuristic. In the heuristic approach, the maximum number of iterations (Δ) and the number of individuals, i.e. solutions (Ψ), are 200,000 and 24, respectively. All experiments were conducted using a laptop equipped with Intel(R) Core(TM) i7-9750H CPU @ 2.60 GHz 2.59 GHz, 16.0 GB of RAM and Windows 11. CPLEX 12.6 was used to obtain the exact solution.

5.1. Illustrative example

We utilize the data presented in Choudhary and Shankar (2014) to demonstrate the impact of the QD scheme on various parameters. The demand is given as $D_t = \{650, 520, 500, 650\}$ for $t = 1, \ldots, 4$. The example in Choudhary and Shankar (2014) employs a fixed discount of 1 per unit for each QD interval, which we refer to as "Case Study 1". We then introduce "Case Study 2", which uses the same parameters as in "Case Study 1" but with variable costs for different QD intervals. In this case, we assume distinct discount levels for each supplier, as shown in Table 6. For Scenario 3, titled "Combined QD", suppliers are assumed to employ different QD schemes. We define six sub-scenarios, ranging from "Combined-1" to "Combined-6", each with variations in the two sets a_t and b_t (Table 7).

Table 8 displays the optimal quantities and inventory levels in each period for Cases 1 and 2. In Case Study 1, the ordered quantities and selected suppliers remain unchanged despite alterations in the QD schemes. This can be attributed to the cost structure, where Supplier 1 is the most affordable option across all price intervals, followed by Supplier 3. Moreover, a positive inventory level can be noticed at the

Table 5
Instance generation rules.

Parameter	Formula	Explanation
n_t	$n_t \sim U(\frac{N}{3}, N)$	U: a discrete uniform distribution N: maximum number of suppliers
R_i	$R_i \sim U(3,5)$	
u_{itR_i}	$u_{itR_i} \sim U(1,15)$	
l_{itr}	$\lfloor \theta_{ir} u_{itR_i} \rfloor$ $\theta_{ir} \sim \mathcal{U}(0.6,1)$	$\mathcal{U}$: a continuous uniform distribution θ_{ir}: a percentage to define the lower limit of the QD interval
vc_{itr}	$vc_t \sim \mathcal{U}(10,18)$ $vc_{it} \sim \mathcal{U}(0.9vc_t, 1.1vc_t)$ $v_{itr} = (1-\mu_{ir})vc_{it}$ $\mu_{ir} \in \{0, 0.1, 0.15, 0.2, 0.25, 0.3\}$	μ_{ir} : discount rate
D_t	$\lambda \sim \mathcal{U}(0,1)$ $D'_t = \lceil \lambda \max_i u_{itR_i} + (1-\lambda) \sum_i u_{itR_i} \rceil$ $D_t = \lceil D'_t - (D'_t - 1) * \frac{vc_t}{\sum_t vc_t} \rceil$	D_t is a function of variable cost, maximum capacity and λ λ: factor affecting number of required suppliers
FC_{it}	$\overline{vc}_i = \frac{\sum_t vc_{it}}{T}$, $\overline{vc} = \frac{\sum_i \sum_t vc_{it}}{N \times T}$ $CF_{it} = \left(\overline{vc} + \frac{\overline{vc}}{\overline{vc}_i}\right) \times \gamma \sum_t u_{itR_i}$	FC_{it} is a function of the average variable cost and the maximum capacity
H_t	$H_t \sim \mathcal{U}(\frac{10\%}{12}\overline{vc}, \frac{20\%}{12}\overline{vc})$	The annual inventory cost is between 10% and 20% of the purchasing cost
S_t	$S_t \sim \mathcal{U}(\frac{25\%}{12}\overline{vc}, \frac{35\%}{12}\overline{vc})$	The annual shortage cost is between 25% and 35% of the purchasing cost
GW_{it}	$GW_{it} \sim \mathcal{U}(0.2,0.7)$	
α_1 and α_2	$\alpha_1 = 0.5,\ \alpha_2 = 0.5$	Equal importance

Table 6
Parameters used in the illustrative example.

	QD intervals	vc_{itr}		FC_{it}	GW_{it}
		Case Study 1	Case Study 2		
	$Q \leq 149$	62	62		
Supplier 1	$150 \leq Q \leq 299$	61	61	1000	0.19
	$300 \leq Q \leq 500$	60	57		
	$Q \leq 199$	72	72		
Supplier 2	$200 \leq Q \leq 349$	71	65	1500	0.46
	$350 \leq Q \leq 450$	70	55		
	$Q \leq 249$	68	68		
Supplier 3	$250 \leq Q \leq 399$	67	60	1400	0.32
	$400 \leq Q \leq 620$	66	59		

Table 7
Sub-scenarios under the combined QD scheme.

	a_t	b_t
Combined-1	{Supplier 1, Supplier 2}	{Supplier 3}
Combined-2	{Supplier 1, Supplier 3}	{Supplier 2}
Combined-3	{Supplier 2, Supplier 3}	{Supplier 1}
Combined-4	{Supplier 3}	{Supplier 1, Supplier 2}
Combined-5	{Supplier 2}	{Supplier 1, Supplier 3}
Combined-6	{Supplier 1}	{Supplier 2, Supplier 3}

end of periods 1 through 3. The reason may be attributed to the savings that can be generated from ordering larger quantities than the demand and storing part of the ordered quantities to benefit from the QD. The savings related to QD are more important than the additional inventory holding costs.

Under Case Study 2, and in the all-unit QD scheme, Supplier 2 is mainly used to fulfill the demand followed by Supplier 1 as they are the least expensive suppliers in the third QD interval. The same applies to “Combined-1” as both suppliers offer all-unit QD in this case. In the incremental QD scheme, Supplier 1 is the main used source followed by Supplier 3. This result is related to the price structure, as the price impact is cumulative depending on the ordered quantity. Consequently, utilizing Supplier 1 is ideal due to the least expensive price in the first interval, and the second least expensive price in the second and third intervals. A similar situation can be seen in the “Combined-6” scenario. In the combined scenarios, the general trend is to rely on one main supplier offering all-unit QD as this results in a less expensive procurement plan than relying on suppliers offering incremental QD. Moreover, almost all the cases, the inventory levels are positive throughout the planning horizon, except in the last period, due to the quantities ordered and that are larger than the demand so that price discounts can be achieved. Only for the scenario “Combined-4”, it is less expensive to have shortages in the first period than ordering larger quantities and storing for the following period. Note that in the case of maximizing the TGVP objective function, Supplier 2 is mainly used followed by Supplier 3 regardless of the QD scheme. The reason is related to the fact that GW_{it} has the highest value for Supplier 2 followed by Supplier 3 and that the TGVP objective function is independent of the unit price of the products and therefore of the QD schemes.

The bi-objective behavior is studied through the Pareto frontier by varying α_1 from 0 to 1 with a step of 0.01. Fig. 5 shows the TCP and TGVP values for the two cases, Case Study 1 and Case Study 2. For both cases, Scenarios 1 and 2 are the two extreme scenarios, and the different combined sub-scenarios within Scenario 3 are bounded between them. The first observation that one can draw from the results is that the all-unit QD scheme allows the customer company to reconcile cost and environmental performance in an easier way that the incremental QD scheme. This result can be seen from the Pareto frontiers in both cases, Case Study 1 and Case Study 2, where the Pareto frontier course of the all-unit scheme is the lowest allowing a better trade-off between the two objective functions, TCP and TGVP. Moreover, the average trade-off between the TCP and the TGVP is calculated and reported in Table 9. As a confirmation to the better performance of the all-unit scheme in terms of reconciliation of the economic and environmental performances, an average of 25.85% improvement of the TGVP of the purchased products can be achieved in Case Study 2 for an increase in the TCP by only 1%. Moreover, increasing the TCP by 1% in Case Study 1 enhances the TGVP by 6.07% on the average. An increase in the TGVP between 3.18% and 25.85% can be observed in Case Study 2 for an increase of the TCP by 1%. Note that in the sub-scenario “Combined-3” of Case Study 2, no trade-off exists since the optimal solution in the case of cost minimization is the same as that in the case of TGVP maximization.

Table 8
Optimal solution for minimizing the TCP under Case Study 1 and Case Study 2.

			$t = 1$	$t = 2$	$t = 3$	$t = 4$
Case Study 1	All schemes	Quantities	$Q_{113} = 500$ $Q_{312} = 320$	$Q_{123} = 500$	$Q_{133} = 500$	$Q_{143} = 500$
		Inventory	$I_1^H = 170$	$I_2^H = 150$	$I_3^H = 150$	$I_4^H = 0$
Case Study 2	All unit	Quantities	$Q_{113} = 470$ $Q_{213} = 450$	$Q_{223} = 450$	$Q_{233} = 450$	$Q_{143} = 500$
		Inventory	$I_1^H = 270$	$I_2^H = 200$	$I_3^H = 150$	$I_4^H = 0$
	Incremental	Quantities	$Q_{113} = 500$ $Q_{312} = 320$	$Q_{123} = 500$	$Q_{133} = 500$	$Q_{143} = 500$
		Inventory	$I_1^H = 170$	$I_2^H = 150$	$I_3^H = 150$	$I_4^H = 0$
	Combined-1	Quantities	$Q_{113} = 470$ $Q_{213} = 450$	$Q_{223} = 450$	$Q_{233} = 450$	$Q_{143} = 500$
		Inventory	$I_1^H = 270$	$I_2^H = 200$	$I_3^H = 150$	$I_4^H = 0$
	Combined-2	Quantities	$Q_{113} = 420$ $Q_{313} = 400$	$Q_{123} = 500$	$Q_{133} = 500$	$Q_{143} = 500$
		Inventory	$I_1^H = 170$	$I_2^H = 150$	$I_3^H = 150$	$I_4^H = 0$
	Combined-3	Quantities	$Q_{213} = 450$ $Q_{313} = 520$	$Q_{223} = 450$	$Q_{233} = 450$	$Q_{243} = 450$
		Inventory	$I_1^H = 320$	$I_2^H = 250$	$I_3^H = 200$	$I_4^H = 0$
	Combined-4	Quantities	$Q_{313} = 620$	$Q_{323} = 580$	$Q_{133} = 500$	$Q_{343} = 620$
		Inventory	$I_1^S = 30$	$I_2^H = 30$	$I_3^H = 30$	$I_4^H = 0$
	Combined-5	Quantities	$Q_{113} = 500$ $Q_{213} = 450$	$Q_{223} = 450$	$Q_{233} = 450$	$Q_{141} = 20$ $Q_{243} = 450$
		Inventory	$I_1^H = 300$	$I_2^H = 230$	$I_3^H = 180$	$I_4^H = 0$
	Combined-6	Quantities	$Q_{113} = 500$ $Q_{312} = 320$	$Q_{123} = 500$	$Q_{133} = 500$	$Q_{143} = 500$
		Inventory	$I_1^H = 170$	$I_2^H = 150$	$I_3^H = 150$	$I_4^H = 0$

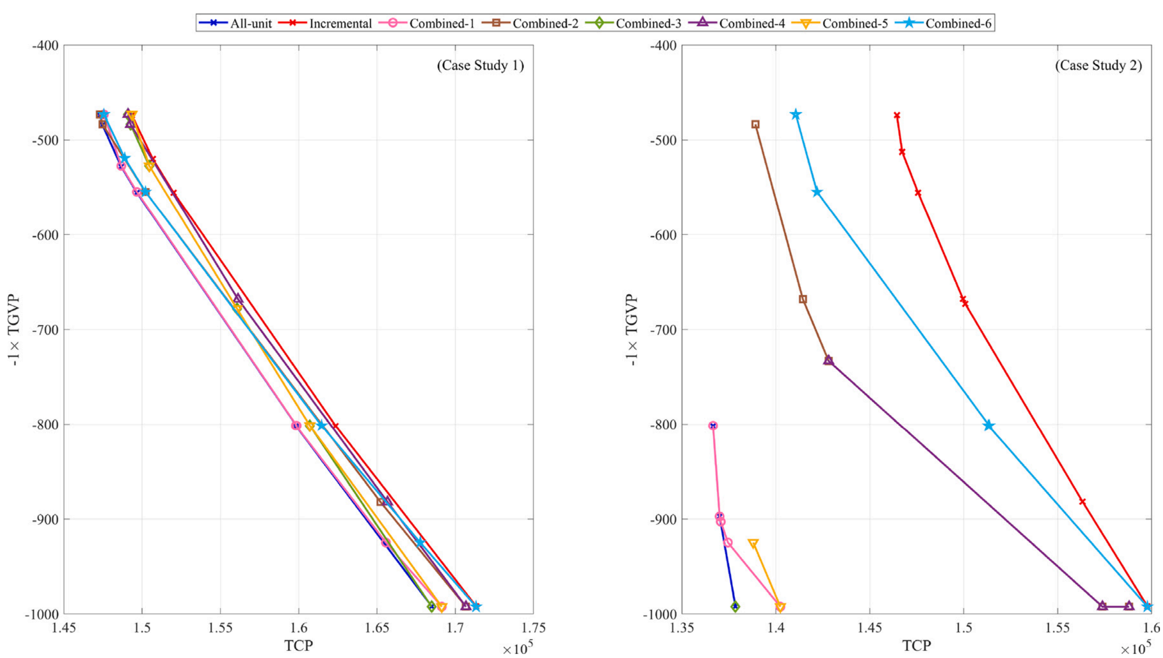

Fig. 5. Pareto frontier for Case Study 1 and Case Study 2.

5.2. Heuristic performance

The population-based heuristic (Algorithm 1) is compared with the exact approach to judge its performance. We generated instances, as explained in Section 5 and used a time limit of three hours as a stopping criterion for the exact approach. All the instances have been solved following the three scenarios defined in Section 5. Table 10 provides the percentage difference between the objective function values obtained using the exact and the heuristic approaches. More precisely, the percentage difference between the TCP values obtained from the exact and heuristic bi-objective solutions, E_{TCP}, is calculated as $E_{\mathrm{TCP}} = 100 \times \frac{\mathrm{TCP}_H - \mathrm{TCP}_{Ex}}{\mathrm{TCP}_{Ex}}$. Moreover, the percentage difference for the TGVP value between the exact and heuristic bi-objective solutions, E_{TGVP}, is obtained using $E_{\mathrm{TGVP}} = 100 \times \frac{\mathrm{TGVP}_{Ex} - \mathrm{TGVP}_H}{\mathrm{TGVP}_{Ex}}$. Note that the subscript Ex

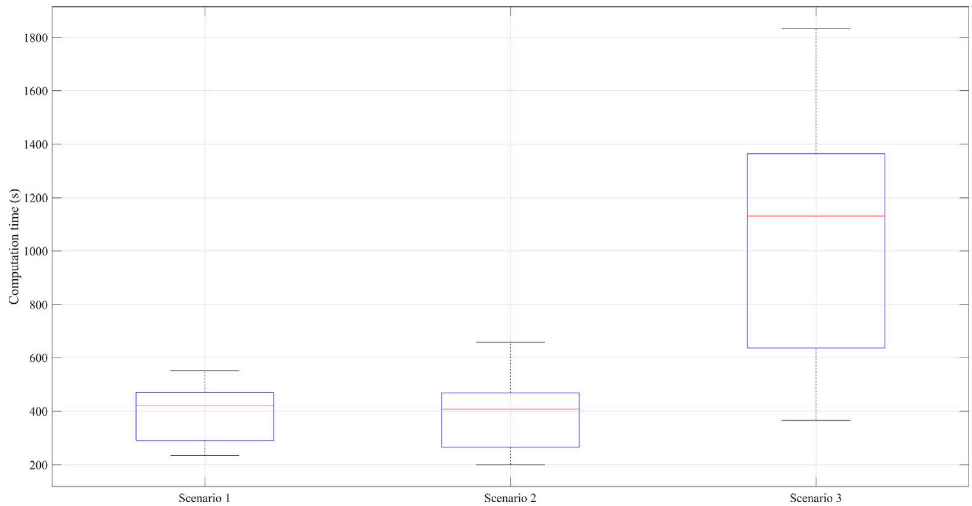

Fig. 6. Heuristic computation time under the three scenarios.

Table 9
Increase in the TGVP for 1% of TCP increase in Case Study 1 and Case Study 2.

	Case Study 1	Case Study 2
All-unit	6.12%	25.85%
Incremental	6.00%	9.17%
Combined-1	6.00%	8.56%
Combined-2	5.79%	5.99%
Combined-3	6.57%	n/a
Combined-4	6.13%	3.18%
Combined-5	6.47%	7.02%
Combined-6	5.47%	6.68%

and H denote the exact and the heuristic solutions. The exact solution is either the optimal one or the best solution within the time limit. The bi-objective error (E_f) is calculated as $\alpha_1 E_{\text{TCP}} + \alpha_2 E_{\text{TGVP}}$, which is also equivalent to the difference between f_{Ex} and f_H. This is because the bi-objective solution is characterized by two values (TCP and TGVP).

Table 10 shows that the average bi-objective error (E_f) is equal to 2.96%, 2.51% and 2.28% for Scenarios 1, 2 and 3 respectively. This indicates that the heuristic approach provides solutions with comparable quality for the different QD schemes. In addition, for some instances, the percentage difference between the exact and heuristic objective function is found to be high for one objective function while it is low for the other objective function, resulting in an overall acceptable (i.e. for the bi-objective function). This is the case for example for P20-40-H-A* and P10-60-M-A. This is due to the contribution of each objective function in the final solution, i.e. due to values of $\alpha_1 = \alpha_2 = 0.5$.

Table 11 reports the computation time in seconds for the exact and heuristic approaches (T_{Ex} and T_H respectively). The time saving is calculated as a percentage using $100 \times \frac{T_{Ex} - T_H}{T_{Ex}}$. It is worth noting that if the exact approach reaches the optimal solution faster than the heuristic approach then the time saving is labeled as n/a. Moreover, for the instances for which the exact solver could not reach and optimal solution after three hours of run time, then $T_{Ex} = 10800$ seconds. The results suggest that the heuristic may yield a time saving between 4.2% and 98% with an average of 87.3% compared to the exact approach for large-sized instances when the solver time limit is set to three hours. Note that the 4.2% time saving corresponds to the instance "P25-60-M-I", which took 550 s in the exact approach to reach optimality. Fig. 6 shows the dispersion of the computation time of the heuristic approach based on all the considered instances for the three scenarios. Fig. 6 indicates that the median computation time is 421, 408, and 1318 seconds for the all-unit, incremental and combined QD schemes respectively. The combined scenario requires the longest computation time with the largest computation time variability, which reflects the high impact of the problem size on the computation time. In contrast, the all-unit QD scheme is the least sensitive to problem size changes.

6. Conclusion

In this paper, we have proposed a SSOA model that considers two schemes of QDs, i.e. the all-unit and incremental QD schemes in addition to their combination. The proposed model can be easily used with only "all-unit" or only "incremental" discounts or with both schemes for different suppliers. The proposed model considers also the variable availability and performance of suppliers in terms of cost and green aspects over a predetermined planning horizon. The objective is to select the suppliers to contract with and the quantities to be ordered for every period of the planning horizon in order to satisfy a deterministic single-product demand. The problem has been modeled using a bi-objective MILP formulation and the model has been solved using the weighted comprehensive criterion method with an exact approach based on the branch-and-cut algorithm and a population-based heuristic approach. Moreover, a numerical analysis has been conducted to analyze the results including the obtained solutions and the corresponding computation time of the exact and heuristic approaches. The exact approach has been effective for the all-unit, incremental, and combined QDs models but only for small to medium-size problems. The optimal solution could not be reached even after a quite long computation time for large-size instances. In addition, the comparison between exact and heuristic approaches has shown that the percentage difference in terms of cost and green value has been small, especially for a large number of iterations of the heuristic approach which led to conclude that the exact approach can be used for small to medium size problems while the heuristic approach is recommended for large size problems, and without any difference in the quality of the heuristic solutions between the considered discount schemes. Moreover, the results have shown that the cost-based solutions and the green-value-based solutions are different and the latter is not sensitive to the discount scheme, which can be expected. Moreover, the all-unit discounts appeared to be better for the green-oriented solutions in the bi-objective configuration. Finally, different avenues for future research can be suggested based on the findings of this paper. First, considering stochastic demand instead of deterministic demand would make the model more realistic although it would become more challenging to be solved. Second, considering other sustainability aspects such as the social performance of the suppliers would be of interest. In addition, considering this problem along with the routing problem between the suppliers to collect the

Table 10
Difference between the exact and heuristic approaches.

Instance	E_{TCP} (%)	E_{TGVP} (%)	E_f (%)	Instance	E_{TCP} (%)	E_{TGVP} (%)	E_f (%)
P10-40-H-A	4.00	0.62	2.31	P10-60-H-A*	3.01	2.91	2.96
P10-40-M-A	0.78	1.42	1.10	P10-60-M-A	9.29	−3.76	2.77
P10-40-L-A	2.90	1.55	2.22	P10-60-L-A*	3.60	1.81	2.70
P15-40-H-A	3.91	0.80	2.36	P15-60-H-A*	3.18	5.28	4.23
P15-40-M-A	5.11	0.49	2.80	P15-60-M-A*	6.48	2.47	4.47
P15-40-L-A	4.13	0.62	2.38	P15-60-L-A*	1.89	3.95	2.92
P20-40-H-A*	8.74	−1.68	3.53	P20-60-H-A	3.60	0.15	1.87
P20-40-M-A	8.73	0.71	4.72	P20-60-M-A*	5.10	2.65	3.88
P20-40-L-A	3.37	3.42	3.40	P20-60-L-A*	3.39	0.40	1.89
P25-40-H-A	7.43	0.97	4.20	P25-60-H-A	1.74	3.84	2.79
P25-40-M-A	7.45	0.74	4.10	P25-60-M-A*	6.30	−0.73	2.79
P25-40-L-A	4.30	3.38	3.84	P25-60-L-A*	3.04	−0.35	1.34
P30-40-H-A	2.27	0.93	1.60	P30-60-H-A*	4.65	3.09	3.87
P30-40-M-A	5.45	0.74	3.09	P30-60-M-A*	6.31	1.82	4.07
P30-40-L-A	3.11	2.50	2.81	P30-60-L-A*	2.50	1.16	1.83
P10-40-H-I*	−0.49	2.38	0.94	P10-60-H-I*	3.17	3.06	3.11
P10-40-M-I	2.72	0.03	1.37	P10-60-M-I	3.99	0.13	2.06
P10-40-L-I	0.80	0.00	0.40	P10-60-L-I*	5.39	0.62	3.00
P15-40-H-I	0.84	−0.09	0.38	P15-60-H-I	3.96	2.05	3.00
P15-40-M-I	3.53	−0.04	1.74	P15-60-M-I*	3.88	0.99	2.44
P15-40-L-I	2.29	3.94	3.12	P15-60-L-I	2.43	−0.02	1.20
P20-40-H-I	3.82	−0.11	1.86	P20-60-H-I	3.72	1.83	2.77
P20-40-M-I	6.14	−1.32	2.41	P20-60-M-I*	7.41	1.73	4.57
P20-40-L-I	3.87	2.07	2.97	P20-60-L-I	4.20	4.26	4.23
P25-40-H-I	2.90	0.56	1.73	P25-60-H-I	3.13	2.20	2.66
P25-40-M-I	5.19	0.67	2.93	P25-60-M-I	4.85	1.49	3.17
P25-40-L-I	4.35	3.20	3.77	P25-60-L-I*	3.50	0.65	2.08
P30-40-H-I*	2.63	0.33	1.48	P30-60-H-I*	6.62	1.73	4.17
P30-40-M-I	2.65	4.13	3.39	P30-60-M-I*	6.64	2.56	4.60
P30-40-L-I	1.82	1.56	1.69	P30-60-L-I*	3.52	0.66	2.09
P10-40-H-C	3.70	−2.18	0.76	P10-60-H-C*	1.26	4.23	2.74
P10-40-M-C	0.61	1.70	1.15	P10-60-M-C	7.36	−1.46	2.95
P10-40-L-C	0.09	0.00	0.04	P10-60-L-C*	1.99	0.16	1.07
P15-40-H-C*	0.14	0.34	0.24	P15-60-H-C*	8.16	−1.29	3.44
P15-40-M-C	0.86	1.22	1.04	P15-60-M-C*	2.23	2.10	2.16
P15-40-L-C	0.64	5.31	2.98	P15-60-L-C	4.34	−0.23	2.06
P20-40-H-C*	2.91	−0.88	1.02	P20-60-H-C	2.81	0.87	1.84
P20-40-M-C	6.38	2.13	4.25	P20-60-M-C*	7.61	−3.90	1.85
P20-40-L-C*	5.49	0.01	2.75	P20-60-L-C*	3.82	3.39	3.61
P25-40-H-C	7.03	−1.03	3.00	P25-60-H-C*	6.61	−1.43	2.59
P25-40-M-C	6.56	−2.36	2.10	P25-60-M-C	5.50	1.36	3.43
P25-40-L-C*	3.66	2.25	2.95	P25-60-L-C*	3.68	0.19	1.93
P30-40-H-C	2.74	1.92	2.33	P30-60-H-C*	7.10	−1.09	3.00
P30-40-M-C	4.45	1.41	2.93	P30-60-M-C*	6.93	−0.49	3.22
P30-40-L-C	1.11	2.70	1.90	P30-60-L-C*	4.93	0.91	2.92

purchased products, while minimizing cost and the CO_2 emissions from the transportation vehicles is worth investigating.

CRediT authorship contribution statement

Sadeque Hamdan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Ali Cheaitou:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Amir Shikhli:** Writing – original draft, Writing – review & editing. **Imad Alsyouf:** Writing – review & editing.

Data availability

Data will be made available on request.

Appendix. Mathematical model with optimal QD scheme selection

The bi-objective integer LP model that allows to optimize the selection of the QD scheme is defined by introducing a new index $j = 1, \dots, J$ that represents the QD scheme. We use $j = 1$ to indicate "all-unit" QD and $j = 2$ to indicate "incremental" QD. The formulation can be given as follows:

$$\max \text{TGVP} = \sum_{t=1}^{T} \sum_{i=1}^{n_t} \sum_{r=1}^{R_i} GW_{it} \times \sum_{j=1}^{J} Q_{itr}^{j}, \tag{25}$$

$$\min \text{TCP} = \sum_{t=1}^{T} \sum_{i=1}^{n_t} \left(V\left(Q_{it}\right) + \sum_{r=1}^{R_i} \sum_{j=1}^{J} Y_{itr}^{j} \times FC_{it} \right) + \sum_{t=1}^{T} \left(H_t \times I_t^H + S_t \times I_t^S \right), \tag{26}$$

where

$$V\left(Q_{it}\right) = \sum_{r=1}^{R_i} vc_{itr} Q_{itr}^{j=1} + \sum_{r=1}^{R_i} \left(vc_{itr} \left(Q_{itr}^{j=2} - u_{it(r-1)} Y_{itr}^{j=2} \right) + \left(Y_{itr}^{j=2} \sum_{k=1}^{r-1} vc_{itk} \left(u_{itk} - u_{it(k-1)} \right) \right) \right) \tag{27}$$

Subject to

$$\sum_{j=1}^{J} \sum_{r=1}^{R_i} Y_{itr}^{j} \le 1, \qquad \forall i = 1, \dots, n_t \ , \ t = 1, \dots, T, \tag{28}$$

Table 11
Computation time of the exact and heuristic approaches under all scenarios.

Instance	T_{Ex} (s)	T_H (s)	Time saving (%)	Instance	T_{Ex} (s)	T_H (s)	Time saving (%)
P10-40-H-A	3651.98	234.88	93.57	P10-60-H-A*	10800.00	278.26	97.42
P10-40-M-A	42.69	239.04	n/a	P10-60-M-A	728.59	242.68	66.69
P10-40-L-A	104.32	242.95	n/a	P10-60-L-A*	10800.00	253.84	97.65
P15-40-H-A	825.61	287.40	65.19	P15-60-H-A*	10800.00	425.46	96.06
P15-40-M-A	47.23	297.59	n/a	P15-60-M-A*	10800.00	397.39	96.32
P15-40-L-A	2529.10	291.17	88.49	P15-60-L-A*	10800.00	396.80	96.33
P20-40-H-A*	10800.00	382.82	96.46	P20-60-H-A	679.91	441.06	35.13
P20-40-M-A	3670.37	353.91	90.36	P20-60-M-A*	10800.00	445.10	95.88
P20-40-L-A	1473.76	378.27	74.33	P20-60-L-A*	10800.00	470.79	95.64
P25-40-H-A	309.80	416.98	n/a	P25-60-H-A	4095.77	537.43	86.88
P25-40-M-A	4068.48	430.01	89.43	P25-60-M-A*	10800.00	531.43	95.08
P25-40-L-A	4216.13	448.89	89.35	P25-60-L-A*	10800.00	522.15	95.17
P30-40-H-A	5338.03	517.29	90.31	P30-60-H-A*	10800.00	537.52	95.02
P30-40-M-A	293.41	459.37	n/a	P30-60-M-A*	10800.00	551.12	94.90
P30-40-L-A	4301.07	452.13	89.49	P30-60-L-A*	10800.00	538.27	95.02
P10-40-H-I*	10800.00	209.44	98.06	P10-60-H-I*	10800.00	253.12	97.66
P10-40-M-I	34.88	200.35	n/a	P10-60-M-I	46.66	267.29	n/a
P10-40-L-I	14.82	220.68	n/a	P10-60-L-I*	10800.00	254.74	97.64
P15-40-H-I	39.07	255.46	n/a	P15-60-H-I	5490.46	385.90	92.97
P15-40-M-I	2189.51	256.55	88.28	P15-60-M-I*	10800.00	444.87	95.88
P15-40-L-I	2529.10	265.83	89.49	P15-60-L-I	4168.23	393.51	90.56
P20-40-H-I	85.82	355.06	n/a	P20-60-H-I	310.86	461.81	n/a
P20-40-M-I	3670.37	371.93	89.87	P20-60-M-I*	10800.00	451.09	95.82
P20-40-L-I	78.66	372.04	n/a	P20-60-L-I	3921.00	468.96	88.04
P25-40-H-I	111.54	404.70	n/a	P25-60-H-I	5185.49	524.43	89.89
P25-40-M-I	4049.77	410.99	89.85	P25-60-M-I	550.70	527.58	4.20
P25-40-L-I	154.45	431.25	n/a	P25-60-L-I*	10800.00	549.67	94.91
P30-40-H-I*	10800.00	453.10	95.80	P30-60-H-I*	10800.00	582.02	94.61
P30-40-M-I	240.34	446.47	n/a	P30-60-M-I*	10800.00	605.53	94.39
P30-40-L-I	224.68	476.60	n/a	P30-60-L-I*	10800.00	657.29	93.91
P10-40-H-C	3651.98	425.45	88.35	P10-60-H-C*	10800.00	695.46	93.56
P10-40-M-C	120.62	365.84	n/a	P10-60-M-C	220.38	552.47	n/a
P10-40-L-C	32.49	383.16	n/a	P10-60-L-C*	10800.00	603.80	94.41
P15-40-H-C*	10800.00	612.54	94.33	P15-60-H-C*	10800.00	1163.64	89.23
P15-40-M-C	85.86	636.29	n/a	P15-60-M-C*	10800.00	941.24	91.28
P15-40-L-C	2529.10	629.77	75.10	P15-60-L-C	379.87	1089.40	n/a
P20-40-H-C*	10800.00	778.69	92.79	P20-60-H-C	296.95	1611.30	n/a
P20-40-M-C	3670.37	969.17	73.59	P20-60-M-C*	10800.00	1363.03	87.38
P20-40-L-C*	10800.00	1093.63	89.87	P20-60-L-C*	10800.00	1336.90	87.62
P25-40-H-C	527.78	1231.29	n/a	P25-60-H-C*	10800.00	1754.27	83.76
P25-40-M-C	4049.77	1099.86	72.84	P25-60-M-C	1120.13	1735.81	n/a
P25-40-L-C*	10800.00	1364.81	87.36	P25-60-L-C*	10800.00	1671.17	84.53
P30-40-H-C	3463.71	1344.02	61.20	P30-60-H-C*	10800.00	1803.32	83.30
P30-40-M-C	179.43	1240.10	n/a	P30-60-M-C*	10800.00	1781.55	83.50
P30-40-L-C	696.76	1350.19	n/a	P30-60-L-C*	10800.00	1833.46	83.02

$$Y_{itr}^{j} l_{itr} \le Q_{itr}^{j} \le Y_{itr}^{j} u_{itr} \quad \forall i = 1, \dots, n_t,\ t = 1, \dots, T,\ j = 1, \dots, J,\ r = 1, \dots, R_i, \tag{29}$$

$$I_{t-1}^{H} - I_{t-1}^{S} + \sum_{i=1}^{n_t} \sum_{j=1}^{J} \sum_{r=1}^{R_i} Q_{itr}^{j} - I_t^{H} + I_t^{S} = D_t, \tag{30}$$

$$\sum_{t=1}^{T} \sum_{i=1}^{n_t} \sum_{j=1}^{J} \sum_{r=1}^{R_i} Q_{itr}^{j} + I_0 = \sum_{t=1}^{T} D_t, \tag{31}$$

$$\epsilon Y_t^{S} \le I_t^{S} \le M Y_t^{S}, \qquad \forall t = 1, \dots, T, \tag{32}$$

$$\epsilon Y_t^{H} \le I_t^{H} \le M Y_t^{H}, \qquad \forall t = 1, \dots, T, \tag{33}$$

$$Y_t^{H} + Y_t^{S} \le 1, \qquad \forall t = 1, \dots, T, \tag{34}$$

$$Q_{itr}^{j} \in \mathbb{N},\ Y_{itr}^{j} \in \{0, 1\}, \qquad \forall i = 1, \dots, n_t,\ t = 1, \dots, T,\ r = 1, \dots, R_i, \tag{35}$$

$$I_t^{H} \in \mathbb{N},\ I_t^{S} \in \mathbb{N},\ Y_t^{H} \in \{0, 1\},\ Y_t^{S} \in \{0, 1\}, \qquad \forall t = 1, \dots, T. \tag{36}$$

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