



Development of a supply chain configuration model for new product development: a multi-objective solution approach

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Abstract

Early supplier involvement in new product development is strategically important for the success of most firms. We therefore discuss how to configure an appropriate supply chain network for new product development. First, we propose a supply chain configuration model under a multi-objective optimization framework. We then develop a solution procedure based on a multi-objective evolutionary algorithm, i.e. NSGA-II (Non-Sorting Genetic Algorithm-II), to minimize the total supply chain cost and time-to-market. The efficiency of the proposed solution procedure is discussed along with a laptop assembly case study. The results obtained from NSGA-II are also compared from SPEA-II (Strength Pareto Evolutionary Algorithm-II).

Keywords New product development · Multi-criteria decision-making · Supply chain environment · Multi-objective optimization

Abbreviations

n Index for stage of the model ($n \in N$)
 r Index for retailers ($r \in R$)
 w Index for warehouses ($w \in W$)
 s Index for suppliers ($s \in S$)
 t Index for time periods ($t \in T$)
 m Index for manufacturing plants ($m \in M$)

Notations

C_n^p Production cost at stage n
 T_n^p Production time at stage n
 γ_n Compatibility index at stage n
 S_n Supplier option is selected for stage n
 $C_{nS_n}^p$ Production cost for stage n with option S_n
 $T_{nS_n}^p$ Production time for stage n with option S_n
 γ_{nS_n} Compatibility index for stage n with option S_n
 I_n Inventory coverage period for stage n
 R_n^L Replenishment lead time for stage n
 O_n^{out} Guaranteed output services of stage n

IN_n^{in} Guaranteed input service time for stage n by its predecessor stage
 β_n Service level at stage n
 C_n^{wip} Cumulative cost of work-in process item at stage n
 C_n^f Cumulative cost of finished items at stage n
 C_n^h Inventory holding cost per unit at stage n
 T Time interval of interest to the decision-maker
 $AOHI_n$ Average on-hand inventory level at stage n
 α_{CI} Optimal compatibility index value (When the compatibility model is solved as single objective) = target value for compatibility
 C_{df}^{pe} Penalty production cost due to delivery failure
 C_{so}^{pe} Penalty production cost due to sales opportunity loss
 $C_{\text{ewt}}^{\text{pe}}$ Penalty production cost due to extra working time
 $C_{\text{st}}^{\text{pe}}$ Penalty production cost due to safety stock
 T_{dt}^p Total down time of the production system
 $T_{\text{pt}}^{\text{st}}$ Necessary production time for the safety stock at the output
 α_{df}^{pe} Fixed penalty per delivery failure
 $\alpha_{\text{sp}}^{\text{pe}}$ Loss of sales profit for a quantity equivalent to one hour of production
 $\alpha_{\text{ewt}}^{\text{pe}}$ Hourly cost rate for the extra working time
 $\alpha_{\text{st}}^{\text{pe}}$ Cost of holding a safety stock equivalent to one hour

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Decision variables

m	Is the maximum extra working hours
$Y_{i,oi}$	Number of unit produced for stage i with option O_i
T_n	Production time at stage n
L_i	Replenishment lead time for stage i
μ_i	Average demand rate for component i
M_i	Maximum replenishment time
d_i	Demand at stage i

1 Introduction

The manufacturing industry over the past few decades has faced critical challenges such as diverse customer demands, shorter product life cycle and cost pressure due to global competition, which include manufacturing a paradigm shift from traditional one-size-fits-all mass production to mass customization (Tseng and Hu 2014). Many studies have been carried out, in order to develop new strategies for design, manufacturing, logistics and service for mass customization (MacCarthy, Brabazon and Bramham 2003). For example, modular design, reconfigurable manufacturing systems and e-logistics for different stages of product life cycle have received great attention of researchers over the past few decades (Daaboul et al. 2011). Very few attempts have, however, been made to develop an integrated approach that allows simultaneous consideration of all aspects of product life cycle in a supply chain environment.

Many researchers have suggested some critical success factors (CSFs) for new product development. There is, however, no commonly accepted finite set of CSFs which may be always considered the most important factors, regardless of product types, firm's strategies, business environment, etc. (Afonso et al. 2008; Lester 1998). Nevertheless, in general, some major factors play important role for the success of a new product, especially in a global competitive scenario, for example (i) efficient communication among marketing, design and manufacturing; (ii) early involvement of suppliers and customers in new product development; (iii) functionalities of product exactly as needed; and (iv) timeliness of product development.

In particular, it has been observed that a systematic consideration of supply chain management (SCM) issues during the new product design and development at conceptual design stage is very important for the success of a new product (Frohlich and Westbrook 2001; Vanteddu et al. 2011). For example, early involvement of suppliers in new product development process is an effective mechanism, aimed at evolving a better solution, as it generally enhances its potential to develop products, which are

innovative in nature. This also involves utilization of emerging technologies, which thus leads to reducing the time-to-market and also in minimizing the involved uncertainties in decision-making (Petersen et al. 2005; Schiele 2010; Garai and Roy 2020).

Some researchers have, however, observed that supplier involvement in a new product development process may not most of the times lead to development of better products and processes (Karadağ et al. 2018). On the contrary, it may also lead to issues like undesired increased cost and time in product development (Hartley et al. 1997; McCutcheon et al. 1997; Wynstra et al. 2001; Lawson, Krause and Potter 2015; Arasteh 2019; Chouhan 2020). Therefore, it becomes imperative to investigate proper ways of supplier integration in a new product development process from various aspects (Clark 1989; Gupta and Wilemon 1990; Fisher 1997; Ulrich and Pearson 1998; Ghodspour and O'Brien 2001; Koufteros and Marcoulides 2006; Kim and Wagner 2012; Chang and Lin 2012; Sinha and Anand 2018).

Jiao et al. (2007) presented a framework for integration of product family and supply chain. Kim and Wagner (2012) systematically addressed the issue of product development from the perspective of supplier selection. Product selection is also a group decision-making process under multiple criteria in a fuzzy environment. Many researchers have established the relationships between product design and SCM, for example (Fisher 1997; Randall and Ulrich 2001; Koufteros and Marcoulides 2006).

In this research paper, we propose a multi-objective decision-making model to determine whether consideration of SCM issues in a new product development process is profitable mainly in terms of total supply chain cost and time-to-market. As a prerequisite for developing such a decision-making model, we have first of all considered the key decision attributes from the SCM literature such as number of suppliers, types of raw materials, manufacturing parts, manufacturing process and product assembly. These attributes are eventually used to define the total supply chain cost and quantify time-to-market.

The complexity of the proposed multi-objective decision-making problem increases exponentially with an increase in the numbers of suppliers, warehouses and customers. In other words, the problem is characterized as a combinatorial optimization problem which, in general, is hard to find an optimal solution within a reasonable time using exact optimization methods (Gen and Cheng 2000). Therefore, we have developed a meta-heuristic, based on an evolutionary algorithm, i.e. Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al. 2002), in order to find a near-optimal solution in considerably less computational time.

Based on the literature survey, a significant research gap is observed between new product development and its effective and efficient supply chain network. Available literature survey under the banner of NPD and SCN mainly focused on the involvement of suppliers in the early design stage of NPD. Now, due to global competitive environment, it is necessary to investigate in a systematic way for developing an integrated supply chain network for NPD. Literature survey reveals that an integrated framework of SCN and NPD is a challenging task for practitioners and researchers. To address the above discussed issues of integrated framework of SCN and NPD, this study is carried out with following highlighted objectwise:

- A systematic integral framework of supply chain management (SCM) and new product development (NPD) has been proposed.
- Total supply chain cost and time-to-market for integral framework of SCM and NPD have been developed.
- NSGA-II-based solution procedure has been developed which gives better results than SPEA-II-based procedure.
- Early supplier involvement during new product development has been studied.
- A case study of laptop computer assembly (Graves and Willems 2005) has been carried out for validation purpose of the proposed integrated framework of SCN and NPD.

The rest of the paper is organized as follows. Section 2 provides related work. The supply chain configuration model for new product development process is proposed in Sect. 3, and Sect. 4 describes the solution method of the model in detail. Section 5 demonstrates the efficiency of the proposed methodology with a comprehensive case study. Section 6 discusses results and sensitivity analysis of the case study. Finally, concluding remarks and discussion on future research requirements are presented in Sect. 7.

2 Related work

Many researchers have earlier carried out some investigations to study the impact of product variety on performance of supply chain (SC) from various perspectives. Efforts were also made to develop various integrated models, which systematically takes into account the vital SCM issues during the early phases of product development (Fisher 1997; Randall and Ulrich 2001; Thonemann and Bradley 2002; Koufteros and Marcoulides 2006; Pero et al. 2010; Eydi and Fazli 2019). Huang et al. (2007) suggested a mathematical model based on game theory approach which leads towards mass customization by configuring

product family and SC. Petersen et al. (2003) proposed a model (on the basis of a case study, which takes into consideration 17 Japanese and American manufacturing organizations). The study revealed that involvement of suppliers in a team has a significant impact in NPD projects.

To et al. (2009) presented a simulation integrated model based on product variant in the domain of supply chain environment (SCE). Amini and Li (2011); Sjoerdsma and van Weele (2015) studied the interaction between new product development and the corresponding supply chain configuration. These researchers also proposed an integrated new product development–supply chain configuration (NPD-SCC) model which has several advantages. Feng and Wang (2013) investigated the impact of supply chain performance on new product development. In this study, the researchers observed that early involvement of supplier significantly reduces the various types of costs involved in NPD. Kim and Wagner (2012) carried out a research study, which considers the role of interrelationship between suppliers in a NPD environment.

Salvador and Villena (2013) suggested that effective integration of suppliers in the NPD process has a great impact on design competence of buyer. It means the effective integration of suppliers into new product development explore the improvements in new product design. Li and Amini (2011) proposed an integrated optimization model based on multiple sourcing and safety stock placement decision which deals with the dynamic demands during the new product development process.

The future trends of decision support tools for collaborative design and manufacturing, supply chain and workflow management can be found in Xie et al. (2003). Cakravastia et al. (2002) suggested a decision-making model for designing supply chain networks in new product family design approach for efficient SCM. Huang et al. (2005) suggested a mathematical model of SCC and PD decisions by considering various product varieties.

Afonso et al. (2008) have tried to develop a relationship between the use of new product firm's practice and the product's development time as well as cost, but lastly they conclude that it is hard to find any direct relationship between total cost and time-to-market of new products.

Graves and Willems (2005) suggested how to select an optimum supply chain network configuration (SCNC) for NPD where design of NPD is already decided. Due to appropriate selection of suppliers for raw materials, parts of product, manufacturing processes and their assembly processes, mode of transportations at each stage of SCN converges towards optimum trade-off between lead time and direct cost associated during the NPD (Graves and Willems 2005). Graves and Willems (2005) proposed a dynamic program formulated on the basis of spanning tree

for optimizing the supply chain network configuration for NPD.

Afrouzy et al. (2016a) have developed a fuzzy system-based multi-objective SCCN for NPD and they also try to identify the effect of NPD on SCCN through performing various sensitivity analysis. Afrouzy et al. (2016a, b) investigated the three objectives: (a) maximum profit of SC, (b) optimum customer satisfaction and (c) maximum production of the product which is newly developed through fuzzy stochastic programming-based model of SCCN for NPD.

Carrillo and Franza (2006) presented an investigation based on timing taken for designing and process capacity for NPD over a systematic planning horizon. Time-to-market and ramp-up time for NPD has been established by Carrillo and Franza (2006) and their relationship is also investigated in terms of mathematical modelling. Decisions related to time-to-market and ramp-up time not only plays a vital role but also provides managerial insights during early design stage of NPD (Carrillo and Franza 2006).

Integration of sustainability issues along with supply chain cost and lead time at early design stage has been considered by Olson et al. (2011). Supply chain performance matrix in terms of cost and lead time has been proposed by Olson et al. (2011). Although Olson et al. (2011) have not developed any mathematical modelling, they provided enough space to think how to formulate best trade-off between cost and time-to-market based on any artificial intelligence tools.

Hilletoft and Eriksson (2010) at first identify the correlation between NPD and SCM and lastly, suggested a framework for coordination of NPD with SCM. NPD processes not only provide a systematically coordination for flow of new products efficiently but also helpful for manufacturing, transportation, distributions and other supply chain activities that support for commercialization of the new product (Hilletoft and Eriksson 2010).

Hasan et al. (2014) identify some key requirements which are necessary for integration of NPD and SCM and also discuss the effect of integration of NPD with SCM. The contributions of Hasan et al. (2014) can be observed in terms of development and analysis of framework which facilitates the integration of NPD activities within OEM (original equipment manufacturers) and supply chain activities like involvement of suppliers.

Efficient and responsive supply chain network is a critical success factor for NPD (Afrouzy et al. 2016b). Genetic algorithm-based supply chain profit optimization model has been developed for NPD.

Willems (1999) proposed a framework for addressing how to configure a supply chain network for NPD while considering various available options from the pool of raw materials, manufacturing processes, different assembly

processes, mode of transportations and distributions till end customers. Each of different options is differentiated by its direct cost associated and production times; therefore, Willems (1999) suggested a methodology for selecting those vendors which will facilitates minimum supply chain cost as well as lead time.

Lamothe et al. (2006) identify not only various available solutions for product family and their bill of materials but also a mixed-integer linear programming-based supply chain optimized model while considering supply chain cost has been proposed. Lamothe et al. (2006) proposed a decision-making model for selecting product variants on the basis of minimum total supply chain cost. A new product design approach and its integration with SCM have been proposed by Lamothe et al. (2006) by considering a large variety of customer demands.

Goal programming with genetic algorithm-based framework for supply chain network configuration with NPD has been investigated by Monplaisir et al. (2011). A multi-objective in terms of supply chain cost and lead time optimization model is developed by Monplaisir et al. (2011).

Nepal et al. (2012) proposed a mathematical model for incorporating the product development (PD) and SCM to examine the effect of product architecture (PA) on SCM. Nepal et al. (2012) suggest finalized the product architecture at conceptual design stage of product life cycle. A weighted goal programming-based integrated product architecture with supply chain decision-making model has been developed by Nepal et al. (2012). Minimization of total supply chain costs and maximization of total supply chain compatibility index are two objectives that have been considered by Nepal et al. (2012).

Table 1 shows a comparative literature survey conducted on the integral approach of NPD on SCM. Based on Table 1, the following have been observed:

- Only three types of direct cost, namely cost of goods sold, safety stock cost and pipeline stock cost, have been considered by Graves and Willems (2005) in the supply chain network configuration for NPD. Other cost associated with NPD like penalty cost, manufacturing cost, transportation cost as well as time-to-market can be considered for SCNC of Graves and Willems (2005).
- Afrouzy et al. (2016a, b) have considered only profit of SC. They have not considered total supply chain cost as well as time-to-market during the modelling which is based on fuzzy stochastic programming of SCCN for NPD.
- Carrillo and Franza (2006) have considered only time domain of NPD. They have not incorporated any cost associated with SCM.

Table 1 Comparative literature survey based on integration of SCN with NPD

S. No	Contributors	SCN	NPD	Model solving approaches	Remarks	Research gap
1	Willems (1999)	Supplier selection in terms of raw materials, manufacturing processes, assemblies, different mode of transportations till reach the end customers has been considered	Fixed product design is used Part selection for multi-generation product has been considered	Spanning tree-based dynamic program	Supply chain cost and lead time is considered during supply chain configuration model for NPD Selection of parts and process has been suggested	Breakage of cost in terms of penalty cost, manufacturing cost, etc. are not incorporated during modelling
2	Graves and Willems (2005)	Only three types of direct cost, namely cost of goods sold, safety stock cost and pipeline stock cost	Design of NPD is already decided	Spanning tree-based dynamic program	Supply chain network configuration for NPD is developed	Other cost associated with NPD like penalty cost, manufacturing cost, transportation cost should be considered for modelling Time-to-market is not considered in the modelling
3	Lamothe et al. (2006)	Optimized supply chain cost model for product family has been developed	Product family and their bill of materials has been considered	Mixed-integer linear programming	Supply chain cost optimization model for various product family and their bill of materials has been formulated	Breakage of supply chain cost is not considered during modelling Time frame origin is not considered during modelling
4	Carrillo and Franza (2006)	Only time frame work of SC is considered	Time-to-market and ramp-up time of NPD has been investigated	With the help of Lagrange multipliers, nonlinear dynamic model has been solved	Only design and production capabilities has been considered	Any cost related to NPD is not considered in the modelling
5	Hilletoft and Eriksson (2010)	Manufacturing, distributions, transportations and commercialization of products has been considers	Managing the product life cycle incorporating market concern issues has been highlighted	Literature survey based on a case study concept is used for examine the hypothesis	Hypothesis has been established which shows the strong correlation between SCM and NPD A framework for coordination of NPD and SCM has been developed	No mathematical modelling is proposed for coordination of NPD with SCM
6	Olson et al. (2011)	Cost and time-to-market have been discussed in terms of only performance matrix	At early design stage, supply chain performance matrix in terms of cost and time-to-market has been proposed	No approach has been implemented, but some artificial intelligence tools can be applied	Only information about cost and time-to-market has been provided without any mathematical modelling	The absence of mathematical modelling in terms of supply chain costs, quality and time-to-market
7	Monplaisir et al. (2011)	Supply chain cost and lead time multi-objective optimization model are considered	Product design and development stages are considered	Goal programming-based genetic algorithm methodology	Supply chain configuration during NPD is formulated Product modularization decisions are aligned with supply chain configuration	Penalty cost, manufacturing costs are not incorporated in the supply chain configuration modelling

Table 1 (continued)

S. No	Contributors	SCN	NPD	Model solving approaches	Remarks	Research gap
8	Nepal et al. (2012)	Total supply chain costs and fuzzy-based supply chain compatibility index have been considered	Decision related to product architecture is integrated with SCM	Genetic algorithm	Using weighted goal programming, an integrated product architecture decision with supply chain decisions approach has been established	Penalty cost, procurement cost and transportation cost are not considered in the modelling
9	Hasan et al. (2014)	Suppliers activity is incorporated with NPD	Flow of product development activities is considered	No methodology has been suggested	Development and analysis of framework which facilitates the integration of NPD activities within OEM (Original Equipment Manufacturers) and supply chain activities is considered	No mathematical modelling for integration of NPD with SCM has been proposed
10	Afrouzy et al. (2016a, b)	Maximum profit of SC, optimum customer satisfaction and maximum production	Multi-objective, multi-period, multi-product aggregate procurement and production planning have been considered	Fuzzy stochastic programming	Effect of NPD on SCC has been investigated Customer demands and supplier capabilities have been considered	Supply chain cost and NPD time period are not considered in the modelling
11	Afrouzy et al. (2016b)	Optimized supply chain profit	Product that is decided to be developed has been considered	Genetic algorithm	Genetic algorithm-based optimization model for integrated SCN with NPD has been considered	Only supply chain profit optimization model is developed. No cost analysis as well as time-to-market or lead time has been considered during modelling

- Systematic modelling which can identify the effect on SC at various stages of NPD is not holistically investigated (Appelqvist et al. 2003).
- Olson et al. (2011) have not developed any mathematical modelling either in terms of cost or time-to-market.
- Hilletoft and Eriksson (2010) have not proposed any mathematical modelling for coordination of NPD with SCM.
- Hasan et al. (2014) have not developed any methodology for NPD-SCM integration procedure
- Afrouzy et al. (2016b) show absence of cost analysis as well as time-to-market or lead time in the proposed modelling
- Willems (1999) has not considered breakage of cost in terms of penalty cost, manufacturing cost, etc. which is not incorporated during supply chain configuration model for NPD.
- Lamothe et al. (2006) have not considered breakage of supply chain cost and time frame origin during modelling
- Monplaisir et al. (2011) have not considered penalty cost, manufacturing costs in the supply chain configuration modelling.
- Nepal et al. (2012) have not considered penalty cost, procurement cost and transportation cost in the modelling

Therefore, there is a need for systematic investigation how the modelling could be applied at conceptual design stage in order to design new product with optimal total supply chain costs and time-to-market. Majority of product life cycle cost has been determined in product development phase (Appelqvist et al. 2003). However, modelling of supply chain effect on various stages of NPD is not holistically developed till now. Therefore, analysis of total supply chain cost in terms of unit-level activity cost, batch-level activity cost, product-level activity cost, facility sustaining activity level, penalty cost for delivery failure, cost corresponding to the sale, cost corresponding to the extra work, cost of the safety cost, procurement cost and transportation cost has been carried out in this study.

Although many researchers are trying to incorporate SCM issues into new product development projects, still it is a challenging task in front of practitioners and researchers. Therefore, a systematic integral framework of SCM and NPD needs more emphasize from practitioners point of view because each industry has their personal rules and regulations.

3 Supply chain configuration model for new product development

In this section, we propose a supply chain configuration model (SCCM) for new product development. In this graph-theoretic model, nodes represent stages in a supply chain such as procurement of raw materials, component manufacturing, subassembly manufacturing or final assembly of the finished goods, while arcs denote the precedence relationships among the stages (design, manufacturing and distributions) that connote the flows of material, information, service and cash. The SCCM includes new design criteria for optimal supply chain configuration that involves selections of the best options for each stage of supply chain. For example, the decision to incorporate configuration involves selection of suppliers for raw materials, selection of transportation modes and also the selection of various manufacturing strategies. The proposed SCCM model includes modular design supply chain network problem.

A knowledge-based data system is formed on the basis of experience from marketing fluctuations, sales of the product and order placed by the retailer of the product. The present data system influences the planning system of a new product development. The planning section of the new product development is an important stage of the SCM. In the planning stage, decision-makers develop a plan, how to introduce a new product in supply chain network, and they also set up an essential qualification limits for the suppliers who will supply raw material for manufacturing plant. Also in the planning stage data mining algorithm such as association rule, clustering and decision tree can be widely used for providing information about customer relationship management, market analysis and desire of customers. Song and Kusiak (2009) describe the use of data mining algorithm in the customer requirement data and historical sales data to extract the knowledge for different stages of product development.

In a decision-making framework, uncertainties play a significant role while assigning the values to attributes. In some situations, it becomes imperative for the decision-maker to adopt deterministic models, which facilitate in decision-making process. However, in real-life industrial scenarios, it sometimes becomes a trivial affair while

deciding about deterministic or stochastic data. The same has been adopted in the proposed framework.

Figure 1 depicts the main feature of SCCM, i.e. consideration of two ways or multiple sources for every individual stage. In this model, we have assumed that inventory holding cost is determined by not only capital and storage related costs. Moreover, we have incorporated the cost of risk that the company is taking for maintaining high level of inventory for maintaining safety stock. Each stage in this model operates according to base stock policy. The base stock level of single stage takes into account replenishment lead time, of which production lead time is a major component. Replenishment lead time is assumed to be normally distributed in this model. The demand is considered constant and is independent for various non-overlapping intervals. The mean demand for period μ and standard

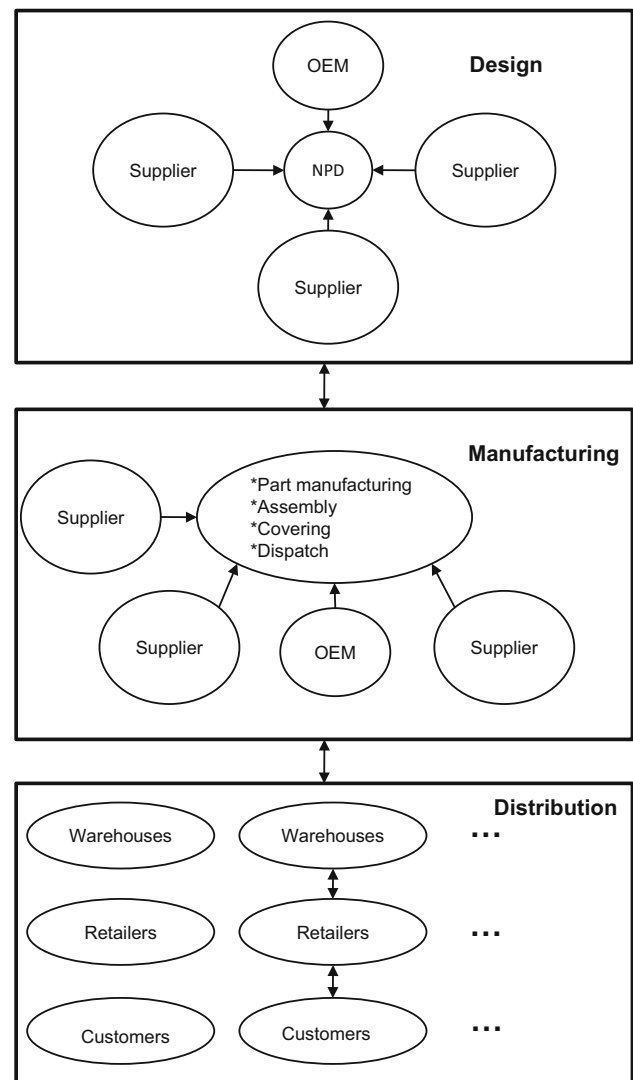


Fig. 1 Supply chain configuration network for new product development

deviation σ for every stage are deterministic. This includes the time required to convert an item at a particular stage.

In this model, the following assumptions are made for simplicity:

- (1) During every period, the stage records the demand, and accordingly, a replenishment order is placed.
- (2) No capacity constraint is considered.
- (3) Waiting time, manufacturing time and transportation time are included in processing time.
- (4) There is an absence of any time delay, while ordering.
- (5) Lead time is deterministic throughout the model

In this model, at each stage of SC network several alternative options have been considered such as multiple suppliers/alternatives for raw materials, and several manufacturers or technologies form manufacturing and various transportation modes for delivery.

The role of the materials management organization (MMO) is not only identifying but also selecting the best options among a bunch of options. Options in this paper are differing in terms of their direct costs and time-to-market. Therefore, the choices of specific options in one portion of the supply chain can affect the cost and responsiveness of the rest of the supply chain. MMO faces a critical trade-off between increased manufacturing cost through responsive supply chain and reduced manufacturing cost in a supply chain environment. We have considered four different types of cost for this model like: investment cost, procurement cost, production cost and transportation cost. The hierarchy of the cost analysis is shown in Fig. 2.

A. Inventory Cost:

- A.1. Average On-hand inventory (AOHI) Cost: The cost of holding the items finished at each stage.
- A.2. Work-in Process inventory (WIP) Cost: The cost of holding the items being proposed at each stage.

B. Total Production Cost: The cost of production during the manufacture ring.

- B.1. Manufacturing Cost: Cooper and Kaplan (1988) and Khataie et al. (2010) presented a model considering manufacturing cost, which takes into account overhead costs. These include:
 - B.1.1. Unit-level activity (material, total machining time, labour, etc.) costs, which vary directly according to number of units produced.
 - B.1.2. Batch-level activity (planning cum tactical management, material handling, set-up, etc.), other types of costs which are involved as and when a batch is processed.
 - B.1.3. Product-level (order-level) activity (process engineering, design, etc.), costs which comes into action, as and when a particular product is manufactured.
 - B.1.4. Facility sustaining activity costs: These include maintenance, rent, utilities, etc.

- B.2. Penalty Cost: On-time product delivery is very important for the overall performance of supply chain. Therefore, there are always business contracts between buyers and sellers in any stage of supply chain and these contracts often

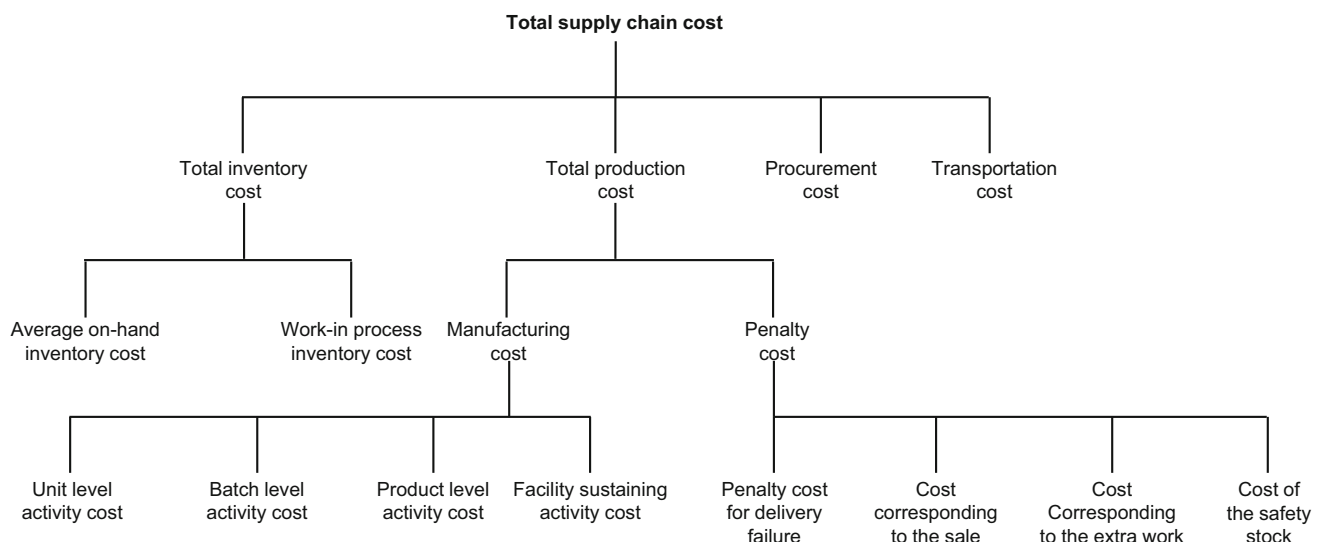


Fig. 2 Cost analysis for supply chain configuration model for new product development

specify expected service levels and define penalties that would be imposed to suppliers if they are not able to fulfil the requirement of delivery plan. Thus, the following four types of penalty cost defined by Faria et al. (2010) have been considered.

- B.2.1. The penalty cost for delivery failures: which is a cost proportional to the number of failures (C_{df}^{pe}).
- B.2.2. The cost corresponding to the sales opportunity loss: This is proportional to the number of products not delivered to customers (C_{so}^{pe}).
- B.2.3. The cost corresponding to additional working time: required to ensure replenishment of actual safety stock to its nominal level, SS_{nl} , which is proportional to downtime and (C_{ewt}^{pe}).
- B.2.4. The cost of safety stock: This is proportional to buffer size and denoted by (C_{st}^{pe}).

- C. Procurement Cost: The cost of raw material procurement during the manufacturer’s time interval.
- D. Transportation Cost: The transportation cost of end products to customers during the manufacturer’s time interval of interest.

The inventory cost during every stage of a typical multi-stage inventory system, in general, includes AOH and WIP inventory. Therefore, the basic objective of the proposed model is selection of best alternative during every stage and also to determine the optimal service time at every stage, thereby minimizing the total supply chain cost, which is presented in Fig. 2.

The daily production costs, C^{pe} , by incorporating only penalty cost resulting from the sum of above four components are given by:

$$C^{pe} = \begin{cases} \alpha_{ewt}^{pe} T_{dr}^p + \alpha_{st}^{pe} T_{pt}^{st} & \text{for } T_{dr}^p \leq T_{pt}^{st} \\ \alpha_{df}^{pe} + \alpha_{sp}^{pe} (T_{dr}^p - T_{pt}^{st}) + \alpha_{ewt}^{pe} T_{pt}^{st} + \alpha_{st}^{pe} T_{pt}^{st} & \text{for } T_{dr}^p > T_{pt}^{st} \end{cases} \tag{1}$$

where T_{dr}^p : total down time of the production system during a working day; T_{pt}^{st} : necessary production time for the safety stock at the output; α_{df}^{pe} : fixed penalty per delivery failure; α_{sp}^{pe} : loss of sales profit for a quantity equivalent to one hour of production; α_{ewt}^{pe} : hourly cost rate for the extra working time; and α_{st}^{pe} : cost of holding a safety stock equivalent to one hour of production.

Figure 3 shows the graphical representation of all the four different penalty cost components (see B.2.1, B.2.2, B.2.3, B.2.4) vs. T_{pt}^{st} .

As this model is evaluated at design time, only the expected values of the cost components can be estimated by:

$$E[C^{pe}] = E[C_{df}^{pe}] + E[C_{so}^{pe}] + E[C_{et}^{pe}] + E[C_{st}^{pe}] \tag{2}$$

In general, the total downtime, T_{dr}^p , of a production system during a working day depends upon two random variables: the number of failures that have occurred during the mission time frame and the duration of each failure. It is important to note that the presented cost model is a non-linear function of T_{dr}^p , and the cost components therefore cannot be assessed using the asymptotic value of T_{dr}^p . Therefore, Faria et al. (2010) suggested to utilize the probability density function of failure occurrence, denoted as $fT_{dr}^p(t)$, for calculating the expected production cost, C^{pe} , where it is considered that a failure occurs if $T_{dr}^p > T_{pt}^{st}$:

$$E[C^{pe}] = \int_0^\infty fT_{dr}^p(t) \times PC(T_{dr}^p) dT_{dr}^p \tag{3}$$

Furthermore, the expected cost caused by delivery failures $E[PeC_{df}]$ can be calculated by multiplying the fixed penalty per delivery failure by the integral of $fT_{dr}^p(t)$ (Faria et al. 2010):

$$E[C_{df}^{pe}] = \alpha_{df}^{pe} \int_{T_{pt}^{st}}^T fT_{dr}^p(t) dT_{dr}^p \tag{4}$$

In a similar way, we can also calculate the expected cost caused by sales opportunity loss $E[C_{so}^{pe}]$, the expected cost corresponding to the extra working time $E[C_{et}^{pe}]$ and the expected cost of the safety stock $E[C_{st}^{pe}]$ as follows (Faria et al. 2010):

$$E[C_{so}^{pe}] = \alpha_{df}^{pe} \int_{T_{pt}^{st}}^T fT_{dr}^p(t) (T_{dr}^p - T_{pt}^{st}) dT_{dr}^p \tag{5}$$

$$E[C_{et}^{pe}] = \alpha_{et}^{pe} \sum_{n=1}^m n fT_{dr}^p(t) dT_{dr}^p \tag{6}$$

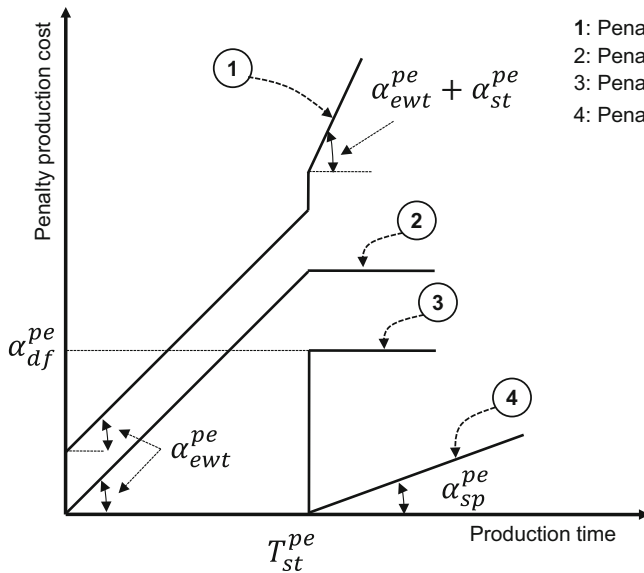
where m is the maximum extra working hours

$$E[C_{st}^{pe}] = \alpha_{st}^{pe} SS_{nl} \tag{7}$$

Average pipeline/Working inventory (WIP) at stage n:

$$WIP_n = \mu_n T_n \tag{8}$$

T_n : Production time at stage n



- 1: Penalty production cost due to safety stock (C_{st}^{pe})
- 2: Penalty production cost due to extra working time (C_{et}^{pe})
- 3: Penalty production cost due to delivery failure (C_{df}^{pe})
- 4: Penalty production cost due to sales opportunity loss (C_{so}^{pe})

α_{af}^{pe} : Fixed penalty per delivery
 α_{ewt}^{pe} : Hourly cost rate for the extra working hour
 α_{sp}^{pe} : Loss of sales profit for a quantity equivalent to one hour of production
 α_{st}^{pe} : Cost of holding a safety stock equivalent to one hour of production
 T_{pt}^{st} : Necessary production time for the safety stock of the output

Fig. 3 Penalty production cost versus production time

Total cost of goods sold and inventory carrying cost at stage $n =$ Average on-hand inventory cost $= C_n^h \times C_n^f \times AOH_n$ (9)

C_n^f : Cumulative cost of finished item at stage n
 Average pipeline/Working inventory cost $= C_n^h \times C_n^{wip} \times WIP_n$ (10)

C_n^h : Inventory holding cost at stage i . C_n^{wip} : Cumulative cost of work/in process at stage n . WIP_n Average pipeline inventory at stage n

Replenishment time for supplier i at stage j (as a random variable) $= \tau_j = L_j + \max_{i:(i,j) \in A} \{\Delta_i\}$ (11)

L_j : Replenishment lead - time for stage i
 where Δ_i is delay for supplier i as a random variable
 $\tau_j = L_j + \sum_{i:(i,j) \in A} \pi_{ij} L_i$ (12)

where π_{ij} implies the fraction of order from i to j that experience the store nominal lead time, proposed by (Ettl et al. 2000):

$$\pi_{ij} = \frac{1 - \phi(K_i)}{\phi(K_i)} \times \frac{1}{1 + \sum_{h:(h,j) \in A} \frac{1 - \phi(K_h)}{\phi(K_h)}} \quad (13)$$

where ϕ : standard normal probability density function. The on-hand inventory at stage j is calculated by:

$$I_j = k_j \sigma_j(\tau_i)^{1/2} + \sigma_j(\tau_i)^{1/2} \int_{z=k_j}^{\infty} (z - k_j) \phi(z) dz \quad (14)$$

Total safety stock cost of the stochastic service model is calculated by:

$$C^{ssm} = \sum_{j=1}^N C_j^s \sigma_j(\tau_i)^{1/2} \left(k_j + \int_{z=k_j}^{\infty} (z - k_j) \phi(z) dz \right) \quad (15)$$

In this supply chain configuration model, design of product has been fixed. It means that variation in product configuration is not allowed. Now, the major problem is how to select the parts and procedure during product development. Say, for example, same raw materials, technology/machines, assembly systems and mode of transportation can be provided by different suppliers. In this regard, major theme is how to select the optimal suppliers for different technology/machine, assembly system and mode of transportation, respectively. Each of these different options can be easily differentiated by its time-to-market and total supply chain cost. Willems (1999) discussed that in a given pool of the set of choice, the main problem is to click the options from pull of suppliers which optimizes the total supply chain cost as well as time-to-market.

In general, time-to-market is a major aspect of global competition. Time-to-market is a major factor for making competitive advantages for any industries especially in dynamic market segments. Folgo (2008) mentioned that time-to-market and total supply chain cost is a key factor for success of any industry particularly in the area of NPD.

Finally, the two objectives of the supply chain configuration model for new product development have been formulated: one is total supply chain cost whose unit is monetary and the other one is time-to-market whose unit is time. This leads us to formulate a multi-objective optimization model where the objectives are incommensurable.

(1) Minimize total supply chain cost.

$$\begin{aligned} \text{minimize} \quad & \sum_{j=1}^N h_j w_j \mu_j T_j + \sum_{j=1}^N h_j c_j k_j \sigma_j(\tau_j)^{1/2} + \\ & \left[\sum_{j=1}^N \left[\sigma_j(\tau_j)^{1/2} \int_{z=k_j}^{\infty} (z - k_j) \phi(z) dz \right] \right. \\ & \left. + \sum_{j=1}^N \left[C_j^s \sigma_j(\tau_j)^{1/2} \left\{ \left(k_j + \int_{z=k_j}^{\infty} (z - k_j) \phi(z) dz \right) \right\} \right] \right] \\ & + \left[\alpha_F \int_{T_{ss}}^T f T_D(t) dT_D + \alpha_S \int_{T_{ss}}^T f T_D(t) (T_D - T_{ss}) dT_D + \alpha_X \sum_{n=1}^m n f T_D(t) dT_D \right] \end{aligned} \tag{16}$$

(2) Minimize total time-to-market of the supply chain configuration.

$$\text{minimize} \quad \sum_{j=1}^N \left[L_j + \sum_{i:(i,j) \in A} \left\{ \frac{1 - \phi(K_i)}{\phi(K_i)} \times \frac{1}{1 + \sum_{h:(h,j) \in A} \frac{1 - \phi(K_h)}{\phi(K_h)}} \right\} L_i \right] \tag{17}$$

Subject to: Production time constraint

$$\left\{ \sum_{O_i \in S(i)} T_{iO_i} Y_{iO_i} \right\} - T_i = 0; \quad i \in N \tag{18}$$

Production cost constraint

$$\left\{ \sum_{O_i \in S(i)} C_{iO_i} Y_{iO_i} \right\} - C_i = 0; \quad i \in N \tag{19}$$

$$Y_{iO_i} : \text{Number of unit produced for stage } i \text{ with option } O_i \tag{20}$$

Inventory coverage time constraint (since back order is not allowed)

$$\sum_{i \in N} Y_{iO_i} \beta_{iO_i} - \beta_i = 0$$

$$\beta_{iO_i} : \text{Compatibility index at stage } i \text{ with option } O_i \tag{21}$$

$$\beta_i : \text{Compatibility index at stage } i$$

Single sourcing constraint (only one supplier is selected at each node)

$$\sum_{O_i \in S(i)} Y_{iO_i} = 1; \quad i \in N \tag{22}$$

Positivity constraint

$$\left\{ \begin{matrix} S_i^{\text{out}} \\ O_i \\ \beta_{ij} \end{matrix} \right\} \geq 0 \tag{23}$$

It can be said that the proposed model extends the single-criterion supply chain optimization approach of Graves and Willems (2003) in terms of four aspects. Firstly, Graves and Willems (2003) assumed that inventory is the only level to counter demand. However, we have considered two levels to counter demand: inventory and time-to-market. Secondly, we have permitted the possibility of having dual or multiple sources for each individual activity or stage. Thirdly, we have incorporated penalty cost in terms of delivery failure, sales opportunity loss and extra working time in supply chain network design. Finally, we have formulated the supply chain network design as a multi-objective optimization problem. In the following section, we present a Non-dominated Sorting Genetic Algorithm-II (NSGA-II)-based solution procedure and Strength Pareto Evolutionary Algorithm-II (SPEA-II)-based solution procedure for multi-objective supply chain network design problems.

4 Multi-objective optimization for supply chain configuration

Evolutionary algorithms are known to be efficient and easy adaptive for combinatorial optimization problems. Several meta-heuristic search techniques such as genetic algorithm (Fahimnia et al. 2012), non-dominated rank genetic algorithm (Moradi et al. 2011), artificial immune system-based algorithm (Kumar et al. 2011) and particle swarm optimization (Subramanian et al. 2012) are popularly used to solve a broad range of complex problems, especially those where traditional solution methods failed to find good solutions in a reasonable computation time (e.g. mixed-integer nonlinear programming). There are many efficient multi-objective evolutionary algorithms (MOEAs) which are able to quickly find Pareto optimal solutions widely distributed in a solution space.

For example, Khor et al. (2005) discussed solution assessment methods and presented several principles for solution search in evolutionary multi-objective optimization. Rachaniotis and Pappis (2008) applied a multi-objective evolutionary algorithm to supply chain network design. In this paper, we have two incommensurable variables: first one is total supply chain cost and second one

is total time-to-market of the proposed supply chain configuration. Since both variables are incommensurable, it is not easy to convert one variable into other. One more thing, the problem of the addition of two incommensurable variables like total supply chain cost and time-to-market become more exaggerated when SCCM has more completed structure. Therefore, we have proposed two objective functions whose solutions will be in the terms of trade-off between them (cost and time-to-market).

In this paper, we develop a solution procedure using NSGA-II for supply chain configuration problems because of (i) its computation efficiency, i.e. the computational complexity of NSGA-II is $O(mn^2)$ where m is the number of objectives and n is the number of population sizes (Deb et al. 2002) and (ii) no need of sharing parameters which is generally an important decision factor of evolutionary algorithms.

Before describing the proposed NSGA-II-based solution procedure, we discuss fast non-dominated sorting procedure, fast crowded distance estimation procedure and simple crowded comparison operator which is the basic of NSGA-II.

Fast non-dominated sorting procedure: To identify solutions for the first non-dominated front in a population of size N , every individual is to be compared with every solution of the population, to verify whether it is dominated or not. During this step, every individual in the first non-dominated front is screened. To determine the next-dominated front, the same procedure which is suggested for first non-dominated front should be repeated after excluding the first-dominated front from the search space. In the same way, third, fourth, fifth, etc., next non-dominated front will be calculated.

Fast crowded distance estimation procedure: To get an estimation of probability of possible solutions, enveloping a particular solution of the given population, the average distance between two points represents the estimated value of perimeter of the cuboids which is formed by the nearest vertices. And this distance is known as crowding distance. This crowding distance is based on sorting in ascending order of the population which is encoded in terms of objective functions (total supply chain cost and time-to-market). Therefore, for every objective function, the boundary population having smallest and largest function values is allocated an infinite distance value. Similarly, the remaining intermediate population is also allocated some value of distance, equal to the absolute value. This exercise is repeated for all the objective functions.

Crowded comparison operator: The crowded comparison operator facilitates the process of selection during various stages of the algorithm.

Here, every population is characterized by two distinctive attributes: non-dominated rank and crowding distance.

The selection between two populations is preferred on the basis of two attributes, namely non-dominated rank and crowding distance. The population which has lower non-dominated rank should be selected. Otherwise, if non-dominated ranks of two populations are same, then the population which has larger crowding distance should be selected.

The developed procedure produces a random population $P(1)$ of size L . Encoding of each objective functions (total supply chain cost and time-to-market) in terms of each chromosome of $P(1)$ will be the input for the proposed algorithm. Now, non-dominated front of $P(1)$ will be arranged in ascending order for each individual chromosome. Next, the binary tournament selection is applied to crossover and mutation operators for generating the children population $C(1)$ of size L . Same procedure will be repeated again and again for next T generation.

The same procedure applies for non-dominated sorting. In the similar manner, next-generation population is obtained.

The proposed NSGA-II-based solution procedure consists of the following 17 steps:

Step 1 Initialization: To create a random parent population (P_0) of population size (N)

The required NSGA-II parameters for initializing includes: number of generation (3000), population size (200) and crossover probability (0.8) and mutation probability (0.01). Encoding of chromosome is the first and important part of initializing process.

Step 2 To evaluate fitness value of each chromosome in the parent population (P_0).

The main aim of the step is to evaluate the fitness function of total supply chain cost and time-to-market for each possible solution (s) in generation (gen) for all population size because this fitness will be carried out for fast non-dominated sorting.

Step 3 To evaluate domination count (n_p), the number of solutions which dominate the solution p , for each solution.

Step 4 To evaluate S_p , a set of solutions that the solution p dominates.

Step 5 To find the sets of non-dominated solutions whose domination count is zero.

Step 6 To visit each member (q) of its set S_p and reduce its domination count by 1.

Step 7 If the domination count becomes zero for any member q , we put it in a separate list Q . These members belong to the second non-dominated front.

Step 8 Go to step 6. And find out third non-dominated front, fourth, fifth and so on.

Step 9 To identify all non-dominated fronts.

Step 10 To assign a fitness (or rank) equal to its non-dominated level (front) where '1' is the best level, 2 is the second-best level and so on.

Step 11 To do binary tournament selection by using a crowded tournament selection operator:

Crowded Tournament Selection Operator ε :

Non-dominated rank (i_{rank}).

Crowding distance (i_{distance}).

A solution 'i' wins a tournament with another solution 'j' if any of the following conditions are true:

Condition 1

$$i \varepsilon_j \quad \text{if}(i_{\text{rank}} < j_{\text{rank}}) \quad (24)$$

or.

Condition 2

$$((i_{\text{rank}} = j_{\text{rank}}) \text{ and } (i_{\text{distance}} = j_{\text{distance}})) \quad (25)$$

Crowding distance computation procedure of all solutions in a non-dominated set I.

Step 11.1 To call the number of solutions in I as l. that is $|I| = l$.

Step 11.2 To first assign $I[i]_{\text{distance}} = 0$, for each "i" in the set.

Step 11.3 To find the sorted indices vector: $I^m = \text{sort}(I, m)$ for each objective functions.

Step 11.4 To assign a large distance for boundary solution for $m=1$ so that boundary points are always selected, that is:

$$I[1]_{\text{distance}} = I[l]_{\text{distance}} = \infty \quad (26)$$

Step 11.5 To assign large distance for boundary solutions for other solutions ($i = 2, 3, \dots, l-1$)

$$I[1]_{\text{distance}} = I[i]_{\text{distance}} + \frac{(I[i+1]m - I[i-1]m)}{(f_m^{\text{max}} - f_m^{\text{min}})} \quad (27)$$

where f_m^{max} and f_m^{min} are the population maximum and minimum values of the mth objective function.

Step 12 To create an offspring population by doing crossover and mutation operations. Let us suppose P_t is the parent population of t th generation and Q_t is the offspring population of size N .

Step 13 To create a combined population $R_t = P_t \cup Q_t$ of size $2N$.

Step 14 Go to Step 11 and get P_{t+1} , parent population of $(t+1)$ th generation by selecting only N population size from the set of R_t .

Step 15 Go to Step 12 and get Q_{t+1} , offspring population of $(t+1)$ th generation.

Step 16 To do a number of iterations and get the best compromising Pareto optimal sets

Step 17 To apply a clustering technique and get the best global Pareto optimal set.

We applied SPEA-II (Zitzler et al. 2001), yet another efficient algorithm, to the same problems in order to compare the computational performances. The proposed SPEA-II-based solution procedure consists of the following six steps:

Note that.

N : Population size, \bar{N} : Archive size, T : Maximum number of generation, A : Non-dominated set.

Step 1 Initialization

- 1.1. To generate an initial population P_0
- 1.2. To create the empty archive $\bar{P}_0 = \phi$
- 1.3. To put $t=0$

Step 2 Fitness assignment

- 2.1. To calculate the fitness value of P_t
- 2.2. To calculate the fitness value of \bar{P}_t

Step 3 Environmental selection

- 3.1. To make a set of all non-dominated individuals in \bar{P}_t
- 3.2. To make a set of all non-dominated individuals \bar{P}_t to \bar{P}_{t+1}

if $\{\text{size of } \bar{P}_{t+1} > \bar{N}\}$ then

reduce \bar{P}_{t+1} by means of the truncation operator

else

fill \bar{P}_{t+1} with dominated individual in \bar{P}_t and \bar{P}_{t+1}

Step 4 Termination

if $\{t \geq T\}$ then

Set A to the set of decision vector represent by the non - dominated individuals in \bar{P}_{t+1}

Stop

else

Go to step 5

Step 5 Mating selection

To do binary tournament selection with replacement on P_{t+1} .

Step 6 Variation

- 6.1. To do recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population.
- 6.2. $t = t + 1$, Go to Step 2.

5 Numerical illustration

For comparison purpose, we used the data in the case study of laptop computer assembly of Graves and Willems (2005) which was formulated as a multi-objective

optimization problem in the frame of the supply chain configuration model for new product development. The original diagnostic model has 34 stages of supply chain with 72 options. We have made an attempt to simplify the actual model by appropriately considering only two end items instead of five end items and also by infusing various miscellaneous components in single stage.

In general, a laptop consists of a number of components such as central processing unit, memory (RAM), graphic card, hard drive, display and cooling fans. It is assumed that components of circuit board are procured from some external suppliers and assembly is carried out by some contract manufacturer. The process of product assembly involves sequential assembly of various subcomponents, followed by quality testing procedures. Figure 4 shows a graphical depiction of the supply chain network of the laptop computer assembly.

As shown in Fig. 4, there are several alternatives available for each component; for example, there are five alternatives for central processing unit: i3-2310 M (2.1 GHz), i5-3210 M (2.56 GHz), E2-1800 (2 GHz), i7-2860QM (2.5 GHz), i7-3612QM (2.1 GHz). It is assumed that at each stage of the supply chain, it is necessary to configure an optimal set of suppliers/alternatives for all components, where the configuration decision must resolve conflicts among suppliers/alternatives in terms of price and delivery time. The price and delivery time of different alternatives at each component/assembly are provided in Table 2.

6 Results and sensitivity analysis

In order to efficiently find an optimal set of suppliers/alternatives from a large search space under conflicting criteria, we have proposed a NSGA-II-based solution procedure that reduces the large search space by finding non-dominated solutions over successive generation of NSGA-II. Since the NSGA-II result is very sensitive to algorithmic parameters, we have performed several simulations to find suitable parameter values (see Table 3).

The Pareto optimal solutions (i.e. non-dominated solutions) in terms of total supply chain and time-to-market are obtained after 3000 iterations; for this, the population size of 200 was selected. Each of these solutions (in terms of total supply chain and time-to-market) represents an optimal subcontracting alternative for each and every alternatives of the network, and it also makes an optimal trade-off between total supply chain cost and time-to-market. In the laptop case study, it is possible for us to make 0.6 million ($= 200 \times 3000$) combinations of alternatives. However, we have observed only a small portion, and 0.04% of the combinations is non-dominated, namely 26 Pareto optimal

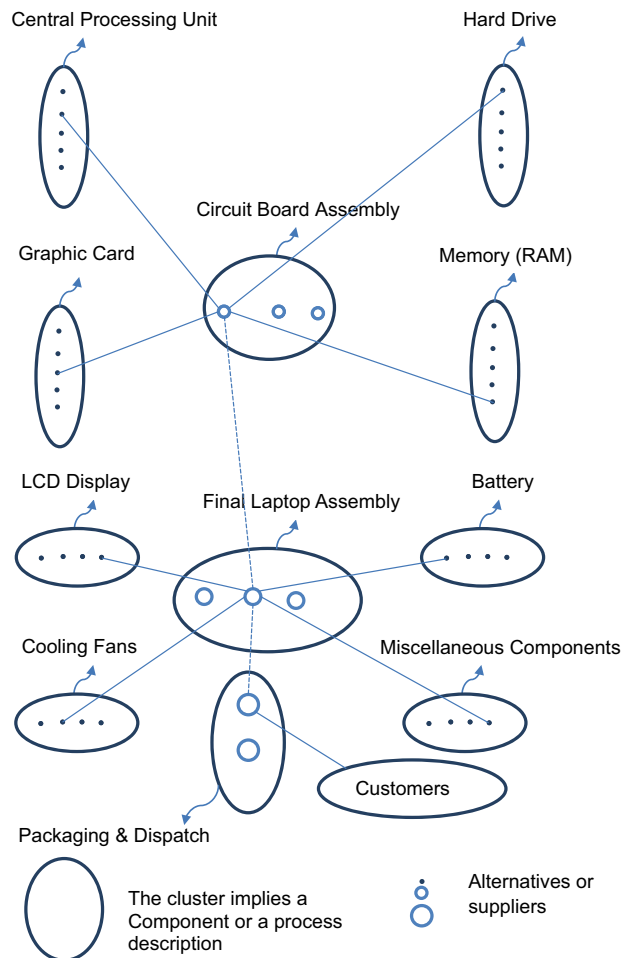


Fig. 4 Graphical depiction of supply chain network for a laptop assembly

solutions. Keeping in view the fact that a result obtained by different simulation test did not always find the all non-dominated point on the trade-off curve, at least 95% of the solutions were found. The Pareto optimal solutions (in terms of total supply chain and time-to-market) obtained by the developed NSGA-II-based procedure are plotted in Fig. 5, where each point implies a combination of total supply chain cost and time-to-market for the assembly of the laptop.

The best compromise solutions with respect to both criteria are listed in Table 4. Table 4 indicates two Pareto optimal for two trade-off objective functions. For instance, the results in Table 4 indicate that the fifth solution exhibits the lowest total supply chain cost, while the seventh solution exhibits the minimum time-to-market.

In order to validate the efficiency of the proposed NSGA-II-based solution procedure, we have compared the computational performances of the NSGA-II-based procedure and the SPEA-II-based procedure. The Pareto optimal

Table 2 Delivery time and prices of different alternatives for laptop components and its assembly processes. (*Source*: notebookparts.com, laptoppartsexpart.com)

Component/process Description	Alternatives	Delivery time (days)	Price (\$)
Central processing unit	i3-2310 M (2.1 GHz)	40	130.00
	i5-3210 M (2.56 GHz)	20	133.25
	E2-1800 (2 GHz)	10	134.91
	i7-2860QM (2.5 GHz)	7	136.59
	i7-3612QM (2.1 GHz)	8	135
Memory	DDR2 4 GB	20	200.00
	DDR3 4 GB	10	202.50
	DDR3 8 GB	8	205.03
	DDR3 16 GB	6	206.00
Graphic card	Intel HD Graphics 3000	10	155.00
	Radeon HD 7670	6	156.93
	Geforce GT640M	4	200.00
	Geforce GTX660M	3	220.00
Hard drive	SATA3 320 GB	4	200.00
	SATA3 500 GB	2	220.00
	SATA3 ITB (1000 GB)	1	250.00
Circuit board assembly	Surface mount board assembly	20	120.00
	Thru-hole board assembly	5	150.00
	Mixed technology board assembly	3	180.00
LCD display	11.6 inches	6	100.00
	16.6 inches	5	150.00
	17.3 inches	2	160.00
Cooling fans and heat sink	3 fans made of plastic	70	25.00
	3 fans made of plastic and metal mesh	30	40.00
	3 fans made of plastic with a groove line surface	20	80.00
Battery	8-cell lithium-ion battery	60	40.00
	9-cell lithium-ion battery	20	45.00
	12-cell lithium-ion battery	10	60.00
Final note book assembly	Note book assembly line 1 (N.B.AL ₁)	5	120.00
	Note book assembly line 2 (N.B.AL ₂)	2	132.00
	Note book assembly line 3 (N.B.AL ₃)	1	145.00
Packaging and dispatch	Local	40	5.00
	National	15	5.50
	International	10	6.00

Table 3 Best NSGA-II parameters for trade-off between the total supply chain cost and time-to-market

NSGA-II parameters	Parameter value
Population size	200
Number of generation	3000
Crossover probability (P_c)	0.8
Mutation probability (P_m)	0.01

solutions obtained by the SPEA-II-based procedure are plotted in Fig. 6.

The same algorithmic parameters such as population size, number of generations, crossover probability and mutation probability are specified for both procedures. The Pareto optimal solutions for both procedures are plotted together in Fig. 7, and it shows that the NSGA-II generally finds more Pareto optimal solutions than SPEA-II.

The performance of NSGA-II is based on the dominance ranking, which is formed layer by layer for each and every

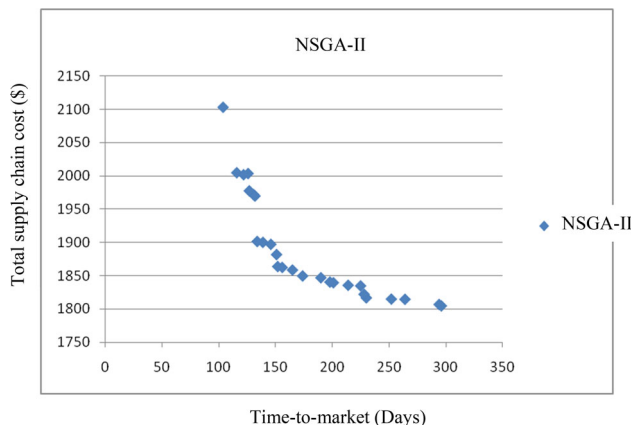


Fig. 5 Pareto front total supply chain cost and time-to-market obtained by NSGA-II

Table 4 Pareto optimal/non-dominated solution with NSGA-II

Solutions	Optimal alternative at each and every components/ process descriptions	Total supply chain cost (\$)	Time-to-market (days)
1	{4,1,2,2,1,3,1,1,2,1,3}	1864.1	152
2	{5,3,1,3,2,3,3,2,3,2,3}	1805	174
3	{5,4,4,2,3,2,4,3,2,2,3}	1900.5	139
4	{3,3,2,1,2,3,1,3,2,1,2}	1836	214
5	{5,3,1,1,3,2,2,2,3,3,3}	1801	296
6	{3,3,2,1,2,3,1,3,2,1,2}	1858.9	165
7	{5,3,2,2,1,3,2,3,3,1,3}	2103.4	104
8	{5,4,1,1,1,3,1,2,3,3,1}	1815.2	252
9	{5,3,1,3,2,3,3,2,3,2,3}	2005.1	116
10	{4,2,1,2,1,2,2,2,3,2,2}	1862.8	156
11	{4,4,4,1,1,3,3,3,2,1,2}	1817.1	230
12	{2,2,1,1,2,3,3,2,3,2,3}	1814.9	264
13	{5,1,2,1,1,1,2,2,3,3,3}	1807.1	294
14	{4,2,2,2,1,1,3,2,2,2,3}	1972	131
15	{4,2,2,2,1,1,3,2,2,2,3}	1839.8	201
16	{5,1,2,1,1,1,2,2,3,3,3}	2002.1	122
17	{4,2,2,2,1,1,3,2,2,2,3}	1897.5	146
18	{2,2,1,1,2,3,3,2,3,2,3}	2003.9	126
19	{4,2,2,2,1,1,3,2,2,2,3}	1977.9	127
20	{4,3,1,3,2,3,2,3,3,2,3}	1882.1	151
21	{2,4,4,2,3,2,4,3,2,2,3}	1822.5	228
22	{3,1,2,1,2,3,1,3,2,1,2}	1847.3	190
23	{5,1,4,1,1,3,1,2,3,3,1}	1970.1	132
24	{3,1,2,1,2,3,1,3,2,1,4}	1901.8	134
25	{2,1,1,1,2,3,3,2,3,2,3}	1835.1	225
26	{4,2,1,2,1,2,2,2,3,2,2}	1840.8	198

individual. On the basis of this strategy, it may be possible that a set of close neighbour individuals in the same layer can be included into the next generation. On the other hand,

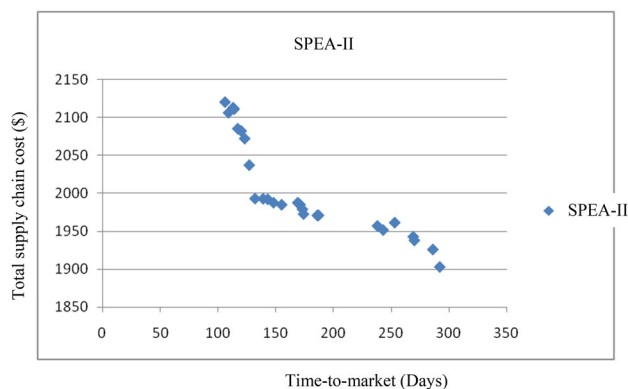


Fig. 6 Pareto front total supply chain cost and time-to-market obtained by SPEA-II

the performance of SPEA-II is based on the density information which acts as a part of the fitness value during selection procedure. Therefore, in case of SPEA-II close-neighbour individuals are likely to be excluded. Due to this reason, SPEA-II provides a wide distribution of the population and facilitates exploration capability better than NSGA-II. In contrast, NSGA-II is more focused as compared to SPEA-II. Another major difference between the performance of NSGA-II and SPEA-II is that NSGA-II uses crowding distance strategy but SPEA-II uses nearest neighbour strategy. In general, the performance of the nearest neighbour strategy is worst especially in case, when we consider end front of the solutions.

To deliver a more clear assessment, we have applied further two well-known heuristics (single-criterion approaches): minimum unit manufacturing cost heuristic (UMC) and minimum time-to-market (MLT) to the Pareto optimal solutions obtained by NSGA-II.

UMC chooses the lowest cost options at each component / process description. By using this heuristics, we have obtained the following combination in our case study.

[i3-2310 M (2.1 GHz),DDR2 4GBIntel HD, Graphics 3000,SATA3 320 GB,Surface Mount Board Assembly,11.6 Inches, M₁,3 Fans made of Plastic, Cell Lithium Ion Battery, N.B.A₁,Local], Cost = 1710, Time-to-market = 374.

MLT chooses the single option at each component/ process description with the shortest lead time. By using this heuristics, we obtained the following path in our case study.

[i7-2860QM (2.5 GHz), DDR3 16 GB,Geforce GTX660M, SATA3 ITB (1000 GB), Mixed Technology Board Assembly, 17.3 Inches, M₄, 3 Fans made of Plastic with a groove line surface, 12 Cell Lithium Ion Battery, N.B.A₃ International], Cost = 2180, Time-to-market = 83.

From Table 4, we have observed that fifth solution exhibits the lowest total supply chain cost (1801\$), which

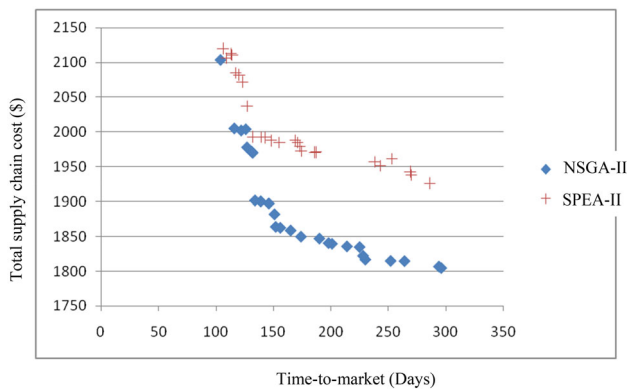


Fig. 7 Comparison of the two algorithms in terms of Pareto front of total supply chain cost and time-to-market

satisfies the condition of UMC heuristic. In the same way, seventh solution exhibits the lowest time-to-market (104 days), which also satisfies the condition of MLT heuristic. As a consequence, we can say that robustness of the NSGA-II-based solution procedure is conformed on the basis of SPEA-II and two heuristics UMC and MLT. Based on the evaluation of various parameters using NSGA-II algorithm, a trade-off has been obtained such that a bridge between total supply chain cost and time-to-market is established.

7 Conclusions

In this paper, we have discussed supply chain configuration issues in new product development by proposing the SCC model for NPD. In order to deal with multi-objective optimization problems of the SCCM, we have developed the NSGA-II-based solution procedure that generates better results than SPEA-II-based procedure.

There are two main directions, to which the approach of this research can be extended. Firstly, the proposed model has discussed only two objectives, total supply chain cost and time-to-market, while many other important decision factors such as quality, sustainability and flexibility may be further considered. This requires first how to quantify those qualitative factors in a reasonable way. Finally, the sensitivity analysis of the laptop case study reveals that the total supply chain cost decreases with time-to-market. However, there is a strong correlation exist between total supply chain cost and time-to-market. Therefore, in future further investigation is necessary for establishing correlation between total supply chain cost and time-to-market.

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Declarations

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