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Supply chain design: guidelines from a simulation approach

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1. Introduction

Supply chain management (SCM) 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 factor for a successful business. World-class organizations now realize that non-integrated manufacturing processes, non-integrated distribution processes and poor relationships with suppliers and customers are inadequate for their success (Chang & Makatsoris, 2001).

A typical supply chain consists of a number of organizations; it starts with suppliers, who provide raw materials to manufacturers, which manufacture products and keep the manufactured goods in the warehouses. Then, products are sent to distribution centres and shipped to retailers. Due to the complexities of supply chain and to the numerous players involved in the product flow, supply chain design is a relevant topic for developing an optimal platform for an effective SCM (Yan et al., 2003). The proper design of a supply chain encompasses a set of decisions, embracing both strategic and tactical levels. Examples of such decisions concern number of echelons required and number of facilities per echelon, reorder policy to be adopted by echelons, assignment of each market region to one or more locations, selection of suppliers for sub-assemblies, components and materials (Chopra & Meindl, 2004; Hammami et al., 2008).

At the same time, there are several expected benefits from a proper supply chain configuration, which include better coordination of material and capacity, reduced order cycle time, decrease in inventory cost and bullwhip effect (Lee et al., 2004), transport optimization, and increased customer responsiveness (Chang & Makatsoris, 2001).

An analysis of the recent literature shows that the problem of optimizing supply chain design is approached by researchers either with linear programming (operational research) models or through simulation models. Linear programming models are exploited with several aims, which encompass determining the number, location, and capacity of DCs, minimizing the total cost, or maximizing the profit of the supply chain (e.g., Yan et al., 2003; Tiwari et al., 2010; Bashiri & Tabrizi, 2010). Furthermore, problems such as supplier

selection or technology management can be included in the model (e.g., Hammami et al., 2009).

As an alternative to operational research models, simulation is recognized as a powerful tool to observe the behaviour of supply chains, assess their efficiency level, evaluate new management solutions, identify the most suitable configuration and optimize the distribution channel (Iannone et al., 2007). Among its advantages, simulation allows evaluating the operating performance of a system prior to its implementation or in conditions different from its current status; moreover, it enables the examination of the sensitivity of a system to its design parameters and initial conditions. Finally, results of a simulation may suggest a better mode of operation or method of organizing (Harrison et al., 2007). By using simulation models, researchers often quantify the benefits resulting from SCM, in order to support decision making either at:

- strategic level, including redesigning the structure of a supply chain; or
- operational level, including setting the values of control policies (Kleijnen, 2003).

Simulation is also useful when complex supply chain configurations (e.g., supply networks) should be examined and investigated in detail. The analysis of the literature, however, shows that the existing studies are often limited to the analysis of simple supply chain configurations, usually referring to two-echelon systems, with one or few players per echelon. However, due to the increased complexity of real systems, the contribution of such studies to the optimization of supply chain design is quite limited. Conversely, there are only few studies which either investigate multi-echelon supply chains or supply networks. Among those works, Hwarng et al. (2005) modelled a complex supply chain and investigate the effects of several parameters, including demand and lead time distribution, and postponement strategies, on the resulting performance. Shang et al. (2004) applied simulation, Taguchi method and response surface methodology to identify the 'best' operating conditions for a supply chain. These authors examined the following supply chain parameters: information sharing, postponement, capacity, reorder policy, lead time and supplier's reliability. By exploiting a discrete-event simulation model, Bottani & Montanari (2010) investigate the behaviour of a fast moving consumer goods (FMCG) supply chain under 30 different configurations, stemming from the combination of several supply chain design parameters. Specifically, among the design parameters, the authors consider two planning decisions (i.e., number of echelons and reorder policy), one exogenous variable (i.e., demand behaviour), as well as some operational elements (i.e., demand information sharing mechanisms and responsiveness of supply chain players). The authors quantitatively assess the effects of different configurations on the resulting costs and bullwhip effect of the supply chain; their findings are summarised in 11 key results, supported by statistical evidence, which can be useful to optimise supply chain design. In another publication (Bottani & Montanari, 2009), the same authors have analysed four network configurations, stemming from the combination of two parameters, namely: (i) number of echelons; and (ii) number of facilities per echelon. As further decision variables, the authors consider the reorder policy (Economic Order Quantity vs. Economic Order Interval) adopted by each player and the service level delivered to customers (low vs. high). Moreover, demand behaviour (seasonal vs. non seasonal demand trend), demand

stochasticity (low vs. high demand standard deviation) and procurement lead time (stochastic vs. deterministic) are examined as exogenous variables. Overall, the authors consider 128 scenarios, for which they compute four main performance parameters, namely the total costs of the network (and the related cost components), the bullwhip effect, the throughput time of items along the chain and the waiting time of customers at the retail store due to out-of-stocks.

Pero et al. (2010) investigate the relationships between some supply chain design parameters and the resulting performance of the supply chain. Design parameters considered by the authors are: (i) number of supply chain levels; (ii) number of players at each level; (iii) number of sources for each node; and (iv) distance between nodes. As a relevant performance parameter, the authors investigate the occurrence and entity of stock-outs at retail stores. In the work by Pero et al. (2010), simulation and statistical analyses of outcomes are exploited to identify statistically significant effects of design parameters on the observed outcomes.

In line with our previous studies on the topic, in this chapter our main goal is to assess the effects of different supply chain configurations on the resulting costs and bullwhip effect. We consider quite complex supply chain configurations, both in terms of number of echelons and number of players per echelon. The configurations we examine are also referred to as supply networks, and aim at being representative of realistic scenarios, so that our analysis can provide effective insights for supply chain optimization. The design parameters considered in this study are:

- number of echelons composing the supply chain;
- number of facilities per echelon;
- reorder policy adopted by each echelon.

As far as the latter point is concerned, in this study we suppose that supply chain echelons operate under an Economic Order Interval (EOI) policy. In a previous publication (Bottani & Montanari, 2008), we have dealt with supply chain design and optimization through simulation, under an Economic Order Quantity (EOQ) policy. This study thus completes our previous work by examining the EOI policy. Moreover, we provide a detailed comparison of the results obtained under EOI and EOQ inventory management policies. To make the comparison effective, in this study we consider the same supply chain configurations examined in our previous work. The analysis performed is based on a discrete-event simulation model, reproducing a FMCG supply chain, and on the computation of the resulting supply chain costs and of the demand variance amplification for each configuration examined. The chapter is organized as follows. Section 2 describes the supply chain simulation model, the supply chain configurations examined, and the corresponding software implementation. The key results of the simulation runs are detailed in section 3. Concluding remarks and future research directions are finally proposed.

2. The supply chain simulation model

2.1 The supply chain configurations examined

The typical structure of a FMCG supply chain may encompass three (i.e., manufacturer, distribution center, retail store) to five (i.e., manufacturer, first-tier distribution center,

second-tier distribution center, third-tier distribution center, retail store) echelons (Bottani and Montanari, 2010), while the number of players per echelon can substantially vary depending on the complexity of the supply and distribution networks.

To be consonant with Bottani & Montanari, (2008), three supply network configurations are examined, referring to 3-, 4- and 5-echelon systems. The supply networks are described on the basis of products and orders flow (Shapiro, 2001), and their structure is proposed in the schemes in Figure 1. As can be seen from Figure 1, the number of retail stores (RSs) is the same (i.e., 500) for all configurations investigated. In addition to RSs, the 3-echelon supply chain is composed of a manufacturer and 25 distribution centers (DCs). The 4-echelon system encompasses a manufacturer, 3 first-tier DCs and 50 second-tier DCs, while the 5-echelon supply chain is composed of a manufacturer, 3 first-tier DCs, 25 second-tier DCs, and 100 third-tier DCs. RSs directly face the final customer's demand, which is modeled as a stochastic variable with normal distribution $N(\mu;\sigma)$.
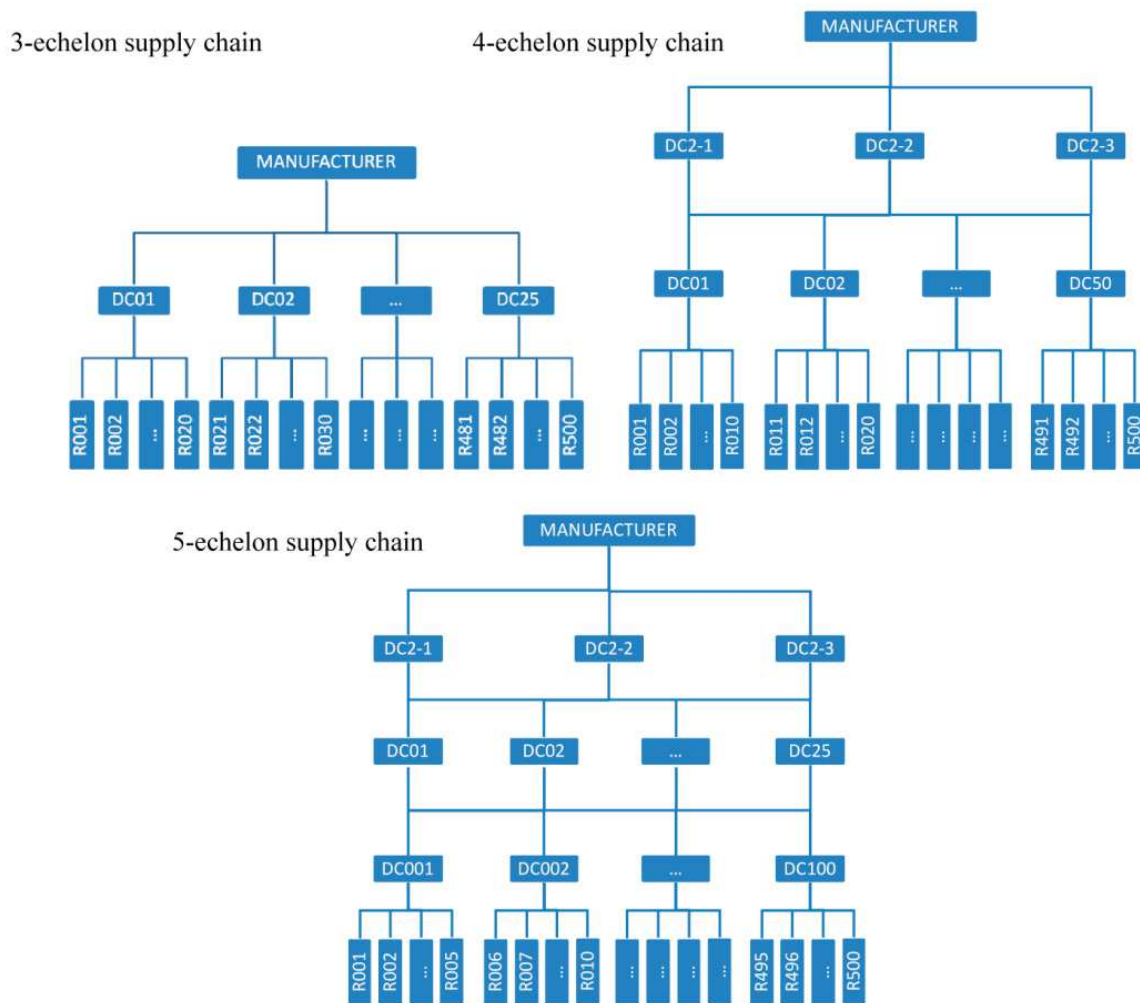

Fig. 1. The network configurations examined (DC=distribution centre; RS=retail store).

2.2 The reorder process

The reorder process of the generic i-th echelon is proposed in Figure 2. The following notation is used to describe the product and order flow:

t simulated day (t=1,…N_{days})
i supply chain echelon (i=1,…N)
$d_{t,i}$ demand value faced by echelon i at time t [pallets/day]. Depending on the supply chain echelon considered, this parameter can reflect the final customer's demand or the order received by the previous echelon
μ mean of the final customer's demand [pallets/day]
σ standard deviation of the final customer's demand [pallets/day]
$I_{t,i}$ inventory position of echelon i at time t [pallets]
$Q_{t,i}$ quantity ordered by echelon i at time t [pallets/day]
$Q_{s\text{-}o,t,i}$ quantity supplied by the external player for echelon i, at time t [pallets/day]
$\mu_{t,i}$ estimated demand mean at time t for echelon i [pallets/day]
$\sigma_{t,i}$ estimated demand standard deviation at time t for echelon i [pallets/day]
m moving average interval [days]
$OUL_{t,i}$ order-up-to level for echelon i at time t [pallets]
EOI_i economic order interval for echelon i [days]
$\mu_{LT,i}$ lead time mean for echelon i [days]
$\sigma_{LT,i}$ lead time standard deviation for echelon i [days]
k safety stock coefficient
$c_{o,i}$ unitary order cost for echelon i [€/order]. This also includes the transportation activities required to deliver the product to echelon i
$c_{s\text{-}o}$ unitary cost of stock-out [€/pallet/day]
h unitary cost of holding stocks [€/pallet/day]

According to Figure 2, at each day t (t=1,…N_{days}) the reorder process of the generic i-th echelon consists of several steps, ranging from the time an order is received from echelon i-1 up to the time an order is placed to echelon i+1. More precisely, each supply chain echelon receives products from the following one, in response to an order from the previous one, or, alternatively, to the daily customer's demand ("*order from echelon i-1*").

Anytime an order is received, echelon i should verify whether the available stock allows fulfilling it ("*can the order be fulfilled with the available inventory?*"). In the case the available stock is insufficient (i.e., $d_{t,i}$>$I_{t-1,i}$), the order is fulfilled by an "*external player*", which is modeled as a warehouse with infinite stock availability. Product supplied by the external player ($Q_{s\text{-}o,t,i}$) is used to compute the cost of out-of-stock for the echelon considered. Conversely, if the available stock is sufficient to fulfill the order (i.e., $d_{t,i}$≤$I_{t-1,i}$), echelon i sends the product to echelon i-1 ("*order fulfillment*").

As a further step, on the basis of the demand faced at each day t, echelon i estimates the demand mean $\mu_{t,i}$ and standard deviation $\sigma_{t,i}$ according to a moving average model with m observations ("*estimation of demand mean and standard deviation*"). The following formulae are used for the computation:

$$\mu_{t,i} = \frac{1}{m} \sum_{k=t-m}^{t} d_{k,i}$$

$$\sigma_{t,i}^2 = \frac{1}{m-1} \sum_{k=t-m}^{t} \left(d_{k,i} - \mu_{t,i} \right)^2$$

(1)

Echelon *i* should now decide whether or not to an order should be placed. As the echelon operates according to an EOI policy, orders are placed at fixed time intervals, which are computed for the generic *i*-th echelon on the basis of the following formula:

$$EOI_i = (2c_{o,i}/(h_i\mu))^{1/2} \qquad (2)$$

The resulting values of EOI_i, computed by exploiting eq.2 and the input data described later in this chapter, are proposed in Table 1. The estimated values of $\mu_{t,i}$ and $\sigma_{t,i}$ are used to compute the parameters of the inventory management policy ("*computation of parameters of the reorder policy*") and in particular the order-up-to level ($OUL_{t,i}$) at time *t*, according to the following formula (cf. Bottani et al., 2007):

$$OUL_{t,i} = (EOI + \mu_{LT,i})\mu_{t,i} + k\sqrt{(EOI + \mu_{LT,i})\sigma_{t,i}^2 + \mu_{t,i}^2\sigma_{LT,i}^2} \qquad (3)$$
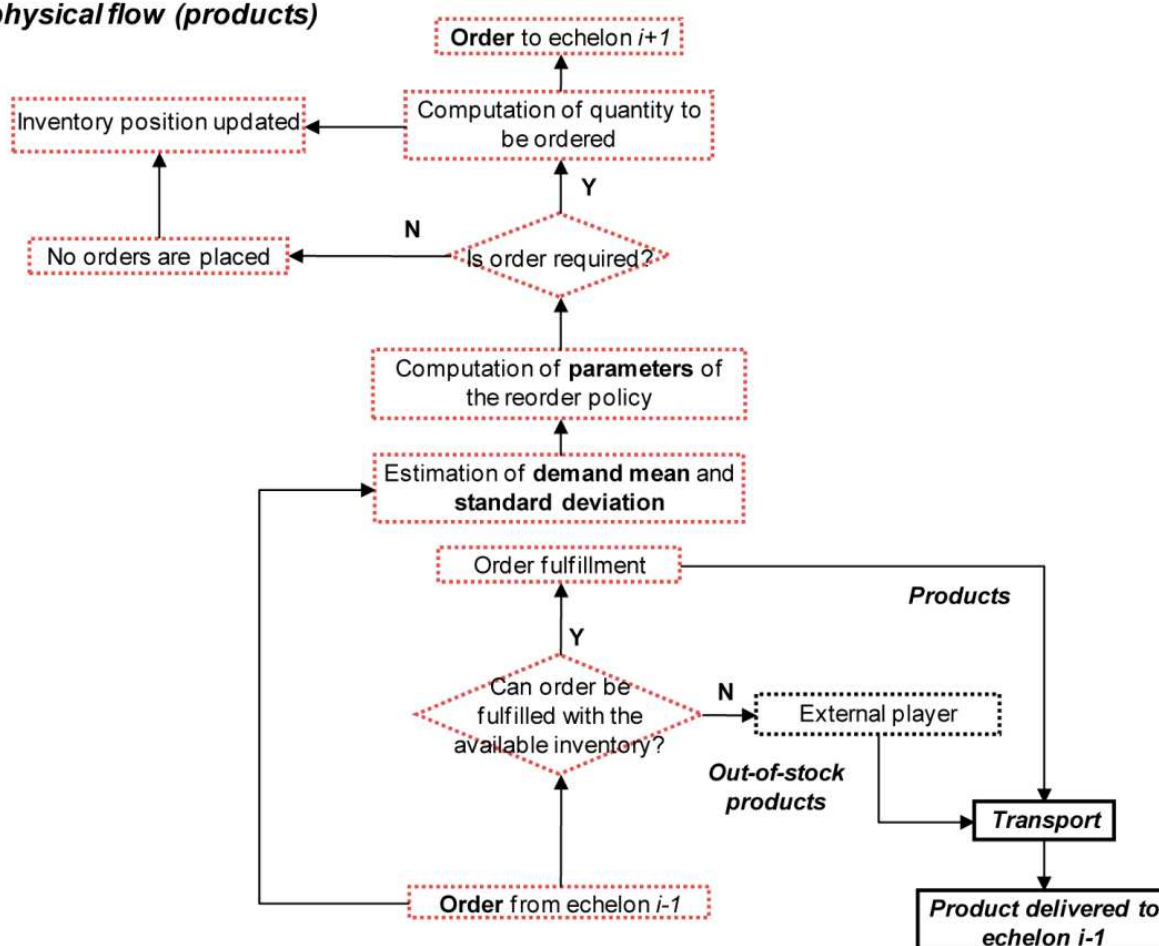

Fig. 2. The reorder process for the *i*-th supply chain player.

In the case an order is placed, the corresponding quantity will be available after a defined lead time (*LT*) has elapsed. The quantity to be ordered $Q_{t,i}$ results from the comparison

between the $OUL_{t,i}$ and the inventory available $I_{t-1,i}$ for the supply chain player considered, i.e.:

$$Q_{t,i} = OUL_{t,i} - I_{t-1,i} \tag{4}$$

Echelon i will not place an order in the case the available inventory exceeds the required $OUL_{t,i}$. Regardless of the order placement, echelon i finally updates the inventory position accordingly ("*inventory position updated*"). The following formula is used to determine the stock level at time t:

$$I_{t,i} = Q_{t,i} + I_{t-1,i} - d_{t,i} \tag{5}$$

In the case the order has not been placed, we have $Q_{t,i}=0$ in the equation above.

The decision process described above is valid for all supply chain players modeled, except the manufacturer. In fact, as per the case of the external player, the manufacturer is modeled as a warehouse with infinite stock availability. Hence, it can always fulfill orders from DCs, and consequently, there is no need for the manufacturer to forecast the demand based on the orders received. For the same reason, we do not compute the total logistics cost of this player.

To make the results comparable to those of our previous study, further assumptions are also made in developing the model. More precisely, we suppose that μ_{LT}, σ_{LT}, c_o, h, k and m are known parameters, whose numerical values are partially deduced from a previous study performed by the authors in the field of FMCG (Bottani & Rizzi, 2008). According to this previous study, numerical values for the above input data could vary depending on the supply chain echelon considered. For instance, it is reasonable that the order cost changes depending on the number of echelons composing the supply chain, and to the echelon considered; in particular, order cost is probably higher when 5-echelon supply chains are considered. In fact, in 5-echelon systems, an increase in the quantity ordered by upstream supply chain players is often observed; hence, transportation activities, whose cost is included in the order cost, are significantly enhanced in those scenarios.

A similar consideration holds for the procurement lead time. We assume that the lead time is higher when considering upstream supply chain players, while it should slightly decrease when considering downstream players. The rationale behind this assumption is that the downstream supply chain players (e.g., RSs or end-tier DCs) should be served regularly, in a short time, to ensure the availability of product at the store shelves and to enhance the efficiency of the whole supply chain. LT is modeled as a stochastic variable, characterized by μ_{LT} and σ_{LT}; we assume a uniform distribution of LT, between two boundaries, which are progressively lower as downstream players are considered. μ_{LT} and σ_{LT} can be easily obtained from the boundaries on the basis of the uniform distribution. The full list of input data is proposed in Table 1 for each supply chain configuration considered.

Finally, according to Bottani & Rizzi, (2008), stock-out costs and costs of holding stock are estimated to account for 0.8 [€/pallet/day] and 0.384 [€/pallet/day] respectively for all echelons, regardless of the configurations considered. The final customer's demand is characterized by an average (μ) of 0.25 [pallet/day] with 0.0625 [pallet/day] standard deviation (σ). Those numerical values reflect the demand of a single product.

3-echelon	4-echelon	5-echelon
DC Lead time: random variable with uniform distribution between 5 and 10 days order cost: 300 €/order EOI : 17 days	*DC$_{1-3}$* Lead time: random variable with uniform distribution between 5 and 10 days order cost: 3000 €/order EOI : 22 days	*DC$_{1-3}$* Lead time: random variable with uniform distribution between 5 and 10 days order cost: 6000 €/order EOI : 29 days
RS Lead time: random variable with uniform distribution between 3 and 7 days order cost: 75 €/order EOI : 40 days	*DC$_{1-50}$* Lead time: random variable with uniform distribution between 5 and 8 days order cost: 225 €/order EOI : 24 days	*DC$_{1-25}$* Lead time: random variable with uniform distribution between 5 and 8 days order cost: 825 €/order EOI : 29 days
	RS Lead time: random variable with uniform distribution between 3 and 7 days order cost: 75 €/order EOI : 40 days	*DC$_{1-100}$* Lead time: random variable with uniform distribution between 4 and 8 days order cost: 150 €/order EOI : 25 days
		RS Lead time: random variable with uniform distribution between 3 and 7 days order cost: 75 €/order EOI : 40 days

Table 1. Input data of the model.

2.3 Software implementation

The decision process described in the previous sections was implemented in a proper simulation model, developed under Microsoft Excel™. In particular, for each supply chain configuration considered, an *ad hoc* spreadsheet is used to reproduce the decision process of each supply chain echelon, as shown in Figure 3. We thus programmed several different Microsoft Excel™ files, corresponding to the supply chain configurations proposed in Figure 1.

According to the orders' flow, a Microsoft Excel™ file starts by reproducing the decision process of RSs, on the basis of a random generation of final customer's demand data. In this file, we thus have 500 spreadsheets corresponding to the RSs composing the supply networks. As the number of RSs is the same in all configurations considered, the spreadsheets reproducing the RSs have been exploited for all subsequent Microsoft Excel™ files. As a result of the implementation of the decision process under Microsoft Excel™, each spreadsheet reproducing a RS provides, as output, the flow of orders from this RS to end-tier DCs.

The orders of RSs should be aggregated to get the demand "seen" by a DC. We note from Figure 1 that the number of DCs is different depending on the supply chain configuration examined, and specifically it accounts for 25, 50 and 100 respectively when considering 3-, 4- or 5-echelon systems. Hence, each DC serves a different number of RSs in the three network configurations examined. For instance, in the case of 5-echelon supply chains (as proposed in Figure 3), the network is composed of 100 DCs; consequently, it can be assumed that each DC approximately serves 5 RSs. Under this scenario, we thus gathered the order flow of 5 RSs and used the aggregate flow as the demand "seen" by a DC; this value has been used as the input in a further Microsoft Excel™ file reproducing the decision process of DCs. As a result of this step, we obtain the flow of orders from end-tier DCs to the upper-tier DCs.

The same procedure is followed to derive the flow of orders for upper-tier DCs, and, in general, it is repeated for all echelons composing the supply chains investigated. Figure 3 graphically shows the full procedure in the case of a 5-echelon supply chain.
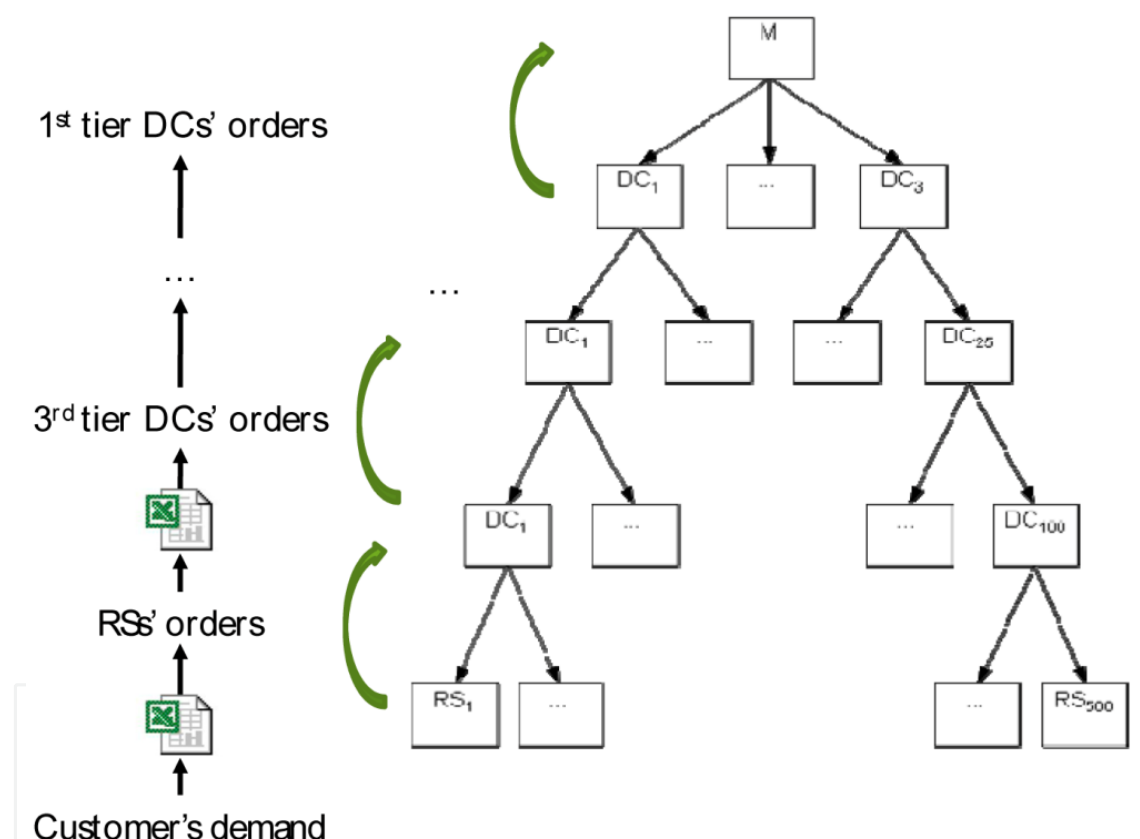

Fig.3. Software implementation of the simulation model for a 5-echelon network.

2.4 Computation of outputs

The simulation duration was set at N_{days}=1000 days, corresponding to approx 4 years operating period of the supply network, having hypothesised 5 working days/week.

For each supply network considered, we assessed several outputs, on the basis of the numerical values proposed in Table 1 and on the simulation outcomes. The output computed for the supply networks are described in the list below.

- Bullwhip effect. We assessed the bullwhip effect as the ratio between variance of orders received by echelon N (i.e., the manufacturer) and the variance of the final customer's demand, i.e. σ_N^2/σ^2. σ_N^2 is computed on the basis of the flow of orders received by the manufacturer;
- Cost of holding stocks (C_{stocks}). For the i-th player, it is computed starting from unitary cost of stocks and amount of stock available at the warehouse, i.e.:

$$C_{stocks,i} = h \sum_{t=1}^{N_{days}} I_{t,i} \qquad (6)$$

The total cost of holding stocks C_{stock} is obtained by adding up the contributions of each supply chain echelon, except the manufacturer, which is excluded from the computation due to infinite stock availability. As an outcome of the computation, we report the daily average value of C_{stock} for each supply chain echelon, which is obtained by adding up the contribution of each echelon (e.g., the RSs) and dividing by the number of players composing the echelon (i.e., the number of RSs) and the simulation duration N_{days}. The average value is thus expressed in [€/echelon/day]. Moreover, we also computed the overall average of C_{stocks} for the network examined, which is again expressed in [€/echelon/day]. The overall average results from dividing the total cost of holding stocks by the total number of players composing the network and the simulation duration.

- Stock-out cost (C_{s-o}). For the i-th player, the cost of stock-out is computed starting from the unitary cost of out-of-stock and from the quantity supplied by the external player $Q_{s-o,t,i}$, according to the following formula:

$$C_{stock-out,i} = c_i \sum_{t=1}^{N_{days}} Q_{s-o,t,i} \qquad (7)$$

The total cost of stock-out is obtained by adding up the contributions of each supply chain echelon, except the manufacturer, for which stock-out cannot occur. As outcome, we report the daily average value of C_{s-o} for each supply chain echelon and the overall average of C_{s-o}. Both values are expressed in [€/day/echelon], according to the computational procedure described for the previous outcome.

- Order cost (C_{order}). For the i-th player, it is computed on the basis of the unitary cost of orders $c_{o,i}$ and of the number of orders placed by the supply chain player $N_{orders,i}$, i.e.:

$$C_{order,i} = c_{o,i} N_{orders,i} \qquad (8)$$

The number of orders is a direct outcome of the simulation model. We thus obtain the total order cost of the supply chain configuration examined by adding up the contributions of the different echelons, except the manufacturer. As outcome, we report the daily average value of C_{order} for each supply chain echelon and the overall average of C_{order}. Again, such values are expressed in [€/day/echelon], according to the same computational procedure described for the previous outcomes.

- Total supply chain cost [€/day]. This is computed for the whole supply chain, by adding up the cost components previously described and dividing by N_{days}.

3. Results and discussion

In this section, we report the relevant results of the study, in terms of order cost, cost of holding stocks, and stock-out cost, for each supply chain echelon. As mentioned, we provide the daily average values of such costs for each echelon composing the supply chain. We also report the total cost and the variance ratio for the whole supply chain. Such outcomes are proposed in Table 2. In the same table, in italic we provide the outcomes resulting in the case the EOQ policy is considered (cf. Bottani & Montanari, 2008).

	Network configuration		
Outcomes	**3-echelon**	**4-echelon**	**5-echelon**
Average stock-out cost [€/player/day]	overall average: 0.09 (*0.01*) DC$_{1-25}$: 1.48 (*0.29*) RS: 0.02 (*0.00*)	overall average: 0.20 (*0.05*) DC$_{1-3}$: 19.02 (*1.01*) DC$_{1-50}$: 1.12 (*0.45*) RS: 0.02 (*0.00*)	overall average: 1.19 (*0.32*) DC$_{1-3}$: 126.35 (*7.16*) DC$_{1-25}$: 9.69 (*5.51*) DC$_{1-100}$: 0.72 (*0.66*) RS: 0.02 (*0.00*)
Average order cost [€/player/day]	overall average: 2.49 (*3.01*) DC$_{1-25}$: 15.67 (*19.24*) RS: 1.83 (*2.20*)	overall average: 3.96 (*3.96*) DC$_{1-3}$: 145.00 (*174.00*) DC$_{1-50}$: 9.79 (*11.41*) RS: 1.83 (*2.20*)	overall average: 4.50 (*4.10*) DC$_{1-3}$: 220.00 (*256.00*) DC$_{1-25}$: 27.39 (*33.99*) DC$_{1-100}$: 5.71 (*6.23*) RS: 1.83 (*2.20*)
Average inventory cost [€/player/day]	overall average: 4.48 (*3.52*) DC$_{1-25}$: 43.58 (*31.49*) RS: 2.53 (*2.13*)	overall average: 5.42 (*5.41*) DC$_{1-3}$: 477.15 (*289.73*) DC$_{1-50}$: 31.50 (*21.20*) RS: 2.53 (*2.13*)	overall average: 21.63 (*6.95*) DC$_{1-3}$: 1680.79 (*482.62*) DC$_{1-25}$: 194.33 (*68.25*) DC$_{1-100}$: 24.18 (*15.97*) RS: 2.53 (*2.13*)
Total costs of the network [€/day]	3,708.50 (*3,438.60*)	6,225.95 (*5,210.47*)	17,118.60 (*7,142.82*)
Bullwhip effect σ_N^2/σ^2	323.73 (*190.19*)	40,115.90 (*15,224.77*)	142,123.70 (*28,006.42*)

Table 2. Results of the simulation runs. Note: *italic* = results under EOQ policy (from Bottani & Montanari, 2008).

The outcomes in Table 2 allow drawing some conclusions and guidelines for supply chain design. They are proposed in the following subsections.

3.1 Stock-out costs

As a first outcome, we note that, no matter the reorder policy considered, the average stock-out cost substantially increases when moving from 3-echelon to 5-echelon systems, suggesting that the occurrence of stock-outs is higher when considering complex scenarios.

A significant increase in stock-out costs is observed in terms of the overall average, which ranges from 0.09 [€/player/day] for 3-echelon systems to 1.19 [€/player/day] for 5-echelon systems, under EOI policy, and from 0.01 [€/player/day] to 0.32 [€/player/day] under EOQ policy. From outcomes in Table 2, it can also be noted that stock-out occurrence is always negligible for retail stores, accounting for 0.02 and 0.00 [€/player/day] respectively under EOI and EOQ policy. Hence, the increase in stock-out cost in complex systems can be ascribed to a corresponding increase in stock-out occurrence for upstream supply chain players. In other words, with the increase of the number of echelons and number of players per echelon, stock-out situations at the upstream echelons are more likely to occur. This is confirmed by the increase in the average stock-out cost for the specific supply chain echelon when moving from 3-echelon to 5-echelon systems. In turn, the occurrence of stock-out situations for 5-echelon systems is a possible consequence of the exacerbated demand variance amplification observed in such scenarios, which leads to irregular orders.

By comparing the results of EOI and EOQ policies, it can also be appreciated that stock-out costs are systematically higher under EOI policy. This is probably due to the fact that EOQ policy requires continuously monitoring the stock level and frequent reordering, thus preventing stock-out occurrence. Nonetheless, this point would probably benefit from a deeper investigation, as other studies provide different outcomes (e.g., Bottani & Montanari, 2009).

3.2 Cost of stocks

The trend of inventory costs is similar to that observed for stock-out costs. In particular, no matter the reorder policy considered, inventory costs tend to increase when moving upstream in the supply chain (i.e., from RSs to DCs). Specifically, in the case of 5-echelon supply networks, such costs account for 2.53 and 2.13 [€/player/day] for RSs, while they reach 1680.79 and 482.62 [€/player/day] when examining first-tier DCs, respectively under EOI and EOQ inventory management policy. This result can be explained based on the increase in safety stocks involved by the bullwhip effect. A direct comparison between EOI and EOQ leads to the conclusion that inventory costs are systematically lower when the supply chain players operate under EOQ policy. Again, this could be justified based on the fact that EOQ policy allows better monitoring the stock level compared with EOI. Bottani and Montanari (2009) found that the reorder policy significantly impacts on the cost of holding stocks, and, in particular, that such cost is higher under EOI than EOQ policy. The main reason for such outcome is that EOI policy causes a higher average stock level, as a consequence of the lower number of orders, with wider quantities. This also explains why the increase in the average stock level is more relevant when the supply network is composed by numerous echelons and numerous players per echelon (i.e., 5-echelon systems).

3.3 Cost of order

Compared with the other cost components, the cost of order shows a slightly different trend. More precisely, we always observe an increase of order cost when moving upstream in the supply chain. Such an increase is particularly evident when considering complex systems, i.e., 5-echelon supply chains. In this scenario, the order cost ranges from 1.83 and 2.20 [€/player/day] for RSs to 220.00 and 256.00 [€/player/day] for first-tier DCs, respectively under EOI and EOQ policies. A corresponding increase is also observed for the overall average of order cost when moving from 3-echelon to 5-echelon systems (2.49 and 3.01 vs. 4.50 and 4.10 [€/day], respectively under EOI and EOQ policies).

However, although the order cost increases when examining upper-tier echelons and 5-echelon systems, it is systematically lower under EOI than EOQ policy, unlike the other cost components. A similar result has been observed by Bottani & Montanari (2009). More precisely, the authors found that the use of EOI policy provides a slight decrease of the order cost, and that the effect is supported by statistical evidence. This result can be justified based on the fact that EOI policy involves periodical ordering, and hence the number of orders in a given time period is almost defined. Consequently, the number of orders is lower compared to EOQ, where, conversely, supply chain echelons should place an order anytime the inventory level is lower than a defined threshold. Such effect is amplified when the supply chain is composed of numerous echelons or numerous players per echelon (Bottani & Montanari, 2009).

3.4 Total cost of the supply network

It is reasonable that the total cost of the supply network experiences an increase when moving from 3- to 5-echelon systems, indicating that complex networks are affected by relevant total costs. As a matter of fact, the increase in the number of supply chain echelons or in players per echelon involves an increase in all cost components previously considered, due to the need of adding the cost contributions of each player. We also note that the total costs are lower under an EOQ policy. This is a known result (cf. Bottani & Montanari, 2009; 2010), which can be explained on the basis of the consideration that the total supply chain cost is mainly determined by the cost of stocks, and that the EOI policy significantly increases such cost component, as already explained. The increase in the average stock level is also expected to be more relevant when considering complex supply networks, composed of numerous echelons and numerous players per echelon. This consideration is supported by this study; in fact, looking at the total cost proposed in Table 2, one can see that the difference between EOI and EOQ policies is significant when considering 5-echelon systems (17,118.60 vs. 7,142.82 [€/day]), while it is substantially lower for 3-echelon systems (3,708.50 vs. 3,438.60 [€/day]).

3.5 Bullwhip effect

From Table 2, one can see that the bullwhip effect substantially increases when moving from 3-echelon to 5-echelon systems. This is an obvious result, directly stemming from the definition of bullwhip effect available in literature (e.g., Chen et al., 2000). Moreover, the bullwhip effect is significantly amplified when the network is composed of numerous players per echelon, as per the case of 5-echelon systems modeled in this study. There are very few studies in literature which address the topic of quantifying the bullwhip effect in a

supply network. Among them, we found the work by Ouyang and Li (2010). This study suggests that a high number of players per echelon has potential to affect the resulting bullwhip effect of the network, and, in particular, it exacerbates the demand variance amplification. In turn, this is a possible consequence of the fact that the bullwhip effect is caused by independent rational decisions in demand signal processing and order batching (Lee et al., 2004; Lee, 2003); with numerous players per echelon, the effect of non-coordinated demand can be amplified.

In addition, EOI policy usually involves a higher bullwhip effect than EOQ. Most studies available in literature (e.g., Jakšič and Rusjan, 2008) suggest that the bullwhip effect is higher when the supply chain operates under an EOI policy, because, in general, "order-up-to" policies have the potential to increase the demand variance. The reason for this outcome, which is also confirmed by our study, is that, under the EOI policy, orders are placed at a defined time interval. This leads to several null orders, and to orders with very wide quantities; thus, an amplification of the demand variance is seen by the upper-tier echelon.

4. Conclusions

The problem of optimizing the design of a supply chain has a direct impact on both strategic objectives of supply chain management and on the costs of the system. This chapter has analyzed the topic of supply network design, with a particular attention to the identification of the optimal configuration of the network to minimize total cost. The topic has been approached through a simulation model, developed under Microsoft Excel™. The model reproduces a FMCG supply chain, whose input data have been partially deduced from previous studies of the authors in that field.

As outputs of the simulation runs, we computed the total logistics cost, including its cost components, and the demand variance amplification, which allows providing an estimate of how the different configurations react to the bullwhip effect. The simulation outcomes can be summarized in the following key points. First, we note that all design parameters investigated (i.e., number of echelons, number of players/echelon and reorder policy) have a direct impact on the observed cost and bullwhip effect. Moreover, both the number of echelons and the number of players/echelon tend to increase the total cost of the network and the bullwhip effect. Conversely, the reorder policy has a different impact on the cost components examined. Specifically, stock-out cost and inventory cost increase when EOI policy is adopted by supply chain echelons, while the order cost tends to decrease under such policy. The above outcomes provide useful guidelines to optimize supply chain design and to identify the optimal supply chain configuration as a function of the total costs.

The present study can be extended in several ways. Specifically, to derive more general results, it would be appropriate to extend the simulation model to include the flow of different products, with different characteristics. Moreover, order crossover phenomena (Riezebos, 2006) and their occurrence in supply networks can be investigated in greater detail.

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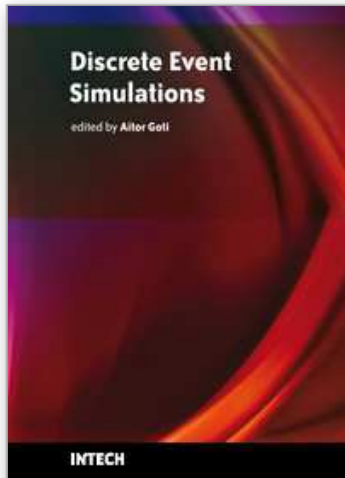
Discrete Event Simulations

Edited by Aitor Goti

Considered by many authors as a technique for modelling stochastic, dynamic and discretely evolving systems, this technique has gained widespread acceptance among the practitioners who want to represent and improve complex systems. Since DES is a technique applied in incredibly different areas, this book reflects many different points of view about DES, thus, all authors describe how it is understood and applied within their context of work, providing an extensive understanding of what DES is. It can be said that the name of the book itself reflects the plurality that these points of view represent. The book embraces a number of topics covering theory, methods and applications to a wide range of sectors and problem areas that have been categorised into five groups. As well as the previously explained variety of points of view concerning DES, there is one additional thing to remark about this book: its richness when talking about actual data or actual data based analysis. When most academic areas are lacking application cases, roughly the half part of the chapters included in this book deal with actual problems or at least are based on actual data. Thus, the editor firmly believes that this book will be interesting for both beginners and practitioners in the area of DES.

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