International Journal of Production Research
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713696255

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First Published on: 05 June 2009

To link to this Article: DOI: 10.1080/00207540902893425
URL: http://dx.doi.org/10.1080/00207540902893425

International Journal of Production Research,
2009, 1–23, iFirst

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Minimisation of supply chain cost with embedded risk using computational intelligence approaches

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(*Received 23 September 2008; final version received 5 March 2009*)

Global supply chains are vulnerable towards different types of risks and are dynamically expanding with the increase in globalisation. Costs are associated with every risk factor that causes disturbances in the allocation of certain goods at the required place and time, and with the required quality and quantity. In this paper, we consider a multi-echelon global supply chain model, where raw material suppliers, manufacturers, warehouses and markets are located in different countries. The paper first identifies all types of operational risk factors, their expected value and probability of occurrence, and associated additional cost. Based on initial information for the risk factors, optimal decisions regarding the inter-echelon quantity flow in the supply chain are made for a single planning horizon. Then, with the change in the expected value of the risk factors, the intra-echelon shift of flow is determined in order to minimise the total cost and risk factors. Considering the complexity involved with the problem, various computational intelligence techniques such as genetic algorithms, particle swarm optimisation and artificial bee colony are applied in the solution evaluation phase. The results obtained using the developed model illustrate that the ability to react to changes in risk factors offers potential solutions to robust supply chain design.

Keywords: supply chain management; risk management; flexibility; computational intelligence techniques

1. Introduction

Risk in supply chains can be defined as the potential deviations from the initial overall objective that, consequently, trigger the decrease of value-added activities at different levels. These activities can be described by the volume and quality of products at different locations and time in the supply chain. A single malfunction of any activity at any level in the supply chain may influence several other activities at different levels. Therefore, in order to have stable value-added activities, risk assessment has become an integral part of the supply chain design process. Risk assessment consists of identifying, evaluating and measuring risks in supply chains and making decisions explicitly to minimise their undesired effect.

A supply chain comprises multiple organisations with several tiers of suppliers and/or customers, which are subject to numerous risks at different levels. Moreover, globalisation

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ISSN 0020–7543 print/ISSN 1366–588X online

DOI: 10.1080/00207540902893425
http://www.informaworld.com

has further intensified the supply chain's susceptibility towards those risks. An effective risk management process decreases the vulnerability of the supply chain by making it resilient and stable. Risk in supply chains arises due to several factors, which are generally classified as internal risk factors and external risk factors. The internal operational risk factors evolve within the supply chain due to improper coordination among different levels. Demand risk, production risk, and supply risk are a few examples of the internal risk factors. External operational risk arises due to the interaction between a supply chain and its environment. Terrorist attacks, natural disasters and exchange rate fluctuations come under this category. The internal and external risk factors may generate inefficiency and disturbances within the supply chain, and are described in more detail below.

- *Demand risk*: Forecasting near accurate demand is the most difficult part in efficient supply-chain management planning. There is always the possibility that the forecasted demand does not meet the actual demand. Both planning and production could have values higher than the actual demand, resulting in undesired inventory, or less than the actual demand, which results in shortages.
- *Production and distribution risk*: This type of risk is due to the failure of producing the desired quality and quantity at the right time.
- *Supply risk*: The flow of goods in terms of time, quality and quantity at different levels or within the same level of the supply chain may result in uncompleted orders, and is identified as supply risk.
- *Interaction risk*: Influences of the supply chain's environment in terms of physical, social, legal, operational, economical and political factors governs the interaction risk.

The above-mentioned risk factors are almost inevitable in modern global supply chains. Such risks can, if not properly accounted for, have a negative impact on the efficiency of the supply chain, through excessive inventory build up, poor customer service, poor capital utilisation and low profits. A few examples of these potential negative impacts are presented below:

- *Avanex Corporation*, together with its subsidiaries, announced huge inventory write offs and a dramatic reduction in annual profit for 2007 (http://biz.yahoo.com/e/070207/avnxavnx10-q.html).
- *Ford Motor Company* recently announced a reduction in assembly capacity of more than 20% as a result of eliminating shifts, and ceasing production at several plants in Michigan (http://seekingalpha.com/article/33706-ford-motor-q1-2007).
- *US car manufacturers* offered large cash-back incentives because of surplus inventories at the end of 2007 (http://www.centredaily.com/living/travel/story/299247.html).
- *Intel Corporation* reported that its fourth-quarter profit in 2007 dropped 39% because of unexpected strength from a smaller rival company (http:www.marketwatch.com/news/story/intel-profit-drops-39-price).

These examples present effects of endogenous risks associated with supply chains. In a global supply chain, all risks factors have the potential to decrease its efficiency by increasing the procurement cost and time. This behaviour is induced through deviations of one or more supply chain parameters from their expected or mean value, disruptions in the supply chain structure, or disasters due to unforeseen catastrophic events (Gaonkar and Viswanadham 2004). A consequence of these risks occurring is the addition to the cost of operation, and therefore a reduction in profits. For an efficient operation of the supply chain, an optimum policy, which minimises the overall risks and associated cost, should be adopted.

This paper addresses such issues by identifying and measuring various risks present at every level in a supply chain and decides the optimal policy with minimum risk factors and overall cost. The key contribution of this work comes as a result of updating the risk factors information in a single planning horizon and altered the policies based on change in risk factors. In the next section, the literature is reviewed. The mathematical model is formally presented in Section 3, where various risks have been evaluated in terms of extra cost coupled with them. The solution methodologies proposed based on computational intelligence techniques, are discussed in Section 4. The results obtained from the generated data set, the needed flexibility of the supply chain, and the changes in the initial decisions as a result of changes in the expected values of risks are presented in Section 5. Finally, the paper is concluded in Section 6.

2. Literature review

The literature abounds with mathematical models used to portray supply chain networks for profit maximisation and risk minimisation. Huchzermeier (1991) developed a stochastic dynamic programming formulation in order to determine the operational flexibility within a multi-country plant network. Reported results of his work are:

(1) a global manufacturing and distribution logistics network can provide a multinational firm with a robust hedge against exchange rate uncertainty and demand risk;
(2) operational flexibility can effectively reduce the firm's downside risks and enhance its shareholder value; and
(3) stochastic recourse using assembly and distribution logistics postponement allows the firm to mitigate against market risk.

Kogut and Kulatilaka (1994) also developed a stochastic dynamic programming for a two-country production switching model with a simple production function. In the results section they analyse the hysteresis effect in the presence of switching costs and determined the hysteresis band.

Kouvelis and Sinha (1995) presented a model that allows for switching of production modes. They developed a multi-period stochastic dynamic program, aimed at profit maximisation, which gives the supply chain the flexibility to switch between different modes of production in the planning horizon. Huchzermeier and Cohen (1996) established a modelling framework that combines the network flow and option evaluation approaches to global supply chain modelling. Their model quantifies the risks, and the results obtained clearly show that excess capacity can provide a real option to tackle exchange rate fluctuation in the long run. Dasu and Li (1997) studied the various optimal policies of a firm having plants in different countries and facing exchange rate variability. Their formulation considers a two-country, single-market model where the combined capacity of the plants exceeds the single product's demand. They concluded that irrespective of the variable product cost function, the optimal policy is always of the two level barrier types, where each plant operates at either maximum or minimum output level. Huchzermeier and Cohen (1999) developed a lattice programming model to determine the benefits of operational and managerial flexibility while dealing with price, exchange rate and demand uncertainty. The results obtained show that the value of operational flexibility can be exploited effectively with enhancement of global coordination, transfer pricing and knowledge sharing, and that the managerial flexibility can be achieved through distribution logistic postponement and stochastic resource.

Agrawal and Seshadri (2000) showed that intermediaries in the supply chain reduce retailers' financial risks. They presented mutually beneficial contracts that can include every retailer's risk, maximise their expected profit, and optimise the value quantity by increasing the order quantity. Risk factors related to government subsidiaries trade tariffs and taxation issues are studied by Kouvelis and Rosenblatt (2002). They developed a mixed integer programming model for designing global facility network. Chun *et al.* (2003) developed a 'dynamic allocation problem' of a perishable commodity in uncertainty of supply caused by seasonal fluctuation or abrupt variation of the weather. The objectives of the problem were to maximise the total net profit and to determine the optimal orders placed to suppliers and the resultant amount of perishable commodities allocated to retailers. They presented a two-stage extended-genetic algorithm (eGA) to control the dynamic orders and allocation quantities to prioritised suppliers and retailers.

Blackhurst *et al.* (2005) presented the multi-industry, multi-methodology empirical study on supply-chain disruptions and discussed some critical issues related to successful disruption analysis and mitigation as well as resilient supply-chain design. Hwarng *et al.* (2005) studied the extent of complicated interaction effects among various factors existing in a complex supply chain. Simple assumption regarding such factors may lead to various risks. They show that the intricacy of these effects can be better understood with a simulation model. Lummus *et al.* (2005) presented the Internet-based Delphi study involving a group of expert practitioners which is used to enumerate the characteristics, and the importance of those characteristics, in making a supply chain flexible.

Suwanruji and Enns (2006) studied the risk between inventory and delivery performance in a stochastic, multi-echelon supply chain involving both production and distribution functions. By simulation they compared the distribution/material requirements planning (DRP/MRP), re-order point (ROP) and Kanban (KBN) replenishment strategies in different demand pattern and capacity constraint environment.

Wu *et al.* (2007) presented the network-based modelling methodology to determine the effect of disruptions in a supply chain system. Through the disruption analysis network (DA_NET) model they studied how changes disseminate through a supply chain system and calculated the impact of the attributes. The goal was to permit better management of the supply chain, lower costs throughout the chain, higher levels of flexibility and agility and lower inventory. Chan *et al.* (2008) studied the effect of flexibility of suppliers in a supply chain by a simulation study on suppliers' flexibility level (SFL), in relation to the information system automation level of the supply chain and physical characteristics of the flexible suppliers.

Canbolat *et al.* (2007) presented the emerging market sourcing risk assessment and management model for sourcing components and sub-systems to emerging markets. They used a process failure mode effect analysis (PFMEA) structure to characterise the risks and developed a simulation model to quantify risk factors in terms of cost to evaluate risk mitigation strategies. Nagurney *et al.* (2003) presented a framework for modelling, analysing and developing solutions for operating global supply chains. These large-scale networks are subject to numerous risks which hinder the smooth operation among different tiers of the supply chain network. The authors attempt to model the behaviour of global supply chain networks in multi-criteria decision-making environments, and identify different levels of risk and their effect on the supply chain operation, with the objective of minimising the total cost of operation.

By detailed scanning of literature review it is clear that these large-scale networks are subject to numerous operational risks, which hinder the smooth operation among different tiers of the supply chain network. In this research work, the authors have attempted to model the behaviour of a global supply chain network in a multi-criteria decision-making environment and have identified the different level of risks and their effects on the supply chain operation, with the objective of minimising the total cost of operation.

3. Proposed model

This section presents a typical global supply chain network subject to numerous risks at different levels. All risks are mathematically formulated to present the additional cost occurring in the supply chain. The objective of this paper is to decide the optimal operational strategy that minimises the risks in terms of cost for a given planning period.

3.1 *Problem environment*

A typical global supply chain network consists of multiple suppliers, manufacturers, warehouses and markets, as shown in Figure 1, each operating in a different country under different environments. The proposed model considers supplier side risks, logistics risks, risks related to manufacturer, distributors, and retailers, and demand side risks (Balan *et al.* 2006). Such risks appear due to the uncertainty inherent to operational environments. Since the uncertainty cannot be completely eliminated, it brings several possible failure modes that can affect the supply chain network. To handle the undesired effect of operational uncertainty, resilient supply chain networks need to be built having the ability to maintain, resume and restore operations after any disruption. This work first identifies the different risks and their costs at various levels and computes the probability of their occurrence and their expected values. An optimal policy is determined on the basis of the initial available information. In the later stages of planning, by considering changes

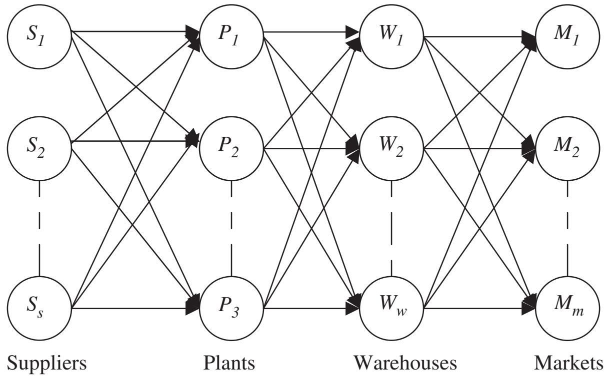

Figure 1. Architecture of a typical supply chain.

in the risks' expected values, a shift in the flow within the supply chain is determined among available alternatives in order to minimise disruptions, and consequently the total cost of operations. The mathematical model is based on the following assumptions:

- All manufacturers operate globally having multiple suppliers, warehouses and are supplying several markets in a global supply chain network.
- All manufactures are producing homogenous products whose quality depends upon the raw material suppliers and the country of location.
  - Finished products are kept in warehouses as inventory.
  - All transactions are converted into a common currency.
  - All decisions are made for just one planning horizon.

3.2 *Mathematical formulation*

3.2.1 *Parameters*

The following notations, presented in Table 1, are used in the mathematical formulation.

3.2.2 *Decision variables*

The following decision variables that consider all the quantities produced and supplied across the supply chain are considered.

Q_m^i	Quantity supplied to market i.
q_{ij}^{wm}	Quantity supplied from warehouse i to market j.
Q_w^i	Quantity supplied to warehouse i.
q_{ij}^{pw}	Quantity supplied from plant i to warehouse j.
Q_p^i	Quantity produced in plant i.
RQ_p^i	Raw material quantity required by plant i.
rs_{ij}^{sp}	Raw material quantity supplied from supplier i to plant j.

Table 1. Notations used in the mathematical model.

Notation	Description
S	Number of suppliers operating globally
P	Number of manufacturing plants located globally
W	Number of warehouses located globally
M	Number of markets or end outlets
$Q_{\max}^{p_j}$	Maximum production capacity of plant j, where $j \in \{1, 2, \ldots, P\}$
$Q_{\max}^{w_j}$	Maximum storage capacity of warehouse j, where $j \in \{1, 2, \ldots, W\}$
$Q_I^{w_i}$	Initial stock in warehouse i, where $i \in \{1, 2, \ldots, W\}$
C_i^P	Cost of unit production for plant i
C_i^F	Fixed cost of operation for plant i
R_q	Raw material quantity required to produce one unit of finished product
I_i^C	Inventory cost per unit of warehouse i

3.2.3 *Cost calculation*

The total cost within the supply chain can be divided into four segments, depending on the organisation that supports it, as presented below:

- Supply cost of raw materials.
  - Production cost.
  - Warehouse associated cost.
  - Market cost.

The objective of this model is to allocate order quantities among the combinations of suppliers–manufacturers, manufacturers–warehouses, and warehouses–markets, such that the expected cost of operating the supply chain and the cost of risk are minimised. This objective function is subject to the constraint that each level should fulfil the order for the next level in the supply chain. The various risk factors and their cost functions considered in this problem can be obtained by analysing their historical performance or by taking into account the probabilities of their non-performance and the associated costs of handling the consequent undesired impacts. Each of the cost function associated with risks is formulated below.

3.2.4 *Supplier cost of raw materials*

For supplying raw materials to plants, each supplier incurs a cost dependent lead time. The cost of raw material supplied can be given as:

$$\sum_{i=1}^{S}\sum_{j=1}^{P}\sum_{t\geq \min SLt_j^i}^{\max SLt_j^i} rs_{ij}^{sp} \times CS_j^i(t) \times P\left(\eta_{ij}^{SP}\right), \tag{1}$$

where $\min SLt_j^i$ is the minimum lead time required for supplier i to deliver raw materials to plant j; $\max SLt_j^i$ is the maximum allowed lead time for supplier i to deliver raw materials to plant j; η_{ij}^{SP} is the set of all scenarios of lead times with probability $P(\eta_{ij}^{SP})$ for delivering raw materials from supplier i to plant j; and $CS_j^i(t)$ is the cost function per unit of raw material supplied in terms of the lead time.

The quality of the raw materials is a risk factor which is always associated with the suppliers. Considering this risk factor the above formulation for the supplier's cost of raw materials becomes:

$$\sum_{i=1}^{S}\sum_{j=1}^{P}\sum_{t\geq \min SLt_j^i}^{\max SLt_j^i} \left(rs_{ij}^{sp} \times CS_j^i(t) \times P\left(\eta_{ij}^{SP}\right)\right) \Big/ \boxed{\left(\sum_{\Omega_i^s} p(\varsigma) \times \varsigma\right)}; \tag{2}$$

where Ω_i^S is the set of all scenarios for supplier i, comprising the reliability of raw material in terms of percentage of total supply; and $P(\zeta)$ denotes the probability of scenario ζ where $\zeta \in \Omega_i^S$, such that $\sum_{\Omega_i^s} P(\zeta) = 1$.

Risk in any echelon in supply chain is directly dependent on the functioning of previous echelon, for example manufacturing of a product in quality and quantity relies on the supply of raw material in terms of quality and time. Risk associated with quality of raw material has been calculated in Equation (2) in terms of additional requirement of raw material. Failure of raw supply can lead to loss of production and associated loss of profit.

So the risk cost due to supplier's failure to deliver the raw materials within the maximum allowed lead time can be given as:

$$\sum_{i=1}^{S}\sum_{j=1}^{P}\boxed{\left(1-\sum_{t\geq \max SLt_j^i} P\left(\eta_{ij}^{SP}\right)\right)}\times L\left(rs_{ij}^{SP}\right), \tag{3}$$

where $L(rs_{ij}^{SP})$ is the loss function in terms of the ordered quantity of supply of raw materials due to failure of suppliers.

Finally, considering the cost in a common currency, the supply cost (SC) becomes:

$$\begin{aligned} SC = {} & \sum_{i=1}^{S}\sum_{j=1}^{P}\sum_{t\geq \min SLt_j^i}^{\max SLt_j^i}\left(\left(rs_{ij}^{sp}\times CS_j^i(t)\times P\left(\eta_{ij}^{SP}\right)\right)\right)\bigg/\left(\sum_{\Omega_i^s} p(\varsigma)\times\varsigma\right)\times er_S^i\right) \\ & +\sum_{i=1}^{S}\sum_{j=1}^{P}\left(\left(1-\sum_{t\geq \max SLt_j^i} P\left(\eta_{ij}^{SP}\right)\right)\times L\left(rs_{ij}^{SP}\right)\times er_S^i\right); \end{aligned} \tag{4}$$

where er_S^i represents the expected exchange rate for supplier i.

3.2.5 *Plant production cost*

Each plant participating in the supply chain has an associated fixed cost of operation and a defined cost per unit of production. Therefore, the total cost of production can be given as:

$$\sum_{i=1}^{P}\left(\sum_{j=1}^{W} q_{ij}^{pw}\times C_i^P\right)+C_i^F \tag{5}$$

The quality of products depends on many factors and can differ among the participating plants due to their geographical location and other factors. The actual plant production cost (PC) that also includes the quality risk can be given as:

$$PC=\sum_{i=1}^{P}\left(\left(\left(\sum_{j=1}^{W} q_{ij}^{pw}\times C_i^P\right)\bigg/\boxed{\left(\sum_{\prod_i^p} p(\omega)\times\omega\right)}\right)+C_i^F\right)\times er_P^i, \tag{6}$$

where Π_i^P is the set of all scenarios for plant i regarding its quality in percentage of total production; $P(\omega)$ is the probability of scenario ω, where $\omega\in\Pi_i^P$, such that $\sum_{\Pi_i^p} P(\omega)=1$; and er_P^i is the expected exchange rate for plant i.

3.2.6 *Warehouse associated cost*

The warehouse associated cost includes the logistics cost between plants-warehouses and warehouses-markets, and the risk cost due to failure of supply. The cost of transportation can be given as:

$$\sum_{i=1}^{P}\sum_{j=1}^{W}\sum_{t\geq \min PLt_j^i}^{\max PLt_j^i} q_{ij}^{pw}\times CP_j^i(t)\times P\left(\mu_{ij}^{PW}\right), \tag{7}$$

where $\min PLt_j^i$ is the minimum lead time required by plant i to supply to warehouse j; $\max PLt_j^i$ is the maximum allowed lead time from plant i to warehouse j; μ_{ij}^{PW} is the set of all scenarios of lead time with probability $P(\mu_{ij}^{PW})$ for supplying from plant i to warehouse j; and $CP_j^i(t)$ is the function representing the cost of supply per unit in terms of lead time, t.

The risk cost associated with disruption of supply between plant and warehouse is given by the following expression:

$$\sum_{i=1}^{P}\sum_{j=1}^{W}\left(1-\sum_{t\geq \min PLt_j^i}^{\max PLt_j^i} P\left(\mu_{ij}^{PW}\right)\right)\times L\left(q_{ij}^{PW}\right), \tag{8}$$

where $L(q_{ij}^{PW})$ is the loss in terms of the ordered quantity of supply to the warehouse due to logistics failure between plant i and warehouse j.

Therefore, the warehouse-plant supply cost (WP) will be:

$$\begin{aligned} WP = &\sum_{i=1}^{P}\sum_{j=1}^{W}\sum_{t\geq \min PLt_j^i}^{\max PLt_j^i} q_{ij}^{pw}\times CP_j^i(t)\times P\left(\mu_{ij}^{PW}\right)\times er_P^i \\ &+\sum_{i=1}^{P}\sum_{j=1}^{W}\left(1-\sum_{t\geq \min PLt_j^i}^{\max PLt_j^i} P\left(\mu_{ij}^{PW}\right)\right)\times L\left(q_{ij}^{PW}\right)\times er_P^i\,; \end{aligned} \tag{9}$$

Similarly, it can be shown that the warehouse–market supply (WM) cost can be defined as:

$$\begin{aligned} WM = &\sum_{i=1}^{W}\sum_{j=1}^{M}\sum_{t\geq \min WLt_j^i}^{\max WLt_j^i} q_{ij}^{wm}\times CW_j^i(t)\times P\left(\chi_{ij}^{WM}\right)\times er_W^i \\ &+\sum_{i=1}^{M}\sum_{j=1}^{P}\left(1-\sum_{t\geq \min PLt_j^i}^{\max PLt_j^i} P\left(\mu_{ij}^{PW}\right)\right)\times L\left(q_{ij}^{PW}\right)\times er_W^i \end{aligned} \tag{10}$$

where $CW_j^i(t)$ is the cost of warehouse per unit in terms of the lead time, t; $\min WLt_j^i$ is the minimum lead time for supplying from warehouse i to market j; $\max WLt_j^i$ is the maximum allowed lead time for supplying from warehouse i to market j; χ_{ij}^{PW} is the set of all scenarios of lead time with probability $P(\chi_{ij}^{PW})$ for supplying from warehouse i to market j; and er_W^i is the exchange rate of warehouse i.

The second term of Equation (10) incorporates the disruption cost between warehouse–market supply.

3.2.7 *Market cost*

The market cost arises due to either an excess of supply or a shortage of supply. When an excess of supply occurs, the market cost will be:

$$\sum_{i=1}^{M}\int_{0}^{Q_m^i}\left(Q_m^i-x\right)f_i(x)R_C^i(x)\mathrm{d}x \tag{11}$$

where $f_i(x)$ is the probability density function of the demand in market i; and $R_C^i(x)$ is the inventory cost function.

In the case of a shortage of supply, the market cost will be:

$$\int_{Q_m^i}^{\infty} \left(x - Q_m^i\right) f_i(x) g_i(x) \mathrm{d}x \tag{12}$$

where $g_i(x)$ is the goodwill loss factor in market i.

Therefore, the total market cost (MC) can be given as:

$$MC = \sum_{i=1}^{M} \int_0^{Q_m^i} \left(Q_m^i - x\right) f_i(x) R_C^i(x) \mathrm{d}x + \int_{Q_m^i}^{\infty} \left(x - Q_m^i\right) f_i(x) g_i(x) \mathrm{d}x \tag{13}$$

3.2.8 *Minimisation of the total supply chain cost*

The mathematical programming formulation that minimises the total supply chain operational cost (TC) is presented below and considers all the supplier, plant, warehouse, and market costs defined above.

$$TC = SC + PC + WA + WM + MC \tag{14}$$

$$\text{Minimise } TC \tag{15}$$

Subject to:

$$Q_i^m = \sum_{i=1}^{w} q_{ij}^{wm} \tag{16}$$

$$\sum_{j=1}^{m} q_{ij}^{wm} \le Q_{\max}^{w_j} \tag{17}$$

$$Q_w^j = \sum_{i=1}^{p} q_{ij}^{pw} \tag{18}$$

$$Q_w^j \le Q_{\max}^{w_j} - Q_I^{w_j} \tag{19}$$

$$\sum_{j=1}^{w} q_{ij}^{pw} \le Q_{\max}^{p_i} \tag{20}$$

$$RQ_p^i = \left(\sum_{j=1}^{w} q_{ij}^{pw}\right) \times R_q \tag{21}$$

$$\sum_{i=1}^{s} rs_{ij}^{sp} = RQ_j^p \tag{22}$$

Equation (15) minimises the total cost incorporated with risk. Constraint (16) maintains the flow equation between warehouse and market. Constraint (17) limits the total flow into market according to its maximum capacity. Constraints (18) and (19) define the flow amount between plants and warehouses and restrict their maximum capacity. Constraint (20) limits the maximum flow through a plant according to its maximum capacity. Constraints (21) and (22) define the raw materials requirement and flow from suppliers to plants.

4. Solution methodology

Figure 1 shows a typical supply chain model, where suppliers, manufacturers, warehouses and markets are globally distributed. The flow of work can be seen as raw materials delivered by suppliers to plants, transformed into finished goods at plant locations, transported to warehouses, and finally reaching the market for customers. A work order, in the form of material flow, can have different routes (i.e. from specific suppliers to specific manufacturing plants to specific warehouses, and finally to specific markets). As the cost of operation and the risk factors are different for each level, each work order will have an assigned cost and level of risk.

Since the capacity of each supply unit, such as a plant or a warehouse, is a constraint, a near optimal solution is necessary for stabilising the supply chain. By selecting an appropriate combination of routing and work-order process sequence, a plan that is effective in maintaining a low cost of operation and minimising risks can be generated for the entire supply chain. This hypothetical supply chain can be structured as a multi-objective mixed integer programming (MOMIP) model. In this paper, the objective is to minimise the total cost, TC, of the supply chain operation which includes supplier cost, production cost, warehouse associated cost and market cost. Since high complexity is involved in the problem space, finding an optimal sequence of operation poses high computational complexity in terms of exponential growth of the search space with just a slight increase in parameter values. While, deterministic techniques can be applied on smaller problem instances, large computation time is required with increasing problem size (Chan and Chung 2004). In recent years, random search techniques have gained popularity in solving computationally complex nondeterministic polynomial (NP) problems, because of their ability to provide efficient solutions in a short amount of time. This section explores the application of various techniques such as genetic algorithms (Goldberg 1987), particle swarm optimisation (Kennedy and Ebherhart 1995) and artificial bee colony (Basturk and Karaboga 2006), and investigates their relative performance on the problem at hand.

4.1 *Genetic algorithms*

Genetic algorithms (GA) have proved to be a powerful optimisation tool, with applications in many areas of engineering. Their evolution has been inspired by the process of natural selection and Darwin's principle of 'survival of the fittest'. GAs have given good results when applied to TSP problems (Grefenstette *et al.* 1985), scheduling problems (Davis 1985), network problems (Cox *et al.* 1991), etc. The main characteristics in developing a GA are chromosome (string) representation, initialisation of population, fitness measurement, and genetic operators, such as crossover, mutation, and selection strategy. Genetic parameters, such as population size, number of generation, probability of crossover and mutation, are determined before the execution stage of GAs.

4.1.1 *String representation*

For the supply chain cost problem, three sets of strings are initially created. The first set of strings represents the amount of product flow from warehouses to markets such that $\sum_{i=1}^{m} q_{ij}^{wm} \leq$ maximum capacity of warehouse i, as presented in Figure 2. Similarly, the second and the third sets represent the flow between plants and warehouses and between raw material suppliers to plants, respectively.

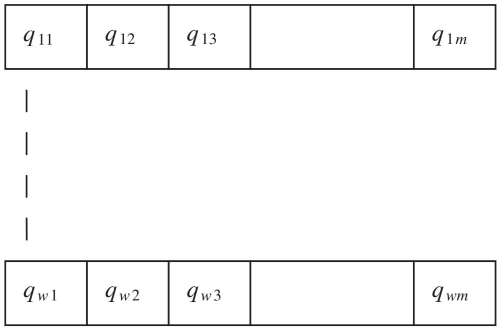

Figure 2. The string representation for the genetic algorithm.

4.1.2 *Selection, crossover, and mutation*

The reviewed literature presents various strategies that have been utilised for the selection process, such as roulette wheel selection, elite selection, and tournament selection. This work experimented with all three of these selection strategies and found that the tournament selection outperformed the other selection strategies on the selected test-bed. Therefore, tournament selection is utilised for the selection of parents in the experimental design stage. Crossover operation combines parents through various methods to produce off-springs. A number of crossover methods are available to achieve the fusion of parents in order to get off-spring such as k-point crossover, partially matched crossover (PMX), cycle crossover (CX), uniform crossover, and uniform order based crossover. In this research the two-point crossover method is applied, by generating two random points in parents' string, such that swapping of genes takes place. Any unfeasible generated off-spring are dealt with penalty function.

In GAs, mutation is applied to explore the solution space and to prevent it from premature convergence. The objective of mutation operation is to bring changes randomly in the genes comprising the chromosome. The swapping mutation method is applied in this work by randomly selecting two bits and, after that, swapping occurs. The GA pseudo-code, including the above genetic operations, is presented in Figure 3.

4.2 *Particle swarm optimisation*

The particle swarm optimisation (PSO) methodology is used for finding optimal regions of complex search spaces through the interaction of individuals in a population of particles. This type of algorithm imitates the metaphor of social interaction and searches a space by adjusting the movement of individual vectors, called 'particles', as they are conceptualised as moving points in multi-dimensional space. The individual particles are drawn randomly toward the positions of their own previous best performance and the best previous performance of their neighbours.

A population of particles is initialised with the random positions $\vec{x_t}$, and velocities $\vec{v_t}$, for which the fitness function f, is evaluated. At each iteration, the position vector and the velocity vector for every particle is adjusted and the fitness function evaluated with the new position vector. When a particle's position vector ($\vec{v_{id}}$) gives a better solution than the previous selected one, it stores it as a particle best position vector ($\vec{p_{id}}$). Similarly, the

```
Genetic Algorithm (GA)

Generate random population of solutions
For each individual: calculate Fitness
while (iter < iter_MAX){
        Perform Crossover operation based on
        probability of crossover;
        Perform Mutation operation based upon
        probability of mutation;
        Compute Fitness;
        Perform Selection operation for population
        of next generation.
        iter++;
}
Output: Best solution for the problem
```

Figure 3. Pseudo-code for the GA.

```
Initialise population
Do
    for i = 1 to pop_size
        Evaluate f (x_i)
        p_i = best(f (x_i) , f (p_i))
        p_gd = best (p_i)
    end
    for i = 1 to string_size
        update velocity using equation (23)
        update position using equation (24)
    end
until termination criterion is met
```

Figure 4. Pseudo-code for PSO algorithm.

global best position vector ($\vec{p_{gd}}$) is also stored. The new velocity vector and the new position vector for each particle are then updated as follows:

$$\vec{v_{id}}=\vec{v_{id}}+\varphi_1(\vec{p_{id}}-\vec{v_{id}})+\varphi_2(\vec{p_{gd}}-\vec{v_{id}}) \tag{23}$$

where, φ_1 and φ_2 are constants.

$$\vec{x_{id}}=\vec{x_{id}}+\vec{v_{id}}\ . \tag{24}$$

Initial population of particles is generated in the same manner as of GA. For the rest, PSO follows the pseudo-code presented in Figure 4.

4.3 *Artificial bee colony*

The artificial bee colony (ABC) technique, initially proposed by Basturk and Karaboga (2006), was used in various complex problems, and imitates the natural behaviour of a honey bee colony, which consists of a queen, a few drones (males) and thousands of workers (infertile females). Workers play a key role in foraging for food (i.e. nectar and pollen). Foraging consists of two main modes of behaviour: recruitment of a nectar source, and abandonment of a source. If any food source is discovered by the scouts, they return back to the hive and pass the information to foragers, which then leave the hive and fly directly to the food source. The information that is communicated to the foragers consists of the odour of the food and its direction and distance from the hive through their physical activities, i.e. a type of dancing (Ratnieks *et al*. 2000).

The ABC model consists of three groups of bees, employed artificial bees, onlookers, and scouts. It is assumed that for every food source, there is only one employed bee. If the other bees abandon the food source of the employed bee, they become scouts. The food source is mapped as a possible solution and the nectar amount as a fitness value, f_i. The onlookers, employed and scout bees evolve through the search procedure of the algorithm, whilst the population is subjected to repetitive cycles until the maximum cycle number (MCN) is achieved. Each employed bee updates its position (solution) in its memory depending on the local information (visual information) and thereby verifies the nectar quantity of the new solution produced. If the nectar quality is better than the quality associated with the previous position, the bee memorises the new position and the old position is deleted from the memory. Otherwise, the bee keeps the old position in its memory and does not memorise the new one. A food source is chosen by an onlooker bee with a probability related to its nectar quality, information obtained by communicating with the employed bees. The probability that a food source, p_i is selected by the onlooker bee is calculated using the following expression:

$$p_i = f_i \Bigg/ \sum_{i=1}^{p} f_1 , \tag{25}$$

where p denotes the population size.

The candidate food position is updated in the memory using the following expression:

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right), \tag{26}$$

where k is part of the population size; j is part of the string size; and $\varphi_{ij} = rand(-1, 1)$.

If x_i^j is not a sound solution and cannot be improved in a pre-determined number of cycles, a new solution is discovered by the scout bee using the equation below:

$$x_i^j = x_{\min}^j + rand(0, 1)\left(x_{\max}^j - x_{\min}^j\right), \tag{27}$$

where j is a part of the string size. Initial population for ABC is generated in the same fashion as GA and PSO. Steps regarding the ABC methodology have been depicted in Figure 5.

5. Results and discussion

This section describes the results obtained by applying the aforementioned computational intelligence techniques on generated supply chain data.

```
Begin
Initialise P(0);
f = Evaluate P(0);
Cycle = 1;
        while (cycle <= MCN)
         for (employed bee)
              produce new solution v_i = { v_ij} using the modified
              expression(26);
              f_temp= Evaluate ( v_i );
               Selection Criteria (f_i , f_temp);
               Calculate probability values P_i  for x_i;
         for(on looker bee)
              produce new solution v_i = {v_ij} depending on P_i using
              the modified expression (27);
              f′_temp' = Evaluate ( v_i );
              Selection Criteria(f_i , f_temp');
        Determine the abandoned solution for the scout
        if (x_i = abandoned solution for the scout)
           Generate new solution using expression(27)
           Replace the old solution with new one;
        end if;
           memorise the best solution achieved so far;
        end for;
        cycle = cycle + 1;
     end while;
end;
```

Figure 5. Pseudo-code for the ABC algorithm.

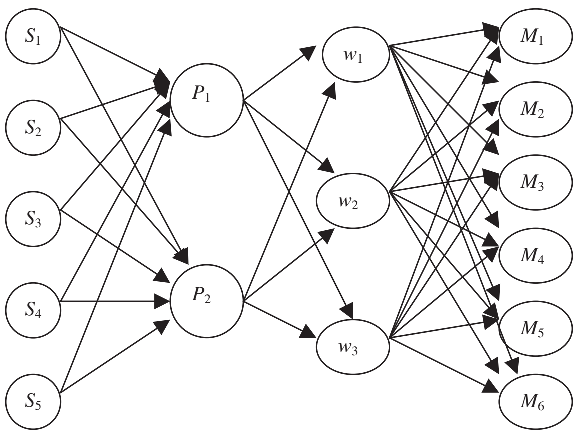

Figure 6. The schematic diagram of the supply chain considered in this model.

5.1 *Experimental results*

The supply chain risk management model used in this work is presented in Figure 6. It consists of five suppliers, two manufacturing plants, three warehouses and six markets. The raw materials are delivered from the suppliers, and transformed into finished products by the manufacturing plants. The finished products are, then, transported to warehouses, and ultimately, delivered to markets for customers. As mentioned earlier, this paper finds the optimal decision policy for two stages. The initial decision is based on the known and expected values of different risk factors, and subsequent changes in the decision-making process are due to changes in the expected value of any of the risk factors.

To study the overall behaviour of the supply chain system, all data is generated randomly in the basic model as shown in Tables 2 to 7. Table 1 depicts the maximum capacity of the supply chain component organisations. Exchange rates are given in Table 3. Lead time, cost factor, reliability of the supplied items, probability of supplying goods within the specified time limit (i.e. max allowed lead time) between suppliers–manufacturers, manufacturers–warehouses and warehouses–markets are illustrated in Tables 4 to 6. Assuming the demand in the markets is normally distributed, the mean and variance of the demand in various markets are shown in Table 7. All cost functions considered in this model have been assumed to be linearly decreasing with the lead time. Ten data sets of demand values were randomly generated between $(D-\sigma)$ and $(D+\sigma)$, where D is the mean demand and σ is the variance of the demand.

Table 8 shows the optimal value obtained by applying GA, PSO and ABC techniques on randomly generated data for 10 problem instances.

Figure 7 presents the convergence graph of GA, PSO, and ABC algorithms, taken as the average of the 10 runs. The figure clearly reveals that the results given by GA and ABC have an almost similar convergence rate, outperforming the PSO algorithm.

In the later period, the updated information of risk factors is obtained, and can differ widely from the initial expected values for various reasons. Therefore, the initial optimal policy may not remain the best choice. To obtain the optimal policy at this stage, the intra-echelon shift in flow needs to be determined. The next section derives the equation for the intra-echelon shift and measures the flexibility of the supply chain.

5.2 *Flexibility in the supply chain*

At the beginning of the planning process, the organisation has all the relevant information regarding the risk factors, including the exchange rate. Therefore, the initial optimal decisions are made based on the expected value of the risk factors. In the later stages, within the planning period, if any risk factor deviates from its expected value, then other

Table 2. Supply chain capacity.

	Plant 1	Plant 2	Warehouse 1	Warehouse 2	Warehouse 3
Maximum capacity (units)	10,000	10,000	7000	8000	9000

Table 3. Exchange rates.

	Suppliers					Plants		Warehouses			Markets					
	1	2	3	4	5	1	2	1	2	3	1	2	3	4	5	6
ER	1.1	0.1	0.5	1	1.5	1.5	0.6	1.2	1.5	2.5	1.2	2.5	1	5	0.1	0.2

Table 4. Plants and suppliers parameters.

	Supply chain/unit	Min lead time (days)	Max lead time (days)	Probability	Reliability (%)
Plant 1					
Supplier 1	15	5	15	0.70	85
Supplier 2	100	10	20	0.80	80
Supplier 3	20	8	20	0.75	85
Supplier 4	10	12	25	0.85	90
Supplier 5	18	10	15	0.65	80
Plant 2					
Supplier 1	20	10	15	0.60	90
Supplier 2	120	5	15	0.60	85
Supplier 3	25	9	18	0.90	90
Supplier 4	12	13	22	0.85	95
Supplier 5	20	12	20	0.80	90

Table 5. Warehouses and plants parameters.

	Inv. cost	Supply chain/unit	Min lead time (days)	Max lead time (days)	Probability	Reliability (%)
Plant 1						
FC				10,000		
PC/unit				20		
Warehouse 1	5	10	10	30	0.70	95
Warehouse 2	4	15	15	30	0.80	97
Warehouse 3	3	12	17	35	0.85	95
Plant 2						
FC				30,000		
PC/unit				50		
Warehouse 1	5	25	17	30	0.75	94
Warehouse 2	4	35	10	30	0.90	97
Warehouse 3	3	40	18	37	0.80	95

FC, factory capacity; PC, production cost; Inv., inventory.

decision variables also need to be changed in order to minimise any cost opportunity. This factor can be measured as the flexibility in the supply chain. In the second stage decision variables can be altered in two ways:

- By changing the flow quantity between supply chain components (inter-echelon shift in flow).
- By changing the flow quantity within supply chain components (intra-echelon shift in flow).

The inter-echelon shift in flow is achieved by altering the initial decision of demand fulfilment and, accordingly, adjusting the other variables (i.e. suppliers quantity, production quantity, etc.). This model assumes that the initial decision of demand fulfilment is not varying in the later stage and considers only the intra-echelon shift in flow in the second stage. However, if we assume the range of demand fulfilment by the

Table 6. Warehouses and markets parameters.

	Supply chain/unit	Min lead time (days)	Max lead time (days)	Probability	Reliability (%)
Warehouse 1					
M 1	15	20	45	0.85	1
M 2	20	25	45	0.95	1
M 3	18	25	45	0.90	1
M 4	22	30	45	0.90	1
M 5	20	35	45	0.85	1
M 6	25	30	45	0.95	1
Warehouse 2					
M 1	20	25	45	0.90	
M 2	25	15	45	0.85	
M 3	15	25	45	0.85	
M 4	30	30	45	0.90	
M 5	25	27	45	0.80	
M 6	20	24	45	0.85	
Warehouse 3					
M 1	45	15	45	0.90	1
M 2	50	20	45	0.85	1
M 3	55	25	45	0.90	1
M 4	50	20	45	0.95	1
M 5	60	22	45	0.90	1
M 6	55	30	45	0.85	1

Table 7. Market demand.

	Markets					
	1	2	3	4	5	6
Mean	2000	2100	2200	2300	1800	2500
Variance	200	300	200	100	200	300

Table 8. Optimal values obtained by running different algorithms.

Problem instance	GA	PSO	ABC
1	558,509	576,823	622,232
2	520,594	446,823	627,921
3	451,429	448,484	554,158
4	538,819	579,993	793,394
5	879,380	887,498	514,471
6	461,898	436,813	556,564
7	512,901	740,658	502,749
8	454,456	519,081	564,016
9	656,420	608,189	470,991
10	490,367	645,321	521,105
Average	552,477.3	588,968.3	572,760.1

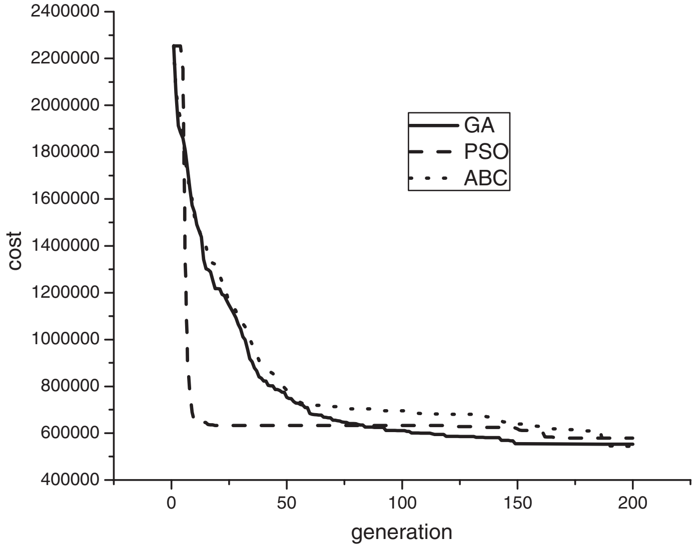

Figure 7. Convergence graph for the three techniques studied.

minimum and maximum defined values instead of a fixed one, inter-echelon shift in flow can be possible. This process can be achieved with few modifications in the mathematical model and its flexibility can be measured in the same manner.

This section shows how the flow in the supply chain shifts in response to the change in the risk factors. Kogut and Kulatilaka (1994) calculated the shift in the manufacturing quantity as a reaction to the change in the exchange rate. There are other risks involved during supply chain operations such as, late shipments, customs delays, quality control problems, logistics and transport breakdowns, and production problems, which can lead to shifts in the supply chain flow. A mathematical model for the shift in the supply chain is presented next.

5.2.1 *Shift in manufacturing quantity*

The risk factor under consideration is the percentage increase or decrease in the unit production cost. For plant i, if the exchange rate changes from er^i_P to er'^i_P, then the amount of common currency saved per unit of local currency is:

$$\left(r^i_p\right) = \left(er'^i_P - er^{\,i}_P\right)/er'^i_P \tag{28}$$

Without any risk factor the shift of production between plants i and j is given by the equation:

$$\left(r^{\,j}_p - r^{\,i}_p\right) \times \alpha^{\,p}_{ij} \times Q^{\,p\text{–}shift}_{ij} \times \Re_{ij}(q), \tag{29}$$

where $Q^{p\text{–}shift}_{ij}$ is the maximum allowable shift from plant i to plant j, depending upon the capacity, raw material availability, and other factors; $\alpha^p_{ij} \in [0, 1]$ determines the percentage of maximum allowable shift occurring and $\Re_{ij}(q)$ is the extra setup and production cost as a function of quantity in terms of common currency.

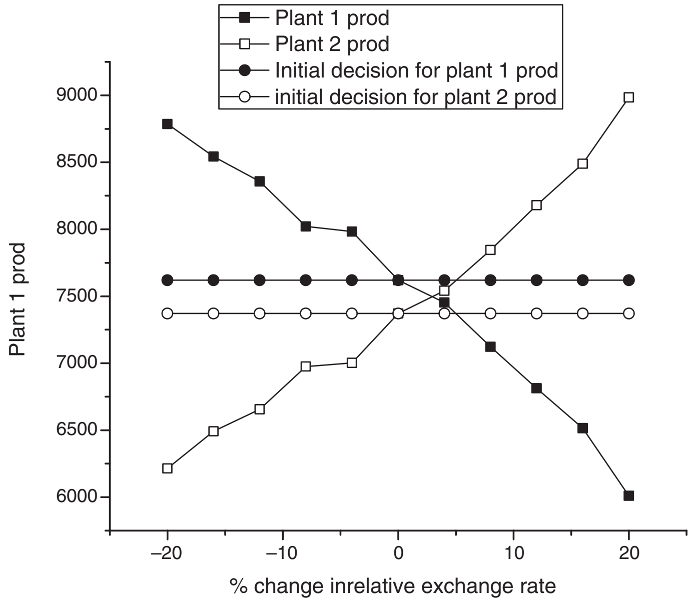

Figure 8. Changes in production triggered by the changes in the exchange rate.

If other risk factors also change and R_{ji} denotes the risk cost associated with the unit of production in plant j instead of plant i, then the cost due to the shift of production is as follows:

$$s_{ij}^{P}(q) = \left(\left(r_p^j - r_p^i\right) - R_{ji}\right) \times \alpha_{ij}^{p} \times Q_{ij}^{p\text{–}shift} \times \Re_{ij}(q), \tag{30}$$

and the cost saved due to shift can be given by:

$$S_{ij}^{P}(q) = \left\{\left(s_i^p(q)/er_i^p\right) \times er_i'^p\right\} - s_{ij}^{p}, \tag{31}$$

where $s_i^p(q)$ is cost of production in plant i with updated risk factors.

Similarly, S_{ij}^R, S_{ij}^W, and S_{ij}^M denote the saving in cost of operation due to the shift in raw material suppliers, warehouses and market supply. The second stage optimisation function can be given as maximising (TS), where

$$TS = \sum_{i,j\in p, i\neq j} S_{ij}^{p} + \sum_{i,j\in S, i\neq j} S_{ij}^{R} + \sum_{i,j\in W, i\neq j} S_{ij}^{W} + \sum_{i,j\in M, i\neq j} S_{ij}^{M} \tag{32}$$

The presented model studied the effect on the initial decisions by changing the risk factors on two manufacturing plants. The intra-echelon shift in flow, determined by the GA, is plotted in Figure 8. This shift is represented by the change in the production quantity between the two manufacturing plants when their relative exchange rate varies from −20% to 20% of their initial value, while all other factors remain constant. It can be inferred from the figure that, in order to lower the total cost of operations, the production has shifted to the plant in which the exchange rate from local currency to common currency has decreased.

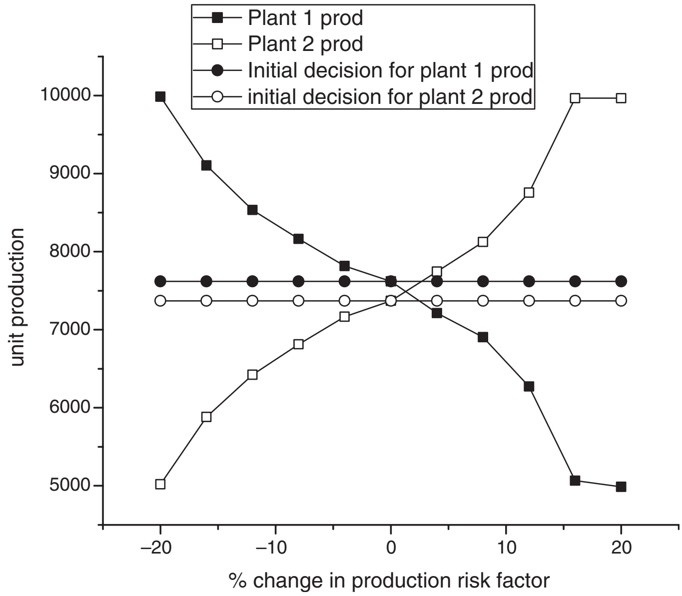

Figure 9. Changes in production triggered by the production risk factor.

The shift in the production quantity triggered by the change in production risk factor is depicted in Figure 9. Production risk cost was varied with respect to plant 1 from −20% to 20% of the initial value, where a negative sign indicates that the cost has decreased for plant 1. The slope of the curves is almost zero when the production risk factor is 20% more than the initial values, because the plants are operating at their maximum capacity level.

The decision regarding the intra-echelon shift of flow in the modeled supply chain depends on many other factors, as discussed in Section 5. The plot in Figure 10 is based on a −20% to 20% change in the exchange rate, and presents the production shift between the two plants, when the shift from plant 1 to plant 2 requires a 10% additional cost. The significant difference in the shift clearly reveals that other factors cannot be neglected during the decision making process. Similar results can be obtained for suppliers, warehouses, and markets. Managerial implications of the above findings are related to the initial optimal operation policy for determining the flow of the modelled inter-echelon supply chain. Later on, due to inherent changes in the expected values of various risk factors, the above findings help in deciding the intra-echelon shift in flow, such that that overall cost and risk in the supply chain can be minimised.

6. Conclusions

This paper discusses the optimal operating policies for a global firm conducting business in different countries. Such policies are influenced by many risk factors such as, late shipments, exchange rates, customs delays, quality control problems, logistics and transport breakdowns, and production risks. The initial model presents the optimal operational strategies for the supply chain based on the expected risks factors. Next, considering a relaxed model, which allows for changes in the risk factors, the paper takes

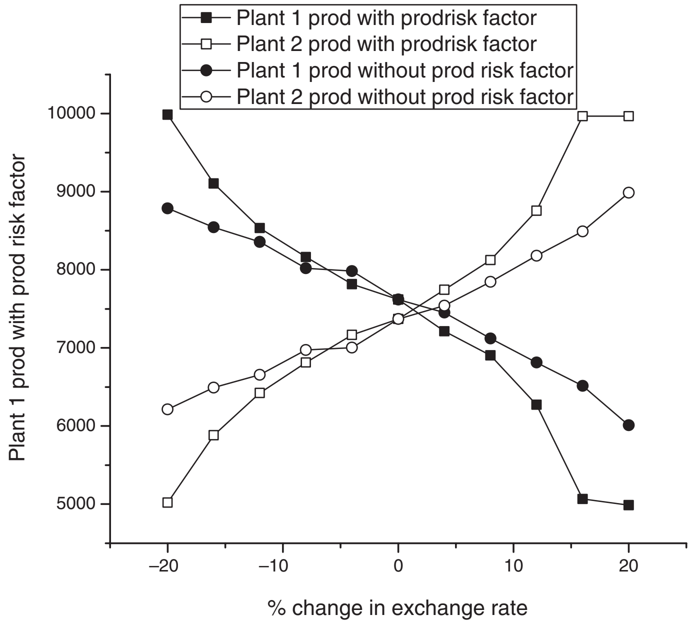

Figure 10. Changes in production when considering, and without considering the production risk factor.

into account the shift of flow between the segments of the supply chain in order to reduce the risk, as well as the overall cost of operation. The mathematical formulation and the results obtained can be expanded to many other situations. One example is the outsourcing of semi-finished or finished products when in-house production risks are very high. The risk and cost minimisation in multi-products environments, with outsourcing option, is considered by the authors as a future research topic.

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