

## Supply chain network design for the diffusion of a new product

G. Dello Stritto<sup>1</sup>, D. Falsini<sup>2\*</sup>, M. M. Schiraldi<sup>1</sup>

<sup>1</sup>Department of Enterprise Engineering, "Tor Vergata" University of Rome, ITALY

<sup>2</sup>Operations Management Team Srl, Rome, ITALY

\*Corresponding Author: e-mail: [diego.falsini@omteam.it](mailto:diego.falsini@omteam.it), Tel +39-328-4585264, Fax +39-06-72597164

### Abstract

Supply Chain Network Design (SCND) deals with the determination of the physical configuration and infrastructures of the supply chain. Specifically, facility location is one of the most critical decisions: transportation, inventory and information sharing decisions can be readily re-optimized in response to changes in the context, while facility location is often fixed and difficult to change even in the medium term. On top of this, when designing a supply network to support a new product diffusion (NPD), the problem becomes both dynamic and stochastic. While literature concentrated on approaching SCND for NPD separately coping with dynamic and stochastic issues, we propose an integrated optimisation model, which allows warehouse positioning decisions in concert with the demand dynamics during the diffusion stage of an innovative product/service. A stochastic dynamic model, which integrates a Stochastic Bass Model (SBM) in order to better describe and capture demand dynamics, is presented. A myopic policy is elaborated in order to solve and validate on the data of a real case of SCND with 1,400 potential market points and 28 alternatives for logistics platforms.

**Keywords:** Supply Chain Network Design, Facility Location, New Product Diffusion, Stochastic Dynamic Model

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### 1. Introduction

Customer satisfaction, globalization and high competition make Supply Chain Management (SCM) a key point to achieve a stable competitive advantage. Effective planning, execution, control and optimization of material and information flows over the entire supply network – from suppliers to customers – are crucial to guarantee the maximum service level at the minimum cost.

Synergies between marketing and SCM have been widely acknowledged (e.g. Ellinger, 2000; Martin & Grbac, 2003; Svensson, 2002), leading some authors to conclude that a better coordination could probably bring competitive superiority in new ways (Piercy, 2002). Moreover, a significant number of managers recently started to adopt marketing models, in order to reach more rational and holistic decisions (Lafnéz, Reklaitis, & Puigjaner, 2010).

Indeed, supply chain design requires taking into account distribution of customers within a certain area and their growth over the years, while marketing decision-making process requires keeping into account logistic constraints to increase the firm competitive advantage. When a product is in the maturity phase of its life cycle, customer demand can be described using a Normal probability distribution and customer locations can be assumed as given. On the other hand, when focusing on the launch period, there is no clear consensus in determining both these two variables: hence, market demand cannot be easily forecasted. In this scenario, integration between Supply Chain Network Design (SCND) models and Market and Marketing dynamics models is required to take the right decision.

Different studies aimed to improve estimation techniques, forecasting ability and model specification, in order to capture the essence of reality; the goal is to enhance understanding of demand phenomenon, which is a matter of substantial interest for a firm manager (Bass, 2004). If *diffusion* can be defined as “the spread of a cultural or technological practice or innovation from one region or people to another, either by trade or conquest”, the New Product Diffusion (NPD) theory deals with the demand evolution during the life cycle of a new product/service. Used as a forecasting tool, a NPD model traditionally describes the

successive increases in the number of adopters, in the same way it forecasts “the process by which an innovation is communicated over time among the members of a social system” (Rogers, 1995).

NPD models, to forecast the first-purchase sales in a life cycle curve, make some assumptions, i.e. that each customer buys a single item, and that there are no repeated sales to the same buyer. Under these assumptions, the adopters number is equally to the unit sold in a given time period for a given product (Mahajan, Muller, & Bass, 1990). Mahajan et al. (1990) also provide a literature review and some research directions, focused on the contributions of management and marketing science to the cumulative understanding of innovation diffusion dynamics. Recently, Peres et al. (2010) updated this survey, reviewing the diffusion modelling literature starting from the early 90's and analysing how diffusion research has broadened its scope to describe the richness and phenomena related to new product growth.

The Bass model (BM) has been long considered the standard model for analysing and forecasting the market penetration of new products; it represents the forerunner for this field, trying to make models “theoretically more sound and practically more effective and realistic” (Mahajan, 1990). Lilien, Rangaswamy and Van den Bulte (2000), and Bass, Gordon, Ferguson and Githens (2001) evidenced the challenges in using the Bass framework to forecast sales and adoption rate in real context. For instance, NPD modelling efforts targeted telecommunications, services and pharmaceuticals industries (Peres, Muller, & Mahajan, 2010). Specifically the BM and its revised forms have been used for forecasting innovation diffusion in retail service, industrial technology, agricultural, educational, pharmaceutical, and consumer durable goods markets. Representative companies that used this model include Eastman Kodak, RCA, IBM, Sears and AT&T (Mahajan, Muller, & Bass, 1990). Other researchers in management science contributed to the development of NPD theory, suggesting analytical models to describe and forecast the diffusion of an innovation in a social system. Although Mahajan and Wind (1986) or Kalish and Lilien (1986) pointed out that sales forecasting is the main goal of a NPD model, they appear to be better applications for descriptive and normative purposes (Mahajan, Muller, & Bass, 1990). In fact, NPD models were applied for testing different hypotheses/problems: impact of perceived product attributes (Rao, 1988), life-cycle dynamics of a new product (Bass, 1980; Olshavsky, 1980), finding the pricing strategy that maximizes the firm discounted net profit (Kalish, 1986). Since 1970, modelling evolution increased the flexibility and accuracy of existing models giving the researchers the possibility to apply these models to solve various Supply Chain Management (SCM) and Operations Management (OM) issues.

A NPD model that takes into account operations constraints can be very useful in analysing, for instance, the growth of a new product market share under constrained production capacity hypothesis (Jain, Mahajan, & Muller, 1991; Ho, Savin, & Terwiesch, 2002) or trade-offs between having a cap on the serviceable demand and investing to increase SC capacity (Láinez, Reklaitis, & Puigjaner, 2010). Moreover, it should be noted that marketing policies and market dynamics have both a great impact on SCM decisions. Indeed, the nowadays requirement of enterprise competitiveness stresses the importance of strategic choices in the SCM and OM, such as inventory control decisions, just-in-time solutions, information flow management, partner selection and SC network design. Understanding interactions between supply and demand is one possible way to allow SC to be quick in self-adapting to market changes, which leads to a sustainable competitive advantage (Lee, 2004). Some opportunities to integrate operational decisions with marketing researches have been carried out, addressing some actual issues such as manufacturer's production planning (Ho T-H, 2002), global facility localization (Canel & Das, 2002), inventory positioning (Li & Amini, 2011) and strategic safety stock placement (Graves & Willems, 2005).

Although recent literature demonstrates the benefits deriving from this kind of integration, from both Marketing and SCM side, there seems to be no contributions that specifically focus on SCND issues. The problem of designing the supply chain for the diffusion of a new product is characterized by both dynamicity – the decision about locating facilities must be made at the beginning of each time period and its impact must be evaluated for the entire remaining planning horizon – and stochasticity – the number and location of customers are uncertain. More specifically, high costs are usually associated with property acquisition and facility construction; thus, facility location/relocation becomes a strategic decision that has a long-lasting effect on the firm. As a consequence, a multi-period (dynamic) approach should be used in order to take into account the impact of decisions over all the planning horizon and to allow to reevaluate an eventually redesign the supply chain, following up changes in demand patterns, product mix, production processes, sourcing strategies, cost of running facilities, etc.. Decision makers should select locations that will not only perform adequately according to the current system state, but also will continue to be profitable for all the product/supply chain life-cycle. For this reason, static models presented in literature and useful to locate facilities in a single time period, are not able to capture many of the characteristics of real-world location problems.

Besides, since the future business environment under which a supply chain will operate is generally unknown, an effective SCND should consider plausible future scenarios: under stochastic assumptions, these scenarios are shaped by the random variables associated to business-as-usual factors such as raw material prices, energy costs, product-market demands, labour costs, finished product prices, exchange rates, etc.. This consideration leads to exclude deterministic models from the set of useful approaches to describe the analysed problem, as well as those facility location models that separately cope with dynamic and stochastic issues, without integrating both aspects. Indeed, despite of the large amount of papers focussed on facility location, very few papers approach dynamicity and stochasticity issues together. Specifically, there seems not to be contributions that present a facility location model for the design of supply chains with a stochastic expanding demand.

The objective of the present work is to present a mathematical model for designing a supply chain network during the diffusion period of an innovative product/service, just knowing the stochastic process, which describes demand and potential warehouse /

customer locations. A stochastic dynamic model is presented in order to incorporate both dynamic and stochastic issues of facility location. Specifically, the integration of a Stochastic Bass Model (SBM) is proposed in order to better describe and capture demand dynamics. A myopic policy is presented in order to solve and validate on the data of a real industrial case.

## 2. Literature review

From a Marketing perspective, works of interest are mainly the ones that analyse how to incorporate SC dynamics into NPD: some papers (Ho, Savin, & Terwiesch, 2002; Jain, Mahajan, & Muller, 1991) suggest a joint analysis of demand and sales dynamics under the presence of supply restrictions (e.g. backordering and customer losses). Jain et al. (1991) investigate the influence of supply restrictions on the growth of a new product (i.e. delay of the diffusion process) for the unavailability of the product due to the production capacity or distribution system limitations. An upgrade of this work is provided by Ho et al. (2002), which highlight how operations/SCM literature usually consider the demand process as given in order to plan capacity, while in marketing literature NPD models are usually assumed not capacity-constrained. The two aforementioned papers modify BM in order to forecast demand but not for the design of optimal manufacturing policies. This is the purpose of the work by Kumar and Swaminathan (2003): they introduce a change in the original Bass framework for modelling the interactions between manufacturing and marketing/sales decisions in monopolistic firms, which sell an innovative product and have a fixed production capacity. The last attempt to consider SC issues in marketing activities is that of Laínez et al. (2010), who develop a holistic mixed integer nonlinear programming model, which optimizes in tandem the SC and marketing strategic decisions to maximize the corporate value. Other important contributions are those of Graves and Willems (2000, 2003, 2005): they examine a SC configuration for a new product, where the multi-echelon network design is already decided and a supply policy has to be set up at each stage of the firm in order to determine the safety stock placement and the sourcing decisions. According to Amini and Li (2011) the aforementioned model is limited because does not take into account the demand evolution during the new product diffusion period. For this reason they assume a demand pattern, endogenously determined, analysing some decisions regarding the placement of safety stock in the SC networks to meet a certain service level. Recently Amini and Li (2011) apply the modified BM, provided by Kumar and Swaminathan, to offer a decision support tool for simultaneously optimizing an innovator's production planning in a multi-period setting and SC configuration. An interesting multi-sourcing version and industrial application of the aforementioned model is provided again by Li and Amini (2011) to configure robust/resilient SCs against possible ubiquitous supply disruptions during the new product life cycle. The most recent work by Amini et al. (2012) comes back to the marketing field, focussing on the problem of supply and demand processes and highlighting two industrial cases: Bandai Tamagotchi and Sony Playstation III. Canel and Das (2002) underline the most important factors that influence decisions on investing abroad and choosing foreign manufacturing locations for a global SC network. Specifically they present a mathematical model that integrates marketing and manufacturing decisions in a global context, determining the country where to locate it, the quantity to produce and which customers of the global market has to serve, for each facility.

The work by Rosenthal et al. (1978) is the first one to analyse a Stochastic Dynamic Location problem. The authors distinguish between new facilities, considered as servers (e.g. ambulance, warehouse, lift truck) and existing facilities, thought as customers (e.g. accident victim, market area, movement requirement). The problem is to locate/relocate servers, considering that relocations of customers are stochastic and described by a stationary Markov chain. The problem is modelled as an infinite-horizon Markov decision chain and solved through a policy iteration procedure. Later, the problem of relocating servers is approached and generalized by Berman and Odoni (1982). Specifically, they investigate the p-median problem, in the case in which the cost of relocating facilities on the network – and the relative decision – depends on changes in the state of the network (e.g. changes in travel times due to the occurrence of probabilistic events). Analogously to the previous analysed case, transition among network states is described by an ergodic Markovian transition matrix. The authors provide a heuristic approach and bounds calculation. An efficient heuristic for the multi-facility multi-state version of the problem is proposed by Berman and LeBlanc (1984). This procedure executes local exchanges within and between the identified scenarios, in order to identify the optimal location of servers. Implicitly dynamic location models that consider random travel times include Mirchandani and Odoni (1979), Weaver and Church (1983), and Louveaux (1986). Carson and Batta (1990). Another dynamic stochastic facility location problem was studied by Jornsten and Bjorndal (1994), who choose where and when to locate facilities over time to minimize the expected time-discounted cost; production and distribution costs are random. Their algorithm uses scenario aggregation and an augmented Lagrangian approach. With the aim of investigating other stochastic aspects of dynamic facility location problem, Current et al. (1997) study the p-median problem when the number of facilities to be located is uncertain, calling this particular problem Number Of Facilities Uncertain (NOFUN). The problem is analysed using the minimization of expected opportunity loss and the minimization of maximum regret. Vairaktarakis and Kouvelis (1999) similarly consider 1-medians on a tree, but in their problem edge lengths and node weights may be linear over time (i.e., not stochastic but deterministic and dynamic) or random and scenario based. They trace the path of the solution over time (in the dynamic case) and present low-order polynomial algorithms for both cases.

Moving from network problems to mixed-integer programming ones, we find the work by Romauch and Hartl (2005) on the Stochastic Dynamic Facility Location Problem (SDFLP). The problem is to make the optimal decisions for production, inventory and transportation, in order to serve customers in a certain planning time horizon. The objective of the problem is to identify a

strategy that minimizes the expected total costs (i.e. opening, transportation, inventory holding, production and shortage costs). The authors modelled the problem through Stochastic Dynamic Programming and proposed a Monte Carlo based heuristic, derived from the Sample Average Approximation (SAA) method, in order to solve larger instances.

In the same year, Aghezzaf (2005) considers capacity planning and warehouse location decisions together. Specifically, he considers the multi-period strategic capacity planning and warehouse location problem with uncertain and unpredictable demands. The problem is to decide, for each period, the capacity to be installed in the plants and the warehouse location to be selected, with the objective of minimizing total capacity investment and operating costs, while satisfying customer demands. Aghezzaf presents a robust optimization model and uses a Lagrangian relaxation method to determine solutions. Upper bounds and lower bounds are calculated by developing a linear program, based on the Lagrangian decomposition, and by solving the Lagrangian dual, respectively.

Recently, Klibi et al. (2008) investigates the Stochastic Multi-Period Location-Transportation Problem (SMLTP), that integrates facility location, customer allocation and transportation decisions. The problem is characterized by multiple transportation options, multiple demand periods and a stochastic stationary demand. The problem is formulated as a stochastic program with recourse and is solved by using a hierarchical heuristic solution approach, which is constituted by a Tabu Search procedure, an approximate route length formula and a modified Clark and Wright procedure.

To our best knowledge, there seems to be no works that present a facility location model for the design of supply chains with a stochastic expanding demand. In addition, the few stochastic dynamic models developed in literature are very complex and hard to apply in real industrial environment: provided solutions usually regard simplified versions of the problem or small instances. In addition, warehouses localization strategies seem to have never been studied in the context of supply chain design for NPD. Thus, the main objective of this paper is to develop an integrated optimisation model, which allows warehouse positioning decisions in concert with the demand dynamics during the new product diffusion process throughout its life cycle.

### 3. Solving the problem

**3.1 Problem description and model formulation:** This work concerns the problem of integrating location of warehouses within the considered area and allocation of customers to warehouses, in order to minimize overall logistics costs and satisfy customer demand. Warehouse location and customer allocation concern the selection of a sub-set of a given set  $W$  of eligible facilities/warehouses and their assignment of a subset of customers that are foreseen to require the product in the considered period.

We consider a business planning time horizon, divided into  $T$  time periods with same length (e.g. one year). At the beginning of each period, a new set of aforementioned decisions has to be made, dealing with the foreseen changes in customer demand. More specifically, for each time period we have to decide which facilities to open, which ones to close and which ones to keep closed / opened. In particular, the following variables are interested:

$$w_i^{(t)} = \begin{cases} 1 & \text{if warehouse } i \text{ is operating in period } t \\ 0 & \text{otherwise} \end{cases} \quad (1.)$$

$$o_i^{(t)} = \begin{cases} 1 & \text{if warehouse } i \text{ is open in period } t \\ 0 & \text{otherwise} \end{cases} \quad (2.)$$

$$c_i^{(t)} = \begin{cases} 1 & \text{if warehouse } i \text{ is closed in period } t \\ 0 & \text{otherwise} \end{cases} \quad (3.)$$

The decision about the location of facilities determines a portion of the objective function, regarding opening/closing costs. In particular, we consider fixed costs  $O_i^{(t)}$  and  $C_i^{(t)}$  occurring respectively if facility  $i$  is open or closed in period  $t$ . As for the Dynamic Uncapacitated Facility Location Problem or simply DUFLP (Van Roy & Erlenkotter, 1982; Klose & Drexler, 2005), we do not take facility capacity constraint into account: we assume that considered facilities have adequate space and can be rightly considered with infinite capacity if compared with quantities to deliver. This assumption is particularly reasonable in the case of third party warehouses.

In addition, during the time period  $t$ , the subset  $N^{(t)}$  of potential customers enters the market and has to be served, together with customers already in the system. We assume to allocate all customers in the system, denoted by the subset  $D^{(t)}$ , in one period with a single decision: from a cost perspective, this assumption is reasonable and equivalent to allocate customers step-by-step during the time period. We assume that the diffusion of the new product follows the Stochastic Bass Model formulated by Niu (2002).

The binary variable  $x_{ij}^{(t)}$  represents the allocation of facility  $i$  to customer  $j$  and is defined as follows:

$$x_{ij}^{(t)} = \begin{cases} 1 & \text{if warehouse } i \text{ is assigned to customer } j \text{ in period } t \\ 0 & \text{otherwise} \end{cases} \quad (4.)$$

Analogously to the work by Gaur and Fisher (2004) in a similar context, we assume that there is a single homogeneous product with deterministic but time-varying weekly demand for each customer. In particular, a classic BM (Bass, 1969) is considered for the evolution of single customer demand, starting at the time period in which the customer adopts the product.  $Q$  denotes the vector of demands over the time horizon and is assumed to be the same for each customer. Since customers enter the system in different period, we need additional variables to describe this phenomenon: integer variables  $q_i^{(t)}$  and  $y_i^{(t)}$  denote total demand of customer  $j$  in period  $t$  and the number of years passed after customer  $j$  enters the system.

In order to take into account the overall logistics cost of our supply chain, we incorporate into the model inventory and transportation costs, as proposed by Shen and Qi (2007). In particular, we assume a simple Economic Order Quantity (EOQ) model (Harris, 1913; Wilson, 1934) for facility inventory management. Thus, if  $n$  and  $h$  are the number of shipments per year from the supplier and the annual inventory holding cost per unit respectively, we can express the inventory costs occurred at the facility  $i$  in period  $t$  as follows:

$$\sum_{i \in I} \sum_{j \in J} x_{ij}^{(t)} q_j^{(t)} \frac{h}{2n}. \quad (5.)$$

Besides, a transportation cost  $l_{ij}^{(t)}$  is taken into account for time period  $t$  in which customer  $j$  is allocated to facility  $i$ . This cost is calculated on the base of the total number  $f$  of shipments to each customer per year, as follows:

$$l_{ij}^{(t)} = f \cdot d_{ij} \cdot l_u \quad (6.)$$

where  $d_{ij}$  is the distance from facility  $i$  to customer  $j$  and  $l_u$  is the cost for each kilometre of distance. When the customer allocation is decided, the effective space required in each facility is automatically determined. The variable  $u_i^{(t)}$  denotes the space allocated in facility  $i$  in period  $t$ .

**3.2 Solution approach:** We assume that a demand forecasting is available only for the current time period and is the only information we have to locate facilities at the beginning of this period. This can be considered a myopic policy. After a location is decided, customers are allocated as for the main problem.

This approach is equivalent to solve the following Linear Programming model for each time period  $t$ :

$$v(MP) = \min \sum_{i \in I} [O_i^{(t)} o_i^{(t)} + C_i^{(t)} c_i^{(t)} + \sum_{j \in J} x_{ij}^{(t)} l_{ij}^{(t)}] \quad (7.)$$

$$s. t. \sum_{i \in I} x_{ij}^{(t)} = 1 \quad \forall j \in D^{(t)} \quad (8.)$$

$$x_{ij}^{(t)} \leq w_i^{(t)} \quad \forall i \in I \quad (9.)$$

$$w_i^{(t)} \leq w_i^{(t-1)} + o_i^{(t)} \quad \forall i \in I \quad (10.)$$

$$w_i^{(t)} \geq w_i^{(t-1)} - c_i^{(t)} \quad \forall i \in I \quad (11.)$$

$$w_i^{(t)}, o_i^{(t)}, c_i^{(t)} \in \{0, 1\} \quad \forall i \in I \quad (12.)$$

$$x_{ij}^{(t)} \in \{0, 1\} \quad \forall i \in I, j \in J \quad (13.)$$

There seems not to be advices in literature on how evaluate the solution approach goodness for SC design in NPD. For this reason, a Lower Bound (LB) is calculated and the distance from the proposed solution is computed. The basic idea of LB calculation is the improvement of current decisions through the knowledge of the future: if we could know demand realization over the whole planning horizon, we would manage to optimally determine the facility location for all time periods.

If demand scenarios are known at the beginning of the first time period, the design of the supply chain is equivalent to a multi-period single-stage facility location/allocation problem. Specifically, the Integer Linear Programming model to solve is:

$$v(LB) = \min \sum_{t \in T} \sum_{i \in I} [O_i^{(t)} o_i^{(t)} + C_i^{(t)} c_i^{(t)} + \sum_{j \in J} x_{ij}^{(t)} l_{ij}^{(t)}] \quad (14.)$$

$$s. t. \sum_{i \in I} x_{ij}^{(t)} = 1 \quad \forall j \in D^{(t)}, \forall t \in T \quad (15.)$$

$$x_{ij}^{(t)} \leq w_i^{(t)} \quad \forall i \in I, \forall t \in T \quad (16.)$$

$$w_i^{(t)} \leq w_i^{(t-1)} + o_i^{(t)} \quad \forall i \in I, \forall t \in T \quad (17.)$$

$$w_i^{(t)} \geq w_i^{(t-1)} - c_i^{(t)} \quad \forall i \in I, \forall t \in T \quad (18.)$$

$$w_i^{(t)}, o_i^{(t)}, c_i^{(t)} \in \{0, 1\} \quad \forall i \in I, \forall t \in T \quad (19.)$$

$$x_{ij}^{(t)} \in \{0, 1\} \quad \forall i \in I, j \in J, \forall t \in T \quad (20.)$$

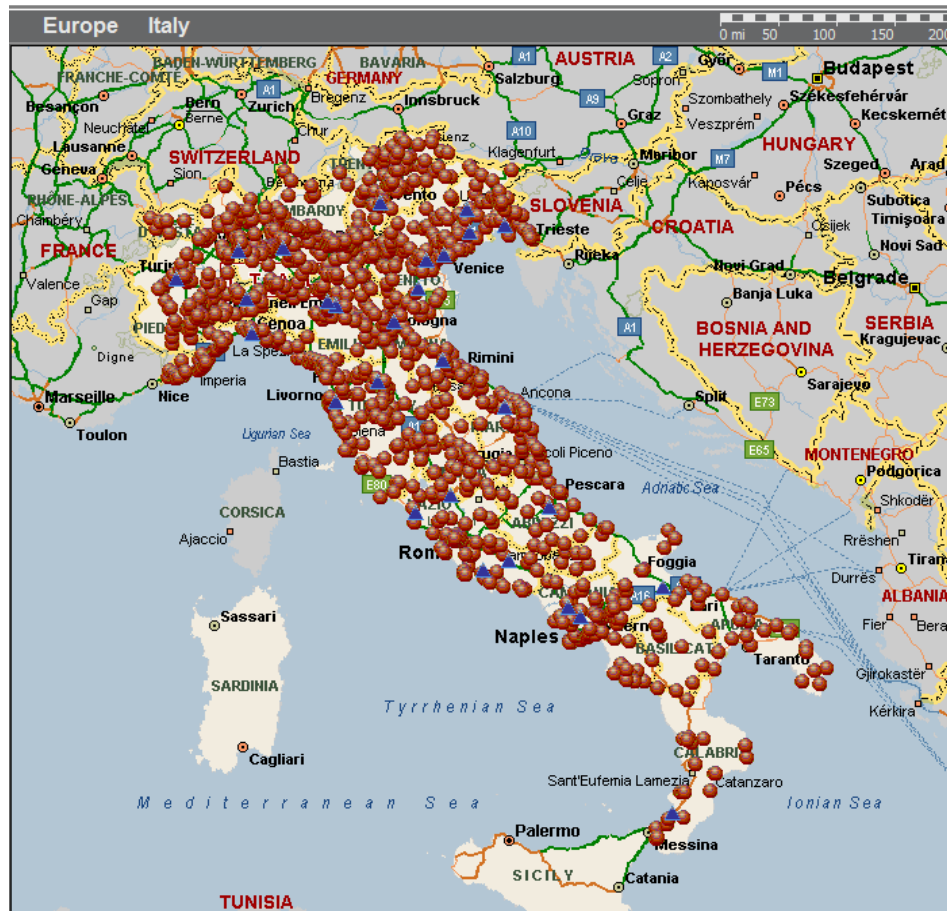
#### 4. Validation on a real case

Model validation has been conducted by applying our solution approach to the case of L.U.C.U.L.L.O. research project. The project, conceived by the Operations Research Group in the Department of Enterprise Engineering of “Tor Vergata” University of Rome, has been funded by the Italian Ministry of Economic Development. It aims at defining a new distribution format for a Made-in-Italy food and wine goods on the national and international consumer market and to develop an integrated web platform, through which better organize and manage the logistic/commercial aspects underlying the innovative distribution format.

Specifically, we focus on the food service market, where the only potential customers are the best quality restaurants in Italy. We apply our model in order to determine the optimal location of warehouses (or store) in order to satisfy restaurant demand and to reach objectives specified in L.U.C.U.L.L.O. business plan.

The analysed case concerns a new business. Thus, there is not an existing supply chain nor any related cost structure. This requires an estimation of the parameters of our problem, based on available information and the experience of supply chain specialists involved in aforementioned project. Here we provide a description of assumptions for estimating model parameters:

- *Potential customers:* we selected 1'400 Italian restaurants by referring to the major and prestigious restaurant guides available. All restaurants have been geo-localized on a map (Figure 1).
- *Potential facilities:* we selected 28 logistics platforms, able to provide the required warehousing services. As for customer, the logistic platforms were geo-localized as well.



**Figure 1.** Potential customers (red circles) and potential facilities (blue triangles) for L.U.C.U.L.L.O. project

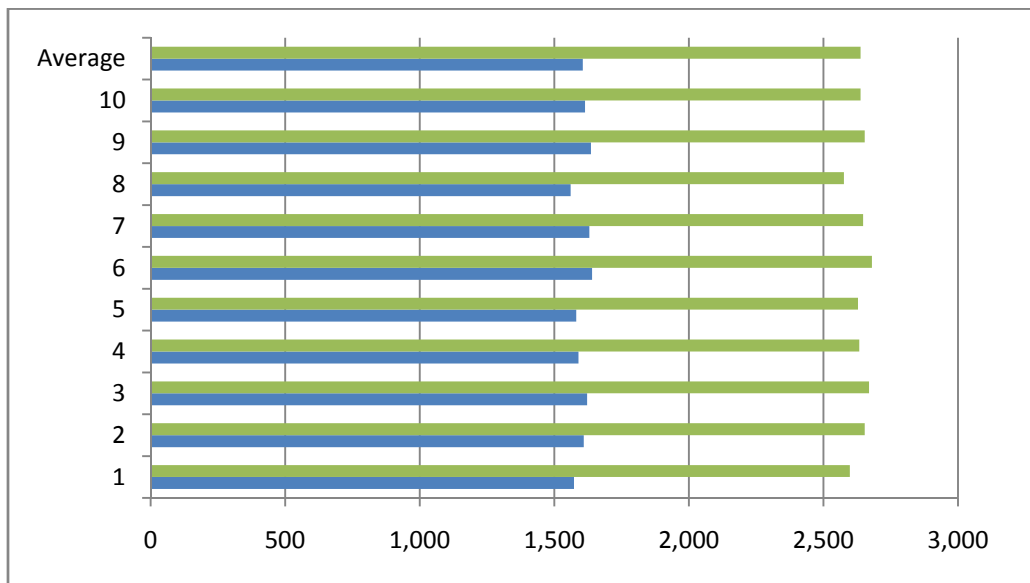
- *Demand forecasting:* referring to L.U.C.U.L.L.O. business plan, we assume an initial demand of 1,600 product units for the first year the customer enters the market. This demand increases over the planning horizon, following a classical BM, with coefficients  $p$  (external influence) and  $q$  (internal influence) respectively set to 0.03 and 0.38. This assumption is based on the average values coming from the meta-analysis of 15 different studies estimating 213 Bass models with aggregate data, presented by Sultan et al. (1990).

- *Logistics costs*: transportation cost has been calculated, by using the same assumptions proposed by Falsini et al. (2009) and equals 1.09 euro/km. The magnitude of other costs has been obtained by consulting with a local 3PL. Specifically, we consider the price for starting/ending to rent a square meter in a controlled-temperature warehouse, without scale economies.

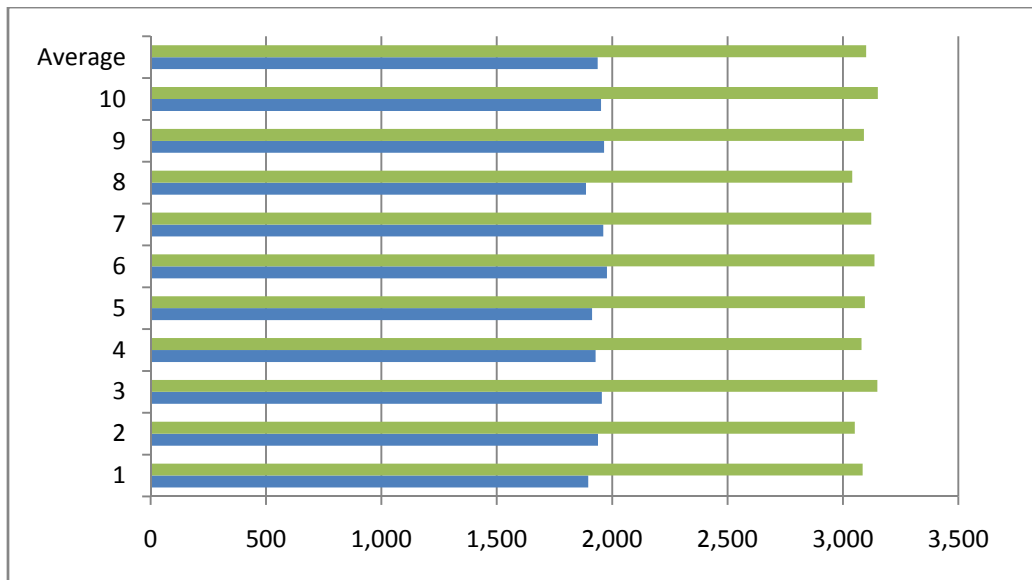
## 5. Results discussion

In order to validate the proposed solution approach, several scenarios have been generated and the LB computed. We created a set of 8 test instances by varying two main parameters, such as the opening costs ( $C$ ) and the total number of shipments to each customer ( $f$ ). Specifically, with the aim of testing the sensitivity of the proposed approach, the above-mentioned parameters  $C$  and  $f$  have been varied among an appropriate set of values, since these are the variables most likely subject to change, with a strong impact on model behaviour. We chose 4 values for the opening cost (5'000, 20'000, 50'000 e 100'000 euro per facility), in order to take into consideration cases in which other costs may occur, e.g. for employing a warehouse manager or for refurbishing a facility. Besides, we chose 2 values for the total number of shipments to each customer per year (12 and 52), by assuming both a weekly and a monthly replenishment frequency. By observing the first results, we noted that the scenarios were stable with the same set of input data. Thus, the number of scenarios was limited to 10 for each set of parameters.

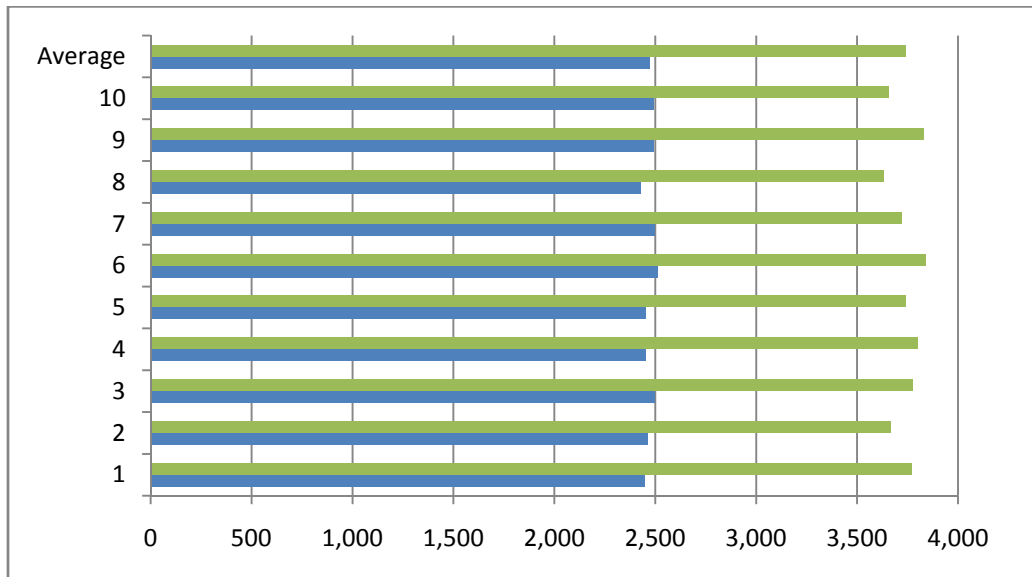
Results are shown in the following Figures 2-9 for all the 8 different parameter combination, comparing the myopic policy, MP, (green bar) to the lower bound (blue bar). The computations were performed on a Intel Core i5-460M processor laptop (2,53GHz, 3MB L3 cache) and 4 GB DDR3 memory. The average computational time for computing myopic policy and lower bound values equals to 36.5 sec. and 5 sec. respectively.



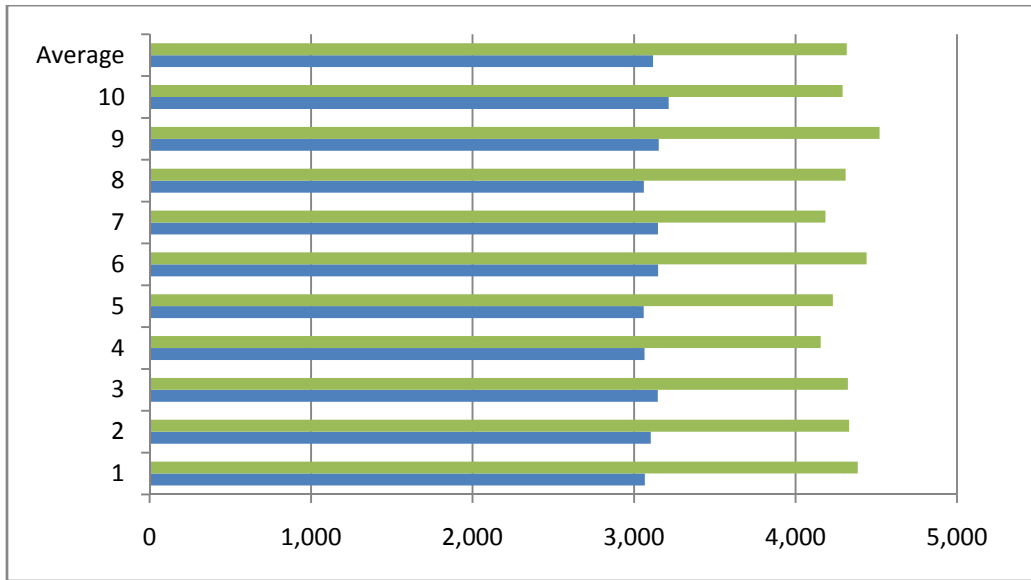
**Figure 2.** Objective function values for  $C = 5'000$  and  $f = 12$  (in thousands of euros)



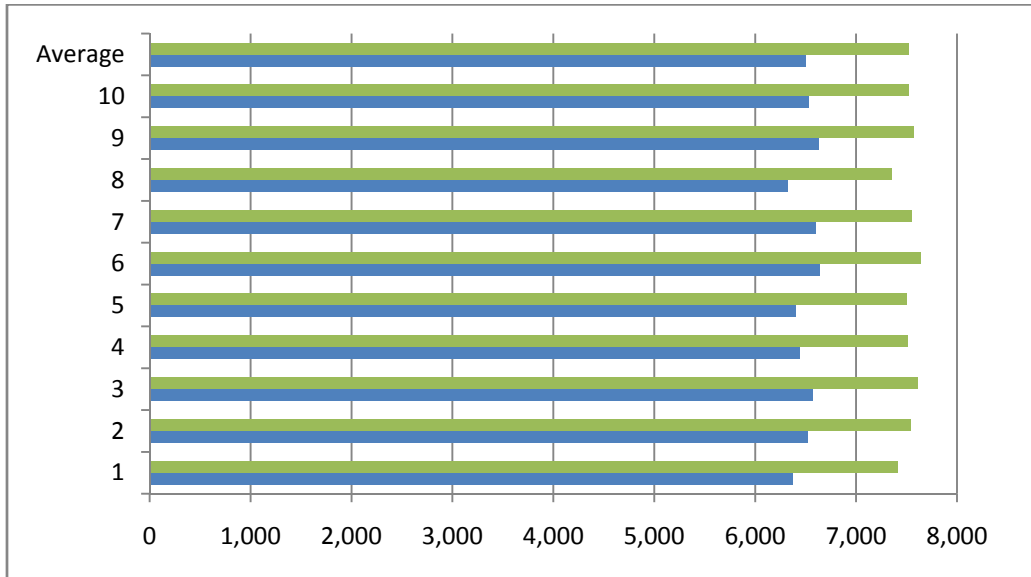
**Figure 3.**Objective function values for  $C = 20'000$  and  $f = 12$  (in thousands of euros)



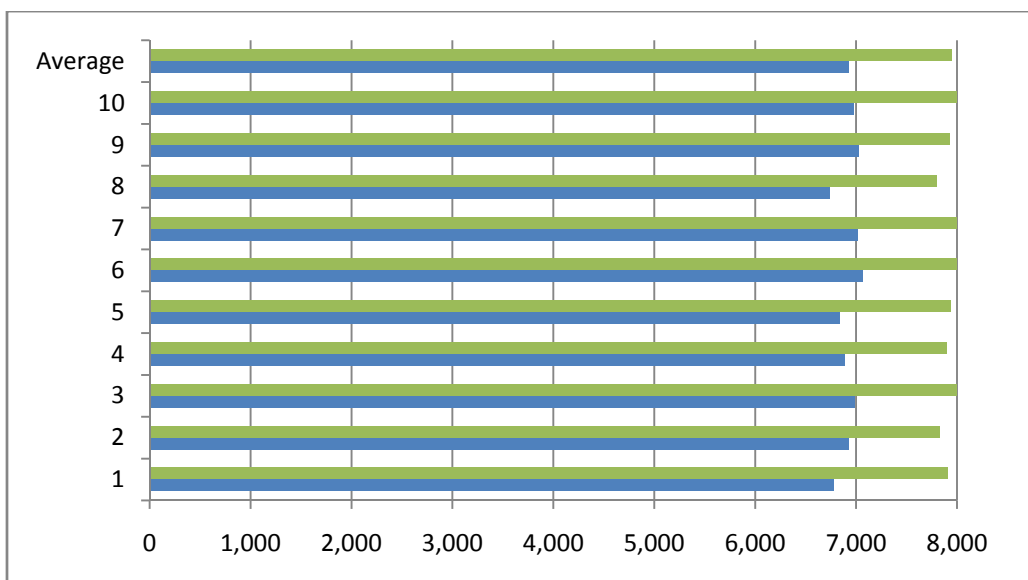
**Figure 4.**Objective function values for  $C = 50'000$  and  $f = 12$  (in thousands of euros)



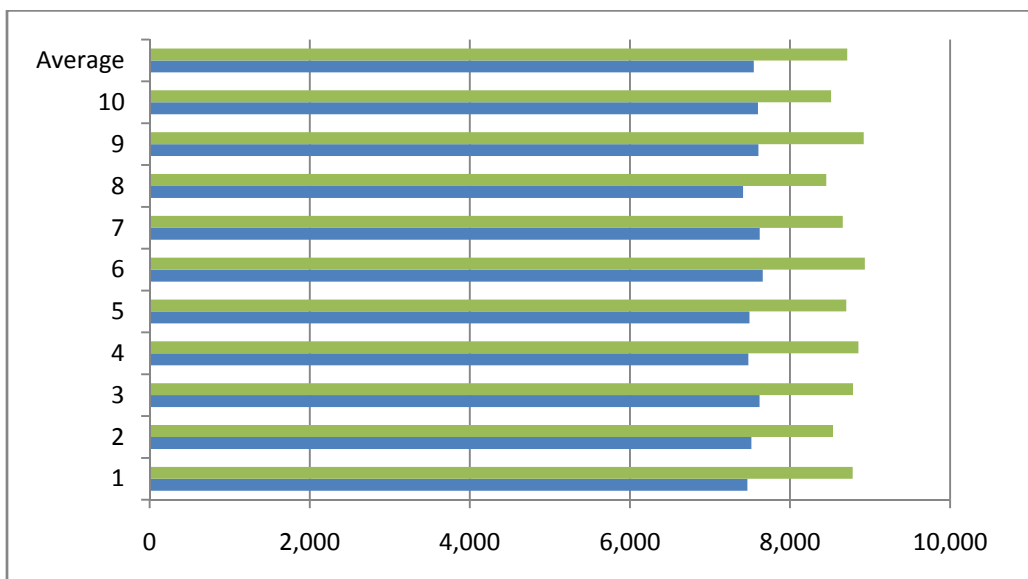
**Figure 5.** Objective function values for  $C = 100'000$  and  $f = 12$  (in thousands of euros)



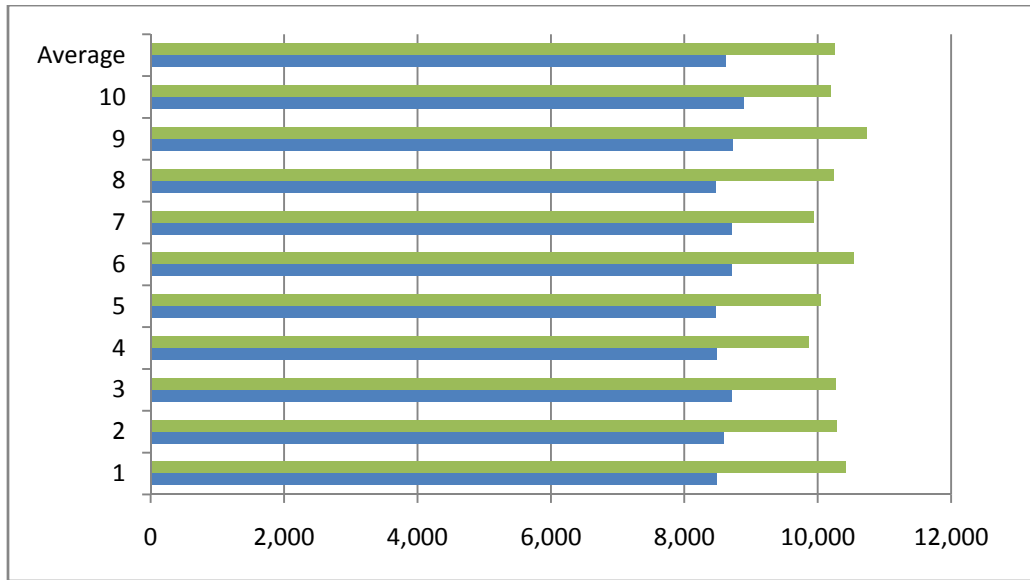
**Figure 6.** Objective function values for  $C = 5'000$  and  $f = 52$  (in thousands of euros)



**Figure 7.**Objective function values for  $C = 20'000$  and  $f = 52$  (in thousands of euros)



**Figure 8.**Objective function values for  $C = 50'000$  and  $f = 52$  (in thousands of euros)

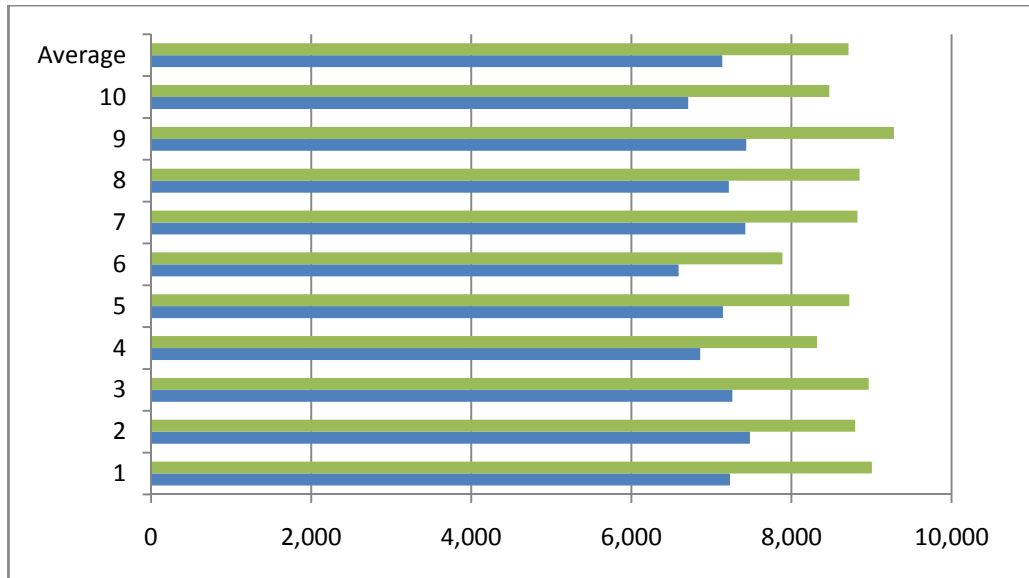


**Figure 9.**Objective function values for  $C = 100'000$  and  $f = 52$  (in thousands of euros)

Analysing the charts we noted that the average percentage difference between MP objective function value and the LB passes from 63.4% (with  $C = 5'000$ ) to 34.8% (with  $C = 100'000$ ) in the case of monthly shipments and from 15.7% (with  $C = 5'000$ ) to 17.2% ( $C = 100'000$ ) in the case of weekly shipments.

Clearly, the greater is the opening cost, the lower is the number of warehouses and the greater is the number of annual shipments, hence the better is the performance of the proposed approach. If the number of facilities to open increases, the behaviour of the two procedures is closer. In the myopic policy, demand is not known, but the stochastic diffusion model gives a good indication on the area where effective customers will be located during each time period. Intuitively, if the opening cost is high, both lower bound and the proposed solution will be configured with few warehouses, located in central positions with respect to market areas. Clearly, the lower bound solution will select the optimal location, while the proposed approach will select the same or a close location. It is noticeable that, by increasing the number of annual shipments (and consequently the transportation cost), the performances of the two approaches are much closer.

In addition, we tested the robustness of our solution approach, modifying the stochastic diffusion model. Specifically, we divided the set of potential customers into three subsets, on the basis of their location. The first subset includes all customers located in North Italy (latitude  $> 44.79663098^\circ$  N); the second one, all customers located in Central Italy ( $41.46167733^\circ$  N  $<$  latitude  $< 44.79663098^\circ$  N); the remaining one, all customers located in South Italy (latitude  $< 41.46167733^\circ$  N). We assume an initial market penetration in North Italy and no customers within the other areas. The diffusion starts in Central Italy and in South Italy, during the second and the third time period, respectively. Related results, for the case with  $C = 10'000$  and weekly shipments, are shown below in Figure 10.



**Figure 10.** Objective function values for  $C = 100'000$ ,  $f = 52$  and modified scenarios (in thousands of euros)

The proposed solution approach confirms its good performance in comparison to lower bound values. The average percentage difference between myopic policy objective function value and the lower equals 21%.

## 6. Conclusions

We focused our attention on the specific case of the SCND for the diffusion of a new product/service, where design issues become more critical. In this case, the problem is both dynamic (multi-period) and stochastic (number and location of customers are unknown). Literature showed a large amount of paper related to facility location, separately treating dynamic and stochastic aspects. We proposed an innovative solution approach in order to solve the problem of designing a supply chain by using a SBM to describe demand over the planning horizon.

For the general case, a myopic policy is proposed. Since problem and solution approach are completely innovative, no benchmarks are available in literature. This forced us to determine a LB, in order to evaluate the performance of the proposed. LB solution represents the optimal solution for the case with known demand, which is a hypothesis that should not be made dealing with real SCND problem, with uncertain future over several years.

A validation has been performed on a real case: the design of a Made-in-Italy food and wine goods distribution network. The application showed the good performance and robustness of our solution approach with respect to the LB. In some scenarios, the proposed approach provided solutions which were only the 15.7% far from the LB, and the myopic policy performed better when the cost of opening a facility is high. However, the change of shipment frequency resulted to have a strong impact on the gap with the LB solution, and this suggests to concentrate on alternative methods to determine a comparison benchmark for evaluating the performance of the proposed solution.

Concluding, we demonstrate our model and our approach are innovative in Supply Chain Management and Facility Location literature, with interesting insight even for Marketing science. Besides, we demonstrate its applicability and effectiveness in a real contest. These fundamental aspects make our work a good starting point to develop models and industrial tools to allow firms to better manage the interface between Marketing and Operations, in order to reduce costs, increase service level and pursue the competitive advantage.

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### Biographical notes

**G. Dello Stritto** is PhD candidate in Management Engineering and MBA student at "Tor Vergata" University of Rome. At the university she collaborates with the Industrial Engineering Research Group of the Enterprise Engineering Department as teaching assistant for the course of Manufacturing System Engineering and consultant for the university spin-off Operations Management Team S.r.l. Visiting Ph.D. student in Managerial Economics & Decision Science Department at Kellogg School of Management(II, USA). She is currently working on a national project dealing with the design of a new distribution structure for a food and wine supply chain. Main research topics: Supply Chain Management, Operations Management, Business Process Management.

**D. Falsini** is cofounder and managing partner at the university spin-off Operations Management Team S.r.l.. As a consultant, he collaborated with the University of Rome "Tor Vergata" and the operations consulting firm Enterprise Solutions Engineering S.r.l., within research projects at national and international level. He worked in the Logistic Department of Procter & Gamble Italia S.p.A. Ph.D in Management Engineering, MBA and Master's Degree in Management Engineering at the "Tor Vergata" University of Rome. Visiting Ph.D. Student in Operations Management at Carnegie Mellon University of Pittsburgh - Tepper School of Business. He is the co-author of fifteen international scientific publications.

**M. M. Schiraldi** is Assistant Professor in Operations Management and he teaches courses of Operations Management since 2001. He received PhD in Engineering and Management and MBA. At "Tor Vergata" University in Rome. He is the lecturer of the courses of Design of Manufacturing Systems and of the course of Production Planning & Inventory Control. Every year he teaches to more than 200 students in the Engineering School, and up to now, he supervised more than 160 students in their thesis work on top of 8 PhDs. He is the author of more than 40 international scientific publications related to Operations Management, and one book on Inventory Management.

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