ON THE OPTIMAL SAFETY STOCK LEVELS IN SUPPLY NETWORKS

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ABSTRACT
In this paper, we address the issue of defining the optimal size and distribution of safety stocks in a supply network. The determination of the appropriate safety stock level in complex and stochastic distribution systems is often a complex task, since safety stocks depend upon the production strategy adopted in response to customer demand, and can be located at different points in the supply chain. Moreover, in a multi-echelon, multi-player supply chain (i.e., a supply network), it is likely that safety stocks are interdependent among the players, and they necessitate decision-making with an integrated view of the supply chain. Our analysis is grounded on a discrete-event simulation model, reproducing a fast moving consumer goods (FMCG) supply network, and on real data related to the FMCG context. By exploiting the simulation model, we aim at optimizing the total logistics cost of the supply network as a function of the safety stock coefficient (k), thus identifying the optimal service level the network should deliver to customers.

Keywords: safety stock; supply network design; simulation model; optimization.

1. INTRODUCTION
Supply chain management is the process of integrating suppliers, manufacturers, warehouses, and retailers in the supply chain, so that goods are produced and delivered in the right quantities, and at the right time, while minimizing costs as well as satisfying customer's requirements (Cooper et al., 1997). Managing the entire supply chain is a key success factor for any business, as non-integrated manufacturing processes, non-integrated distribution processes and poor relationships with suppliers and customers inevitably lead to company failure (Chang and Makatsoris, 2001). Efficiently and effectively managing the supply chain involves different interrelated topics, namely (i) defining the supply chain (or supply network) structure, (ii) identifying the supply chain business processes and (iii) identifying the business components (Lambert, 2001). The first topic, in particular, encompasses a set of decisions concerning, among others, number of echelons required and number of facilities per echelon, reorder policy to be adopted by echelons, service level to be delivered to customers, assignment of each market region to one or more locations, and selection of suppliers for sub-assemblies, components and materials (Chopra and Meindl, 2004; Hammami et al., 2008). Moreover, different supply chain configurations react differently to the bullwhip effect, and they result in different levels of safety stocks required.

Determining the appropriate safety stock level in stochastic distribution systems is often a complex task (Inderfurth, 1991). In fact, safety stocks are determined by the production strategy adopted in response to customer demand, and can be located at different points in the supply chain (Randal and Urlich, 2001). Approaches for optimal determination of safety stocks, taking into account cost objectives and service level required to customers, are limited in literature. Moreover, in a complex multi-echelon, multi-player supply chain (i.e., a supply network), it is likely that safety stocks are interdependent among the players, and they necessitate decision-making with an integrated view of the supply chain. In a recent work, Bottani and Montanari (2011) examined the problem of stocks in supply network, as a function of the safety stock coefficient (*k*). They found that high *k* reduces the stock-out at retail stores, thus improving the service level delivered to the customer, but, at the same time, it involves longer time for a product to reach the final customer, involving the risk of product expiry. Since a trade-off exists between the availability of products at retail stores and supply chain lead time, the authors conclude that the optimal value of *k* should be defined based on a careful consideration of all these effects, as well as on the basis of the operating conditions of the network.

In this paper, we focus on this latter issue, i.e. the definition of the optimal size and distribution of safety stocks in a supply network. The study is grounded on a discrete-event simulation model, which was developed in a previous study and reproduces a FMCG supply network, and on real data related to the FMCG context. By exploiting the simulation model, we optimize the total logistics cost of the network as a function of *k*, thus identifying the optimal service level the network should deliver to customers.

The paper is organized as follows. In the next section, we describe the strategy used for simulations; in section 3, we provide the results obtained from the simulation. Section 4 provides managerial implications and conclusions.

2. METHODOLOGY

To set up this study, we start from a previous publication (Bottani and Montanari, 2011), where we developed a simulation model, under MS Excel, to examine four possible configurations of FMCG networks, and we analyzed in details the corresponding performance of such networks. Those network configurations, which are considered also in this study to derive further insights, stem from the combination of different number of echelons and of facilities per echelons, and are defined as follows:

- Configuration 1 - 3 echelons (i.e. manufacturer, first-tier distribution centers and retailer), with 2 players per echelon;
- Configuration 2 - 3 echelons, with 5 players per echelon;
- Configuration 3 - 4 echelons (i.e. manufacturer, first-tier distribution centers, second-tier distribution centers and retailer), with 2 players per echelon;
- Configuration 4 - 4 echelons, with 5 players per echelon.

The number of retail stores is set at 100 in all configurations. The final customer's demand is assumed to be a stochastic variable with normal distribution, without seasonal trends. Moreover, two reorder policies, namely economic order policy (EOQ) and economic order interval (EOI), are simulated for each network configuration. For the sake of clarity, an overview of the input data used to simulate the FMCG network is proposed in Appendix. The reader is referred to Bottani and Montanari (*in press*) for further details related to the simulation model.

By combining the number of network configurations (i.e., 4) with the reorder policies (i.e., 2), we obtain 8 simulated scenarios. Since our analysis is specifically focused on the identification of the optimal safety stock level, we considered two scenarios for the definition of the safety stocks, which correspond to as many supply chain strategies:

- scenario 1 - all supply chain echelon have the same safety stock coefficient. This corresponds to the situation where all players should deliver the same service level to their customers, and can be motivated by the fact the supply chain echelons operate on a coordinated way;
- scenario 2 - manufacturers/distributors have the same safety stock coefficient, while retailers can have a different level of safety stocks. The rationale behind the choice of allowing different values of k is that retailers may have different (higher) exigencies in terms of safety stocks; in fact, as they directly face the final customers' demand, lack of product implies loss of sale, which should be possibly avoided.

For each simulated scenario, 100 replicates were performed, to obtain significant data.

3. RESULTS

As output, we assess the optimal safety stocks coefficient (or, alternatively, the optimal couple of safety stocks coefficients), as a function of the network configuration, the reorder policy applied and the scenario considered. The "optimal" safety stocks coefficient corresponds to the numerical value of k which minimizes the total logistics cost of the network under the scenario considered.

Moreover, we computed the total cost of the network resulting under optimal conditions. For a better understanding of the results, the total cost was shared among the main cost components, i.e.:

- inventory holding cost [€/day]: it is computed starting from the amount of stock available daily at each site and the unitary cost of stocks;
- order and transport cost [€/day]: it is computed starting from the number of orders placed by each player and the unitary cost of order and transport;
- stock-out cost [€/day]: this cost is computed starting from the amount of stock-out and the unitary cost of stock-out.

The total network cost results as the sum of the above cost components.

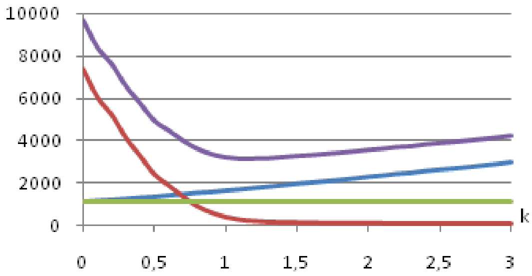
3.1. Results under scenario 1

The first set of simulations was performed by varying *k* within the range [0;3] approximately, and by computing the total network cost under EOQ and EOI policies, for all network configurations considered.

The simulation duration was set at 250 working days, corresponding to approx one year operating period of the network. Results, in terms of the optimal *k* and of the resulting (minimum) total cost, are proposed in Table 1. Detailed outcomes are graphically shown in Figure 1 (a-h).

Table 1: optimum *k* and minimum total cost under scenario 1.

Configuration	EOQ		EOI	
	minimum total cost [€/day]	k	minimum total cost [€/day]	k
1	3130.64	1.1	3853.531	0.6
2	4315.68	1.5	4039.144	0.4
3	5026.72	1.6	6257.308	0.95
4	7578.34	1.5	8337.032	0.65



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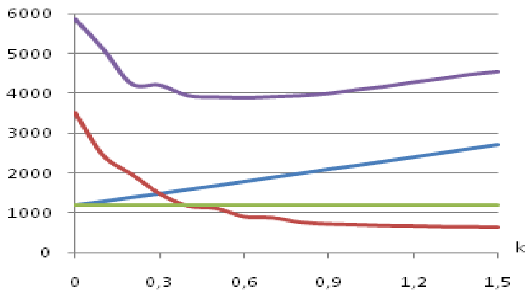

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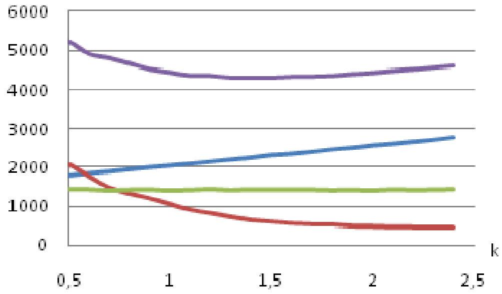

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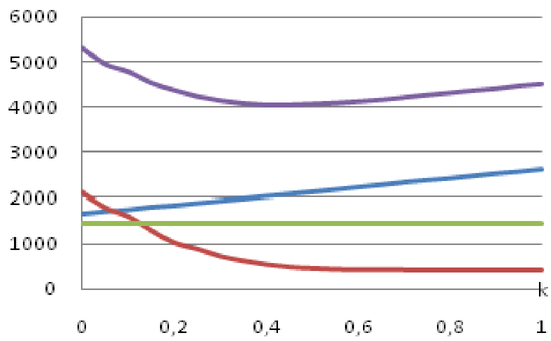

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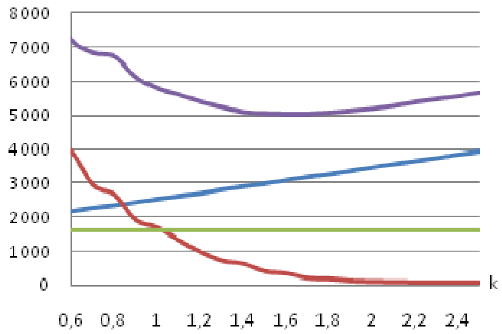

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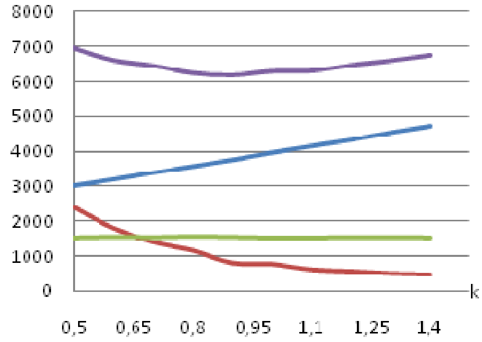

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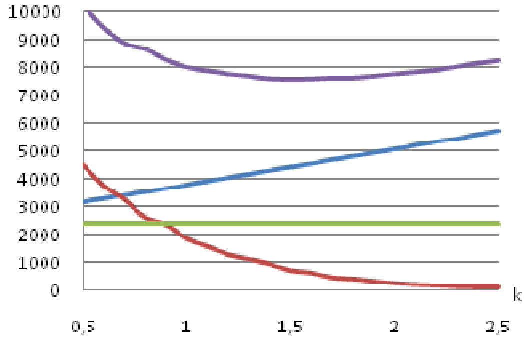

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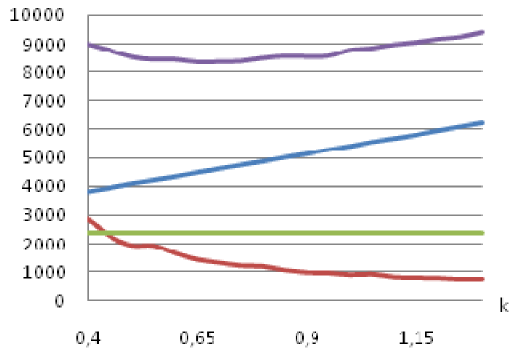


(h)

Figure 1: cost components and total cost under scenario 1, for configuration 1 with EOQ vs. EOI policy (a-b); configuration 2 with EOQ vs. EOI policy (c-d); configuration 3 with EOQ vs. EOI policy (e-f); configuration 4 with EOQ vs. EOI policy (g-h).

From Table 1 it is immediate to observe that the highest total cost is obtained under configuration 4, since both an additional echelons and additional players per echelon introduce cost in the network.

From Figure 1 it can also be appreciated that the service level *k* significantly affects the total cost of the network, and specifically:

- it increases the cost of stocks, since highest *k* means highest average stock in the network;
- it decreases the cost of stock-out, because of the greater amount of stocks available;
- it has a limited impact on the order cost.

Moreover, EOI policy often involves higher inventory cost that EOQ policy; a possible reason is that EOI policy generates a higher inventory level in the supply chain, due to the lower number of orders, with wider quantities. Consequently, the optimal *k* under EOI policy is lower than under EOQ policy.

3.2. Results under scenario 2

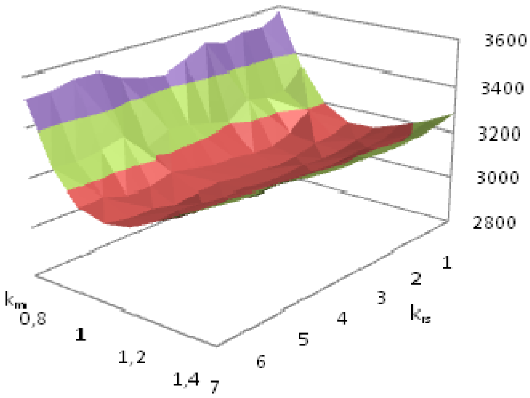
The second set of simulations was performed by allowing different values of *k* for manufacturer or distribution centers and retail stores. They are indicated as k_m for manufacturer or distribution center, and k_{rs} for retail stores.

As per the previous case, we computed the resulting total cost for different couples of k_m/k_{rs}, to identify the combination of such parameters which minimizes the total network cost. Approximately, we varied k_m within the range [0;3] and k_{rs} within the range [0;15].

Results, in terms of the minimum total cost and of the optimal combination of k_m/k_{rs}, are proposed in Table 2, as a function of the network configuration and of the reorder policy adopted. The trend of the total cost as a function of k_m and k_{rs} is provided in Figure 2 (a-h) for all configurations examined.

Table 2: optimum *k* and minimum total cost under scenario 2.

	EOQ			EOI		
Configuration	minimum total cost [€/day]	k_m	k_{rs}	minimum total cost [€/day]	k_m	k_{rs}
1	3069.932	1.1	3	3535.83	0.7	10
2	4280.909	1.3	2	4027.744	0.4	5
3	5009.137	1.5	2	5691.922	0.8	12
4	7577.682	1.4	2	7974.717	0.8	12



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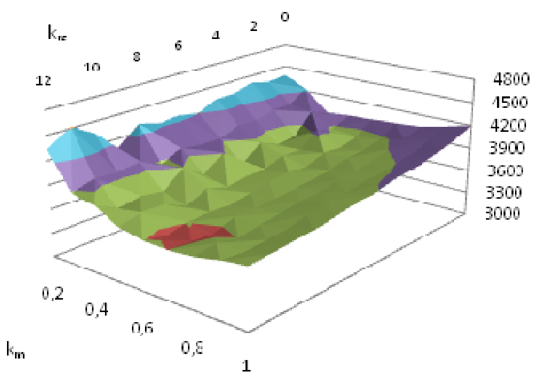

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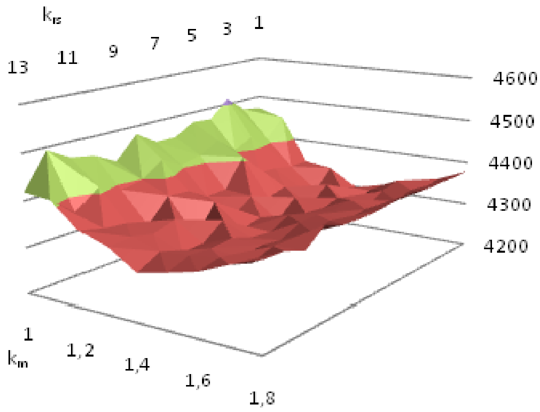

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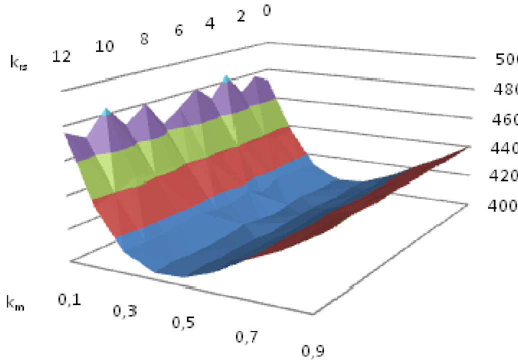

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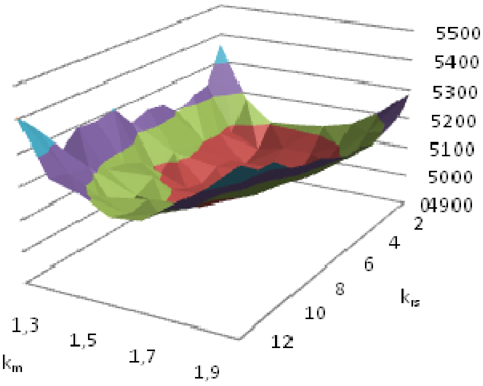

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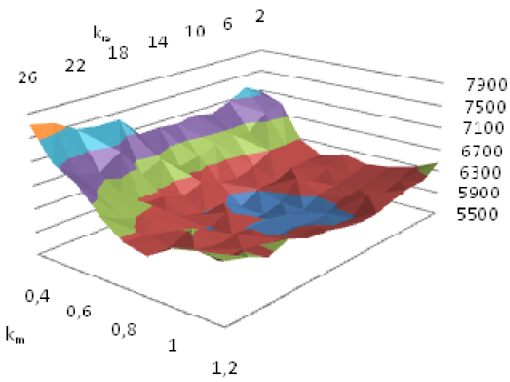

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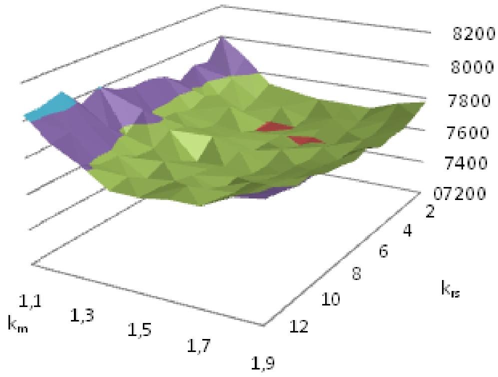

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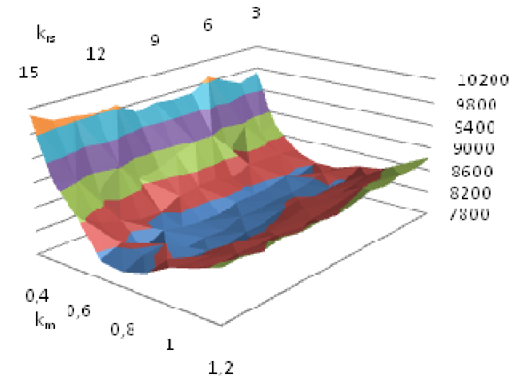

(h)

Figure 2: total cost under scenario 2, for configuration 1 with EOQ vs. EOI policy (a-b); configuration 2 with EOQ vs. EOI policy (c-d); configuration 3 with EOQ vs. EOI policy (e-f); configuration 4 with EOQ vs. EOI policy (g-h).

A first outcome from Table 2 and Figure 2 is that, *ceteris paribus*, the service level k_{rs} set for retail stores affects the resulting total cost to a very limited extent. Conversely, the effect of the service level k_m of manufacturer or distribution center on the total cost of the network is significantly higher, and we can argue that the minimum total cost of the network chiefly depends on k_m. For instance, the optimal couple of k_{rs}/k_m obtained under scenario 2 for configuration 1 and EOQ policy are k_m=1.1/k_{rs}=3. Under scenario 1, for the same configuration and operating condition of the network, we found k=1.1 (cf. Table 1), which is very close to the optimal value of k_m. Similar considerations hold for the remaining network configurations, thus confirming that the total network cost is mainly determined by k_m, while the relevance of k_{rs} is lower.

A further consideration is that, no matter the network configuration, under scenario 2 the minimum total cost is achieved by setting quite high k for the retail store. This is especially true when the network operates under an EOI policy; under that reorder policy, k_{rs} varies from 5 to 12. We acknowledge that such values do not appear to be applicable in practical cases; at the same time, however, such results highlight the retail stores require very high stock levels, which, in turn, could be motivated by the need for avoiding out-of-stock situations. Hence, we deduce that retail stores are particularly sensitive to out-of-stock situations under EOI policy. From a practical perspective, this result could also suggest that retail stores should preferably operate under an EOQ policy, where the incidence of out-of-stock is lower (Bottani and Montanari, 2011).

4. ADDITIONAL SCENARIOS AND FUTURE DEVELOPMENTS

In addition to the above described scenarios, it is interesting to consider further experimental developments related to the investigation of more complex demand models. In particular, the authors are investigating the modeling and the experimentation issues related to the impact of complex demand evolution, with non homogeneous distribution in time and quantities, over the final nodes of the supply chain. In fact, when the demand includes seasonal components and periodic elements, in real cases there are complex behaviors emerging such as temporal waves and quantitative shifts that spreads over the final nodes of the supply chain in relation to geographic and commercial features.

Several seasonal behaviors are related to fixed or variable elements due to their nature; for instance, toys demand is strongly related to holiday periods such as Christmas (Wong et al. 2006). Therefore, even in this case the demand related to Christmas could start into arising early or late due to the financial situation of the consumer in a specific geographic area or within a commercial channel.

Methodologies are available and under test to investigate the possibility to mitigate the impact of this variability on the supply chain efficiency, therefore this is pretty challenging (Bruzzone & Mosca 1999; Wang et al. 2006; Longo and Mirabelli 2008, Rahman et al. 2011); in addition to market demand evolution this phenomena are often introduced and amplified by critical events in term of good contamination that spreads over the different areas within a time frame (Bruzzone & Tremori, 2008).

This fact is usually generated by variables affecting the seasonal behaviors that introduce shifts in term of anticipation/delay of the season and/or increase/decrease of the quantities; as anticipated the forecasting phenomena could generate problems in case of multi channels of vendors and/or final consumers and/or within wide geographic areas (Agrawal et al. 2002). The authors was directly involved in several researches related to retail in term to assess demand within regional networks where there is not an homogeneous impact of seasonal components (i.e. Icecreams, fresh food or fashion) (cf. Bruzzone et. al.2005; Bruzzone & Bocca 2006; De Sensi et al. 2008, Bruzzone et al. 2010). In the current case, the authors are interested in introducing such kind of impact:

$$D_m(x,c,t) = i_m(x,c,t_m) D_r(x,c,t_m) \qquad (1)$$

$$i_m(x,c,t) = F_d(\min|x-x_i|_2) \cdot F_c(\min|c-c_i|) \cdot F_t(\min|t-t_i|) \qquad (2)$$

$$t_m(x,c,t) = t + AD_d(\min|x - x_i|_2) \cdot AD_c(\min|c - c_i|) \cdot AD_t(\min|t - t_i|) \qquad (3)$$

Where:

- x, Final Point of Sales Geographic Location;
- x_i, i-th element of the Set of Critical Locations affecting the Points of Sales;
- c, Commercial channel of the current Point of Sales. Channels have to be indexed in progressive way respecting their ranking in term of average demand per point of sales;
- c_i, i-th element of the Set of Commercial Channels to address final consumers;
- t, current time;
- t_i, i-th element of the Set of Critical Events related to the Final Consumer Demand;
- D_m, Modified Demand for a Point of Sales related to the geographic position, commercial channel & time;
- D_r, Reference Demand for a Point of Sales related to the geographic position, commercial channel and time without considering critical phenomena spreading over time, commercial channels and space (i.e. season anticipation);
- i_m, Overall Impact of the critical components on the reference demand for a specific point of sale;
- t_m, Overall Time shift on the reference demand due to the critical components for a specific point of sale;
- F_d, F_c, F_t, Function regulating the increase/decrease of the reference demand related respectively to location, commercial channels and critical events;
- AD_d, AD_c, AD_t, Function regulating the time shift (anticipation delay) of the reference demand related respectively to location, commercial channels and critical events.

For simplicity, it is proposed to compute the distance from point of sales based on geographic Euclidean distance, therefore sometime this distance could require more sophisticated models considering media and social network affecting the diffusion of the phenomena. The functions F and AD could be modeled in different way, therefore for critical event it is recommend to use functions based on the following Y(y) structure:

$$Y(y) = lv + (hv - lv) \cdot e^{-av \cdot (|y|)} \qquad (4)$$

- lv, minimum value
- hv, highest value
- av, quickness factor.

The use of supply chain simulator allows to measure how quick and how destructive these phenomena; obviously the experimentation on the simulator of use different supply chain management policies allows to measure the capability to anticipate and/or mitigate these issues as well as the logistics networks robustness and resilience (Longo and Oren, 2008).

5. DISCUSSION AND CONCLUSIONS

In this paper, we have explored, through a simulation model, the issue of defining the optimal size and distribution of safety stocks in a supply network. On the basis of previous studies, we examined 4 network configurations, all referring to the context of FMCG, operating under EOQ or EOI policies. We also considered two possible scenarios, referring to the situation where all network players set the same safety stock coefficient k (scenario 1) and where retail stores are allowed to set a different k, referred to as k_{rs} (scenario 2). We exploited the simulation model to compute the total cost resulting under each configuration and scenario, with the purpose of identifying the value of k which allows obtaining the minimum total cost of the network.

Results obtained highlight the following key points:

- under scenario 1, we found that k has a significant impact on the cost of holding stocks and of stock-out, with different effects, while the impact on the order and transport cost is negligible. Moreover, the network is affected by higher total cost when operating under EOI policy,
- under scenario 2, we found that, both under EOQ and EOI policies, the minimum total cost is achieved when retail stores set a very high k, meaning that to minimize the total network cost, it is paramount to increase the service level provided by the retail stores;
- moreover, under scenario 2, the total cost of the network chiefly depends on k_m, while the incidence of k_{rs} on the total logistics cost is limited;
- a further result of scenario 2 is that, under EOQ policy, there is not a relevant difference between the optimal k value of manufacturers/distributors and retail stores, while k_{rs} is significantly higher than k_m under EOI policy;
- by comparing the results obtained under scenarios 1 and 2, it can also be observed that setting different service level for manufacturer/distribution center and retail store allows obtaining lower total cost of the network compared to the situation where the service level is the same for all echelons. This result suggests that setting specific k as a function of the supply chain echelon is a viable strategy to optimize the total cost of the network.

The above outcomes provide interesting guidelines for the optimal design of supply networks. At the same time, some limitations of this study should be mentioned. The main one is that we refer to a specific context, and thus, although the input data used well represent the FMCG industry, our results cannot be generalized to other contexts. Moreover, we assumed the network configurations on the basis of our previous study, to derive further insights about those configurations. Nonetheless, it would be appropriate to also investigate different network configurations, to provide further useful guidelines.

APPENDIX: INPUT DATA USED TO SIMULATE THE FMCG SUPPLY NETWORKS

The input data used to simulate the FMCG supply networks were adapted from previous studies of the authors in the field of FMCG (Bottani and Rizzi, 2008). The main parameters and numerical values are listed below:

- number of RS = 100
- mean of the final customer's = 150 pallets/day;
- standard deviation of the final customer's demand = 25 pallets/day;
- moving average interval = 5 days for retail stores and first-tier distribution centers; 60 days for second-tier distribution centers and manufacturer;
- unitary order and transport cost = 13.3 €/order for retail stores, 2750 €/order for first- and second-tier distribution centers, 5000 €/order for manufacturer;
- unitary cost of holding stocks: 0.572 €/pallet/day for manufacturer and second-tier distribution centers; 0.544 €/pallet/day for first-tier distribution centers; 0.32 €/pallet/day for retail stores;
- unitary stock-out cost: 50 €/pallet
- procurement lead time: 3 days.

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