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REVIEW

Collaborative hospital supply chain network design problem under uncertainty

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Abstract

Since 2016, hospitals in France have met to form Territorial Hospital Groups (THGs) in order to modernize their health care system. The main challenge is to allow an efficient logistics organization to adopt the new collaborative structure of the supply chain. In our work, we approach the concept of logistics pooling as a form of collaboration between hospitals in THGs. The aim is to pool and rationalize the storage of products in warehouses and optimize their distribution to care units while reducing logistics costs (transportation, storage, workforce, etc.). Besides, due to the unavailability and the incompleteness of data in real-world situations, several parameters embedded in supply chains could be imprecise or even uncertain. In this paper, a Fuzzy chance-constrained programming approach is developed based on possibility theory to solve a network design problem in a multi-supplier, multi-warehouse, and multi-commodity supply chain. The problem is designed as a minimum-cost flow graph and a linear programming optimization model is developed considering fuzzy demand. The objective is to meet the customers' demand and nd the best allocation of products to warehouses. Different instances were generated based on realistic data from an existing territorial hospital group, and several tests were developed to reveal the benefits of collaboration and uncertainty handling.

Keywords Optimization model · Network design problem · Product allocation · Collaboration · Fuzzy chance-constrained programming

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1 Introduction

A supply chain refers to a coordinated series of processes to manage system entities involved in procurement, manufacturing, warehousing, and transportation activities. These entities are highly interdependent to improve the performance of the supply chain with minimum costs. Creating both a responsive and cost-effective supply chain is critically difficult and represents a real challenge for companies. Especially when different problems may occur (i.e. warehouse management errors or lack of effective coordination), they can lead to increase inventory costs and decrease profits. To face these challenges, the logistics network design problem is considered a major strategic decision issue in supply chain management, due to its substantial influence on the efficiency of the entire supply chain process.

Over the recent past years, the hospital sector becomes an area of interest for many researchers in the literature due to its conflict with new different challenges and issues (demographic, budgetary, political, etc.). Several research studies have focused on the organization of flows (Chen et al. 2013) and the management of resources and tasks (Toba et al. 2008) to improve the performance of the global hospital supply chain (Tamir et al. 2017). Today, public hospitals have to initiate a reflection on their functioning and their organization and propose an efficient management strategy of the healthcare system to optimize the resources mobilized and rationalize all its activities (Pillay 2008). Before 2016, hospitals tend to manage their logistics process (reception, storage, preparation, distribution) autonomously. Hence, each healthcare establishment admits a logistics process specific to its needs and its functioning which becomes more and more difficult to be managed following the increase of patients number in hospitals. Especially, when they are frequently demanding in terms of service rates, responsiveness, and flexibility as was the case with COVID-19 when thousands of new daily admissions were recorded and hospitals were saturated. Hence, cooperation between hospitals was very important to ensure good management of logistics and overcome the declared health crisis. Consequently, the current hospital logistics systems require the emergence of new forms of governance and rationalization of logistics policies.

Four years ago, public hospitals in France have met officially to form THGs in the interest of reducing logistics costs through better use of their resources (managing products/material flows and distribution circuits). This new type of coordination between health establishments is among the most structuring and ambitious measures of the law on the modernization of healthcare systems. The idea is to establish a shared medical project based on cooperation and coordination between hospitals composing the THG. Among the main advantages of this territorial approach is to improve the quality of public hospital service, rationalize storage means (limitation and/or specialization of THG warehouses) and optimize the distribution system. Therefore, THGs represent an accelerator of the joint work of medical, technical, administrative, and logistics teams. The efforts began with the regrouping of purchasing function between public hospitals as part of "**PHARE**" program (Hospital purchases—Ministry of Solidarity and Health 2011) to generate "smart savings", while arriving at the logistics process and mainly the storage and distribution functions. As it has been proven in the field of industry, university communities, etc., a collaboration strategy will be advantageous and it will strengthen the economic and social efficiency of healthcare organizations through an overall cost reduction, supplier integration, and optimization of logistics employment. Thus, to model this collaboration, knowledge about logistics functions is essential to ensure the proper functioning of the hospital supply chain.

A hospital logistics chain is identified by a set of actors and logistics processes where commodities are distributed from the supplier (origin) to the storage plant (warehouse) and then prepared to be transferred (shipping) to care units (destination). In more realistic supply chain models, the environment's parameters (e.g. customer demands and transportation costs) may change and deterministic optimization reaches its limits (Bai and Liu 2016). Therefore, all strategic, tactical, and operational decisions should be made under uncertainty. Mainly, to deal with uncertain parameters, stochastic approaches have been developed, and precise information about the probability functions of these variables is needed. Besides, for a lack of historical data, we cannot elaborate probabilistic scenarios. Therefore, fuzzy linear programming could be a good solution for such a problem to handle imprecise and uncertain information (Werners and Drawe 2003).

In the present paper, we propose a multi-commodity, multi-supplier, and multi-warehouse optimization model to deal with two echelon network design problems within THG. On the one hand, the objective is to study the economic impact of horizontal collaboration on the total logistics cost generated and on the other hand, to cope with uncertainty in hospital demand through the development of a fuzzy chance-constrained programming approach based on possibility theory. The efficiency of the proposed model is tested and a comparison between the fuzzy chance-constrained programming and the weighted average method is carried out to demonstrate the robustness of the proposed approach. The remainder of this paper is organized as follows: in Sect. 2 we present a literature review on logistics pooling strategy and chance-constrained programming approach to tackle uncertainties in different real-world applications. Section 3 presents a description of the proposed problem and its mathematical formulation. In Sect. 4, a description of the fuzzy programming approach is presented. Generation of instances and discussion of experimental results is done in Sect. 5. Finally, Sect. 6 presents a conclusion with some future research studies.

2 Literature review

Supply Chain Network Design (SCND) can be defined as an integrated decision-making process dealing with different activities (procurement, manufacturing, warehousing, and transportation) to manage system entities and resources involved in distributing products/services from suppliers to end-users (Lin and Wang 2011). Many actors involved in a supply chain may have conict in interests. The main objective when designing a supply chain network is to reduce these conicts and increase the total revenue and/or decrease the total costs (Rabbani et al. 2018). A great deal of research in the scientific literature has been done to propose solutions and decision-support methods for problems related to the SCND. Mainly, collaboration strategies, embedded in SCND problems, are strongly studied by the research committee in recent years. In this section, the logistics pooling strategy, which represents a kind of collaboration between supply chain actors, will be reviewed. Later, methods and approaches to tackle uncertain environments will be discussed.

2.1 Logistics pooling strategy in supply chain network

Studies in the SCND modeling area related to warehousing and transportation/distribution networks could be classified into traditional or collaborative SCND. Therefore, sometimes traditional SCND approaches are not sufficiently effective, especially when there are problems related to the logistics units. Hence the need for developing more efficient logistics strategies, such as collaborative models where different structures cooperate to optimize their logistics processes. According to Moutaoukil et al. (2013), collaborative SCND consists to share logistics means and resources to minimize costs and increase profits, it could be either at the vertical or the horizontal level. The first category concerns partners who belong to the same logistics chain that operate at different levels of the supply network. Unlike the second type, which concerns partners of the same level (providers, manufacturers, distributors, etc.) who do not belong to the same logistics network. After solid and sustainable collaborative approaches, the logistics pooling strategy was born in the 1990s at the initiative of large distributors to increase trucks' filling rate and delivery frequency. Since the 2000s, the pooling strategy is becoming widely developed in the literature (Mrabti et al. 2019) and it is considered as a horizontal collaborative approach (Moutaoukil et al. 2013) used to achieve economies of scale in different real-world domains.

A large number of mathematical models have been proposed for the design, planning, or optimization of the pooled supply chain. Some of these models considered one-echelon supply chain, especially in collaborative hub network problems proposed for the first time by Vermunt (1999). This work has been enhanced in 2005 by Groothedde et al. (2005), authors proposed a heuristic to solve the many-to-many hub network problem for the distribution of consumer goods, in which economies of scale and a sufficient level of reliability were achieved thanks to the collaboration between warehouses and the pooling of products during their transport from the manufacturer to the customer. Then, the pooling of multi-echelon supply chain models becomes more developed in the literature. For example in 2002, a multi-warehouse supply chain was studied in Kim and Benjaafar (2002), where authors presented the advantages of inventory pooling in limited capacity production-inventory systems with multiple plants. In 2005, a multi-supplier, single-warehouse supply chain network was considered in Cheong et al. (2007), Tuzkaya and Önüt (2009), authors developed a linear programming model for the shared network design problem. However, in Tuzkaya and Önüt (2009), a multi-commodity aspect is treated among periodic environment that involves determining the best strategy for distributing the sub-products from suppliers to warehouses and from warehouses to manufacturers in order to maximize the profit. In the same context, (Ballot and Fontane 2010) developed a pooled strategy in a multi-supplier, multi-product supply chain and demonstrated that vertical supply chain optimizations can still be improved by horizontal collaboration with real data from French retail chains. Besides, the authors were interested in the environmental aspect and ignore the economic side. Therefore, Pan's study (2010) dealt with the problem with the aim of massifying flows to increase the filling rate of vehicles and evaluated the economic and environmental indicators within mathematical modeling in Integer Linear Programming.

Other researchers in the literature have used simulation techniques to deal with logistics pooling. The majority of works used simulation to compare different pooling scenarios and indicated the best one to follow. As it was presented in Pooley and Stenger (1992), the authors proposed a simulation approach to evaluate a logistic transportation consolidation strategy within a food manufacturing business. In 2009, authors in Wanke and Saliby (2009) developed a simulation tool to determine the impact of inventory centralization and regular transshipment inventory-pooling models, on holding and distribution costs and service levels. Two years later, authors Leitner et al. (2011), used simulation to apply pooling for projects in the automotive sector in Romania and Spain in order to optimize cost structures. Also, authors Moutaoukil et al. (2013); Mrabti et al. (2019) used several scenarios to compare the performance of a traditional logistics network against a pooling supply chain with a horizontal collaborative logistic strategy by evaluating the economic indicators (transport cost, loading cost, unloading cost, and vehicle filling rate). Recently, in Nicolas et al. (2018), authors presented a simulation approach to provide decision support within THGs. The developed framework helps hospitals to rationalize and pool the warehouses and their associated logistics flows. It allows decision-makers to choose and compare pooling scenarios of products within a THG based on a set of criteria chosen by hospital partners. However, designing and testing pooling scenarios to find a quasi-optimal pooling strategy can be time-consuming. Furthermore, strategic decisions must often deal with data uncertainties about future demand.

2.2 Chance-constrained programming approach

All the above literature considered logistics pooling strategy in SCND problem under deterministic conditions, where customer's demands and logistics costs were treated as a well-known parameter. However, in a real-world environment, SCND problem is full of unpredictable and stochastic elements. Therefore, it appears essential to consider uncertainty in order to build a robust solution, especially, over a long-term decision horizon. According to Zhao et al. (2018) uncertainty can be modeled by several approaches. For example, as a good classification, Sahinidis (2004) categorizes and reviews the main optimization approaches under uncertainty into two groups: (1) stochastic optimization (recourse models, robust stochastic programming, probabilistic models) and (2) fuzzy optimization. In stochastic optimization, there are broadly three types of stochastic programming approaches: expected value models, chance-constrained programming, and dependent chance programming (Liu and Liu 2009). We focus on our research study on chance-constrained programming (CCP) that was first proposed in Charnes and Cooper (1959) to solve optimization problems under various uncertain situations and to ensure that the decisions meet a set of constraints with certain levels. Its main feature is to restrict the feasible region so that the confidence level of the solution is high, see Li et al. (2008). The chance-constrained programming model has been applied widely in different subject areas, such as in energy management problems (Huang et al. 2016; Liu et al. 2016), transportation (Li et al. 2017; Zhao et al. 2018), inventory management (Jurado et al. 2016) (Meng and Rong 2015), biofuel supply chain (Quddus et al. 2018), and even in humanitarian relief network design (Elçi and Noyan 2018).

Despite the presence of stochastic methods in many real-world applications, sometimes, they are difficult to be developed. Precise information about the probability distributions of stochastic parameters is needed (Werners and Drawe 2003), while this is not usually possible because historical data of those parameters are sometimes unavailable. Therefore, in such a situation, an appropriate approach is required. Since the appearance of fuzzy theory (Zadeh 1965, 1974, 1978), the incorporation of fuzziness in the field of combinatorial optimization becomes a challenging problem in terms of modeling and solution. Following the idea of chance-constrained programming with stochastic parameters, in fuzzy decision systems, we assume that the fuzzy constraints will hold with at least a certain degree of possibility called confidence level (Liu 1998). Therefore, several research studies have discussed the integration of chance-constrained programming within a fuzzy possibilistic framework and proposed different approaches to transforming the original chance constraints into a crisp equivalents model by employing possibility theory.

For example, in supply chain transportation problems, authors (Werners and Drawe 2003) treat the capacitated vehicle routing problem under fuzzy demand and proposed a fuzzy multi-criteria modeling approach based on a mixed-integer linear mathematical programming model. The approach presented to handle the fuzzy constraints is similar to chance-constrained programming in stochastic optimization, and the triangular form representation is proposed to represent fuzzy numbers. In 2014, Mousavi et al. (2014) addressed the location and routing problem in the cross-docking distribution networks. To tackle uncertain parameters (costs, vehicle capacity, time, etc.), the authors proposed a hybrid solution approach by combining fuzzy possibilistic programming and chance-constrained programming and represented uncertain parameters as fuzzy membership functions in the constraints. In supply chain inventory management, a traditional inventory control model with two objectives, minimizing costs and risk level, was developed in Nayebi et al. (2012). Different fuzzy parameters are incorporated in the mathematical model such as the available budgetary and presented as a triangular fuzzy number. For the defuzzification of fuzzy constraints, a fuzzy chance-constrained programming approach is proposed. In the healthcare domain, authors in Fazli-Khalaf et al. (2019) proposed a possibilistic chance-constrained programming model for designing a blood supply chain network in emergencies. Most of the main parameters of the mathematical model (demands, transportation time, capacity, costs, etc.) are tainted with uncertainty. Therefore, possibility and necessity measures are applied to cope with uncertain parameters in both objective function and constraints. Recently, in the reverse logistics domain, Ghahremani-Nahr et al. (2019) developed a mathematical programming model for the closed-loop supply chain and proposed a fuzzy formulation to address the effects of uncertainty parameters (customer demand, raw material costs, transportation costs, shortage cost, and availability of return goods and material). The authors used the trapezoidal fuzzy distribution to show the basic fuzzy programming model and the necessity measure to convert fuzzy chance constraints into their equivalent crisp ones. More recently, at the operational level, a fuzzy programming model for the truck-to-door assignment problem has been proposed to tackle the imprecise transfer times inside collaborative cross-docks (ESSGHAIER et al. 2021).

In summary, according to the reviewed literature, we noticed that several studies have approved the advantages of horizontal collaboration at different levels of decision-making (strategical, tactical, and operational) and application areas. However, to the best of our knowledge, none of the existing research works has modeled or studied the impact of horizontal collaboration and pooling strategy in the hospital sector and notably within territory hospital groups, since it is a new concept to consider in the healthcare domain. Studies presented in Sect. 2.1, as almost all studies conducted on collaboration strategy, have been performed assuming perfect knowledge about the problem. Variations in available resources, workload, or possible disruptions in the logistical process have been often neglected. Moreover, to the best of our knowledge, no work combines collaboration and uncertainty handling when dealing with hospital supply chain optimization within THG. An overview of the reviewed papers is presented in Table 1.

With the obligation to join territorial hospital groups, the logistics process within hospitals becomes more and more challenging and difficult to be controlled. Solving this problem requires perfect coordination of several operations (receiving, sorting, and shipping products) taking into account different parameters such as hospital demands or unit costs. Hence, a good logistical system greatly influences the whole hospital's performance. It may considerably enhance the efficiency of the health care service, improve delivery quality, and reduce costs and delays incurred in a hospital supply chain. This provides us with a strong motivation to study in this active research area, especially when dealing with uncertain environments. In addition to collaboration strategy, uncertainty handling in supply chains is one of the latest trends in the literature. Today, several companies have opted for managing unforeseen changes to meet customer requirements and confront economic, environmental, and social challenges. Unlike stochastic optimization, the fuzzy chance-constrained programming approach was not previously considered for collaborative supply chain and could be a well-recognized method that relies on profound mathematical concepts such as the expected value of fuzzy numbers in the objective function and possibility and necessity measures in the constraints. In practice, by using fuzzy logic we can tackle imprecise and uncertain variables, and this represents our second motivation to study, especially in the healthcare domain, where unforeseen changes can frequently occur following recurrent epidemics or pandemics.

The major contributions of this paper are highlighted as follows : (i) introducing a new optimization model to deal with horizontal collaboration within territorial hospital groups and organizing the allocation of products between shared plants to

Table 1 Overview of the supply chain network in the reviewed papers

Structure	Context	Paper	Approach	Multi-S	Multi-Pdt	Multi-E	Objective	Application
Collaborative	D	Leitner et al. (2011)	Simulation	✓			Fuel,CO2	Automobile
		Mrabti et al. (2019)	Simulation	✓		✓	TC,OC,CO2	–
		Groothedde et al. (2005)	Heuristic	✓			TC	Hub network
		Cheong et al. (2007)	Exact method	✓		✓	TC,HC	Hub network
		Tuzkaya and Önüt (2009)	Heuristic	✓	✓	✓	TC,HC	Automotive industry
		Pan (2010)	Exact method	✓	✓	✓	CO2	Agro-food
		Pooley and Stenger (1992), Wanke and Saliby (2009)	Simulation			✓	HC,service level	–
		Moutaoukil et al. (2013)	Simulation	✓	✓	✓	CO2,TC,TT	Agro-food
		Kim and Benjaafar (2002)	Simulation		✓		HC	–
		Ballot and Fontane (2010)	Exact method	✓	✓	✓	CO2	Retail industry
		Nicolas et al. (2018)	Simulation		✓	✓	TC,HC,OC	Health-care
Non-collaborative	S	Elçi and Noyan (2018)	Heuristic	✓	✓		TC	humanitarian relief
		Quddus et al. (2018)	Exact method	✓	✓	✓	TC	Bio-fuel
		Meng and Rong (2015)	Simulation		✓		OC,TC,Penalty	–
		Jurado et al. (2016)	Exact method		✓		HC,OC,TC,Penalty	Drugs distribution
		Huang et al. (2016)	Meta-heuristic				EC	Home energy system
		Li et al. (2017)	Exact-method	✓		✓	OC,TC,HC, penalty	–

Table 1 (continued)

Structure	Context	Paper	Approach	Multi-S	Multi-Pdt	Multi-E	Objective	Application
	F	Zhao et al. (2018)	Heuristic			✓	TC,HC	Sea-rail network
		Werners and Drawe (2003)	Heuristic				TC	–
		Mousavi et al. (2014)	Exact method	✓	✓	✓	TC,HC,OP	–
		Nayebi et al. (2012)	Exact method		✓		HC,OC,SC	–
		Fazli-Khalaf et al. (2019)	Exact method	✓		✓	HC,TC,CC	EB network
		Ghahremani-Nahr et al. (2019)	Meta-heuristic	✓	✓	✓	TC,PC,SC	–
Collaborative	FCCP	This paper	Exact method	✓	✓	✓	TC,FTE,HC,OC,PC	THG

E echelon, *S* supplier, *Pdt* product, *TC* transportation cost, *OC* ordering cost, *PC* purchasing cost, *FTE* full-time-equivalent cost, *HC* holding cost, *OP* operational cost, *EC* electricity cost, *CC* collecting cost, *SC* shortage cost, *EB* emergency blood offer an optimal pooling scenario for the decision-maker (ii) studying its economic impact under the assumption of a fully known environment by considering different logistical costs such as; full-time-equivalent costs, ordering costs, purchasing costs, holding costs and transportation, and then (iii) taking into account uncertainty in demands by developing a fuzzy chance constrained programming approach to merge the advantages of fuzzy set theory and chance-constrained optimization.

3 Problem description and mathematical formulation

Supply chain management aims to make organizations more responsive and efficient for the overall optimization of both costs and service levels. This has given rise to many reflections on the development of new collaboration strategies to create more synergies between the supply chain actors and to reduce the costs in the logistics chain. Among these collaboration strategies, we are interested in logistics pooling which is considered as a collaboration between actors of logistics chains through the sharing of resources and decisions.

In the healthcare domain, logistics pooling remains an understudied concept. Besides, it has been deployed in France's health-care system, since 2016, where hospitals are obliged to join territorial hospital groups to enable different establishments to rationalize, pool, and optimize the storage of products in their warehouses (stores, pharmacies) and optimize their distribution to care units. The objective is to find an optimal allocation of product flows and to set up a pooling scenario that groups these flows in suitable warehouses through transport and warehousing. Depending on local needs and pre-existing cooperation, territorial hospital groups vary mainly according to their establishment's parties, their budget, and the territories served. Generally, a THG is made up of several establishments of different sizes located in a given geographical area characterized by their density and their surface. In our study, the hospital supply chain is presented as a layered network with $|S|$ suppliers who provide commodities to $|W|$ warehouses (stores or pharmacy) where $|P|$ products sub-family (food, cleaning materials, textiles, medicines, etc.) could be stored before being distributed for consumption. Currently, the logistics management policy is illustrated in Fig. 1, where each hospital should manage its supply chain process (reception, storage, deconsolidation, preparation, distribution) and meet the needs of its units (care, catering, laundry, etc.) autonomously. Therefore, warehouses have historically been created for each establishment, knowing that every warehouse has its managing strategy that characterizes its purchasing, procurement, and storage activities and it is dedicated to serving only the set of care units belonging to the same establishment. Consequently, to acquire a product, this logistics process should be iterated independently within each hospital, which requires a lot of human and financial resources.

Due to the important costs that could be generated, our objective is to improve the current situation by developing a logistics pooling strategy between hospitals and specifying which products sub-families will be interesting to be shared, between which hospitals? and in which warehouses?

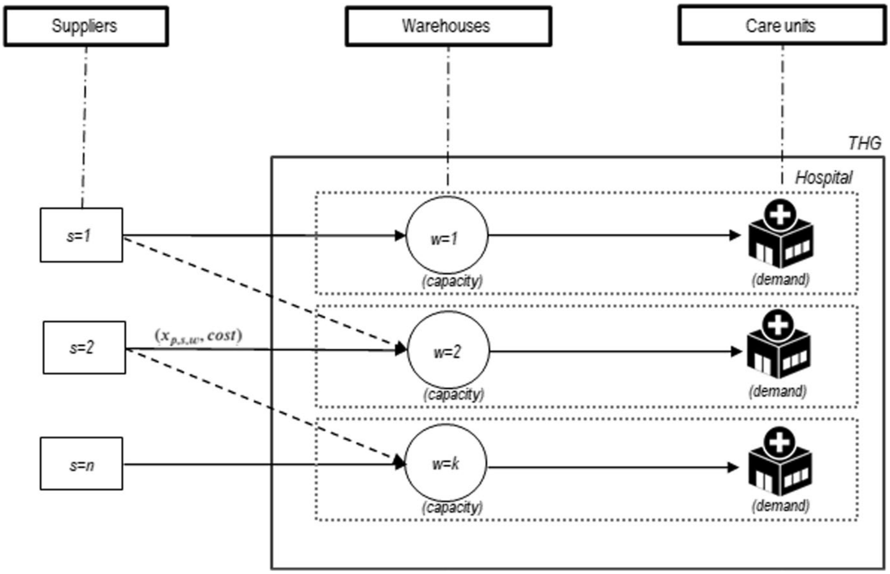

Fig. 1 Autonomous logistics organization (without pooling)

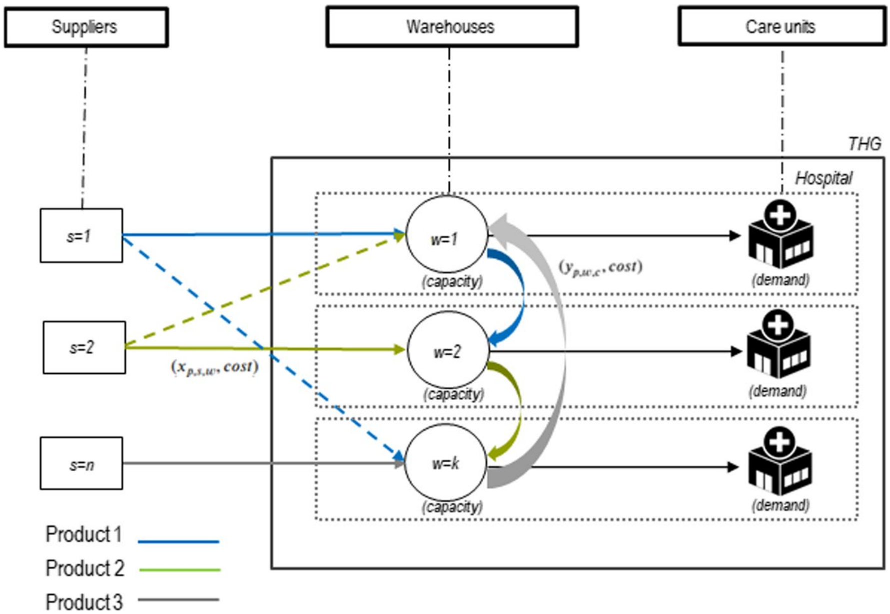

Fig. 2 Hospital supply chain within logistics pooling

Thus, we deploy the concept of shared warehouses and we consider that each warehouse could supply plants of different establishments for one or more product sub-families, as it is shown in Fig. 2. This new method of logistical organization allows the different actors of the supply chain to consolidate their stocks and pool their transport (upstream and/or downstream of the shared warehouse) by reducing synchronization constraints and maintaining high delivery frequencies.

To model the warehouse organization, we consider that each warehouse could have a dual function; a storage activity through the *S*-warehouses to hold the stock of one or more product sub-families for long period, and/or a cross-docking activity through *C*-warehouses to distribute products from the arrival docks to the departure docks, without going through the stock. Knowing that each warehouse could be simultaneously considered as *S*-warehouse for one or more products and as a *C*-warehouse for others. The structure of the proposed supply chain network can be transformed into a minimum-cost flow graph, as it is illustrated in Fig. 3, where the first level represents suppliers, the second level represents the warehouses considering that each warehouse can be represented by two nodes if it is at once a *C*-warehouse and *S*-warehouse and, the last level represents the units care. The pooling scenario is carried out in two stages, (1) the placement of certain products sub-families on one or more *S*-warehouses and (2) their distribution from these plants to one or more *C*-warehouses of other establishments. Therefore, the pooling of products sub-family will lead to a disruption of tasks for the flow considered between *S*-warehouses and *C*-warehouses. At the *S*-warehouse level, the distribution of the usual tasks will be now reduced only to the deconsolidation, storage, and preparation, reception and distribution will be reserved for the cross-docking.

The goals are to select warehouses with the best managing strategy and to determine the optimal product quantity that should be delivered from suppliers while minimizing the overall logistics costs such as the Full-Time Equivalent cost (FTE) that represents the workload of employees, transportation costs which denotes

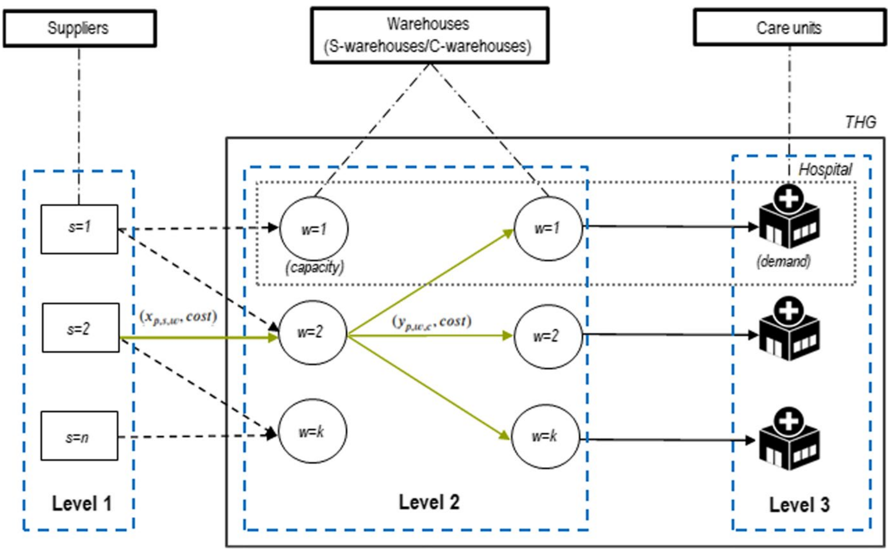

Fig. 3 Flow graph modeling of the hospital supply chain within logistics pooling

expenses related to distributing products from S-warehouses to cross-docks, purchasing cost related to the products' prices, ordering cost concerns the preparation of supplier's order, and lastly, the holding cost related to the inventory storage. Different constraints should be respected; the product demands must be satisfied and the maximum storage capacity of warehouses should not be exceeded. The following assumptions are assumed in this research to model the THGs supply chain network:

- *Hypothesis*

  - Suppliers have unlimited delivery capacity.
  - A given product can be distributed by one or more suppliers at different prices.
  - The product price proposed by a given supplier is fixed for all warehouses.
  - The local managing strategies applied at each warehouse (i.e. storage and procurement strategies: procurement periods, unit costs, etc.) are maintained where the pooling of products takes place.
  - Numbers and locations of warehouses are assumed to be fixed and known.

Notations used in the mathematical model are described as follows:

- *Decision variables*

  - $x_{p,s,w}$: quantity of product p transported from supplier s to warehouse w.
  - $y_{p,w,c}$: quantity of product p transported from S-warehouse w to C-warehouse c.

- *Sets and parameters*

  - S: set of suppliers, $|S| = 1..s$;
  - W: set of S-warehouses, $|W| = 1..w$;
  - C: set of cross-docks, $|C| = 1..c$;
  - P: set of products, $|P| = 1..p$;
  - PC: total purchasing cost;
  - OC: total ordering cost;
  - TC: total transportation cost;
  - HC: total holding cost;
  - FC: total Full-time equivalent cost ;
  - $PC_{p,s,w}$: unit purchasing cost of products p by the warehouse w from the supplier s that includes transportation costs;
  - $HC_{p,w}$: possession rate of product p in a warehouse w;
  - $OC_{p,w}$:unit ordering cost of product p for a warehouse w;
  - $FTE1_{p,w}$: full-time equivalent unit cost of product p in the S-warehouse w;
  - $FTE2_{p,c}$: full-time equivalent unit cost of product p in the C-warehouse (cross-dock) c;

- $TC_{p,w,c}$: unit transportation cost of product p from warehouse w to cross-docks c;
- C_w: maximum storage capacity of warehouse w;
- $d_{p,c}$: demand of product p by cross-dock c;
- $a_{p,w}$: unit surface occupied by product p in the warehouse w (m^2);
- t: calendar days=365;
- $PP_{p,w}$: procurement period of product p for warehouse w ($PP_{p,w} \neq 0$);

- *Variables/expressions*

- $I_{p,w}$: average inventory level of product p in a warehouse w:

$$I_{p,w} = \frac{x_{p,s,w}}{2 * (\frac{t}{PP_{p,w}})} \tag{1}$$

- $IL_{p,w}$: inventory value of products p in warehouse w:

$$IL_{p,w} = \frac{PC_{s,w,p}x_{p,s,w}}{2 * (\frac{t}{PP_{p,w}})} \tag{2}$$

Different economic costs that occur at all levels of the supply chain were considered to achieve economy:

1. Supplier/Warehouse

- Purchasing cost: the purchase amount set by suppliers in order to acquire a new product.

$$PC = \sum_P \sum_S \sum_W PC_{p,s,w}x_{p,s,w} \tag{3}$$

- Holding cost: related to storage expenses of inventory (insurance, depreciation of facilities, rental and maintenance of premises, etc.).

$$HC = \sum_P \sum_W HC_{p,w}IL_{p,w} \tag{4}$$

2. Warehouse

- Full-time equivalent cost (FTE): represents the FTE payroll cost used by each product sub-family (Number of FTEs x FTE salary per establishment).

$$FC = \sum_P \sum_S \sum_W (FTE1_{p,w}x_{p,s,w} + FTE2_{p,c}y_{p,w,c}) \tag{5}$$

- Ordering cost: generated during the management of orders and varies according to the number of annual purchases (personnel costs, administrative and logistical monitoring, reception and handling charges, etc.).

$$OC = \sum_{P} \sum_{S} \sum_{W} x_{p,s,w} OC_{p,w} \left(\frac{t}{PP_{p,w}} \right) \tag{6}$$

3. Warehouse/Cross-dock

- Transportation cost: direct or indirect costs of all order tracking and transport activities to ensure the delivery of products to care units.

$$TC = \sum_{P} \sum_{W} \sum_{C} TC_{p,w,c} y_{p,w,c} \tag{7}$$

- *Objective function*

$$Minimize \quad PC + HC + TC + FC + OC \tag{8}$$

- *Constraints*

$$\sum_{C} y_{p,w,c} \geq d_{p,c} \quad \forall w \in W, p \in P \tag{9}$$

$$\sum_{S} \sum_{P} 2I_{p,w} a_{p,w} \leq C_w, \quad \forall w \in W \tag{10}$$

$$\sum_{S} x_{p,s,w} - \sum_{C} y_{p,w,c} = 0, \quad \forall w \in W, p \in P \tag{11}$$

$$x_{p,s,w} \geq 0, \quad \forall w \in W, p \in P, s \in S \tag{12}$$

$$y_{p,w,c} \geq 0, \quad \forall w \in W, p \in P, c \in C \tag{13}$$

The objective function 8 aims to minimize the summation of five logistics costs; total ordering cost, inventory holding costs, purchasing cost, FTE cost, and finally transportation cost. Constraints 9 ensure that the unit care's demands for each product subfamily are satisfied. Constraints 10 guarantee that the total product quantity at each warehouse should not exceed its storage capacity. Constraints 11 represent the balance among supplies, inventory, and deliveries at each warehouse and cross-dock. Finally, constraints 12 and 13 represent the types of decision variables.

To demonstrate the impact of logistics pooling, we define two different scenarios. The first one (pooling scenario) represents the collaboration between warehouses and it is illustrated by constraints 9–13. The second one represents the pre-pooling scenario where sharing commodities between warehouses is restricted and it is formulated by adding constraints 14 to the previous model.

$$y_{p,w,c} = 0, \quad \forall p \in P, c \in C, w \in W, c \neq w \tag{14}$$

Constraints 14 prohibit the sharing of product flows between warehouses and force each warehouse to receive only the quantity of products needed by its care unit.

4 Fuzzy chance constrained programming approach

Because of the unavailability and incompleteness of data in real-world situations, especially on the long-term horizon, several critical parameters embedded in supply chains such as customer demands, costs, and future plant capacities have an imprecise nature and could be quite uncertain. Frequently, experts and decision-makers do not precisely know the value of those parameters. If exact values are suggested, these are only statistical inferences from past data (Jiménez et al. 2007) and their stability is doubtful. Therefore, stochastic probabilistic modeling approaches may not be the best choice for the simple reason of unreliability of historical data and unavailability of information about the probability functions of the uncertain parameters. Hence, the obligation to resort to another representation of this uncertainty.

In this paper, we consider a fuzzy chance-constrained programming approach, where the uncertain variable is modeled as a triangular form of fuzzy numbers. Based on possibility theory, we propose to solve the problem using a possibilistic programming method. Whereas, in conjunction with the theory of fuzzy subsets to treat imprecise data, the theory of possibilities, introduced by Zadeh (1978) and developed by Dubois and Prade in (1988), offers a means of managing knowledge marred by uncertainties. According to several models that have been presented in the literature to deal with imprecise data, fuzziness could be considered in the parameters of the objective function and/or constraints, or, it could be related to the flexibility degree of constraints (Inuiguchi and Ramık 2000). Our proposed approach could be considered as a new variant of probabilistic chance-constrained programming based on possibility theory (Liu 1998) to insure the defuzzification of the fuzzy model and its effective resolution.

The fact that predicting market demands is one of the most challenging issues in SCND problems regarding its fast variation (Ruoning and Zhai 2010), especially with short product life cycle and the growing of innovation rate, motivated us to study the problem considering that hospitals' demand (i.e. quantities to be delivered) is not known with certainty (i.e. at the time of planning) and characterized by variable possibility distributions and a certain necessity degree. To represent fuzziness, the demand constraints 9 need to be reformulated differently and it is redefined as follows:

$$\sum_{c \in C} y_{p,w,c} \ \tilde{\geq}\ \tilde{d}_{p,c} \quad \forall p \in P, w \in W \tag{15}$$

The fuzzy demand $\tilde{d}_{p,c}$ has a triangular possibility distributions based on a triplet of real numbers $d_{p,c} = (\underline{d_{p,c}}, \hat{d}_{p,c}, \overline{d_{p,c}})$ with $\underline{d_{p,c}} \leq \hat{d}_{p,c} \leq \overline{d_{p,c}}$ (Fig. 4). The terms $\underline{d_{p,c}}$, $\hat{d}_{p,c}$ and $\overline{d_{p,c}}$ represent, respectively, the most optimistic value, the most possible value and the most pessimistic value (Lai and Hwang 1993). $\underline{d_{p,c}}$ and $\overline{d_{p,c}}$ have a low possibility to belong to the set of available values, but $\hat{d}_{p,c}$ is definitely belongs to the set.

The possibility and necessity measures, corresponding to the satisfaction of the fuzzy demand constraints, are defined by a crisp equivalent formula (Klir and Yuan

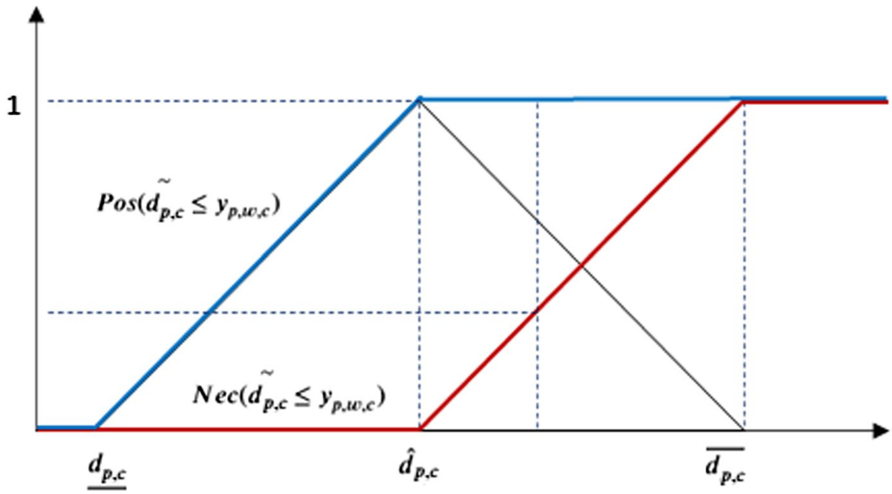

Fig. 4 Possibility and necessity measures of triangular fuzzy number $\tilde{d}_{p,c} = (\underline{d_{p,c}}, \hat{d}_{p,c}, \overline{d_{p,c}})$

1996) as it is developed below. In what follows, the abbreviations }}Pos'' and }}Nec'' represent respectively possibility and necessity.

$$Pos(\tilde{d}_{p,c} \le y_{p,w,c}) = \begin{cases} 1, & \hat{d}_{p,c} \le y_{p,w,c} \\ \frac{y_{p,w,c} - \underline{d_{p,c}}}{\hat{d}_{p,c} - \underline{d_{p,c}}}, & \underline{d_{p,c}} < y_{p,w,c} < \hat{d}_{p,c} \\ 0, & y_{p,w,c} \le \underline{d_{p,c}} \end{cases}$$

$$Nec\ (\tilde{d}_{p,c} \le y_{p,w,c}) = \begin{cases} 1, & \overline{d_{p,c}} \le y_{p,w,c} \\ \frac{y_{p,w,c} - \hat{d}_{p,c}}{\overline{d_{p,c}} - \hat{d}_{p,c}}, & \hat{d}_{p,c} < y_{p,w,c} < \overline{d_{p,c}} \\ 0, & y_{p,w,c} \le \hat{d}_{p,c} \end{cases}$$

In fuzzy set theory, possibility and necessity measures are employed to describe the chance of fuzzy events (Yang and Iwamura 2008). Hence, the satisfaction of the demand constraints is perfectly determined by the degrees of these measures. The possibility value implies the feasibility degree to satisfy these constraints. Besides, the necessity value indicates the degree of certainty of the constraints. Therefore, as suggested above, constraints 16 and 17 are modeled as crisp equivalents of the fuzzy constraints 15:

$$Pos(\tilde{d}_{p,c} \le y_{p,w,c}) \ge \alpha \tag{16}$$

$$Nec(\tilde{d}_{p,c} \le y_{p,w,c}) \ge \beta \tag{17}$$

In decision-making systems, an optimistic decision-maker deals with possibility measure, unlike the pessimistic decision-maker, who opts to deal with only necessity degree (Yang and Iwamura 2008). In our case, we suppose that the decision-maker is eclectic, hence, we use a combination of possibility and necessity measures to deal with the problem. Constraints 16 and 17 specify that the possibility and the necessity measures linked to the satisfaction of the demand constraints must be, respectively, greater than a threshold α and β that are chosen by the decision-maker between 0 and 1 to express his vision towards risk. The closer the possibility degree is to 0, the more the decision-maker is optimistic, thus, the closer the degree is to 1, the harder the constraints become and the problem will be more restrictive. As well as for the necessity measure, an elevated threshold implies hard constraints and a pessimistic attitude of the decision-maker. According to the choice of values for α and β, we distinguish different possible combinations of constraints defuzzification:

1. $\alpha = \mathbf{0}$ **and** $\beta = \mathbf{0}$ With this configuration, since the measures of possibility and necessity are between 0 and 1, constraints 16 and 17 are verified whatever the values of these measurements. Therefore, the fuzzy demand constraints are always checked regardless of the value of the demand $d_{p,c}$. This combination of thresholds is the least restrictive but the riskiest situation.

$$Pos(\tilde{d}_{p,c} \leq y_{p,w,c}) \geq 0$$
$$Nec(\tilde{d}_{p,c} \leq y_{p,w,c}) \geq 0$$

2. $\mathbf{0} < \alpha < \mathbf{1}$ **and** $\beta = \mathbf{0}$ The possibility constraints 16 will be replaced by:

$$Pos(\tilde{d}_{p,c} \leq y_{p,w,c}) \geq \alpha \Rightarrow \frac{y_{p,w,c} - \underline{d_{p,c}}}{\hat{d}_{p,c} - \underline{d_{p,c}}} \geq \alpha \Rightarrow \alpha\hat{d}_{p,c} + (1-\alpha)\underline{d_{p,c}} \leq y_{p,w,c}$$

   As in the previous case, with $\beta = 0$, the necessity constraints 17 are always verified ($Nec(d_{p,c} \leq y) \geq 0$) regardless of all $d_{p,c}$ possible values. With this combination of thresholds, the fuzzy demand constraints become more restrictive comparing with the first case.
3. $\alpha = \mathbf{1}$ **and** $\beta = \mathbf{0}$ When $\alpha = 1$, inequalities 16 will be defined as below:

$$Pos(\tilde{d}_{p,c} \leq y_{p,w,c}) \geq 1 \Rightarrow Pos(\tilde{d}_{p,c} \leq y_{p,w,c}) = 1 \Rightarrow \hat{d}_{p,c} \leq y_{p,w,c}$$

   According to the necessity definition, constraints 17 are verified ($Nec(d_{p,c} \leq y_{p,w,c}) \geq 0$) whatever the values of $d_{p,c}$. Consequently, the fuzzy demand constraints are satisfied when the quantity delivered to the warehouse is greater than the average value of demand ($d_{p,c}$), which represents the deterministic case.
4. $\alpha = \mathbf{1}$ **and** $\mathbf{0} < \beta < \mathbf{1}$ Since the necessity constraints $Nec(\tilde{d}_{p,c} \leq y_{p,w,c}) \neq 0$, the possibility measure constraints 16 are always verified whatever the values of $d_{p,c}$. Therefore, the satisfaction of the demand constraints implies the satisfaction of the necessity constraints 17:

$$Nec(\tilde{d}_{p,c} \leq y) \geq \beta \Rightarrow \frac{y_{p,w,c} - \hat{d}_{p,c}}{\overline{d_{p,c}} - \hat{d}_{p,c}} \geq \beta \Rightarrow \beta\overline{d_{p,c}} + (1-\beta)\hat{d}_{p,c} \leq y_{p,w,c}$$

With this combination of thresholds, the fuzzy demand constraints are more difficult to be satisfied.

5. **$\alpha = 1$ and $\beta = 1$** Constraints with regards to the necessity measure 17 will be defined as below:

$$Nec(\tilde{d}_{p,c} \leq y_{p,w,c}) \geq 1 \Rightarrow Nec(\tilde{d}_{p,c} \leq y_{p,w,c}) = 1 \Rightarrow \overline{d_{p,c}} \leq y_{p,w,c}$$

Satisfying the necessity constraints involves usually the satisfaction of the possibility measure ($\hat{d}_{p,c} \leq y_{p,w,c}$). This is the most challenging situation because the delivered quantity y should be greater or equal to the upper bound $\overline{d_{p,c}}$.

The combination where both $\alpha \in]0,1[$ and $\beta \in]0,1[$ is not possible to be modeled, because by definition (Klir 1999):

$$Nec(\tilde{d}_{p,c} \leq y_{p,w,c}) > 0 \Longrightarrow Pos(\tilde{d}_{p,c} \leq y_{p,w,c}) = 1$$

5 Computational experiments

In this section, we present experimental results to validate the computational efficiency and effectiveness of the model and to determine the impact of logistics pooling on our economic objective function in both deterministic and fuzzy environments. Two different configurations are used, firstly we consider the pre-pooling scenario where each hospital manages its procurement process independently, then, we consider the polling scenario, where collaboration between functional units of the THG is authorized and shared warehouses are considered. We perform computational experiments on a set of randomly generated test instances based on a realistic case study. The procedure used to generate these instances is described in Sect. 5.1, followed by a summary of computational results for pooling and pre-pooling scenarios of the deterministic approach in Sect. 5.2. In Sect. 5.3 we investigate the efficiency and robustness of the proposed model throughout a comparison between the FCCP approach and the weighted average method to tackle imprecise/uncertain variables (Lai and Hwang 1992).

5.1 Characteristics of test instances

All modeling development has been done on IBM CPLEX solver v.12.5 on a PC with an Intel i5 core processor (2.90 GHz) with 8.0 GB RAM. We performed computational experiments on a set of randomly generated test instances based on realistic parameter value ranges obtained from several logistics networks of existing territorial hospital groups in France. We considered a set of 25 instances (Table 2) according to assumptions that strike a balance between realism and ease of generation. Instances

Table 2 Problem instances: warehouses and products number (2 suppliers)

Instance	#Warehouses (|*W*|)	#Products (|*P*|)
1	2	4
2		12
3		20
4		28
5		36
6	5	4
7		12
8		20
9		28
10		36
11	15	4
12		12
13		20
14		28
15		36
16	20	4
17		12
18		20
19		28
20		36
21	25	4
22		12
23		20
24		28
25		36

vary according to two main dimensions: network size and cost values. The size of an instance is given by the number of suppliers ($|S|$) (fixed at 2 suppliers with all instances), the number of potential warehouses ($|W|$), and the number of products ($|P|$). The 25 test instances are devised into 5 main groups according to the number of warehouses/cross-docks ranging from 2 to 25. However, instances in the same group vary according to the number of products, each group holds 5 instances with commodities numbers ranging between 4 and 36 products. Continuous uniform distributions denoted by "U", independent from each other, were considered in the random number generation of all the variables. The cost structure and parameter values are determined as illustrated in Table 3.

Table 3 Values of input parameters

Parameter	Value	Parameter	Value
$PC_{p,s,w}$	~ U (1€, 20€) per unit	$TC_{p,w,c}$	~ U (0.1€, 0.9€) per unit
$HC_{p,w}$	~ U (20€, 30€) per unit	$a_{p,w}$	~ U ($0.1m^2$, $10m^2$) per unit
$OC_{p,w}$	20 €per unit	$FTE2_{p,c}$	~ U (0.1€, 0.9€) per unit
$FTE1_{p,w}$	~ U (0.1€, 0.9€) per unit		

5.2 Results of the deterministic approach

5.2.1 Comparison between pre-pooling and pooling scenarios

In this section, we focus on the results of the deterministic approach for pre-pooling and pooling scenarios in a fully known environment. In Table 4, we summarize the optimal objective values as well as the CPU times for each problem instance and for both scenarios.

We can notice that computational time increases with an increase in problem size, specifically with the number of potential warehouses and products. Additionally, it is important to note that the pooling scenario is always more time-consuming than the pre-pooling configuration (an average of 87.8 s against 191.4 s in the pooling scenario). This is noticeable especially for *instance*25 where the CPU time of the pre-pooling scenario is too much lower than the pooling scenario. However, computation times in both configurations are still quite acceptable in the case of all problem instances.

In addition to computational time, to compare the quality of the optimal solution obtained, we use the relative gap of the solution which gives an idea of the gain percentage achieved for each instance:

$$Gap\% = \frac{PrePooling_{sol} - Pooling_{sol}}{Pooling_{sol}} * 100 \tag{18}$$

We can see that from an economic point of view, horizontal collaboration has shown better performance compared to that of the current state (without pooling). For all instances, the total cost relative to the pre-pooling scenario is higher than the one obtained after pooling. There is an average cost reduction of approximately 16.1%. Economies are at least equal to 4.3% for instance 13 and achieve 39.6% for instance 22. Realized gains confirm that after collaboration, only warehouses with optimal supply strategies are selected for the procurement process. Besides, Fig. 5 displays details about gains realized among all instances. The total economic cost minimized is composed of purchasing cost relative to suppliers, holding cost associated with inventories at warehouses, FTE cost relating to the workforce and employment, ordering cost, and finally, an additional transportation cost is generated only after pooling and represents the charges of products shipping between warehouses. We note that 13% for the FTE cost, 19% of the inventory holding cost, and 14% for ordering cost are reduced. Hence, despite the generation of the additional

Table 4 Optimal total cost for pre-pooling and polling scenarios

Instance	Pre-pooling (€)	CPU (s)	Pooling (€)	CPU (s)	Gap (%)
1	2160 10^3	2.5	1792 10^3	4.2	20.5
2	3200 10^3	2.8	2654 10^3	7.0	20.6
3	3876 10^3	112.4	3367 10^3	135.2	15.1
4	4652 10^3	94.0	4120 10^3	162.4	12.9
5	5023 10^3	175.6	4728 10^3	206.4	6.2
6	4845 10^3	1.6	4332 10^3	2.4	11.8
7	6120 10^3	2.1	5526 10^3	3.7	10.7
8	7200 10^3	100.0	6857 10^3	147.2	5.0
9	8065 10^3	143.1	7128 10^3	171.3	13.1
10	9142 10^3	215.0	8454 10^3	276.1	8.1
11	7246 10^4	14.2	6366 10^4	23.0	13.8
12	8465 10^4	17.8	7297 10^4	21.4	16.0
13	9125 10^4	128.4	8745 10^4	152.5	4.3
14	1018 10^4	134.0	8907 10^4	145.4	14.2
15	1125 10^4	236.7	9478 10^4	314.6	18.2
16	1316 10^4	12.0	1171 10^4	31.2	12.3
17	1744 104	16.4	1268 10^4	46.2	37.5
18	2226 10^4	124.0	1748 10^4	242.0	27.3
19	2447 10^4	114.6	2180 10^4	462.0	12.2
20	3214 10^4	136.0	2953 10^4	649.0	8.8
21	2053 10^4	23.4	1592 10^4	57.6	28.9
22	3671 10^4	28.0	2832 10^4	74.2	39.6
23	5042 10^4	111.4	4421 10^4	321.3	14.0
24	6340 10^4	109.0	5334 10^4	418.7	18.8
25	7845 10^4	141.0	6107 10^4	710.4	28.4
Average	1838 10^4	87.8	1543 10^4	191.4	16.1

transportation cost that is usually absorbed by the gain realized, we conclude that the pooling solution approach is efficient and effective as it provides better quality solutions in all instances and allows cost-saving.

In addition to the economic indicator, different performance metrics can be used to assess the pooling strategy:

- *Occupancy rate (%):* this performance indicator tracks the percentage of available storage space in a potential warehouse. It is obtained by dividing the total quantity stored by the total capacity among the overall warehouses.

$$\frac{Occupied\_Surface}{Warehouse\_Capacity} \times 100 \tag{19}$$

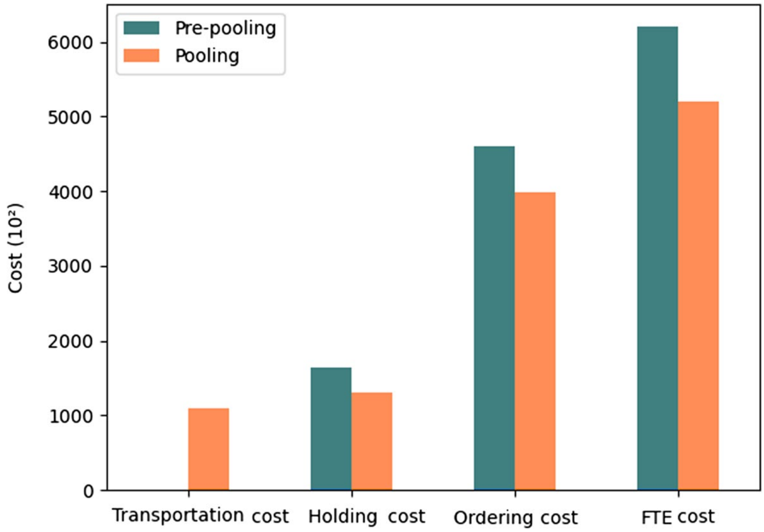

Fig. 5 Comparison of logistics costs in pre-pooling and pooling scenarios

- *Pooled product rate (%):* this performance metric allows us to assess the percentage of products that have been shared or grouped partially / totally after collaboration. It is obtained by dividing the number of product subfamilies pooled by the total product number.

$$\frac{NbPooledProduct}{TotalProductNumber} \times 100 \tag{20}$$

- *#S-warehouses:* this indicator represents the number of warehouses that have kept their functions as storage and cross-dock stores after pooling among those considered only as cross-docks (i.e. the number of S-warehouses remained open after pooling).

According to Table 5, the occupancy rate of warehouses decreases with an average improvement of 4%. Therefore, we can confirm that horizontal collaboration ensures better stock management and allows us to save more free space for other internal use. Moreover, according to the pooled product rate, more than 50% of the products' sub-families have been pooled among the overall instances, which confirms that collaboration is usually more advantageous. Finally, based on the number of warehouses that remained open after pooling (#S-warehouses) and kept their functions as storage and cross-dock stores, for the majority of instances, we can see that there are always at least two or more warehouses that have been considered as cross-docks only. This allows us to realize gains through null storage and ordering costs at the S-warehouses level.

Table 5 Warehouses occupancy rate, percentage of pooled products and number of *S*-warehouses after polling

Instance	Warehouse filling rate (%)		% Pooled product	#S-warehouse
	Pre-pooling	Pooling		
1	17	14	100	1/2
2	29	26	100	2/2
3	54	50	85	2/2
4	78	72	100	2/2
5	83	77	88	2/2
6	35	29	100	2/5
7	88	63	100	5/5
8	60	56	85	3/5
9	67	61	78	4/5
10	72	68	100	4/5
11	13	10	100	6/15
12	21	18	75	9/15
13	47	41	90	12/15
14	65	61	82	13/15
15	76	70	100	13/15
16	19	15	100	7/20
17	25	21	100	8/20
18	42	38	100	14/20
19	56	52	68	17/20
20	74	68	100	18/20
21	14	9	100	6/25
22	31	28	83	11/25
23	63	58	70	16/25
24	80	76	100	20/25
25	73	69	92	19/25
Average	50	46	91.8	–

5.2.2 Sensitivity analysis

The solution quality and the target variables generated could be affected based on changes in values of the input parameters such as hospital demand, warehouse capacity, unit logistics costs, etc. Therefore, sensitivity analysis is a way to predict how changes in coefficients of the model can affect the optimal solution obtained. In what follows, different experiments were conducted on unit transportation cost, warehouse capacity, and demand. Only one of those input parameters was varied each time, and all others remained unchanged from their previously-tested values.

As a first study, considering the importance of transportation cost ($TC_{p,w,c}$) generated during pooling, we motivated the analysis by changing the unit transportation cost upwards and downwards and evaluating the impact of its variability on the optimal solution, all the other parameters remained unchanged from their previously-tested baseline values. This study was carried out considering the most challenging instance (*instance*25). We observe that the obtained optimal solution (network structure) remains the same following the gradual increase in unit transportation cost until $TC_{p,w,c}$=$TC_{p,w,c}$+24%. However, only the total cost is impacted and it has slightly increased by 0.7%. Above 24% increase in unit transportation cost, the optimal procurement and distribution plan (optimal solution) is no longer maintained and the solver offers new solutions that further reduce costs. On the other side, by decreasing unit transportation cost even by 100% (i.e. $TC_{p,w,c}$=$TC_{p,w,c}$+100%) the solution remains the same. In this case, we can conclude that the optimal solution is insensitive to the decrease of $TC_{p,w,c}$.

Afterward, we focus our sensitivity analysis on the warehouse's capacity (C_w) considering the same instance (25). Therefore, we have varied it upwards and downwards and we noticed that the optimal solution (network structure) remains the same until the warehouse's capacity value is decreased by 28% (i.e. $C_w = C_w - 28\%$). Only the total objective cost generated is affected. Above 28%, the solver offers new solutions that generate a new collaborative schema. Besides, by increasing the maximum storage capacity value even with 100% the optimal solution is unchanged.

Since demands tend to be varied at the time of delivery, it is important to answer the question; at each demand value, the optimal solution remains unchanged? Therefore, we have displayed the right-hand side sensitivity analysis results of constraint 9 by using CPLEX display sensitivity command. Then, we check for each product the difference between the current demand value, and the up value that corresponds to the maximum tolerated demand increase and we calculate an average percentage for all products. The obtained results demonstrate that for all warehouses the optimal solution remains unchanged by increasing the demand value until reaching an average demand increase of 25%. Above this value, a new optimal solution will be generated and the network structure will be changed (new distribution schema). From this analysis, we can deduce that even the variation of a single demand in a single warehouse could generate changes in our optimal solution as well as in our network architecture. Thus the interest and the motivation behind our study on uncertainty in the next sections by considering the demand as a fuzzy parameter.

5.3 Results of the fuzzy approach

Given the incompleteness of data in real-world situations, we deal in this section with uncertain demand values modeled as a fuzzy number and solved as a possibilistic chance constraint programming model for both pre-pooling and pooling scenarios. Firstly, we present the changes made on instances to manage the fuzzy demands, then, we determine the influence of possibility and necessity degrees (threshold parameters: α and β) variation on the total cost.

5.3.1 Problem instances: fuzzy demand

We are modifying the instances generated to adapt them to SCND problem with fuzzy demand. The updates concerns only hospital demands represented by fuzzy numbers with symmetrical triangular form $\underline{d_{p,c}}, \hat{d}_{p,c}, \overline{d_{p,c}}$ where

$\hat{d}_{p,c} - \underline{d_{p,c}} = \overline{d_{p,c}} - \hat{d}_{p,c}$. A new parameter labeled uncertainty rate is added to model the fuzzy demand and denoted by r_{uncert}. In real-life, we noticed that the demand can vary between 0.15 and 0.2, therefore, we decided to fix the uncertainty rate's value at 0.15 for all our next experiments. The three components of the fuzzy demand $d_{p,c}$ are determined as follows:

- Normalization: $\hat{d}_{p,c}$ represents the initial demand in the deterministic model.
- The lower bound (best scenario): $\underline{d_{p,c}} = \hat{d}_{p,c} * (1 - r_{uncert})$.
- The upper bound (worst scenario): $\overline{d_{p,c}} = \hat{d}_{p,c} * (1 + r_{uncert})$.

5.3.2 Configuration of thresholds α and β of the FCCP model

Thresholds α and β given by the decision-maker have a great influence on the fuzzy demand constraints and consequently, on the problem costs that allow a certain degree of flexibility to the constraints satisfaction. Therefore, in this section, we look for several solutions to the problem corresponding to different combinations of thresholds. The execution of the FCCP optimization approach has been performed on both uncertain collaborative and non-collaborative scenarios, considering *instance*25, which has been chosen because of its challenging warehouses and products number. Besides, In order to reduce the number of simulations, we create a set of threshold combinations as follows: we increase the value of possibility degree alpha from 0 to 1 in steps of 0.1 with necessity degree beta fixed at 0. Then, when α is equal to 1, we increase in the same way the β value from 0 to 1. Results are given in Table 6.

Concerning the generated solution (Table 6), we noticed that we can confirm conclusions made in Sect. 5.2 about the deterministic model. According to the computed gap through Eq. 18, the pooling strategy is the most advantageous scenario that produces lower costs compared with the pre-pooling configuration with an average gain of 27.7%. In addition, the variation of α and β had a great influence on the solution quality. The best solution corresponding to the lowest total cost obtained is

Table 6 Fuzzy approach: thresholds (α and β) variation of the FCCP model

α	β	Pre-pooling	CPU	Pooling	CPU	GAP (%)
≤ 0.4	0	$7621\ 10^4$	145.6	$5920\ 10^4$	624.8	28.7
]0.4, 0.6]	0	$7704\ 10^4$	137.0	$6037\ 10^4$	615.2	27.6
]0.6, 1[	0	$7794\ 10^4$	124.3	$6084\ 10^4$	614.3	28.1
1	0	$7845\ 10^4$	152.0	$6107\ 10^4$	824.5	28.4
1	≤ 0.2	$7863\ 10^4$	142.0	$6189\ 10^4$	817.0	27.0
1	]0.2, 0.4]	$7945\ 10^4$	139.6	$6210\ 10^4$	765.0	27.9
1	]0.4, 0.7]	$7972\ 10^4$	156.2	$6232\ 10^4$	675.2	27.9
1	]0.7, 1[	$7983\ 10^4$	124.8	$6275\ 10^4$	745.3	27.2
1	1	$8015\ 10^4$	155.6	$6298\ 10^4$	784.0	27.2

generated with a null necessity degree and a low possibility degree ($\alpha \le 0.4$). The worst solution is obtained when $\alpha = 1$ and $\beta = 1$. With this threshold combination, the decision-maker considers the worst scenario with a maximal value of demand, therefore, a higher total cost is generated. This cost represents the price to pay for not being out of stock when the demand is higher than expected. For $\alpha = 1$ and $\beta = 0$, the solution is equal to that generated by the deterministic model. We note that the combinations of thresholds α and β represent an increasingly strict evolution of the fuzzy demand constraints. The larger their values, the stricter the fuzzy demand constraints, the greater the cost generated, and the less the risk of changes. However, a low degree's values represent an optimistic attitude against the risk and generate a more economically advantageous solution.

5.3.3 Comparison of deterministic and fuzzy approach

Since collaboration has shown better performance in all instances (Sect. 5.2), we will compare the results of the deterministic approach obtained in Table 4 with the configuration of the fuzzy model in a pooling scenario. High value of α and β ($\alpha = 1$ and $\beta = 0.7$) is considered to deal with a challenging and constraining case which is close to the worst scenario ($\alpha =$ 1and $\beta = 1$). As shown in Table 7, the tests were performed on 25 instances with an uncertainty rate equal to 0.15. The CPU time increases depending on the instance size and the configuration of the scenario considered. Comparing the results in Tables 4 and 7, we observed that the FCCP model had a slower temporal performance compared with the deterministic model (an average CPU equals to 208.8s against 191.4s in the deterministic approach). Even in an uncertain environment, the collaborative configuration is more time-consuming compared with the non-collaborative scenario (Table 6). In terms of solutions quality, we use the relative gap of the solution to compare the results of the fuzzy approach (Table 7) against the deterministic one (Table 4):

$$Gap\% = \frac{Fuzzy_{sol} - Deterministic_{sol}}{Deterministic_{sol}} \times 100 \tag{21}$$

we notice that the collaboration between warehouses in a fuzzy environment with elevated values of thresholds allows the increase of costs compared to the deterministic configuration on all instances with an average gap equals to 1.7% in Table 7. The obtained results confirm our observation deduced previously; the higher the threshold values, the stricter the fuzzy demand constraints, the greater the cost generated, and the less the risk of changes. Hence, gains or losses will depend on the scenario that will be considered by decision-makers.

5.4 Solution robustness

In order to test the effectiveness of our fuzzy programming approach, a comparison between the FCCP and the weighted average method (Hossain and Mahmud 2016; Paksoy et al. 2012) is considered and different comparative techniques are proposed such as TOPSIS method. The objective is to test the robustness of the solution under

Table 7 Optimal total cost in fuzzy configuration with $\alpha = 1$ and $\beta = 0.7$

Instance	Total cost (€)	CPU (s)	Gap (%)
1	1810 10^3	5.8	1.0
2	2697 10^3	7.0	1.6
3	3434 10^3	147.2	1.9
4	4208 10^3	174.1	2.1
5	4782 10^3	221.3	1.1
6	4393 10^3	3.6	1.4
7	5613 10^3	3.7	1.5
8	6934 10^3	147.2	1.1
9	7203 10^3	171.3	1.0
10	8593 10^3	276.1	1.6
11	6456 10^4	34.8	1.4
12	7384 10^4	21.4	1.1
13	8791 10^4	152.5	0.6
14	8997 10^4	154.6	1.0
15	9593 10^4	314.6	1.2
16	1246 10^4	31.2	6.4
17	1291 10^4	46.2	1.8
18	1763 10^4	257.3	2.4
19	2234 10^4	485.6	2.4
20	3015 10^4	663.4	2.0
21	1614 10^4	63.1	1.3
22	2876 10^4	96.0	1.5
23	4512 10^4	347.9	2.0
24	5440 10^4	486.2	1.9
25	6232 10^4	784.4	2.8
Average	1574 10^4	208.8	1.7

the two proposed fuzzy methods against unforeseen changes in demand when the pooling scenario is defined. The weighted average method is detailed in the Appendix A. The experimental results have been performed on two groups of instances with 15 and 25 plants (medium and large instances). Therefore, we re-played the optimal planned solution obtained when the demand is normalized to $\hat{d_{p,c}}$ identified as a reference scenario for both deterministic and fuzzy methods. Moreover, we re-execute the optimal solution for the case when the worst scenario ($\overline{d_{p,c}}$) occurs and determine the additional costs that will be generated and how the planned solution could be significantly affected. Knowing that the additional quantity generated will not be penalized and will be integrated at the usual cost. To deal with the most constrained scenario, the thresholds α, β and γ are fixed to 1 for the FCCP and the weighted average method, respectively. Table 8 presents the cost values for planned and worst case scenarios in the deterministic and uncertain configurations considering the FCCP and the weighted average method to solve the fuzzy demand.

Table 8 Optimal cost value for planned and worst scenarios

Inst	Deterministic			FCCP			Weighted Average		
	PS (10^4)	WS (10^4)	Gap%	PS (10^4)	WS (10^4)	Gap%	PS (10^4)	WS (10^4)	Gap%
11	6366	6500	2.1	6451	6470	− 0.5	6410	5489	− 0.2
12	7297	7557	3.4	7443	7486	− 0.9	7398	7540	− 0.2
13	8745	9107	4.0	8996	9015	− 1.0	8863	9100	− 0.1
14	8907	9256	3.8	9100	9153	− 1.1	9021	9214	− 0.5
15	9478	9781	3.1	9594	9638	− 1.5	9537	9749	− 0.3
21	1592	1666	4.4	1610	1615	− 3.1	1600	1647	− 1.2
22	2832	2965	4.5	2895	2908	− 2.0	2867	2922	− 1.5
23	4421	4641	4.7	4560	4592	− 1.1	4495	4620	− 0.5
24	5334	5558	4.0	5420	5467	− 1.7	5378	5500	− 1.1
25	6107	6380	4.3	6292	6317	− 1.0	6278	6380	0.0
Average	6107	6341	3.7	6236	6266	− 1.4	6184	6316	− 0.5

PS planned scenario, *WS* worst scenario

Table 9 Original data matrix

	Cost PS	Cost WS	GAP	Filling rate
FCCP	6236	6266	−1.4	48.2
Weighted average	6184	6316	−0.5	50.7

According to the obtained results, when the worst scenario occurs, the optimal target solution for the deterministic configuration becomes irrelevant since costs increase by 3.7% on average. Then, we compute the gap between the solutions generated in each fuzzy method (FCCP and weighted average method) against that generated in the deterministic case when demand increases more than was planned (worst scenario). Although solutions of the weighted average method are more interesting when the planned scenario is considered (6184 against 6236 in FCCP), they become irrelevant and generate more additional costs compared to the FCCP when the worst scenario is considered (– 0.4% against – 1.4 in FCCP%).

To develop more decisive conclusions about both methods, we propose a multi-criteria analysis method known as TOPIS (Technique for Order of Preference by Similarity to Ideal Solution). It was developed by Ching-Lai and Kwangsun (1981) to compare a set of alternatives based on a pre-specified criterion. It can be defined as a sort method to approximate the ideal solution based on the similarity degrees of finite evaluation objects and idealized criteria (Wang and Duan 2018). More details about the TOPSIS algorithm could be found in Bulgurcu (2012). To develop the data matrix in Table 9, we consider FCCP and the weighted average method as an alternative set. For the criterion set, we consider measures derived from our experimental results such as total costs in planned and worst solutions, the gap between the worst solutions in deterministic and fuzzy situations, and the total filling rate of warehouses in the worst-case scenario. Then, each criterion is normalized to be between 0 and 1 according to an appropriate formula as demonstrated in Table 10. Next, different weights should be given for each of those criteria based on decision-maker experience, so that the total of weights must be equal to 1 and the weighted normalized matrix in Table 11 is formed by multiplying each value by their weights. We consider that the weights of all criteria are equal to 0.25. After that, we compute the distance between the target alternative and the best/worst alternative according to the euclidean distance. Finally, the ranking of the fuzzy methods (alternatives) according to their performance index value is obtained. From Table 12, looking to the higher performance index value of the FCCP, we can further confirm that it is the best performance alternative compared to the average weighted method to be used to solve possibilistic linear programming problems.

To conclude, we can affirm that the FCCP approach confirmed its ability to absorb more risk compared with the weighted average method and consequently, its effectiveness to deal with fuzzy optimization. In general, the consideration of uncertainty has been proven by both methods to enable better handling of unplanned changes with a more stable and advantageous solution compared to the deterministic case. Notably, when dealing with bad situations and adopting a more realistic attitude (high necessity and possibility degree) to avoid considerable losses.

6 Conclusion and future work

Logistics management is essential for the proper functioning of healthcare organizations to meet the efficiency and effectiveness required by the hospitals. In this study, a horizontal collaborative strategy within territorial hospital groups was proposed. The objective is to demonstrate the performance of the pooling strategy and to propose an optimal scenario for the allocation of products to improve economically the hospital supply chain by reducing costs (order cost, transport cost, inventory keeping cost, and FTE costs) and increasing revenue. Therefore, a multi-supplier,

Table 10 Normalized matrix

	Cost PS	Cost WS	GAP	Filling rate
FCCP	0.7101	0.7043	0.9247	0.6890
Weighted average	0.7041	0.7099	0.3363	0.7247

Table 11 Weighted normalized matrix

	Cost PS	Cost WS	GAP	Filling rate
FCCP	0.1775	0.1761	0.2354	0.1723
Weighted average	0.1760	0.1775	0.0841	0.1812

Table 12 Performance indexes

	C^*	Rank
FCCP	0.990	1
Weighted average	0.009	2

multi-warehouse, and multi-product linear programming model is developed to organize product pooling within care units. A set of several instances, inspired from a real THG database, are randomly generated and experiments have been done on both pre-pooling and pooling scenarios. However, due to the unavailability and incompleteness of data in real-world situations, various additional costs could be incurred when an unexpected change occurs. To deal with such a situation, a fuzzy chance-constrained programming approach with uncertain demand is developed to provide risk-averse and robust solutions to the decision-maker. The robustness of the model was evaluated for the deterministic and fuzzy configurations by comparing the weighted average method using the TOPSIS method. According to the obtained results, the pooling strategy could be beneficial and involve cost saving even when dealing with fuzzy demand and unexpected events.

This work could be extended to several future studies. First, other large-scale instances could be generated and tested. Then, a multi-period optimization model could be proposed as an extension to deal with operational decisions in the supply chain. Later on, dealing with a multi-objective supply chain problem could be a good idea to incorporate other different aspects of sustainability such as environmental and social objectives in the context of horizontal collaboration.

Appendix

To compare the FCCP method with the weighted average method, the pattern of symmetric triangular distribution representation is implemented to demonstrate the fuzzy demands in constraints. The main reason to employ triangular fuzzy number in this study is that it represents a good trade-off between expressiveness, simplicity, and flexibility of the fuzzy arithmetic operations (Dubois et al. 2004). The weighted average method is applied to convert $\tilde{d}_{p,c}$ into a crisp number using the most and least possible values. Following the thresholds of possibility and necessity used in FCCP, a minimum acceptable membership level, γ, could be given by the decision maker according to his / her attitude towards risk. Therefore, the corresponding auxiliary crisp inequality of the triangular fuzzy demand can be expressed as follows:

$$\tilde{d}_{p,c} = w1\underline{d^{\gamma}_{p,c}} + w2\hat{d}^{\hat{\gamma}}_{p,c} + w3\overline{d^{\gamma}_{p,c}} \tag{22}$$

where $w1 + w2 + w3 = 1$, $w1$, $w2$ and $w3$ represent the weights of the most pessimistic, most likely and most optimistic attributes, respectively. However, according to the knowledge and the experience of decision makers, the weights of $\underline{d_{p,c}}$, $\hat{d}_{p,c}$, $\overline{d_{p,c}}$ can be modified subjectively and adapted to different real-world situations based to the definition below:

- $w1 = \frac{1-\gamma}{2}$
- $w2 = \frac{1}{2}$
- $w3 = \frac{\gamma}{2}$

In several relevant studies (Wang and Liang 2004; Liang 2006; Paksoy et al. 2012; Pourjavad and Mayorga 2019), authors usually used a minimum acceptable membership level for all the fuzzy constraints and applied the concept of the most possible values for the deffuzification of their models. The reason of defining the above weighted average values is that the most possible values are generally the most important ones, thus, a larger weights values should be assigned (Liang 2006). Besides $\overline{d_{p,c}}$ and $\underline{d_{p,c}}$ represent the boundary solution of the fuzzy demand for each care unit since they are the too pessimistic and too optimistic values, then smaller weights can be often considered. Consequently, changes to the values of γ affect the values of the critical weights and the solution generated. Hence, the corresponding auxiliary crisp inequality expression of constraints 9 can be presented using the weighted average method, as following;

$$\sum_{c\in C} y_{p,w,c} \geq \frac{1}{2}[(1-\gamma)\underline{d_{p,c}} + \hat{d_{p,c}} + \gamma\overline{d_{p,c}}] \quad \forall w \in W, p \in P \tag{23}$$

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