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A genetic algorithm-based optimisation model for designing an efficient, sustainable supply chain network under disruption risks

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Abstract: Existing supply chain designs focus on efficiency and cost minimisation, particularly in just-in-time (JIT) systems. At the same time, sustainability requires designs that preserve resources and minimise environmental impact; thus, companies should design their supply chains to be simultaneously flexible, sustainable, and efficient. This study proposes a genetic algorithm-based optimisation model to address the trade-off between the total supply cost and the carbon emission cost during supply network disruption. The model is tested using a case study to validate its applicability using the particle swarm optimisation (PSO) approach. A number of factors are analysed: lead time, order quantity variance, and transportation mode selection. Performance variables include the total supply chain cost which comprises production, transportation, and CO₂ costs. The model has many opportunities for application where the supply chain is disrupted, such as in the recent pandemic, especially when companies do not want to compromise efficiency and sustainability.

Keywords: genetic algorithm; optimisation model; supply chain design; resilience; sustainability; efficiency; disruptions; carbon tax; just-in-time; JIT; particle swarm optimisation; PSO.

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1 Introduction

One key characteristic of supply chains is that they are frequently disrupted by unexpected events, the coronavirus pandemic being the latest example. Other examples include the Icelandic volcano eruption which disrupted air transport for a week and hurricane Katrina in 2005. In this case, Wal-Mart was able to recover quickly by proactively overstocking its nearby distribution centres with items likely to be affected (Leonard, 2005; Klibi et al., 2010). Other examples include hurricane Floyd (Norrman and Jansson, 2004), the Japanese tsunami and the Thai flooding in 2011 (Chopra and Sodhi, 2014). In each case, severe disruptions of supply chains caused discontinuation of operations and forced companies to look for alternative supplies and reconfigure their supply chains (Smith, 2013). One reason why operations were affected so severely is that companies implemented just-in-time (JIT) operations, such as in the case of Western digital (WD) who had to shut down two of their factories due to the Thai floods. WD had proactively moved inventory from JIT processes at supplier warehouses to a safe place and managed to resume operations after 48 days (Wai and Wongsurawat, 2013). Natural disasters now occur more often around the globe, with increasing severity, with the result that natural disaster has climbed into the top two risks for businesses globally (Kleindorfer and Saad, 2005). This can be attributed to the fact that operations rely on JIT production with global supply chains.

On the other hand, solutions that mitigate risks from natural disasters, such as increasing inventory, keeping inventory at dispersed locations, having backup suppliers, procuring from multiple locations, etc. undermine JIT cost efficiency (Chopra and Sodhi, 2014). Despite the extensive literature on risk mitigation and supply chain design, no prior studies model how JIT production can recover from a natural disaster.

Companies therefore need to achieve two conflicting goals simultaneously: supply chain efficiency and disruption risk minimisation. Recently, a new requirement is becoming apparent: the sustainability of supply chains, making the design of supply

chain networks (SCNs) a priority for researchers and professionals. However, few empirical studies have attempted to present an integrated model which is capable of coping with unexpected disruptions in a sustainable way that protects JIT operations.

Rose (2011) points out that natural disasters not only disrupt supply chain operations, they may have a negative impact on environmental sustainability, which adds to the complexity of how to effectively model supply chains, yet necessitates that both resilience and sustainability be modelled together in order to manage them appropriately.

An increasing number of studies, (e.g., Scheel, 2016; Thomas et al., 2016) consider that there is a simultaneous need to achieve efficiency, resilience, and sustainability. Thus, the design of SCNs, apart from business implications, has direct practical and policy implications. The motivation for undertaking this study concerns the lack of empirical studies that holistically model supply chain design; a gap that has been identified in previous literature reviews, as pointed out by Jauhar and Pant (2016), that most of the previous studies consider these two elements (resilience, sustainability) in isolation from each other.

This study introduces a new integrated model and computational algorithm that are simultaneously resilient in terms of dealing with disruption risks, sustainable regarding CO₂ emissions, and efficient in terms of reducing supply chain cost and lead time waste. The presented research considers three pillars playing a significant role in improving SCN resilience including robustness (ability to stand against disruptions), leanness (reducing waste by adopting a JIT system), and sustainability (reducing environmental impact). This study aims to develop a genetic algorithm-based optimisation model to determine the minimum total cost (total cost and tax charges) in companies operating JIT business models. A number of scenarios are also analysed hypothesising various order quantities of raw materials (RM) shipped by local and/or external suppliers through various transportation options.

The developed model is demonstrated by a manufacturing case study based on real data. The next section reviews the relevant literature concerning optimisation of the design for a sustainable supply chain. The proposed model is presented in a subsequent section. Then, a case example illustrates how the model can be applied in a real case. Various scenarios are presented including a sensitivity analysis. In the last section, results and discussion are then presented, and the paper concludes with limitations and recommendations for future research.

2 Literature review

2.1 Supply chain design

During recent decades, companies have increasingly focused on supply chain management (SCM) to reduce costs and improve the bottom line in order to give them a competitive edge (Tang, 2006). Initially, the focus was on fundamental decisions in designing supply chains regarding the production facilities' size, location and capacity as well as transportation modes such as road, rail, or sea available to serve the markets in a manner that ensures cost minimisation (Speier et al., 2011; Chopra and Meindl, 2013). However, a combination of global mega-trends such as globalisation, market volatility, trade wars, and environmental concerns put pressure on companies to rethink their supply

chains beyond cost efficiency. Supply chain design needs to achieve two performance objectives at the same time:

- 1 cost efficiency
- 2 sustainable performances, i.e., reducing their environmental impact by eliminating black carbon emissions (Sodhi et al., 2012).

Meeting all demands simultaneously increases the complexity of the SC design; for example, in global supply chains, designs should incorporate international trade routes, port locations, incoterms, possible tax advantages, multi-modality and demand factors (Meixell and Gargeya, 2005).

Attributable to the inherent complexity of the SCN and the need to meet multiple objectives' efficiency, resilience, and sustainability, supply chain models need to address this complexity in unison.

2.2 *Supply chain modelling*

Although many articles and books have discussed the issue of modelling supply chains (Seuring and Müller, 2008), few have considered optimisation of both efficiency and sustainability constrained by disruption uncertainties (Olhager et al., 2015). As noted in the introduction section, companies face increasing high-impact uncertainties (Fang and Shou, 2015); yet, Eskandarpour et al. (2015) reviewing empirical studies on SCN design, conclude that scarce empirical studies deal with all dimensions of sustainability, while the majority of the studies do not incorporate uncertainty at all (Tsao et al., 2018).

The majority of previous studies adopt known parameters, thus they do not have to include uncertainty in their models (Cordeau et al., 2006; Özceylan and Paksoy, 2013) or model the supply chains stochastically (Listeş and Dekker, 2005). However, these assumptions are further from today's supply chain realities than the need to address both efficiency and sustainability while operating in uncertain environments (Tang, 2006). For example, reviews from Koberg and Longoni (2019), Rebs et al. (2019) and Srivastava (2007) show a growing interest in sustainable supply chains and an emerging need to model them realistically.

Linton et al. (2007) suggest incorporating waste when modelling the total cost of the supply chain as a way to include sustainability as a decision goal apart from efficiency, solely. In this regard, additional to cost efficiency, supply chain design should consider black carbon tax that increases total supply chain cost (Peng et al., 2016).

2.3 *Supply chain optimisation models*

Prior studies have examined various sources of SCN risks including disruptions (Samson and Gloet, 2018) and optimisation models to minimise risks (Allaoui et al., 2018). However, this literature stream has few overlaps with sustainable supply chain optimisation modelling. Cousins et al. (2004) develop a model on green supply chains, considering two main aspects: the role of risk and the motivations of companies to undertake the different types of environment issues related to supplier initiatives. Mari et al. (2014) introduced an optimisation model which incorporates taking into account the sustainability aspect via carbon emission and resilience via location-specific risks. Also, regarding the sustainability issue and risk disruptions, the mathematical model presented

by Saffar et al. (2015) focuses on minimising total costs and environmental impact. Rotaru et al. (2014) and Davarzani et al. (2015) have introduced modelling approaches concerning analysing the effects of disruption risks on SCN designs.

Fathollahi-Fard et al. (2018) found that meta-heuristics outperform other analytical models in SCN design. Ardalan et al. (2016) model supply chains with multi-mode demand as a multi-objective problem with an iterative Lagrangian relaxation based on heuristics.

However, few studies have modelled efficiency, uncertainty and sustainability at the same time.

El Dabee et al. (2013) propose an optimisation model that resembles the model in this study. In their model, El Dabee et al. (2013) consider an optimisation model for supplier selection during risk of disruption while JIT is the preferred operational model. However, the model in the current study differs in terms of presenting a structural modelling approach which is used to identify the interrelationship between JIT (lean strategy) and environmentally friendly transportation (green strategy), taking into account the fact that both strategies are influenced by potential disruption risks.

3 Proposed optimisation model

3.1 Problem statement

Price variations of a product in global markets require the assumption that the distribution network consists of external suppliers of the RM involved in manufacturing that product. Essentially, effective implementation of a JIT strategy in an assembly system requires instantaneously replenishment of the RM. Accordingly, costs of replenishing stocks and the inventory cost of final products will not be included in the analysis. The causes of risks and uncertainties can be numerous and unpredicted, such as the case of the COVID pandemic, trade wars, demand fluctuations, natural disasters accidents (the Beirut port explosion); all these risks affect external suppliers. Without a doubt, all these unforeseen events impose significant risks on production processes, threaten the managerial control and put into test the entire supply chain. One way of risk mitigation is having excess suppliers, e.g., both locally and globally, in case an emergency supply is required. However, dependence on local suppliers is typically costlier compared to global suppliers due to the high prices, which is related to the low level of risk incidence and short lead times.

In this study, the proposed optimisation model, to address the undertaken problem, considers both local and global (external) suppliers, using the available transportation modes, that may be (sorted by cost): waterways, railways, roads and airways.

3.2 Model assumptions

The model is subject to a number of assumptions to arrive at an optimal solution. Due to existing uncertainties in the SCN, assumptions are made related to order size, product price, availability of all RM, reliability of local backup suppliers, cost of transport, and labour payments in order to bring the model closer to reality. Additionally, assumptions are used for evaluating the proposed model in terms of their ability to provide accurate predictions. Therefore, model assumptions are as follows:

- Regardless of order size, we consider the ordering cost at a constant rate for each order of input RM.
- Regardless of inventory batch size, there is no change in the final product price.
- As it is commonly accepted, the utilities cost is calculated as percentage of total product cost associated to batch size decision.
- The availability of all RM in the production system is committed by the key external supplier. In this case, disruption risk is considered nil. In case of losing one or more key suppliers in the event of a potentially significant disruption, companies have the option to procure RM locally.
- Relying on local procurement ‘RSLB_j’ influences the total cost provided by local backup supplier ‘SLE_j’. Procuring locally would require an additional cost compared to procuring from regular external suppliers ‘S_{Ej}’.
- The model views the cost of transport as proportional to distance and the type of transport facilities used.
- The employee or labour payment is under the fixed rate cost system. In this system, no consideration is given to the quantity or quality of work done.
- In the case of disruption, the additional cost is calculated as a percentage of the total cost. The exact percentage rate depends on the impact of the disruption on the JIT production.
- Duties cost will be considered in the proposed model only when external suppliers ‘S_{Ej}’ supply RM to the company since local supply does not incur import duties.
- A percentage of the total cost CRM is used as a reference to calculate the transfer price cost which is needed to procure RM from regular external supplier ‘S_{Ej}’.
- A reliability index j (0–1) is developed to assess and reflect the availability of supplying RM by local backup suppliers.
- Some RM types can be supplied by either the external or local supplier, or both.
- Carbon dioxide emissions from both production and recovery are uncertain.
- The purchase price can be negotiated and varies considerably. Such factors are dependent on order size, discounts, payment terms, and historical relationships, amongst other mitigating factors.

3.3 *Decision variables*

N_{SELB} number of suppliers of RM to the production facility (unit). This includes both external and local suppliers used during disruption:

$$S_{Ej} = \begin{cases} 1, & \text{if the external supplier } j \text{ is active} \\ 0, & \text{if the external supplier } j \text{ disrupted} \end{cases}$$

$$S_{LBi} = \begin{cases} 1, & \text{if the local backup supplier } j \text{ is active} \\ 0, & \text{if the local backup supplier } j \text{ not used} \end{cases}$$

- d_p daily final product demand by customer (unit)
- t_m critical measurement of transportation of RM delivery using mode of transportation ‘m’
- Q_M required weekly demand quantity from RM ‘i’ which is ordered to produce the final product (unit).

3.4 Model constraints

In the proposed model, there are two of constraints imposed by capacity related to stack buffer and production. First, the buffers have a finite capacity. Regardless of order size, the amount of materials (RM, finished products and so on) for each order is restricted; the buffer will not grow or overflow. Second, the production system has enough capacity to fulfil the required demand. The production scenario is producing the maximum output possible from the system under working one daily shift. However, when the demand is more than the production capacity, the company needs to work three daily shifts.

3.5 Mathematical modelling

This research uses the same notations of El Dabee et al. (2013) which set to describe the indexes and parameters relating to the modelling. For more detail, the reader can refer to El Dabee et al.’s (2013) research.

The multi-objective optimisation of SCN design is presented below.

The objective functions of the proposed model are to minimise both the total production cost (C_T) and the carbon cost (C_{tax}) in the SCN:

$$\text{Minimise } C_{Total} = \sum (C_T + C_{tax}) \quad (1)$$

Different direct and indirect costs are associated with the operation of SCN. The components of total cost are calculated in equations (2)–(8). First, purchase cost of materials from different suppliers ‘ C_{RM} ’ can be computed in equation (2). Then, the cost of the employee, ‘ C_W ’, represents the wages paid to the employee to perform the required duties in the company, which is calculated based on the unit of time, as shown in equation (3). The utilities cost ‘ C_U ’ is calculated using equation (4) and the next equation (5), calculates the supply chain cost ‘ C_{TP} ’ (for explanation on equations, see El Dabee et al., 2013). The cost breakdown in equations (1)–(5) is as follows: purchasing cost ‘ C_P ’, ordering cost ‘ C_O ’, transportation cost ‘ C_{tr} ’, holding cost ‘ C_H ’, transfer price cost ‘ T_P ’ and, finally, duties cost ‘ C_D ’.

$$C_{RM} = \sum_{s=1}^{NSLB} C_{UOs} \times OF + \sum_{i=1}^{NP} \sum_{s=1}^{NSLB} (C_{UHi})_s \times \%d_{RM} \times (LT_j + SF) \\ + \sum_{i=1}^{NP} \sum_{s=1}^{NSLB} (C_{UMSLBi})_s + \sum_{s=1}^{NSLB} \sum_{l=1}^{NT} \sum_{i=1}^{NP} T_{SLBs,V,m} \times t_{m_i} \times \%V_i \quad (2)$$

$$C_W = \sum_{i=1}^{NP} C_W = \sum_{i=1}^{NP} C_{Li} + h_i \quad (3)$$

$$C_U = \sum_{i=1}^{N_p} \%Util \times C_{RM_i} \quad (4)$$

$$C_{Tp} = C_{RM} + C_W + C_U \quad (5)$$

C_{Tp} comprises the procurement cost of the RM and component parts bought from an external supplier. The equation to calculate this cost is shown in equation (6):

$$\begin{aligned} C_{Tp} = & \sum_{j=1}^{NSE} C_{UOj} \times OF + \sum_{i=1}^{N_p} \sum_{j=1}^{NSE} (C_{UH_i})_j \times \%d_{RM} \times (LT_j + SF) \\ & + \sum_{i=1}^{N_p} \sum_{j=1}^{NSE} (C_{UMSEi})_j + \sum_{j=1}^{NSE} \sum_{l=1}^{N_T} \sum_{i=1}^{N_p} T_{SLB_{j,V,m}} \times t_{m_i} \times \%V_i \\ & + \sum_{i=1}^{N_p} \sum_{j=1}^{NSE} C_{UPi} (1 - IF_j) \times D_j + \sum_{j=1}^{NSE} \sum_{i=1}^{N_p} tp_j \times C_{UPi} \\ & + \sum_{i=1}^{N_p} C_{L_i} + h_i + \sum_{i=1}^{N_p} \%util \times C_{RM_i} + \sum_{i=1}^{N_p} \sum_{k=1}^{LH_k} \frac{LH_k \times I_k}{Max(LH_k \times I_k)} \times C_{p_i} \end{aligned} \quad (6)$$

Managing disruption risks to avoid supply chain breakdown requires local procurement which entails a higher wholesale price. In this case, the expected cost regarding C_{Tp} can be written by modifying (6) as follows:

$$\begin{aligned} C_{Tp} = & \sum_{s=1}^{NSLB} C_{UOs} \times OF + \sum_{i=1}^{N_p} \sum_{s=1}^{NSLB} (C_{UH_i})_j \times \%d_{RM} \times (LT_j + SF) \\ & + \sum_{i=1}^{N_p} \sum_{s=1}^{NSLB} (C_{UMSLB_i})_s + \sum_{s=1}^{NSLB} \sum_{l=1}^{N_T} \sum_{i=1}^{N_p} T_{SLB_{j,V,m}} \times t_{m_i} \times \%V_i \end{aligned} \quad (7)$$

$$C_{Tp} = \sum (C_{RM} + C_W + C_U) \quad (8)$$

Each supplier is assessed by a risk score depending on the risk it poses to the total supply chain. Consequently, equation (9) calculates this cost resulting from the impact of supplier disruption risk.

$$C_R = \sum_{i=1}^{N_p} \sum_{k=1}^{LH_k} \frac{LH_k \times I_k}{Max(LH_k \times I_k)} \times C_{p_i} \quad (9)$$

$$C_T = \sum (C_{Tp} + C_R) \quad (10)$$

With regard to CO₂ emissions, equation (11) has been adopted to compute the total of those emissions that occur during RM transportation. Q_{Mi} is the volume (MT) of RM, v_i is the distance (miles) that RM need to travel, E_{fmi} is the emissions in kg CO₂/MT (note: MT = metric ton).

$$C_{Ei} = Q_{Mi} \times v_i \times E_{fmi} \quad (11)$$

The computed CO₂ emissions using the above equation, is only the emission of the black carbon resulting from using the RM i across the supply chain to meet the weekly production cycle (unit). E_{fmi} is the emission factor associated with the mode of transportation used for shipping RM. Meanwhile, the destination travelled of needed RM is v_i . Therefore, for computing quantities of CO₂ emissions which arise for producing one product:

$$C_E = \sum_{i=1}^{N_P} Q_{Mi} \times v_i \times E_{fmi} \quad (12)$$

The GHG emissions protocol created standards that are applicable to the companies (DEFRA, 2013). Based on these standards, the CO₂ emissions factors for the various transport modes used by companies to procure resources are as follows: 2.31 for road (diesel and petrol), i.e., 1.51 for LPG fuel, 0.03 for rail, 0.57 for air, and 0.06 for sea transportation. In order to determine the cost of emitting the amount of carbon from logistical operations, this paper takes a moderate fee level of carbon tax as m.u 25 for each ton of carbon dioxide emitted. Depending on this assumption, the total CO₂ cost is calculated as:

$$C_{tax} = C_E \times 25 \quad (13)$$

3.6 Genetic algorithm

Due to globalisation, technological advances, and competition, SCNs are becoming increasingly complex. Most SCNs consist of several intricate processes, multiple sources of products, variety and diversity of RM with significant resource constraints (Altıparmak et al., 2006). The inherent complexity of SCNs makes their optimisation an ND-hard problem.

On the other hand, supply chains need to deal with the challenge of stochastic demand (Cardona-Valdes et al., 2011). Hence, any adopted mechanism to solve this type of problem should be effective enough to cope with these challenges. The main obstacle for obtaining an optimal solution for supply chain design is the existence of many variables in relation to uncertainty and the system's structure. Using traditional mathematical programming techniques to solve such a problem has limitations. It can easily become trapped in the local optimum solution area due to the large number of decision variables and constraints being too complex (Franca et al., 2010). An alternative solution is to use genetic algorithms that use random inferential approaches and problem-solving techniques that simulate the processes that occur during natural evolution (Gupta and Ghafir, 2012).

Added to that, the processing time of these techniques is too long and also results in low efficiency. As a consequence, GA has been proposed to derive solutions through the optimisation process for different types of SCN problems. Jauhar and Pant (2016) analysed around 220 papers that applied GA for this purpose. Following guidelines and applications of this method in previous studies, this study adopts the GA method for the following reasons:

- 1 it has been proved as an effective mechanism in solving the p-median problem, which is the undertaken problem of this research

- 2 it is fast and relatively easy to apply in this type of problem
- 3 as a computational tool, it can be easily adaptable to deal with infeasible alternative solutions.

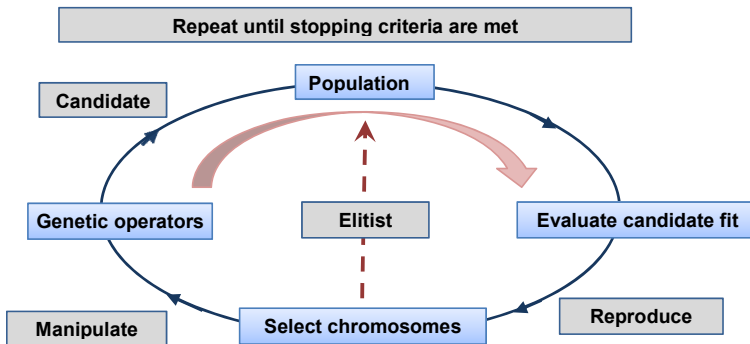
3.6.1 GA structure for optimising the SCN design

The GA emulates the Darwinian evolution process: initially, a population is defined and then a number of candidates are created and selected using different fitness functions; the algorithm is based on genetic operators (crossover/mutation) and continues to generate candidates by ‘mating’ parents until a stopping criterion is satisfied and a solution is achieved (Reeves and Rowe, 2003).

Figure 1 describes the GA scheme adopted in this paper. For an addressed problem, each cycle generates an individual (or candidate solution). The cycle will be repeated until reaching the promised solution which satisfies the imposed constraints and where, consequently, a termination condition is achieved. From using GA in this research, it is expected to find high-quality solutions with the capacity for simultaneous cost-risk reduction to the problem when designing an SCN which adopts a JIT approach to reduce waste.

This paper uses GA to design a sustainable SCN which works under a JIT approach and probably exposes potential risk disruptions. As stated before, the aim is to find the optimal design solution for this network which can offer minimum cost as well as the ability to handle different constraints. In the developed GA, real numbers are used for chromosome representation. Consequently, representation of the chromosome will only produce feasible solutions which do not need high computational time as this is what is required by the developed GA.

Figure 1 GA scheme of an SCN optimisation design (see online version for colours)



3.6.2 Fitness function

A fitness function is a single figure of merit which is needed to assess how close produced chromosomes are to achieving the set objectives. Normally, the fitness function is a particular type of objective that is used to summarise, as a single scalar value, how close a given design solution is to the optimal design solution (Garg, 2010).

The fitness function (F) aims to minimise the total cost C_{Total} comprised of total product cost C_T and estimated CO₂ emissions cost C_{tax} in candidate designs of SCN:

$$F = \frac{100}{(C_{Total} + 1)} = \frac{100}{((C_T + C_{tax}) + 1)} \quad (14)$$

To avoid the unwanted error, ‘divide by zero’, in the last equation [equation (14)], a constant of 1 was added for this purpose.

3.6.3 Selection

A selection approach is used in the developed GA as a procedure for selecting a part of the chromosomes (individuals) that are generated from the initial solution in order to contribute to their features. In this research, the replacement selection method is chosen for extracting a subset of the chromosomes from an existing population, based on the quality of index used here.

3.6.4 Stopping criterion

A stopping or termination criterion is the last step in the GA process. It occurs in two cases:

- 1 when the chance of achieving major changes in the future generation is too low or
- 2 after a fixed number of generations (Leuveano et al., 2012).

Prior studies have used a fixed number of generations to terminate the GA execution (Mahmudy et al., 2012). The same criterion was used in this study.

4 Case example

Using a real case scenario, we demonstrate the algorithm presented above. The case example concerns a simple assembly process for a hollow-shaft electric motor. The final product consists of 25 parts ($N_p = 25$). The case company has 11 external suppliers ($N_{SE} = 11$) and procures from them RM in fixed lot size. The risk of dependence on outsourcing from ‘external suppliers’ has become great, thus it is assumed that the best course of action is dependent on seven domestic (local backup) suppliers ($N_{SLB} = 7$) who can supply the RM with shorter lead times, less risk of shortage, but with extra cost. The adoption of a JIT production strategy means that the ordering and receiving of the right amount of RM from suppliers (whether local or external) is time dependent, i.e., it depends on the actual and immediate need for the production system (Table 1).

The production system consists of five main operations. The company hires five employees (w_1, w_2, w_3, w_4 and w_5 respectively). Each employee runs each operation individually.

We assume that each day has eight working hours (N_h), and each working week has five days. Each employee receives a fixed wage of 14 monetary units per hour (mu/h). Mostly, the suppliers, whether external or local, offer price discounts when the company buys RM in bulk. Price discounts range between 5% to 14%. Utilities cost is also fixed at 10% of RM cost.

The system has a scheduled production capacity of 70 units per day, and the main dependence is on the external suppliers (S_E) to regularly supply RM. In cases of one or

more from those external suppliers being disrupted, then local backup suppliers (S_{LB}) could be resorted to fill the shortage of assembly RM.

When the supplier’s lead time is uncertain, it affects the system in terms of both cost and services perspectives. Therefore, it is imperative that this be taken into account when it comes to meet the needs of customers in fixed periods and at normal times. When the supplier’s lead time is uncertain, it affects the system in terms of both cost and services perspectives. Therefore, it is imperative that this be taken into account when it comes to meet the needs of customers over fixed periods and during normal times.

The focus is on the timely delivery of RM to avoid any delay which would affect the performance of JIT production. The price of the final product is set at 485 m.u.

Table 1 Model parameters

Part no.	Weight (pounds)	Supplier type					
		Local backup supplier			External supplier		
		Supplier no. S_{LB}	Lead-time (LT) (Days)	Destination of required RM (v) (miles)	Supplier no. S_E	Lead-time (LT) (Days)	Destination of required RM (v) (miles)
1	6.62	1	4	218	1	24	3,108
2	5.51	1	4	218	1	24	3,108
3	0.33	2	6	311	2	32	3,108
4	6.62	1	4	218	1	24	3,108
5	1.65	3	3	186	3	18	4,661
6	0.22	4	5	249	4	38	3,729
7	4.85	4	5	249	4	38	3,729
8	13.23	4	5	249	5	42	4,040
9	0.55	4	5	249	5	42	4,040
10	1.65	3	3	186	3	18	4,661
11	0.44	2	6	311	2	32	3,108
12	5.51	5	2	155	6	28	3,108
13	2.65	5	2	155	7	35	4,972
14	0.33	5	2	155	7	35	4,972
15	0.66	5	2	155	6	28	3,108
16	0.33	3	3	186	9	20	2,175
17	0.55	6	8	311	8	45	2,486
18	0.22	2	6	311	2	32	3,108
19	0.33	6	8	311	8	45	2,486
20	0.55	3	3	186	9	20	2,175
21	0.33	6	8	311	8	45	2,486
22	0.55	7	7	373	10	28	3,108
23	0.33	7	7	373	10	28	3,108
24	0.55	7	7	373	10	28	3,108
25	0.55	7	7	373	11	21	2,486

5 Results and analysis

The GA was used to optimise the JIT SCN of the case example with the following results. One of the key decisions is the number of international suppliers (S_{Ej}) of RM, which are 11 in this model.

S_{Ej} can take two values 0 or 1 depending on the selection, or not, of the specific supplier. Using $S_{Ej} = 1$, this means the SE can provide RM, and the total cost C_T can be computed using equation (3). Meanwhile, C_T computation relies on equation (4) when $S_{Ej} = 0$, i.e., S_{Ej} has disruption. In both equations, dp remains the same. Herein, the computation of C_T is associated with changes in dp at four levels, 1, 2, 3 and 4. One of the model's components is 'tm' which can take four distinct values, each value represents one transportation mode and, specifically, road: 1, rail: 2, air: 3, ship: 4.

Lastly, the order quantity 'QM' has seven levels: 350, 700, 1,050, 1,400, 1,750, 2,100, and 2,450.

5.1 Applying developed model for finding optimal solution

Using the main GA parameters with the values shown in Table 2, the developed GA generates the optimal SCN design taking into account the total cost under various disruption risk scenarios. The GA code was developed using Java programming language micro edition. A standard personal computer was used with an i5-3210M CPU with two cores working at its base frequency and minimal memory of four gigabytes. After 249 iterations, the GA found an optimal solution-chromosome (Table 3). Table 3 shows the details of the optimal chromosome after 249 generations.

Table 2 GA parameter values

Parameter	The values
Crossover rate (P_c)	0.7
Mutation rate (P_m)	0.15
Population size (N)	500
Maximum generations (G_{max})	5,000
Generation stop (G_{max_Stop})	30,000

Table 3 Best chromosomes (decision variables) obtained using a replacement selection method

N_{SELB}											dp										
1	0	0	0	1	0	1	0	1	0	0	210										
t_m											Q_M										
1	3	4	2	1	3	2	4	1	3	4	1	1	1	1	1	1	1	1	1	1	1

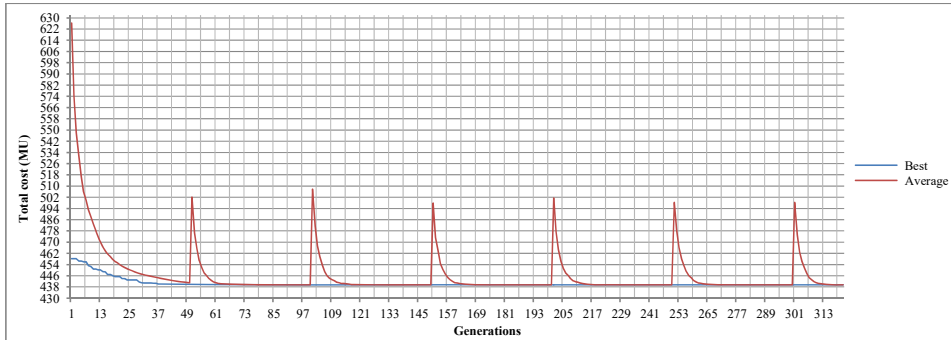
Table 4 Best GA solution

Iter	Time(S)	dp	C_O	C_H	C_P	C_{tr}	C_D	T_P	C_W	C_U	C_{pt}	C_R	C_T
252	47.30	210	6.95	9.92	314.97	36.26	2.92	2.24	8.0	37.33	418.58	20.90	440.0

Figure 2 illustrates the cost scores of best and average of all chromosomes over specified run generations (3,000). The optimal chromosome fluctuations are a natural outcome of

the population diversity that is caused by the adopted selection strategy. Replacement selection strategy and adaptive adjustment of crossover and mutation operators (P_c and P_m) will create new children which can explore alternative directions in the solution space which can protect optimal chromosomes of every generation from being trapped and replicate them to the next generation.

Figure 2 Diagram of comparison between best and average score of chromosomes related to total final product cost (see online version for colours)



5.2 Comparison of GA with other optimisation methods

This section compares the performance of GA and with particle swarm optimisation (PSO) as an alternative optimisation method to design a sustainable SCN under disruption risks. Similar to GA, PSO is a metaheuristics algorithm with an ability to find global optima. Details regarding the design structure and implementation of PSO are beyond the scope of this paper. More on PSO can be found in Kennedy and Eberhart (1995) and Eberhart and Kennedy (2001). Implementations of GA and PSO algorithms are coded and run using Java programming software. The specified parameters related to the GA and PSO are shown in Table 5. Here, it should be noted that these parameters are the same as those used in the GA run (Table 2) to find the optimal design solution which resulted in Figure 2. The fitness function [presented in equation (14)] is used to reflect the goodness of each algorithm.

Table 5 GA vs. PSO comparison

<i>GA</i>	<i>PSO</i>
Crossover rate (P_c): 0.7	C1: 2.0, C2: 2.0
Mutation rate (P_m): 0.15	W_{start} , W_{end} inertia weight coefficients: 0.9, 0.4
Population size (N): 300	Swarm size (N): 300
Maximum generations (G_{max}): 1,000	Maximum generations (G_{max}): 1,000

Note: C1: cognitive acceleration coefficient, C2: social acceleration coefficient.

Each algorithm was run ten times to test its performance and obtain the best chromosome that solves the identification problem. The results are provided in Table 6 which shows the characteristics of the best run optimised by the two algorithms.

Table 6 Optimised decision variables and corresponding fitness function obtained by GA and PSO

<i>Iter.</i>	<i>Time (S)</i>	d_p	C_{pt}	C_R	C_{T-max}	C_{T-ave}	$F.F_{max}$	$F.F_{ave}$
<i>Genetic algorithm</i>								
223	48.1	210	418.6	21	439.5	440	0.23	0.23
<i>PSO</i>								
126	48	210	418.6	21	439.5	446.7	0.23	0.23

The results confirm one GA drawback; it has expensive computational cost. The developed GA reached the optimum solution after 223 iterations, while PSO achieves this after 126 iterations.

PSO is sub-optimal because the final cost is higher than the cost achieved with GA; therefore, these findings indicate that the GA-proposed model is superior to the PSO approach.

The improvement in performance of GA with the given fitness function is clearly attributed to the result of population diversity caused by the adopted selection strategy. Herein, the operators' crossover or mutation generates a new offspring which can move in different directions in the solutions space and, consequently, enable the GA to avoid being trapped in local optimal areas.

As shown in Table 6, PSO is faster in reaching the optimal solution design (126 iterations while GA 223 iterations) but both algorithms take the same time (around 48 seconds) to determine their results. The PSO algorithm is appropriate to a system which is linear, time-invariant, and deterministic. However, SCNs are considered from stochastic systems – as detailed before – so, none of these characteristics are perfectly achieved.

5.3 Sensitivity analysis of decision variables

The assumption, here, is that the supply chain designers decide to run the proposed model using each of three assumed optimisation run designs (also known as scenarios) and then analyse the results. The sensitivity analysis strategy represents the beauty of supply chain design modelling.

Computational experiments are carried out to ascertain how the optimised solutions are affected by the changes in different levels of decision variables.

5.3.1 Scenario one: different cases of occurrence for external suppliers' disruptions and decision variable changes are made to different levels

The main concern of many companies that mainly depend on the selection of local/global suppliers ($N_{SE} = 11$, $N_{SLB} = 7$) to procure RM is the potential disruption that may occur to the supply chain system. For completed understanding of this concern, the possibility of disruption for both suppliers is assumed as follows: the company has one major supplier (denoted by j) who is prone to disruption, and one backup local supplier who can replenish the inventory, i.e., $S_{Ej} = 0$ else $S_{Ej} = 1$.

For simplicity, the same assumption takes place for both scenarios of local or external procurement.

Table 7 shows how disruption affects the key decision variables. Through a closer look at the table, and depending on the obtained C_{Total} , for each design, it becomes clear that the optimal combination of all decision variables was superior in comparison with those costs obtained by making separate optimisations for each decision variable. Clearly, C_{Total} is a function of examined decision variables in this research: the customer's demand the quantity of RM, lead times, and transport mode.

Any change in these variables that may occur during the possible disruption of the system will alter C_{Total} . Based on the above results, the reliance on the local supplier when all external suppliers are exposed to disruption may change several costs. Specifically, C_p has the highest rate of change when it comes to compare to other disruptions. Thus, with these changes, the change in C_{tr} value does not appear to be a significant change. This is because these slight changes are attributed to the transporting of RM from the original to the production system.

Table 7 Disruption impact on key decision variables

No.	<i>External supplier position in the supply chain</i>											$Q_{RM}/week$ (unit)	d_p/day (unit)	t_m (unit)	C_T (m.u)	C_{tax} (m.u)	C_{Total} (m.u.)
	1	2	3	4	5	6	7	8	9	10	11						
1	1	1	1	1	1	1	1	1	1	1	1	350	70	1	393.40	230.1	623.5
2	1	1	0	0	1	1	0	0	1	0	1	350	70	2	428.00	183.7	611.74
3	1	0	1	1	0	0	1	1	0	0	0	350	70	1	447.95	148.3	596.27
4	0	0	0	1	1	0	0	0	0	0	0	1,050	140	4	444.54	1,799	2,243.14
5	1	0	1	0	0	1	0	1	0	1	1	350	70	1	458.79	141.5	600.26
6	1	1	0	1	1	0	0	0	1	0	0	1,050	140	1	412.15	553.8	965.90
7	0	1	1	0	0	1	1	0	1	0	1	350	70	1	464.23	87.96	552.19
8	1	1	0	1	1	0	1	0	0	1	1	350	70	1	430.95	206.7	637.67
9	0	1	1	1	0	0	0	1	1	0	0	350	70	1	449.90	70.50	520.40
10	1	1	1	0	0	1	0	1	1	1	0	350	70	1	456.35	145.4	601.73

5.3.2 Scenario two: different cases of occurrence for external suppliers' disruptions and decision variables remain unchangeable

Two cases are taken into consideration:

- 1 risk-free, where there is no disruption and all external suppliers send their RM without any disruption risk
- 2 a disruption breaks down the capacity of the external suppliers in providing the materials to the system.

Results are depicted in Figure 3 that demonstrates how the costs are alternated under supplying with the local backup suppliers and without externals. Considering a backup local supplier to provide the material to satisfy the demand when disruption occurs, the expected production cost will be increased. When the disruption is widespread to the total number of suppliers, C_p and C_R increase compared to less disruption events where C_H , C_{tr} , T_p and C_D become minimal.

5.3.3 Scenario three: sensitivity analysis of disruption risks

A number of analyses examined the sensitivity of the model under different conditions of disruption risks. Specifically, external suppliers were split into two groups; the first group were the odd numbers and the second group the even numbers. Under this scenario, the second group was disrupted. The results are shown in Table 8. The minimum total cost objective is small ($C_T = 418.2$) and another objective is relatively high. This means the impact of disruption probability on the sustainability aspect of the system is costly. In addition, the optimal value of other cost components: C_{tr} , C_U and C_R are high. This implies that even disruption of some external suppliers would increase the production cost. According to Table 8 results, C_{tr} is directly influenced by disruption probability. This is because this type of cost is linked to the transportation mode. C_U is a fixed cost calculated as a percentage of purchase cost [equation (4)] thus disruption indirectly affects this cost. Consequently, C_R increases due to using extra suppliers as an alternative to reduce the impact of supply disruptions.

Figure 3 Comparison of disruption effect on different costs (see online version for colours)

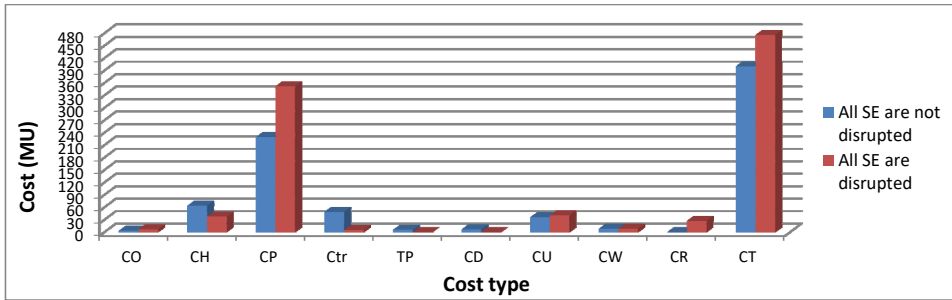


Table 8 Sensitivity analysis: $SE_1, SE_3, SE_5, SE_7, SE_9$ and SE_{11} are active ($SE_J = 1$ not distributed), other external suppliers: SE_2, SE_4, SE_6, SE_8 and SE_{10} , are distributed ($SE_J = 0$)

No.	External supplier situation in the supply chain											$Q_{RM}/week$ (unit)	d_p/day (unit)	t_m (unit)	C_T (m.u.)	C_{tax} (m.u.)	C_{Total} (m.u.)
	1	2	3	4	5	6	7	8	9	10	11						
1	1	0	1	0	1	0	1	0	1	0	1	350	70	1	435.8	197	632.76
2	1	0	1	0	1	0	1	0	1	0	1	350	70	3	447.8	31.75	479.55
3	1	0	1	0	1	0	1	0	1	0	1	700	95	1	428.3	394	822.28
4	1	0	1	0	1	0	1	0	1	0	1	1,050	140	2	425.4	50.5	475.89
5	1	0	1	0	1	0	1	0	1	0	1	1,750	115	3	484.1	158.5	642.59
6	1	0	1	0	1	0	1	0	1	0	1	2,100	140	4	523	6,165	6,688.2
7	1	0	1	0	1	0	1	0	1	0	1	1,050	170	1	418.2	591	1,009.2
8	1	0	1	0	1	0	1	0	1	0	1	1,400	210	2	425.7	67.5	493.2
9	1	0	1	0	1	0	1	0	1	0	1	2,100	155	3	489.9	190	679.9
10	1	0	1	0	1	0	1	0	1	0	1	1,050	210	4	462.5	3,083	3,545.3

5.4 Impact of transportation on carbon emissions

Comparison of CO₂ emissions by different transport modes was analysed using all possible combinations (Figure 4). Figure 5 presents the distance travelled by each transportation mode for the same energy expenditure. Here, the assumption is made that one batch weights 20 tonnes. Figure 4 shows that shipping by water is a small contributor to environmental impact for long distance transportation compared to road, rail, and air cargo. Cargo ships are by far the most energy efficient mode of transportation, suitable for long-haul, global transportation of containerised goods. Numerically, shipping is recognised as the most efficient mode of transport with 0.45 metric tonnes of black carbon emissions.

Figure 4 CO₂ emissions by transportation mode (see online version for colours)

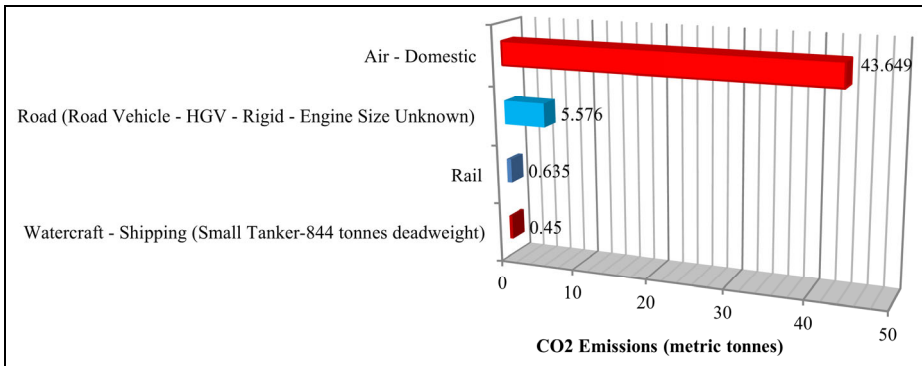
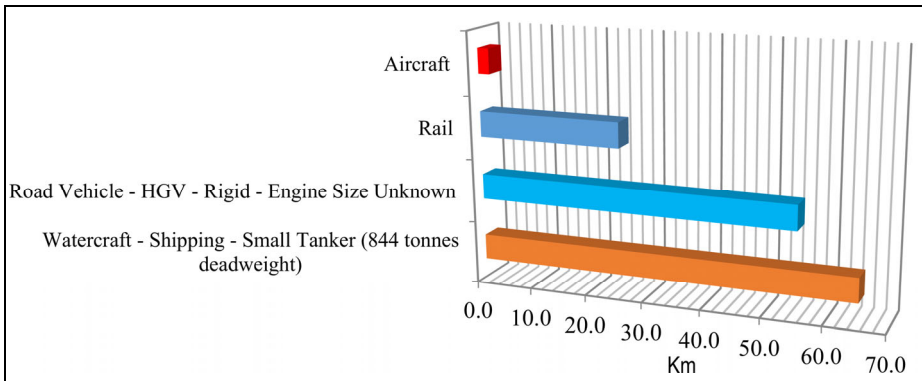


Figure 5 Distance travelled with the same energy expenditure (see online version for colours)



Rail transportation always comes out better than other modes (truck and air), often by a lot. The results indicate rail emits 0.635 metric tonnes; these emissions are very low in comparison with road diesel carbon emissions of 5.5567 metric tonnes or air cargo of 43.649 metric tonnes. In summary, the cost incurred by ships decreases with increased transport volumes while emissions are less than other transportation means. Ships are the preferred transportation mode in terms of sustainability performance. Major savings in

energy can be achieved with shipping by watercraft for transporting RM in supply chain systems. In this regard, shipping one ton of cargo only requires 1 kWh.

5.5 Managerial implications

In an increasingly complex and uncertain environment, companies are seeking ways to achieve multiple objectives at the same time, yet few studies, so far, have examined the simultaneous optimisation of efficiency, resilience and sustainability. As such, the proposed model has significant practical applications. One of the key decisions is to source locally or globally; the other decision that managers face is how to prioritise between efficiency, resilience and sustainability; the recent COVID pandemic demonstrated how important it is to reconsider disruptions and their effects on SCN design.

The proposed model can be considered as a baseline for the models intending to consider multi manufacturers and multi retailers. Further, the results indicate that considering production and distribution design optimisation separately negatively affects the performance during disruptions of SCNs. These two findings should be considered when designing supply chains or re-designing existing ones:

- 1 Using local suppliers to handle a disruption which results from natural disasters and causes stopping external suppliers is mostly like to increase the total production cost.
- 2 CO₂ emissions increase with increasing transaction quantities and when using aircraft as a quick transportation mode to cope during the disruption of an SCN.

The results also show that companies should strategise their supplier selection, incorporating disruption risks into their decision-making process. A disruption may affect not only the supply side but, at the same time, the demand side (such as in the case of the recent pandemic). In this case, companies need a holistic approach, which this model can offer.

6 Conclusions and further research

This paper presented a unique optimisation approach concerning how to mitigate against potential supply chain disruption risks. The approach included an optimisation model applied to obtain optimal design of an integrated SCN. Also, the model developed in this paper considered the impact of introducing carbon tax into the suggested supply chain design. The model assumes that there are two kinds of suppliers, local and global/external, which are responsible for providing RM. Procuring from local/global suppliers is subject to a variety of costs and lead times depending upon disruptions due to unexpected risks.

Both local and external suppliers have to manage potential disruptions in supply chains caused by natural or man-made disasters, or economic crises. The development of GA and the optimisation design of SCNs were presented in detail and the fundamental structure of GA was outlined. To ensure the validity and for improving the proposed model, it was applied to an industrial case example, and the results of the experiments validated the model and its parameters. Specifically, the experimental results show that the model measures the SCN performance in various design scenarios effectively. Also,

the results confirmed that the model can be used to obtain a design that can meet desired expectations. Finally, to provide a contribution that the performance of the proposed GA in this research is superior to find optimal solutions to undertaken problems in terms of accuracy and iterations, the PSO approach was chosen for the purpose of performance comparison. The results indicate that the GA proposed model is superior to the PSO approach.

One characteristic of any GA model is that, specific to the problem it tackles, the derived solution cannot directly be transferred to other problems without proper re-adjustment, calibration and parameterising. Nevertheless, the model can be easily applied by companies to evaluate how they perform in terms of efficiency, sustainability and resilience. However, as with all models, it is subject to some limitations that need to be taken into account before the model is applied in practice. Specifically, it considers one product, one process and one retailer, while the many real cases are multi products involving several processers and retailers.

Future research areas may extend from the work presented in this paper in various directions: First, multi-modal transportation is a popular option that can be easily achieved by modifying the model parameters. Then, operations can produce more than one product whereby, in this case, the daily demand would concern multiple products. Such research offers opportunities to explore quantitative models that integrate different sources of disruption risks. In addition, the assumption in the presented model is that demand is deterministic, which may not be the case due to the stochastic nature of SCNs in most cases. This issue could be a valuable recommendation for further research.

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