Optimal supply chain design with product family: A cloud-based framework with real-time data consideration

ABSTRACT

When the product family (PF) and the supply chain designs (SCD) are aligned and integrated, original equipment manufacturers (OEM) are more likely to improve their operational performance. In this paper, we propose a novel approach, which demonstrates how both the product and the supply chain can simultaneously be designed based on real-time data. At the heart of the proposed model is the utilisation of a cloud-based management system comprising of three steps. In the first step, a generic bill of materials is modelled to design a set of product families using "AND" and "OR" nodes. In the second step, a cloud-based framework is designed to manage real-time costs viz. echelons. In the third step, a mixed integer linear programming model is then applied, which optimizes the SCD based on real-time costs. We use a metaheuristic method based on Genetic Algorithm (GA) to solve the optimization problem. We further illustrate the model using power transformer numerical example. Then the critical parameters of GA are examined to determine the best settings. We believe that the proposed SCD is an intelligent and expert management system, which can facilitate effective decision-making support by taking into account real-time cost data. This is particularly important when there are uncertain and volatile market conditions.

Keywords: Supply chain design, Product family design, Cloud computing technology (CCT), Mixed Integer Linear Programming and Genetic Algorithm (GA).

1. Introduction

To respond to the growing needs of customers from various market segments, many manufacturers have adopted a product family (PF) design concept. This refers to a set of similar products that are derived from compound modules and a product variant configuration enabled by the effective implementation of modularization strategies. Such strategies essentially outsource common platform modules to supply chain partners to simplify the production / distribution processes and improving operational performance. Thus, the success of a particular product does not only depend on the optimal supply chain design or technical performance, but also on the performance of the OEM supply chain in fulfilling uncertain customer demand. In this context, the SCD primarily determines the structure or links amongst the partners to make structural and (optimal) coordinated decisions. The key question, therefore, is: how do we optimally integrate the PF and the SCD in such as a way that factors such as globalisation, increased market competition, varying costs and modular product demand can be taken into account in a timely manner?

Traditionally, the PF design has been limited to the product design level, with less consideration given to the downstream and globally distributed supply chain. In this context, the PF design essentially involves an 'assembly-to-order' production system in which globally distributed operators and manufacturers collaborate (Wang et al. 2016; Jiao et al. 2009). Such a supply chain considers issues such as facility locations, sourcing, distribution and selection of nodes in a supply chain network (Hong et al. 2018). Therefore, there is a need to constitute a SCD that addresses the configuration of the supply chain for a particular PF. This involves the joint configuration decisions for the optimal PF planning and the selection of supply options on each supply chain echelon (Wang et al. 2016; Ma et al. 2016; Shahzad and Hadj-Hamou, 2013).

Numerous studies have been conducted on the joint optimization of the PF and supply chain to maximise the performance of the end product (Ulrich, 1995; Fine et al. 2005; Graves and Willems, 2005; Huang et al. 2005; ElMaraghy and Mahmoudi, 2009; Nepal et al. 2012). More recently, Mohammed & Duffuaa (2020), Liu et al. (2020), Du et al. (2019), Baud-Lavigne et al. (2016), Wang et al. (2016) and Yang et al. (2015) have all considered the simultaneous configuration of PF and SCD. A bill of materials (BOM) is a very important concept for PF design since it helps to generate various product variants. However, there are very few SCD studies which consider BOM for PF design in multiple periods (Paquet et al. 2004). Appelqvist et al. (2004) present a literature survey on the modelling of the PF and the SCD. In their study, they present a generic BOM for PF design, which matches the SCD in order to satisfy market requirements. ElMaraghy and Mahmoudi (2009) consider BOM for optimal SCD. Zhang et al. (2016) propose an integrated model for strategic SCD on BOM-related constraints.

In all these decision models, the PF design determines which components, modules and finished end products should flow through the supply chain on the basis of overall costs. However, given the nature of the contemporary globalized supply chain, variations in costs (setup costs, opening costs, production costs, holding costs, ordering cost, transportation costs) should be carefully considered. Hence, real time data should be incorporated when designing the supply chain.

In this paper, we contribute to the existing literature on product and SCD by proposing a new method, which simultaneously links the two by personalizing the operational decisions based on real-time data. Our proposed method is based on cloud computing technology (CCT), which has transformed the evolution of the Internet to pay-as-you-go business model using web-based technologies (Xu, 2012). CCT is not a new technology but a combination of existing IT technologies such as utility computing, parallel computing, grid computing, virtualization, Internet technology and open source software (Wu et al. 2015). Some of the main benefits of cloud computing are elasticity, scalability, on-demand computing and agility (Putnik et al. 2013). More importantly, CCT can help manufacturing companies achieve better linkages with their supply chain partners through integration and alignment of internal and external business processes, real time information sharing and coordination of information flow to optimise the supply chain (Zafar et al. 2017). We argue that, given the complexity of coordinating the product and SCD decisions, comprehensive optimization of both the PF and SCD is one of the most efficient ways to reduce costs and achieve "distinctive competence". To the best of our knowledge, the optimal integration of SCD and PF design based on real-time costs has not yet been studied.

To integrate the PF design decisions with the SCD based on real-time data, we extend the model proposed by Graves and Willems (2003). Our proposed cloud-based management system follows three steps to simultaneously consider the PF and optimal SCD. In the first step, a generic bill of materials is modelled to design a set of product families using "AND" and "OR" nodes. In the second step, a cloud-based framework is designed to manage real-time costs viz. echelons. In the third step, a mixed integer linear programming model is then applied, which optimizes the SCD based on real-time costs. We use a metaheuristic method based on Genetic Algorithm (GA) to solve the optimization problem. Finally, we evaluate the performance of our decision support model using a power transformer numerical example.

The rest of the paper is organized as follows. In the next section, we review the related literature on PF, SCD and GBOM. Section 3 contains a description of proposed cloud-based framework while Sections 4 and 5 elucidate the mathematical model. Section 6 identifies the solution approach based on Genetic algorithm. In Section 7, we provide a transformer numerical example and analyse the computational results. Finally, we conclude the paper in Section 8 and identify directions for future research.

2. Related Literature

2.1 Product Family Design

A PF design refers to a set of similar products that are derived from compound modules and a product variant configuration based on a common product platform (Wang et al. 2016). The range of product variants offered to customers by companies has drastically increased due to the effective implementation of modularization strategies (Park and Kremer, 2015). For example, Volkswagen has saved $1.7 billion annually on production and development costs by adopting a modularization strategy that outsources common platform modules to supply chain partners (Dahmus et al. 2001). Modularization strategies can generally simplify the processes and improve operational performance (Miltenburg, 2003). Products usually exhibit a certain form of architecture, which impacts on their performance, variety, component standardization, and development (Xiao et al. 2018; Wu et al. 2016; Zhu et al. 2010).

Over the last decade, research has analysed the merits of modular PF architecture. Shahzad and Hadj-Hamou (2013) adopt a GBOP (Generic Bill of Products) as a platform to meet the customer demand of specific product variants. Fujita et al. (2013) propose a mathematical model for the simultaneous design of product architecture and supply chain configuration through the selection of manufacturing sites for module production, assembly and distribution. Tseng and Hu (2014) review the logical mapping of PF architecture, which mainly includes functionality, modularity, commonality and structural aspects of the product. Ma et al. (2016) propose a hierarchical joint optimization game for the modular design of the PF, focussing on technical system modularity. Mohammed & Duffuaa (2020) analyse an optimal design of a supply chain based on multi-objective, multi-product supply chain networks. Liu et al. (2020) formulate an optimal design of low-cost supply chain for new products.

2.2 Product and supply chain design coordination

The success of a product does not just depend on the optimal design or technical performance, but also on the performance of the OEM supply chain in fulfilling uncertain customer demand. In this regard, Graves and Willems (2000) develop the first stationary demand multi-stage optimization model to determine the optimal stock level at each tier of the supply chain. The main goal is to improve the SCD and eventually performance. In this context, SCD primarily determines the structure or links amongst the partners to make (optimal) structural and coordinated decisions (Truong and Azadivar, 2005). These decisions are at the strategic and tactical level. The strategic decisions for the company are long term: e.g. the choice of production facility location, facility selection and production capacities. The tactical decisions are mid-term decisions, such as the selection of potential suppliers, allocation of production to suppliers and the flow of modules or products amongst sub-assemblies within the supply chain network (Cordeau et al. 2006). The parameters considered in the SCD are related to costs (setup costs, opening costs, production costs, holding costs, ordering cost, transportation costs).

There has been considerable research on SCD models and cost optimization to improve supply chain performance. Bachlaus et al. (2008) optimize multi-echelons of supply chain, formulating a multi-objective optimization model. They apply a hybrid taguchi-particle swarm optimization (HTPSO) to minimise the supply chain costs and maximise plant and volume flexibility. Akanle and Zhang (2008) present an agent-based model, which optimises the overall supply chain configuration. Hua and Willems (2016) propose a mathematical model to configure a two-stage serial supply chain under guaranteed service. All of the above-mentioned research studies highlight the importance of supply chain configuration and decisions for optimal supply chain.

A number of studies have focussed on supply chain configuration based on the linking of the product design and the supply chain. Truong and Azadivar (2005) develop a configuration for the optimal structure of the supply chain, linking components and the supply chain. However, the term 'supply chain configuration' was first introduced by Graves and Willems (2005) for the design of the supply chain for a new product. They configure the supply chain through a coordinated decision-making process of inventory and selection of partners. They assume that the product is designed well before the supply chain configuration.

Nonetheless, properly integrated approaches for PF and SCD involve complex models, which are poorly investigated in the literature. In order to make the product development simpler and comprehensive, a pre-defined BOM approach is usually adopted for the product architecture. Two approaches are listed in the literature for BOM. The first approach defines a PF architecture, which satisfies the specific market needs. The design of the PF is done through various solutions for the set of product parts called generic BOM (GBOM). For example, Huang et al. (2005) and Lamothe et al. (2006) design a supply chain, which incorporates GBOM constraints. They develop a mathematical model that integrates PF and supply chain decisions to product variants to meet specific market needs. The second approach is assembly-to-order. In this approach, the final product is fixed with less flexibility in BOM. Along these lines, ElMaraghy and Mahmoudi (2009) propose an integrated supply chain management decision support tool. This tool simultaneously takes decisions related to the selection of modules for modular product design and corresponding globally distributed supply chain. They use an automobile wipe system as a case study and they use the final assembly time as a constraint.

Several researchers have extended the above work. Fixson (2005) provides a comprehensive overview of product architecture and its influences on manufacturing, product development and supply chain decisions. Fine et al. (2005) suggest that the PF architecture and SCD should be aligned along the integrality-modularity spectrum. They show that, in modular supply chain, the partners are dispersed geographically with close organisational ties but with limited electronic connectivity; whereas, in integral supply chain, the suppliers are in close proximity measured under the four dimensions of geography, culture, organization and electronic connectivity. Huang et al. (2007) adopt a game theoretic approach, which integrates platform products with the supply chain to achieve mass customisation. Lee et al. (2009) propose oncology architecture to integrate the product and supply chain information.

Khalaf et al. (2011) simultaneously design the supply chain with PF using bill of materials. These authors apply the Tabu search algorithm to assemble the finished products based on logistical costs. Cheng (2011) emphasizes the importance of modular design model for product customisation and for managing the supply chain. Nepal et al. (2012) match the PF design with the supply chain using multi-objective optimization framework. Shahzad and Hadj-Hamou (2013) propose an integrated model for supply chain and PF architecture. They build a product customisation model on the concept of GBOP. Yang et al. (2015) formulate a bi-level optimization model to configure the PF and supply chain. Zhang et al. (2016) develop a mixed integer linear programming model (MINLP). They coordinate the SCD with PF using BOMs. They then use an artificial bee colony approach to solve the MINLP model. Wang et al. (2016) apply Stackelberg game for the joint optimization of PF architecture planning and supply chain configuration with consideration of leader-follower relationship. Some of the other relevant studies in this area include Pham & Yenradee, (2017), Wu et al. (2017), Du et al. (2019), Mohammed & Duffuaa (2020) and Liu et al. (2020). Table 1 in the appendix summarises the most important research contributions on integrated product and SCD issues.

We argue that, given the complexity of coordinating the product and SCD decisions, comprehensive optimization of both the PF and SCD is one of the most efficient ways to reduce costs and achieve "distinctive competence". The need to integrate the PF and SCD can be framed in the context of the resource-based theory of the firm and the dynamic capabilities approach (Barney, 1991; Eisenhardt and Martin, 2000). In particular, both theoretical traditions emphasise the importance of adjusting the firm's processes and routines in response to uncertainty and volatility in, for example, their dynamic supply chains. Thus, the firm can improve its competitive edge by taping into valuable and real-time data (e.g. via cloud-based technologies, IoT, blockchain etc.).

2.3 Solution approaches

The integrated PF and SCD problems have been mostly solved using mathematical programming approaches and metaheuristics (Wu et al. 2017; Bottani et al. 2019). Recent work suggests that the use of metaheuristics is increasing when solving complex PF and SCD problems (Liu et al. 2020). Among the metaheuristic algorithms, the most popular technique utilized to solve SCD problems is genetic algorithm approach (Mohammed & Duffuaa, 2020). He et al. (2007) develop a MILP model to integrate forward and reverse SCD by minimising the total cost and maximizing customer satisfaction. The model is solved using genetic algorithm. Farahani & Elahipanah, (2008) develop a multi-period, multi-product and multi-channel network. A bi-objective model is then setup to optimize the costs, backorders and surplus of products in all periods. Other studies that have utilized metaheuristics for solving products and SCD problems include Prasanna Venkatesan & Kumanan (2012), Validi et al. (2014), Arabzad et al. (2015), Pasandideh et al. (2015), Sarrafha et al. (2015), Wang et al. (2016), Pham & Yenradee, (2017), Du et al. (2019), Liu et al. (2020), Mohammed & Duffuaa (2020).

Based on the above review, it is evident that genetic algorithm is used by the majority of researchers to solve PF and complex SCD problems. Table 1 in the appendix summarises the most important research contributions on integrated product and SCD issues. However, to the best of our knowledge, there is a gap in the literature when it comes to the design of an integrated optimal SCD and PF design based on real-time costs. Thus, we aim to fill this gap by designing a cloud-based framework to manage real-time costs viz. echelons. We propose a metaheuristic-based method for linear model formulation and optimisation, as will be explained later.

2.4 How to integrate the PF design to SCD

Product customization (commonality and modularity) strategy by the manufacturing company has become a widely researched topic (Huang et al. 2003). In order to achieve customisation, the concept of GBOM has commonly been adopted (Jiao et al. 1998; Huang et al. 2003; 2005). GBOM is a tree-like structure, consisting of AND/OR nodes. AND nodes represent commonality, while OR nodes represent modularity. For example, assume a product X, which comprises of compound modules with fixed number of slots and base modules. Each product variant is configured by selecting the compound modules with respective base modules.

Figure 1 shows an example of GBOM for product X. The PF comprises of 4 compound modules and 8 base modules. Compound module 1.1 and 1.2 are specified with an 'AND' node, which reflects product commonality that a PF must possess. So, compound module 1.1 comprises base module 1 AND 2 and similarly compound module 1.2 comprises of base module 3 AND 4. On the other hand, compound modules 1.3 and 1.4 are specified with an 'OR' node, which reflects product modularity. The product variant can either have base module 5 OR 6 for compound module 1.3 and base module 7 OR 8 for compound module 1.4. The combination of the compound modules and base modules with AND/OR constitutes a product variant. In Figure 1, product X comprises a total of 6 base modules, which formulates the product platform. They can be distinguished by their unique base modules such as base module 5 OR 6, 7 OR 8, which makes a product variant.

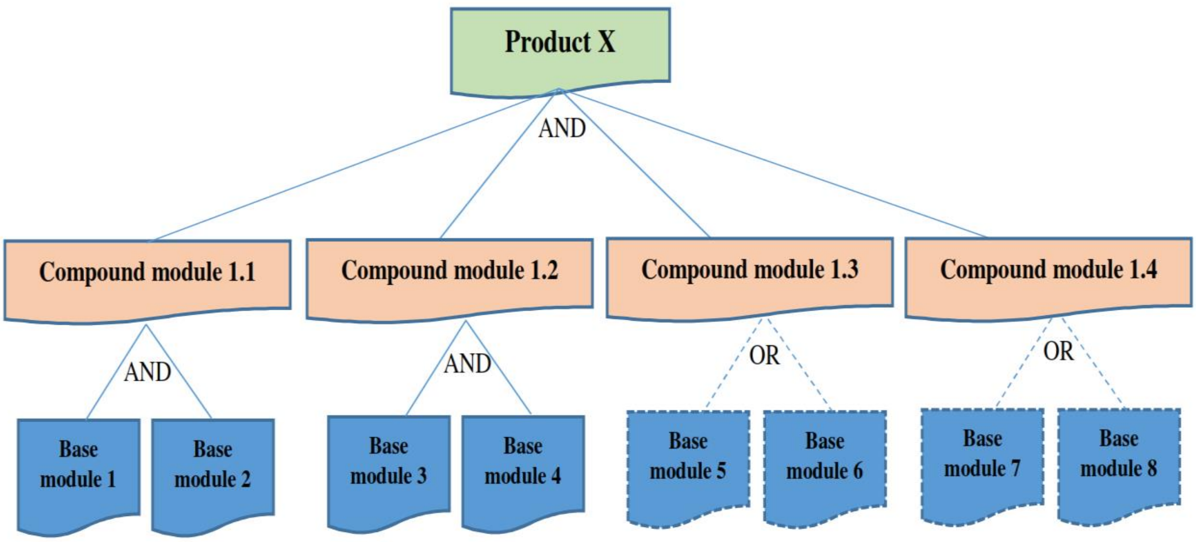

Figure 1: GBOM for Product

A specific strategy for PF design needs to be established in the early stage of the product development. Therefore, it is important to integrate decisions of the PF design and the SCD in the early stage of the product development.

Figure 2 illustrates the two-level model matching of a PF with a SCD. The upper layer represents the PF, constituting compound modules and base modules to make the products for target market segments. The lower layer represents the supply chain partners comprising of suppliers, manufacturing plants, assembling plants and distribution centres. The partners are geographically distributed. The connectivity of partners is strategically decided on the basis of possibilities, availabilities and policies. The SCD addresses the PF design in terms of the selection of suppliers for specific base modules, the selection of manufacturing plants for compound modules, the assembly plants for assembling products and the distribution centres for delivery of the product variants to specific market segments.

3. Description of the Cloud-based Framework

Cloud computing technology (CCT) has emerged as a new innovative technology. It has transformed the evolution of Internet to pay-as-you-go business model using web-based technologies (Xu, 2012). CCT is not a new technology but a combination of existing IT technologies such as utility computing, parallel computing, grid computing, virtualization, Internet technology and open source software (Wu et al. 2015). Key features of cloud computing are elasticity, scalability, on-demand computing and agility (Putnik et al. 2013). In CCT, the IT resources are virtualized, distributed, and demand-driven. These are particularly important given the globalized nature of the world economy.

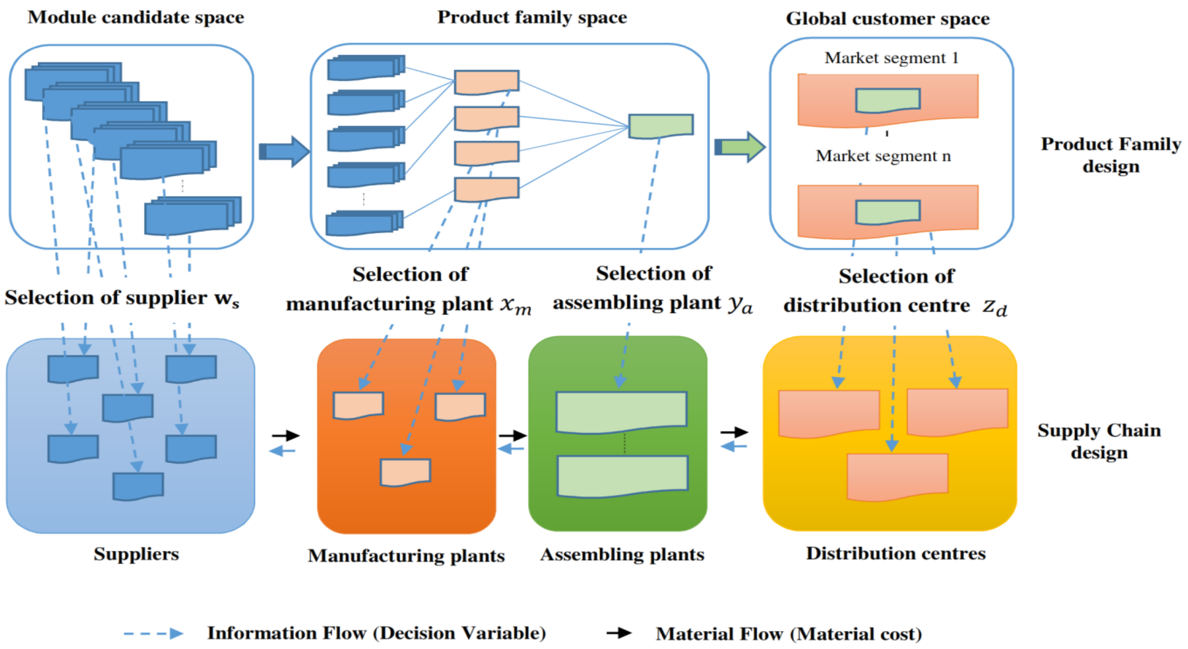

Figure 2: Product family design matching supply chain design

We hypothesise that manufacturing companies would be in need of new frameworks to fulfil their IT requirements in order to achieve reliant, scalable, globalised, distributed and agile business (Helo and Hao, 2017). The key features of CCT are that they can help facilitate better linkages of supply chain partners through the integration and alignment of internal and external business processes, real time information sharing and coordination of information flow to optimise the overall supply chain (Zafar et al. 2017).

In this paper, we consider a globally distributed multi-stage, SCD, where there are multiple partners on each stage and each partner can supply or provide items for two or more market segments. An example of such a supply chain is shown in Figure 3. The first stage is the supplier, where base modules are

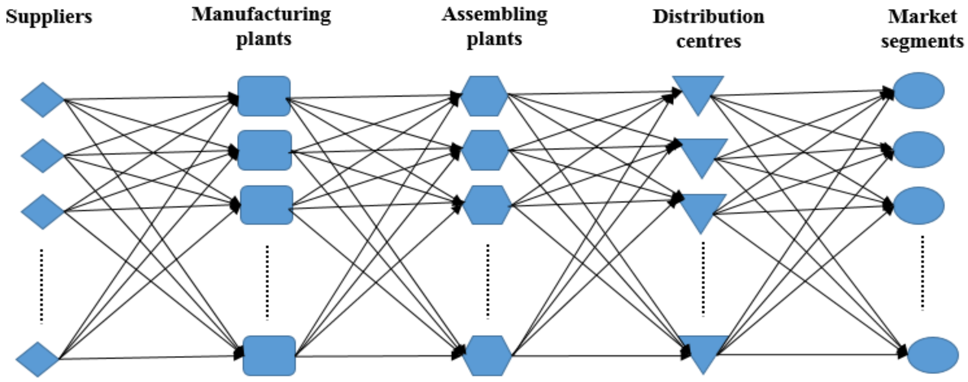

Figure 3: Supply Chain Design (SCD)

produced and transported to manufacturing plants. The second stage is the manufacturing plant, where compound modules are produced and transported to assembly plants. The third stage is the assembly-plant, where the compound modules are assembled into final product variants as per market segment requirements and then transported to appropriate distribution centres. The fourth stage is the distribution centre, where the final product variants are transported to market segments. The fifth stage is the market segment, where the final product variants are sold to the customer.

We propose a cloud-based management system as shown in Figure 4 that follows a three-step approach, which simultaneously considers the PF along with SCD. These steps include:

1) *Selection of product family design* - product designers access the cloud-based framework through interface. The selection of potential PF design involves modular PF design strategies such as GBOM. A knowledge base is used to represent module relationship and compatibility for the creation of product variants. Once the product GBOM is developed, the next step is to identify and collect the partner's information.

2) *Real-time data integration of partners through cloud interface* – the partners' information is identified and collected through interface. The partners in turn use the interface to access the cloud and update costs and operational status in the appropriate pool of cloud databases.

3) *Optimal supply chain design* - once the product GBOM details are acquired by the decision model in 1, the next step is to extract the real-time data from the pool of cloud databases. A mixed integer linear programming model is then applied, which optimizes the SCD based on real-time costs. We use a metaheuristic method based on Genetic Algorithm (GA) to solve the optimization problem

The proposed three-step approach forms an intelligent and expert management system providing an effective decision-making support in optimal SCD by managing real-time costs. Therefore, the proposed management system distinguishes itself from existing approaches in the literature such as Zhang et al. (2016), Baud-Lavigne et al. (2016), Pham & Yenradee, (2017), Du et al. (2019), and Liu et al. (2020).

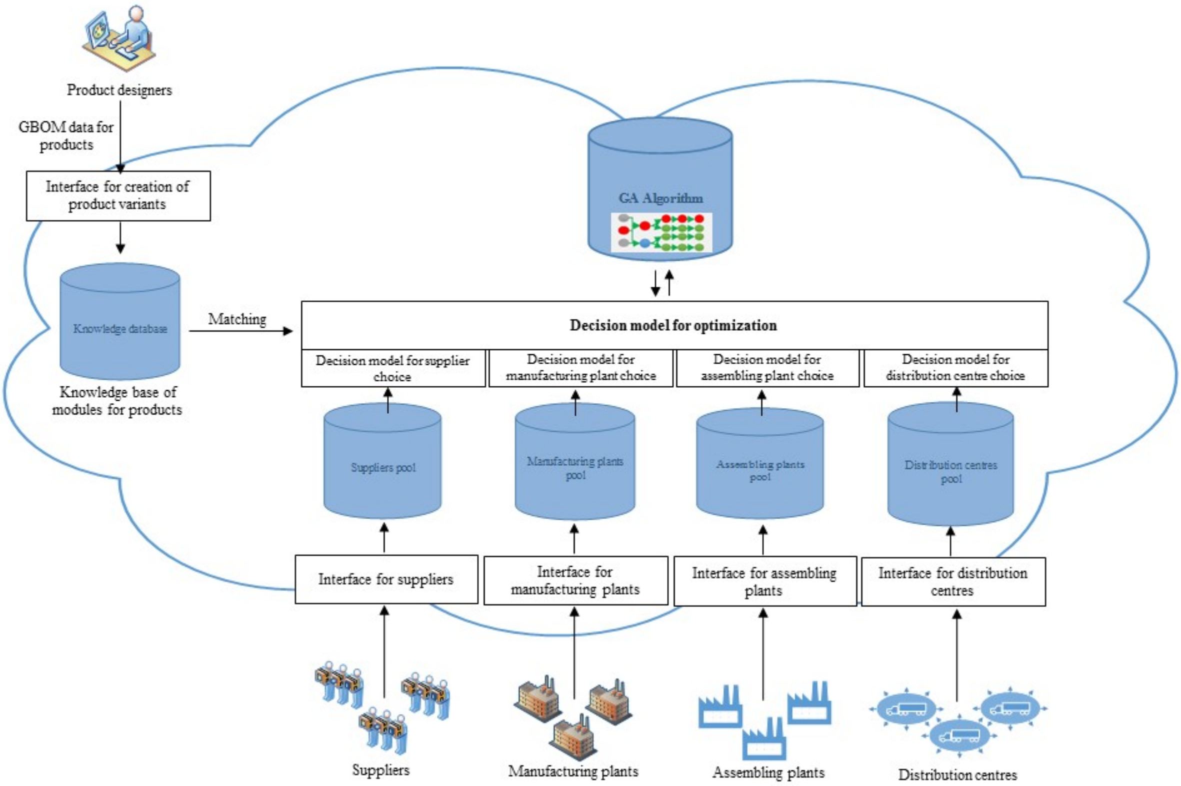

Figure 4: A comprehensive cloud-based management system

4. Problem description and formulation

In this section, a mathematical model is developed to determine the optimal SCD in order to match the PF. To deliver the final product variant to the market segment, the decision model selects the optimal choice from each stage (distribution centre, assembling plants, manufacturing plants and suppliers) to constitute a SCD. Thus, the decision model for the SCD involves decision making concerning: distribution centres for distributing the final product variants to the various market segments; assembling plants for assembling the final product variants; manufacturing plants for producing compound modules and suppliers for producing base modules. The SCD model is formulated by an integer multiplier coordination mechanism, where partners on each stage use the same cycle time and the cycle time of each stage is an integer multiplier of adjacent downstream stage (Khouja, 2003; Seliaman and Ahmad, 2009).

In the following, we explain the practical assumptions, notations and decision variables. Afterwards, we formulate the decision models for the optimization with parameters and constraints for all stages (distribution centre, assembling plants, manufacturing plants and suppliers).

4.1 Assumptions

We make the following assumptions:

1. Orders are processed immediately.
2. Queuing systems are used to process the orders (Mohtashami et al., 2020). Multi-server queuing system helps in the effective management of orders under uncertainty with capacity and control constraints (Adan and Resing, 2015; Vahdani et al., 2012).
3. Facilities have large capacities, cost of production, production rate, holding cost, setup/ordering cost for suppliers, manufacturing plants, assembly plants, distribution centres are known in advance and can be updated by the partners on real-time basis.
4. The cost of transportation from suppliers to manufacturing plants, from manufacturing plants to assembly plants and from assembly plants to distribution centres are known and can be updated by the partners in the pool of cloud databases on real-time basis. Customs and money exchange rates are not considered in our model (but these could be added if needed).
5. Potential global location sites for suppliers, manufacturing plants, assembly plants, distribution centres are known in advance and can be updated by the partners on real-time basis.
6. Any supplier that has capability can provide the base module. Equally, the compound module can be produced in all manufacturing plants. However, only one assembly plant can be selected to assemble any final product variant.
7. Only one distribution centre can be selected for the distribution of the final product variant to one specific market segment.

Note: If the first assumption is relaxed then the cloud-based management system, which provides real-time visibility, can initiate immediate capacity increase using existing equipment more effectively i.e. overtime or outsourcing. The resulting effective decision-making process can overcome the capacity problem in which the equipment is not used anywhere near its true capacity (Sabet et al., 2020).

4.2 Notations

The notations used in the formulation of the model for the optimization are shown in Table 2.

Table 2

Sets

$S(\ s \in S)$	Set of suppliers indexed by *s*
$R(\ r \in R)$	Set of raw material indexed by *r*
$J(\ j \in J)$	Set of base module type J indexed by *j*
$M(\ m \in M)$	Set of manufacturing plants indexed by *m*
$K(\ k \in K)$	Set of compound module type K indexed by *k*
$A(\ a \in A)$	Set of assembling plants indexed by *a*
$L(\ l \in L)$	Set of final product variant type L indexed by *l*
$D(\ d \in D)$	Set of distribution centres indexed by *d*
$G(\ g \in G)$	Set of global market segments indexed by *g*

4.3 Decision variables

The decision variables used in the formulation of the model are shown in Table 3.

Table 3

Decision Variables

η_j	$\begin{cases} 1 & \text{if base module type } j \text{ is provided by supplier} \\ 0 & \text{othewise} \end{cases}$
θ_k	$\begin{cases} 1 & \text{if compound module type } k \text{ is provided by manufacturing plant} \\ 0 & \text{othewise} \end{cases}$
λ_l	$\begin{cases} 1 & \text{if final product variant type } l \text{ is provided by assembling plant} \\ 0 & \text{othewise} \end{cases}$
ε_l	$\begin{cases} 1 & \text{if final product variant } l \text{ demand is fullfilled by corresponding market segment} \\ 0 & \text{othewise} \end{cases}$
$X_{s,m}$	$\begin{cases} 1 & \text{if there is link between supplier } s \text{ and manufacturing plant } m \\ 0 & \text{othewise} \end{cases}$
w_s	$\begin{cases} 1 & \text{if supplier } s \text{ is selected} \\ 0 & \text{othewise} \end{cases}$
α_{js}	$\begin{cases} 1 & \text{if base module type } j \text{ is provided by supplier } s \\ 0 & \text{othewise} \end{cases}$
$Y_{m,a}$	$\begin{cases} 1 & \text{if there is link between manufacturing plant } m \text{ and assembling plant } a \\ 0 & \text{othewise} \end{cases}$
x_m	$\begin{cases} 1 & \text{if manufacturing plant } m \text{ is selected} \\ 0 & \text{othewise} \end{cases}$

β_{km}	$\begin{cases}1 \\ 0\end{cases}$	if compound module type k is provided by manufacturing plant m / othewise
$Z_{a,d}$	$\begin{cases}1 \\ 0\end{cases}$	if there is link between assembling plant a and distribution centre d / othewise
y_a	$\begin{cases}1 \\ 0\end{cases}$	if assembling plant a is selected / othewise
γ_{la}	$\begin{cases}1 \\ 0\end{cases}$	if final product variant type l is provided by assembling plant a / othewise
z_d	$\begin{cases}1 \\ 0\end{cases}$	if distribution centre d is selected / othewise
δ_{ld}	$\begin{cases}1 \\ 0\end{cases}$	if final product variant type l is provided by distribution centre d / othewise
d_{js}	Integer variable denoting the total demand of base module type j at supplier s	
d_{km}	Integer variable denoting the total demand of compound module type k at manufacturing plant m	
d_{la}	Integer variable denoting the total demand of final product variant type l at assembling plant a	
d_{ld}	Integer variable denoting the total demand of final product variant type l at distribution centre d	

5. Decision Model for Optimization

The decision model for the optimization with parameters and constraints for all stages i.e. suppliers, manufacturing plants, assembling plants and distribution centres are as follows:

Table 4

Parameters

C_s	Fixed setup cost of supplier *s*
C_m	Fixed cost of opening a manufacturing plant *m*
C_a	Fixed cost of opening an assembling plant *a*
C_d	Fixed cost of opening a distribution centre *d*
PC_{js}	Unit product cost of base module type *j* at supplier *s*
PC_{km}	Unit manufacturing cost of compound module type *k* at manufacturing plant *m*
PC_{la}	Unit assembling cost of final product variant type *l* at assembling plant *a*
TC_{jsm}	Unit transportation cost of base module type *j* from supplier *s* to manufacturing plant *m*
TC_{kma}	Unit transportation cost of compound module type *k* from manufacturing plant *m* to assembling plant *a*
TC_{lad}	Unit transportation cost of final product variant type *l* from assembling plant *a* to distribution centre *d*
TC_{ldg}	Unit transportation cost of final product variant type *l* from distribution centre *d* to global market segment *g*
H_{js}	Annual Holding cost of base module type *j* at supplier *s*
H_{km}	Annual Holding cost of compound module type *k* at manufacturing plant *m*
H_{la}	Annual Holding cost of final product variant type *l* at assembling plant *a*
H_{rs}	Annual Holding cost of raw material *r* at supplier *s*

H_{jm}	Annual Holding cost of base module type *j* at manufacturing plant *m*
H_{ka}	Annual Holding cost of compound module type *k* at assembling plant *a*
H_{ld}	Annual Holding cost of final product variant type *l* at distribution centre *d*
O_s	Fixed ordering cost of supplier *s*
O_m	Fixed ordering cost at manufacturing plant *m*
O_a	Fixed ordering cost at assembling plant *a*
O_d	Fixed ordering cost at distribution centre *d*
P_s	Production rate of supplier *s*
P_m	Production rate of manufacturing plant *m*
P_a	Production rate of assembling plant *a*
T	Common cycle time
$TCAP_{sj}$	Total capacity of supplier *s* for base module type *j*
$TCAP_{mk}$	Total capacity of manufacturing plant *m* for compound module type *k*
$TCAP_{al}$	Total capacity of assembling plant *a* for final product variant type *l*
$TCAP_{dl}$	Total capacity of distribution centre *d* for final product variant type *l*
$SCAP_{jsm}$	Total shipping capacity of base module type *j* from supplier *s* to manufacturing plant *m*
$SCAP_{kma}$	Total shipping capacity of compound module type *k* from manufacturing plant *m* to assembling plant *a*
$SCAP_{lad}$	Total shipping capacity of final product variant type *l* from assembling plant *a* to distribution centre *d*
$SCAP_{ldg}$	Total shipping capacity of final product variant type *l* from distribution centre *d* to global market segment *g*
N_{sj}	Number of suppliers selected for base module type *j*
N_{mk}	Number of manufacturing plants selected for compound module type *k*
N_{al}	Number of assembling plants selected for final product variant type *l*
$\emptyset_s$	Integer multiplier of the cycle time for all suppliers
$\emptyset_m$	Integer multiplier of the cycle time for all manufacturing plants
$\emptyset_a$	Integer multiplier of the cycle time for all assembling plants

5.1 Decision Model for Supplier

The suppliers produce the base modules and provide these to manufacturing plants. The total costs of suppliers consist of fixed setup cost, the production cost of base module, transportation cost of base module to manufacturing plants, and inventory cost. Therefore, the decision model of the supplier can be formulated as:

$$IC_s = \sum_{j \in J} \sum_{r \in R} \sum_{s \in s} \sum_{m \in M} \sum_{a \in A} \left[\frac{\emptyset_s\, \emptyset_m\, \emptyset_a\, T\, {d_{js}}^2}{2P_s} H_{js} + \frac{\emptyset_m\, \emptyset_a\, T\, d_{js}}{2} \left(\emptyset_s \left(1 + \frac{d_{js}}{P_s}\right) - 1 \right) H_{rs} + \frac{O_s}{\emptyset_s\, \emptyset_m\, \emptyset_a\, T} \right]$$

(1.0)

The inventory cost at each stage, except for the final stage (distribution centre), comprises of two parts: a production portion and a non-production portion of the cycle as shown in Figure 5 by Khouja, (2003). The production portion comprises of holding cost of raw material as it is being converted into a final product (base module). The non-production portion is the holding cost of the final product. During the production portion, the annual holding cost of the final product is equal to $\frac{\emptyset_s \emptyset_m \emptyset_a T d_{js}^2}{2P_s}$. During the non-production portion, inventory drops every T years by $T d_{js}$ starting from $(\emptyset_s - 1) d_{js}$ (Khouja, 2003). The third term of Eq. (1.0). i.e. $\frac{1}{\emptyset_s \emptyset_m \emptyset_a T}$ indicates the cycles per year. The total annual inventory cost at supplier stage is shown in Eq. (1.0).

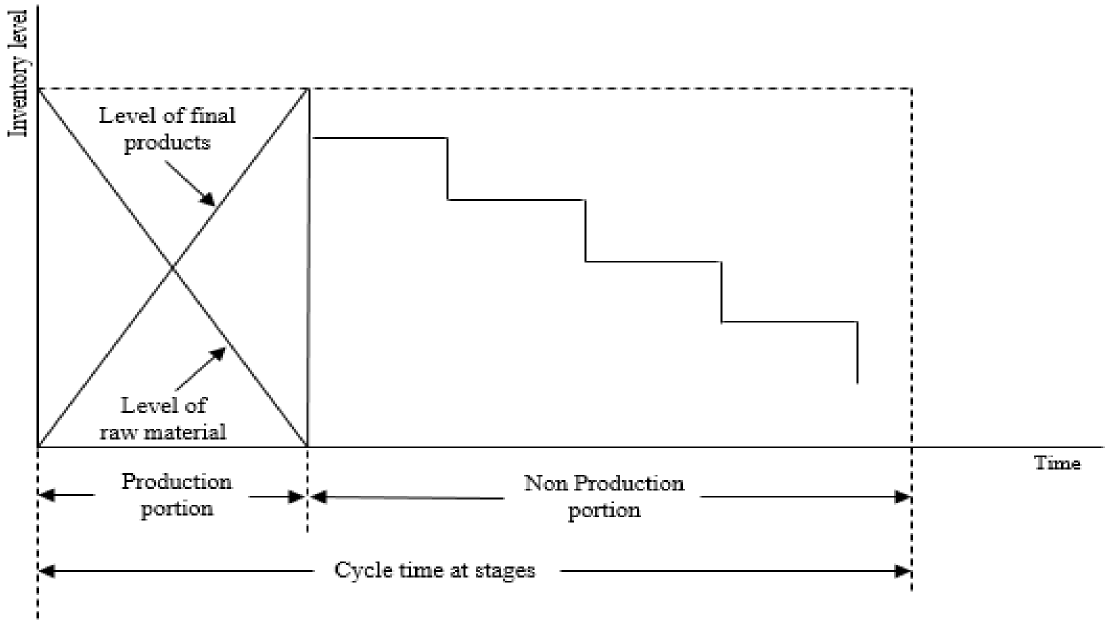

Figure 5: Raw material and finished goods levels at a firm with cycle time 3T (Adopted from **Khouja, 2003**)

$$TC_s = \sum_{s \in S} C_s w_s + \sum_{j \in J} \sum_{s \in S} PC_{js} \alpha_{js} d_{js} + \sum_{j \in J} \sum_{s \in S} \sum_{j \in J} TC_{jsm} \alpha_{js} d_{js} + IC_s \qquad (1.1)$$

The total cost of the supplier is shown in Eq. (1.1), where the first term is the fixed setup cost, second term is the production cost of base modules, the third term is the transportation cost of the base modules to manufacturing plants and the last term is the annual inventory cost of supplier.

$$s.t. \sum_{s \in S} \alpha_{js} = \eta_j \ \forall \ j \in J \qquad (1.2)$$

$$\alpha_{js} \leq w_s \ \forall \ j \in J, \forall \ s \in S \qquad (1.3)$$

$$\sum_{j \in J} d_{js} \leq SCAP_{jsm} \; \forall \, s \in S, \forall \, m \in M \tag{1.4}$$

$$\sum_{j \in J} d_{js} \leq TCAP_{sj} \; \forall \, s \in S \tag{1.5}$$

$$X_{s,m} \leq x_m \quad \forall \, s \in S, \forall \, m \in M \tag{1.6}$$

Constraint Eq. (1.2) indicates that only one type of base module can be supplied by each selected supplier. Eq. (1.3) is the logic linking constraint between the base module and the supplier. Eq. (1.4) is the shipping capacity restriction of base module from suppliers to manufacturing plants. Eq. (1.5) is the capacity restriction of the supplier for making the base module and Eq. (1.6) is the logical linking constraint between the supplier and manufacturing plants.

5.2 Decision Model for Manufacturing Plants

A manufacturing plant produces compound modules with the base modules provided as raw material by suppliers. Therefore, the decision model for manufacturing plants can be formulated as:

$$IC_m = \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \sum_{a \in A} \left[\frac{\emptyset_m \, \emptyset_a \, T \, {d_{km}}^2}{2 \, P_m} H_{km} + \frac{\emptyset_a \, T \, d_{km}}{2} \left(\emptyset_m \left(1 + \frac{d_{km}}{P_m} \right) - 1 \right) H_{jm} + \frac{O_m}{\emptyset_m \, \emptyset_a \, T} \right] \tag{2.0}$$

Eq. (2.0) indicates the total inventory cost at the manufacturing plant, which includes the inventory of the final product (compound module) and that of raw material (base module) on the basis of integer multiplier coordination mechanism.

$$TC_m = \sum_{m \in M} C_m \, x_m + \sum_{k \in K} \sum_{m \in M} PC_{km} \, \beta_{km} d_{km} + \sum_{k \in K} \sum_{m \in M} \sum_{a \in A} TC_{kma} \, \beta_{km} d_{km} + IC_m \tag{2.1}$$

The total cost of manufacturing plant is shown in Eq. (2.1). The first term is the fixed setup cost of opening the manufacturing plants, the second term is the production cost of compound modules, the third term is the transportation cost of compound modules to assembling plants and the last term is the annual inventory cost of manufacturing plants.

$$s.t. \sum_{m \in M} \beta_{km} = \theta_k \; \forall \, k \in K \tag{2.2}$$

$$\beta_{km} \leq x_m \; \forall \, k \in K \tag{2.3}$$

$$\sum_{k\in K} d_{km} \leq SCAP_{kma} \; \forall\, m\in M, \forall\, a\in A \tag{2.4}$$

$$\sum_{k\in K} d_{km} \leq TCAP_{mk} \; \forall\, m\in M \tag{2.5}$$

$$Y_{m,a} \leq y_a \quad \forall\, m\in M, \forall\, a\in A \tag{2.6}$$

Constraint Eq. (2.2) expresses that only one type of compound module can be supplied by a selected manufacturing plant. Eq. (2.3) is the logic linking constraint between the compound module and manufacturing plant. Eq. (2.4) is the shipping capacity restriction of the compound module from manufacturing plant to assembling plants. Eq. (2.5) is the capacity restriction of manufacturing plant for making the compound module and Eq. (2.6) is the logical linking between the manufacturing plants and assembling plants.

5.3 Decision Model for Assembling Plants

The assembling plant is the place where the compound modules are assembled to make various product variants to meet market segment requirements. The total cost at assembling plant comprises of fixed cost of opening an assembling plant, assembling cost of final product variant, transportation cost of final product variant to distribution centres and inventory cost. Therefore, the decision model for assembling plants can be formulated as:

$$IC_a = \sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{a\in A}\left[\frac{\emptyset_a T\, {d_{la}}^2}{2\, P_a} H_{la} + \frac{T\, d_{la}}{2}\left(\emptyset_a\left(1+\frac{d_{la}}{P_a}\right) - 1 \right) H_{ka} + \frac{O_a}{\emptyset_a T}\right] \tag{3.0}$$

Eq. (3.0) indicates that the total inventory cost at assembling plants on the basis of integer multiplier coordination mechanism. It includes the inventory of final product (product variant) and that of raw material (compound module).

$$TC_a = \sum_{a\in A} C_a\, y_a + \sum_{l\in L}\sum_{a\in A} PC_{la}\, \gamma_{la} d_{la} + \sum_{l\in L}\sum_{a\in A}\sum_{d\in D} TC_{lad}\, \gamma_{la} d_{la} + IC_a \tag{3.1}$$

The total cost of assembling plant, as shown in Eq. (3.1), contains the fixed cost of opening the assembling plants, the assembling cost, the transportation cost and the inventory cost, respectively.

$$s.t. \sum_{a\in a} \lambda_a = 1 \quad \forall\, a\in \mathrm{A} \tag{3.2}$$

$$\gamma_{la} \leq y_a \; \forall\, l\in L \tag{3.3}$$

$$\sum_{l \in L} d_{la} \leq SCAP_{lad} \, \forall \, a \in A, \forall \, d \in D \tag{3.4}$$

$$\sum_{l \in L} d_{la} \leq TCAP_{al} \, \forall \, a \in A \tag{3.5}$$

$$Z_{a,d} \leq z_d \quad \forall \, a \in A, \forall \, d \in D \tag{3.6}$$

Constraint Eq. (3.2) enforces that only one assembling plant is selected for assembling the final product variant. Eq. (3.3) is the logic linking constraint between the final product variant and assembling plant. Eq. (3.4) is the shipping capacity restriction of the final product variant from assembling plant to distribution centres. Eq. (3.5) is the capacity restriction of assembling plant for making the final product variant and Eq. (2.6) is the logical linking between the assembling plant and distribution centres.

5.4 *Decision Model for distribution centre*

Final product variants are distributed from distribution centres to market segments. The total costs of distribution centres include the fixed cost of opening a distribution centre, the transportation cost of final product variant from distribution centre to market segment and inventory cost. It is assumed that all distribution centres can deliver any final product variant to the market segment. Therefore, the decision model for distribution centre can be formulated as:

$$IC_d = \sum_{l \in D} \sum_{d \in D} \left[\frac{T \, d_{lD}}{2} H_{ld} + \frac{O_d}{T} \right] \tag{4.0}$$

Eq. (4.0) indicates the total inventory cost at distribution centres that includes only the inventory of final product (product variant).

$$TC_d = \sum_{d \in D} C_d \, z_d + \sum_{l \in L} \sum_{d \in D} \sum_{g \in G} TC_{ldg} \, \delta_{ld} d_{ld} + IC_d \tag{4.1}$$

The total cost of distribution centre contains the fixed cost of opening the distribution centre, the transportation cost and the inventory cost.

$$\delta_{ld} \leq z_d \quad \forall \, d \in D \tag{4.2}$$

$$\sum_{g \in G} d_{ld} \leq SCAP_{ldg} \, \forall \, d \in D, \forall \, g \in G \tag{4.3}$$

$$\sum_{l \in L} d_{ld} \leq TCAP_{dl} \; \forall \; d \in D \tag{4.4}$$

Constraint Eq. (4.2) indicates the logic linking constraint between the final product variant and distribution centre. Eq. (4.3) is the shipping capacity restriction of final product variant from distribution centres to market segments and Eq. (4.4) is the capacity restriction of distribution centres for making the final product variant.

5.5 Optimization Model of Supply Chain Design

The model is defined in Eq. (1.0) to Eq. (4.4). The objective function is then formulated as the following mixed integer model:

$$\text{Minimum Total Supply chain cost} = \min \{ TC_s + TC_m + TC_a + TC_d \} \tag{5.0}$$

Subject to,

Constraints (1.2) – (1.6)

Constraints (2.2) – (2.6)

Constraints (3.2) – (3.6)

Constraints (4.2) – (4.4)

6. Genetic algorithm for the optimization

The problem mentioned in this paper is a combinatorial optimization problem with a finite number of feasible solutions. For these types of problems, metaheuristic methods perform well as a portion of the solution space is searched heuristically with near optimal solution. Population-based evolutionary algorithms are now widely used for solving engineering, business and supply chain optimization problems (Kumar and Chatterjee, 2013; Ahmadizar et al. 2015; He at al., 2015; Musavi & Bozorgi-Amiri, 2017; Pariazar & Sir, 2018; Azizi & Hu, 2020). To validate the results and evaluate the performance of the model, meta-heuristics GA is utilized to solve the test problem.

6.1 Genetic Algorithm and Solution representation

The Genetic Algorithm (GA) was first introduced by Holland (1975). GAs initially start with random population of solutions – referred to as chromosomes. The genes can be further categorized by locus – the position of the gene within the chromosome structure and allele – the value it takes (Afrouzy et al. 2016). To illustrate the GA strategy, encoding is the first essential step to select the right encoding scheme, otherwise the GA will run endless without finding a solution. GA uses different types of genotype representations like a string of binary, integer or real numbers. For our purpose, we employ the genotype as a string of integer numbers to address the supply chain problem. Every integer represents a decision made which selects an individual node (e.g. supplier, manufacturing plant, assembling plant and distribution centre) from a number of available nodes (partners) on a particular stage. We apply modulus (%) operator on the integer value by the number of nodes in that stage which results in mapping that integer to an individual node on a specific stage (i.e., mapping that gene to the individual node based on its position in the genotype). With this simple scheme, we maintain the properties of the encoding mentioned earlier, while the mapping takes place from genotype to phenotype, see Figure 6.

The fitness function is the same as our objection function (Eq. 5.0), which determines the performance of the solutions. Hence, a selection procedure is applied on the population, such that the best-fitted individuals will be selected as parents to produce offspring for the next generation. Different GAs use different selection strategies. Within the context of a supply chain problem, GA requires a set of limited search space to address such problem. With this consideration in mind, our study uses two selection strategies – namely, Roulette-wheel and Tournament base selections. Both methods perform effectively with no significant performance differences observed. The highest fitness value chromosomes are then selected using roulette wheel method, which takes the fitness value of chromosomes as probability value for selecting the next generation fairly (Chang, 2010).

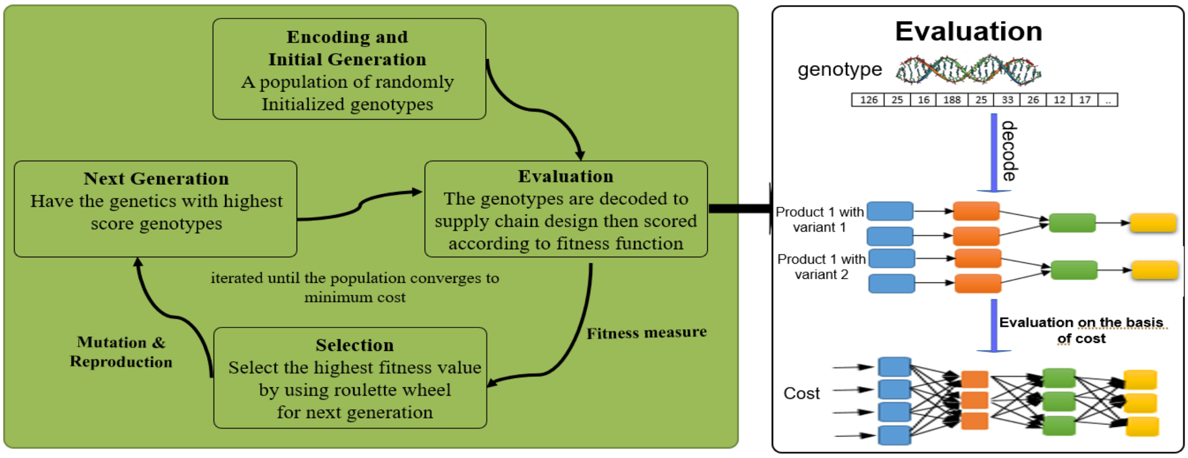

Figure 6: GA Evolutionary process

After that, parent selection crossover and mutation operators are applied. The crossover is done to explore new solution space by exchanging the genes of the chromosome between the selected parents. Uniform crossover with a single locus is employed in this study by randomly choosing two parent chromosomes and exchanging a fragment of their genes with low probability (i.e., 0.3). The main goal of the crossover is to increase the search space and speed to acquire an optimal solution.

Mutation is done to prevent premature convergence and to increase the genetic variability of the chromosome population. During the GA cycle, all integer-valued vector components are constrained to remain within the range [0, 255]. Mutation entails that a uniform random distribution offset is applied to each integer-valued vector component encoded in the genotype, with a low probability (i.e., 0.1). This allows a maximum of 256 nodes in every supply chain stage. This number is chosen to minimize the computation overhead by reducing the search space.

In summary, the population contains 300 genotypes. Initially, a random population of vectors is generated by initialising each fragment of the genotype to the values chosen from uniform random distribution within the range [0, 255]. Generations following the first one are produced by a combination of selection with elitism, crossover, and mutation. For each new generation, the 20 highest scoring individuals (the elite) from the previous generation are retained unchanged. The remainder of the new population is generated by fitness proportional selection (Roulette-wheel or Tournament) from the 200 best individuals of the old population. Each genotype is a vector comprising of integer numbers as a coding for the decision (selection of nodes in supply chain at every stage). Each new genotype has a low probability of being created by combining the genetic material of two parents. During crossover, one crossover point is selected. Genes from the beginning of the genotype to the crossover point are copied from one parent to the second parent. Mutation is applied by uniform random distribution. The offset is applied from the range [1, N-1] where N corresponds to the maximum number of nodes in that stage. This refers to the position of the gene in the genotype, while maintaining the constraints of the gene values to remain within the range [0, 255]. This strategy ensures that the mutation will always result in the selection of different nodes when applied to the gene. The process is iterated until the population converges or a specific number of generations are reached.

7. Computational results

In this section, a power transformer numerical example is presented and analysed to evaluate the model. Then, the performance and efficiency of the model is tested using two experiments. The problem is benchmarked with changes in a supply chain partner costs. The experiments conducted are:

> Experiment 1 (E1): The cost optimization is based on uniformly distributed costs. The parameters and costs of the supply chain partners are summarised in Tables 5 and 6.
>
> Experiment 2 (E2): The cost optimization is based on real-time costs, which are extracted from the pool of cloud databases. The parameters and costs are summarised in Tables 7 to 13.

The computations are run on CyberServe Xeon SP2-R2312 Intel R2312WF0NP ® 2U, Dual Intel Xeon Scalable processor to get good results in a reasonable time. The reason for doing two experiments are: first, to test the universality of the SCD; second, to quantify the influence of real-time partner costs on the SCD when the PF design is integrated, and third, to analyse the implications of fixed/deterministic and real-time partner costs for the performance of the supply chain (Tables 6 – 13). In Table 6, the objective function parameter values are summarised. The values are generated from a uniform distribution. The fixed production costs for the supplier, manufacturing plant and assembling plants are shown in Table 7. The additional real-time costs (product, ordering, setup/opening), associated capacities and transportation costs are extracted from pool of cloud databases, as depicted in Tables 8 – 13. The approach of the calculations is that, first the model is solved with uniform costing. Then we subsequently consider real-time costs.

Table 5

GA Parameters used to solve medium-scale problem

Parameters	Values
Population size	{100, 400, 800}
Crossover probability	0.3
Mutation probability	0.1
Max number of iterations	100

Table 6

Parameters and values

Parameters	Values
C_m, C_a, C_d	U(4000,7000)
P_s, P_m, P_a	U(8000,11000)
$TC_{jsm}, TC_{kma}, TC_{lad}, TC_{ldg}$	U(3,8)
H_{js}	U(0.08,0.13)
H_{rs}	U(0.02,0.07)
H_{km}	U(0.18,0.22)
H_{jm}	U(0.13,0.18)
H_{la}	U(0.28,0.34)
H_{ka}	U(0.22,0.28)
H_{ld}	U(0.34,0.40)
O_s, O_m, O_a, O_d	U(110,150)
T	0.0073529
$\emptyset_s$	8
$\emptyset_m$	4
$\emptyset_a$	2

Table 7

Supply chain stages and production cost

Item no.	**Stage**	**Module Type**	**ID**	**Option**	**Production Cost**
S1	Supplier	EGL-02	B_{11}	1	250.00
				2	234.00
				3	260.00
				4	265.00
S2	Supplier	UBB	B_{51}	1	263.00

				2	275.00
				3	290.00
				4	295.00
…	…	…	…	…	…
M17	Manufacturing plant	Tank Body	C2	1	245.00
				2	287.00
				3	210.00
				4	260.00
…	…	…	…	…	…
A27	Assembling plant	Power Transformer	B0	1	425.00
				2	432.00
…	…	…	…	…	…

Table 8

Product Variant	Module Type
V1	$\{B_{11}, B_{51}\}$
V2	$\{B_{12}, B_{53}, B_{62}\}$
V3	$\{B_{13}, B_{53}, B_{61}, B_{72}\}$
V4	$\{B_{14}, B_{54}, B_{63}, B_{74}\}$
…	…

Table 9

Potential suppliers producing base modules

Item no.	Stage	Module Type	ID	Option	Capacity	Production Cost	Ordering Cost	Fixed Setup Cost
S1	Supplier	EGL-02	B_{11}	1	15,000	240.00	115.00	181.00
				2	22,000	260.00	147.00	193.00
				3	25,000	285.00	125.00	211.00
				4	12,000	245.00	131.00	227.00
S2	Supplier	DW-N6	B_{14}	1	15,000	335.00	115.00	181.00
				2	22,000	380.00	147.00	193.00
				3	25,000	355.00	125.00	211.00
				4	12,000	340.00	131.00	227.00
…	…	…	…	…	…	…	…	…

Table 10

Potential manufacturing plants producing compound modules

Item no.	Stage	Module Type	ID	Option	Capacity	Production Cost	Ordering Cost	Fixed Opening Cost
M1	Manufacturing plant	Bushing	C1	1	22,000	331.00	149.00	4011.00
				2	27,000	362.00	111.00	6025.00
				3	32,000	342.00	125.00	5225.00
				4	19,000	350.00	145.00	6750.00
M2	Manufacturing plant	Tap Changer	C5	1	22,000	281.00	149.00	4011.00
				2	27,000	265.00	111.00	6025.00
				3	32,000	272.00	125.00	5225.00

				4	19,000	292.00	145.00	6750.00
…	…	…	…	…	…	…	…	

Table 11

Potential assembling plants with assembling product variants

Item no.	Stage	Module Type	ID	Option	Capacity	Production Cost	Ordering Cost	Fixed Opening Cost
A1	Assembling plant	Power Transformer	B0	1	25,000	422.00	115.00	4500.00
				2	38,000	435.00	147.02	6000.00
…	…	…	…	…	…	…	…	

Table 12

Potential distribution centres for delivering final product variant

Item no.	Stage	Module Type	ID	Option	Capacity	Ordering Cost	Fixed Opening Cost
D1	Distribution centre	Power Transformer	B0	1	100,000	125.00	4500.00
				2	85,000	112.00	6500.00
…	…	…	…	…	…	…	

Table 13

Transportation costs

TC_{jsm}	Manufacturing plants			
Supplier	M1	M2	M3	M4
S1	3.01	3.10	3.15	3.30
S2	7.46	7.38	4.02	4.25
S3	6.69	4.87	7.60	3.71
S4	5.72	6.73	5.40	1.72

TC_{kma}	Assembling plants	
Manufacturing plants	A1	A2
M1	3.01	5.0
M2	7.38	5.74
M3	4.87	7.14
M4	6.73	3.06

TC_{lad}	Distribution Centres		
Assembling plants	1	2	3
A1	3.01	5.00	6.50
A2	5.74	7.60	5.40

TC_{ldg}	Market segments		
Distribution Centres	MS1	MS2	MS3
D1	4.00	5.50	8.00
D2	5.67	7.25	8.00
D3	8.00	5.25	11.00

7.1 Numerical example

To consider the performance of the proposed model, we present a power transformer numerical example which we adopt from Yang et el. (2015). The production of the power transformers is achieved through modular and globally distributed multi-stage supply chain. The GBOM for the power transformers is shown in Figure 7, which comprises of a set of base modules (like B_{11}: EGL-02, B_{14}: DW-N6, B_{61}: Porcelain) provided by suppliers, compound modules (like C1: Bushing, C5: Tap Changer, C6: Insulation) provided by manufacturing plants and final product variants to be provided by assembling plants. To fulfil the market segment requirements, various transformer variants and alternatives are selected from the base modules and compound modules to form a product.

The objective is to minimize the total supply chain cost by selecting the product variants. It is assumed that there are 4 suppliers, 4 manufacturing plants, 2 assembling plants and 3 distribution centres with specific setup costs, opening costs, production costs, holding costs, ordering cost and transportation costs.

Commercially available software and tools find it hard to solve optimally the medium and large multi-stage supply chain design problems with facilities such as manufacturing plants, assembling plant and distribution centres that are opened as constraints. Such problems are referred to as multiple-choice Knapsack problem, which are known as NP-hard (Gen & Cheng, 1997). With these constraints, the real-world applicability becomes significantly difficult. Hence, numerical examples are used as a case study to test the model (see for example, Zhang et al. 2016; Tang & Gong, 2019; Mohammed & Duffuaa, 2020; Azizi & Hu, 2020; Mohtashami et al. 2020; Samuel et al. 2020; Rahmani et al. 2020).

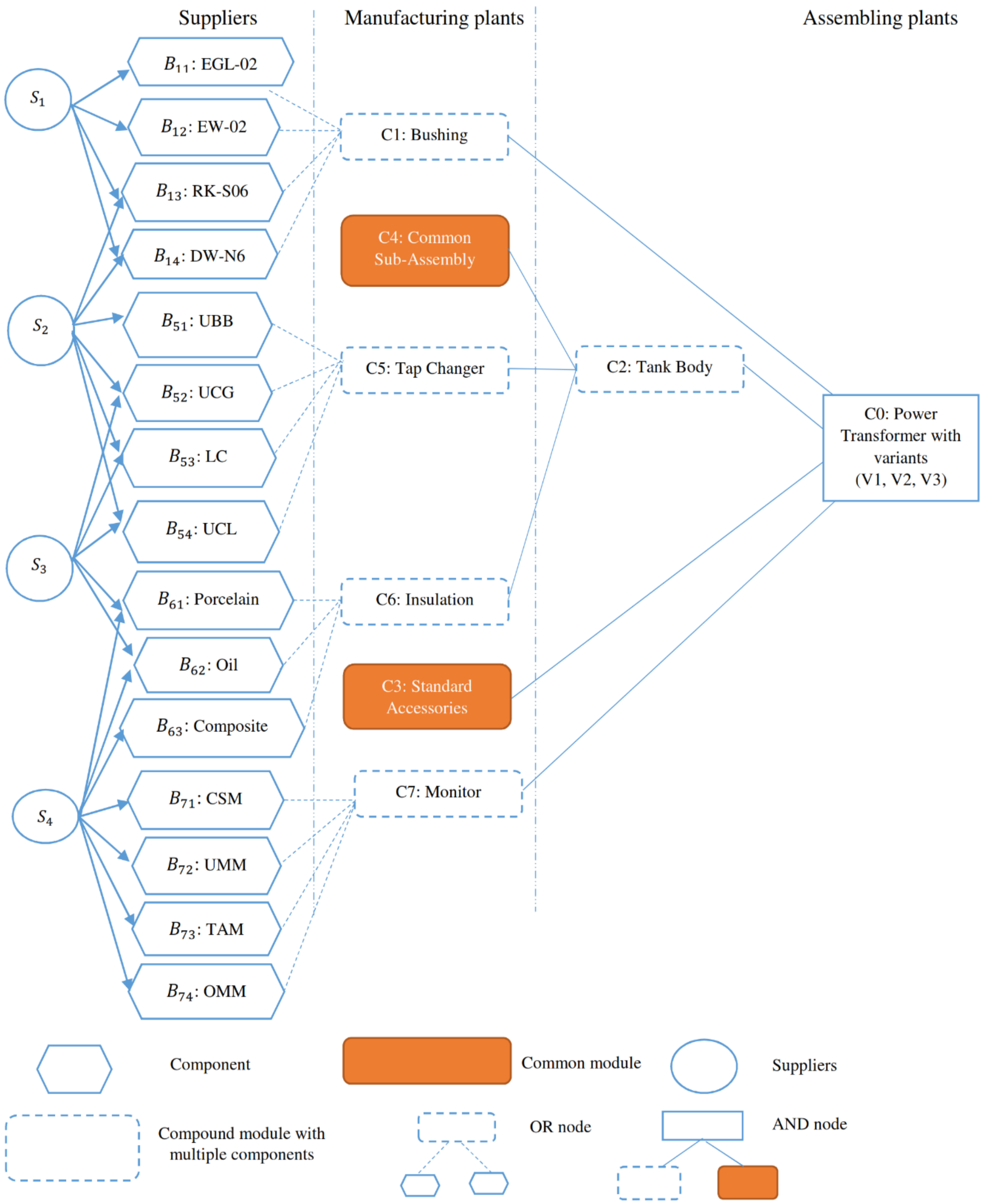

Figure 7: Power Transformer GBOM for multi-stage supply chain

7.2 Experiments with medium-scale problem

A medium-scale problem is used to study the effectiveness of our proposed model. Based on the literature, different population sizes and iterations are considered to evaluate the performance of the proposed solution, as shown in Table 5. In order to demonstrate the efficacy of the model while designing a supply chain network, we analyse different configurations and values (Tables 6 - 13). Figure 8 shows that after 90 iterations, the optimized result is achieved for the optimal SCD.

Analysis of the configuration shows that, regardless of the GA parameter combination, the changes do not significantly affect the total supply chain cost. Thus, this shows that our SCD is not sensitive to variations in input values.

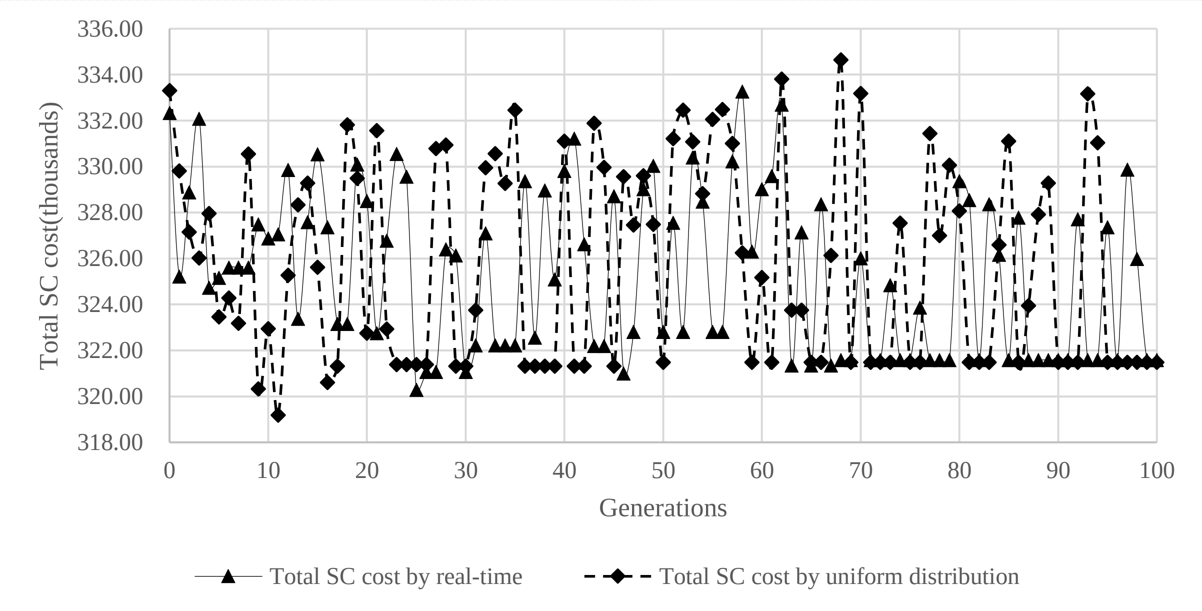

Figure 8: Evolutionary process of GA

7.3 Sensitivity analysis

In order to study the effects of parameter changes based on real-world conditions, the behaviour of the objective function is assessed. Various GA parameters such as population sizes, crossover probability and mutation probability are tested, as listed in Table 14. These parameters play an important role in the SCD with optimal cost. By performing sensitivity analysis on two approaches (costs with uniform distribution and real-time) with various parameter adjustments, our results suggest that the objective function shows only 0.05% cost difference. A larger population size leads to no further improvement.

Thus, the size of the population is set to 100. Furthermore, the crossover and mutation probability are set to 30 and 10%, respectively for best combination. We also iterate the GA process up to 800 iterations and notice that after 100 iterations the results remain unchanged. Therefore, 100 iterations are used as a stopping criterion.

The results in Table 14 also show that there is a weak relationship between the number of generations produced and the total supply chain cost. The total supply chain cost remains unchanged with varying generation sizes, combinations of crossover and mutation. It should be emphasised that the mutation enables a small number of random searches, and thus, ensures that the GA search does not quickly converge at a local optimum. But this should not occur very often in any case; otherwise the GA becomes a pure random search method. Thus, it is recommended that the mutation rate be set to be a small number to get better results.

Table 14

Sensitivity analysis of GA parameters

Size of SC (Supplier x Manufacturing plants x Assembling plants x Distribution centres)	Generations Produced	Crossover Probability (%)	Mutation Probability (%)	Total Supply Chain Cost with uniform distribution	Total Supply Chain Cost with real-time
4 X 4 X 2 X 3	400	40	20	319,780.00	319,625.00
4 X 4 X 2 X 3	800	40	20	319,780.00	319,625.00
4 X 4 X 2 X 3	400	30	15	319,780.00	319,625.00
4 X 4 X 2 X 3	800	30	15	319,780.00	319,625.00
4 X 4 X 2 X 3	400	20	10	319,780.00	319,625.00
4 X 4 X 2 X 3	800	20	10	319,780.00	319,625.00
4 X 4 X 2 X 3	400	10	5	319,780.00	319,625.00
4 X 4 X 2 X 3	800	10	5	319,780.00	319,625.00

In order to explore further, we analyse the relationship between varying mutation probability and the total supply chain cost, as shown in Figure 9. The results indicate that, for uniform distribution, the total supply chain cost was lowest with mutation probability of 10 or 20%. However, as the mutation probability increases, the total supply chain cost also increases. The pattern is identical with real-time cost. This indicates that a low mutation probability (i.e. 10%) gives better results (i.e. lower supply chain cost for both uniform distribution and real-time costs).

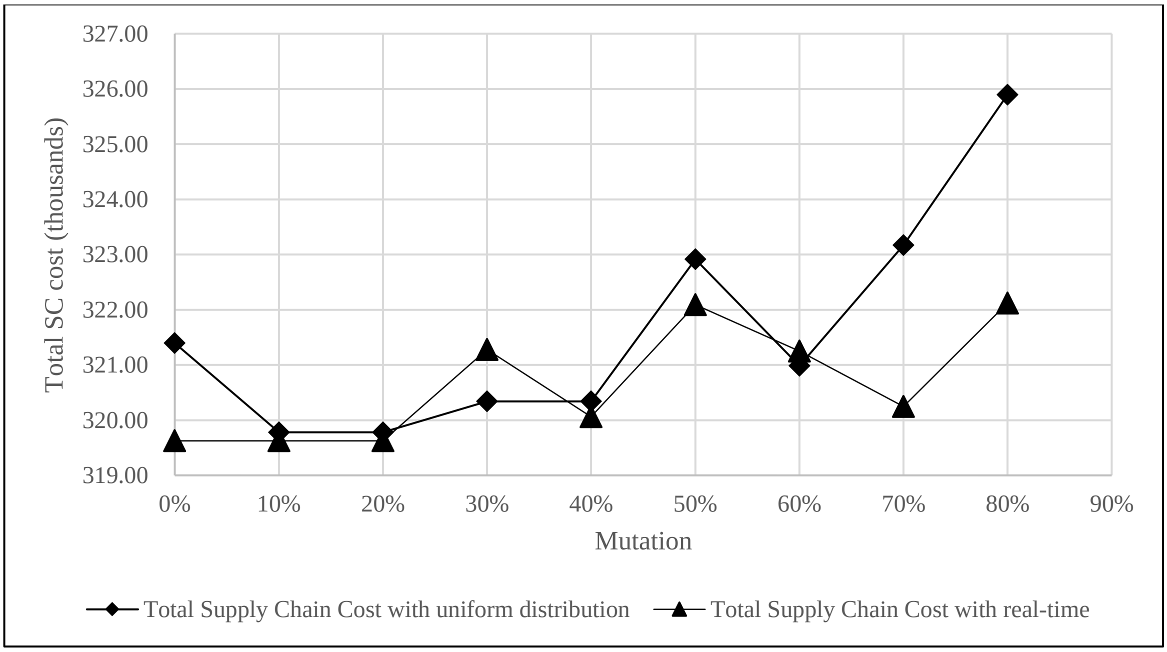

Figure 9: Total supply chain cost with varying mutation probability

The holding cost rate is an important strategy parameter in the design of a supply chain. To investigate the effects of the holding cost rate, we define the rates from 0 to 100. It can be observed in Figure 11 that the total supply chain cost increases slightly linearly as the holding cost increases. The results show that varying the holding costs makes a small variation in the total supply chain cost. Our results are consistent with the findings of Graves and Willems (2005) and Huang et al. (2005). Both of these studies found that the holding cost rate does not have a significant effect on the model selected.

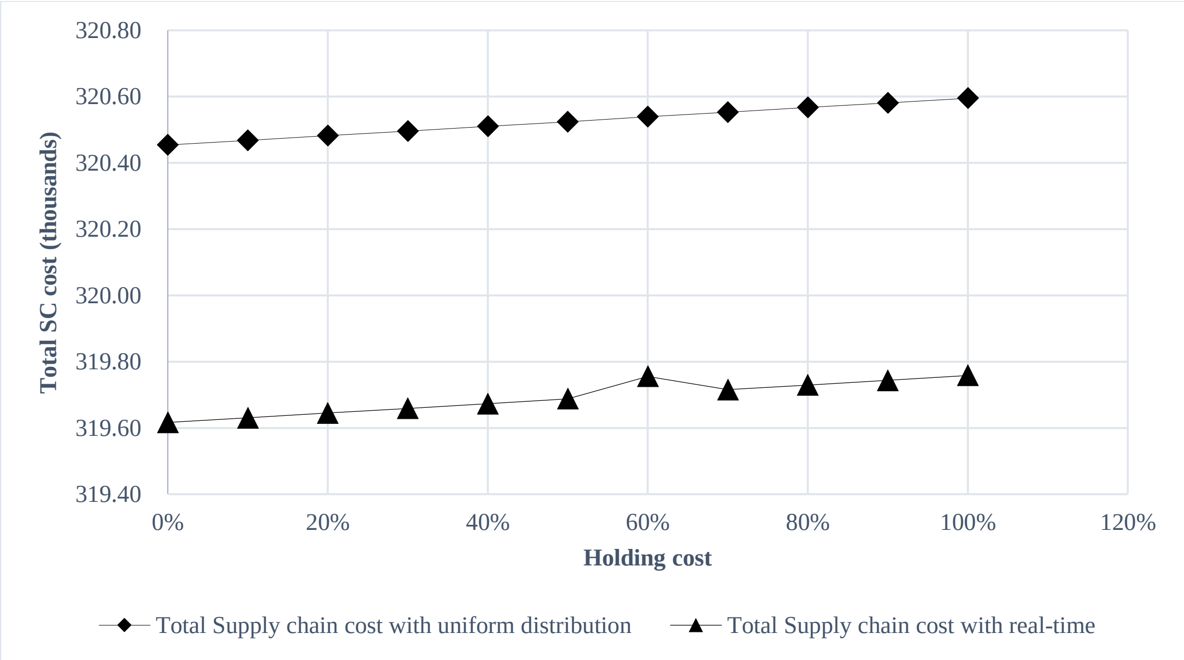

Figure 11: Total supply chain cost with varying holding costs

In other words, by changing the problem parameters, the value of the objective function in both approaches (uniform distribution and real-time cost) changes slightly but with direct relationship. For example, Figure 8 compares these two approaches. The real-time costs in the beginning of the generations are approximately 2-2.5% lower than uniform costs. The ability of GA algorithm is to generate multiple solutions that are increasingly more efficient, which can be seen at later generations with reduction of cost difference between the two approaches i.e. 0.05%. Hence, the ability of the proposed algorithm is confirmed when it comes to generating cost efficient solutions with good performance. This can help decision makers to find an appropriate trade-off between costs (i.e. real or uniform) and the optimal design of the supply chain.

7.4 Summary

In testing the proposed SCD model, our primary objectives were to show: (1) the universality of the proposed SCD, (2) the versatility of the model in dealing with both fixed/deterministic and real-time data, and (3) the importance of incorporating real-time partner costs when selecting product variants. Based on different population sizes, iterations, configurations and values, our results show that the proposed SCD is effective in achieving cost-efficient solutions. In particular, we find that variations in the GA parameter combinations do not significantly affect the total supply chain cost.

To probe our results further, we subject them to a sequence of sensitivity analyses based on real-world conditions. For instance, we choose various GA parameters such as population sizes, different combinations of crossover and mutation probabilities but also we introduce variations in holding costs. All of these variables play a pivotal role in cost-efficient SCD. Our sensitivity analyses show that the total supply chain costs remain efficient based on both uniform distributions and real-time costs.

We postulate that managers routinely adjust their decisions based on the prevailing environment in which they operate. Accordingly, it is reasonable to assume that they would act differently in turbulent/unstable real-world conditions. Thus, by analysing the sensitivity analysis results, managers can determine their optimal decision based on an evaluation of the total cost by changing the parameter values. In order words, our framework can be easily used as an effective managerial tool to design an optimal supply chain at relatively lower cost, which in turn has the potential to increase firm performance, particularly under turbulent market conditions.

8. Conclusion

Many companies are now able to offer a vast range of product variants enabled by the effective implementation of modularization strategies. Such strategies essentially outsource common platform modules to supply chain partners to simplify the production and distribution processes and improve operational performance. Thus, the success of a particular product does not only depend on the optimal supply chain design or technical performance, but also on the performance of the OEM supply chain in fulfilling uncertain customer demand. In this context, the SCD primarily determines the structure or links amongst the partners to make structural and (optimal) coordinated decisions. The key question, therefore, is: how do we optimally integrate the PF and the SCD in such as a way that factors such as globalisation, increased market competition, varying costs and modular product demand can be taken into account in a timely manner?

In this paper, we propose a novel approach, which details how both the product and the supply chain can simultaneously be designed based on *real-time* data, which then can improve operational decisions. To address the joint PF and SCD problem, we utilise a cloud-based management system comprising of three steps. In the first step, a generic bill of materials is modelled to design a set of PFs using “AND” and “OR” nodes. In the second step, a cloud-based framework is designed to manage real-time costs viz. echelons. In the third step, a mixed integer linear programming model is then applied, which optimizes the SCD based on real-time costs. Once the costs are optimized by genetic algorithm, an optimal supply chain is then achieved. The overriding objective is to minimize the total supply chain costs, including the selection of suppliers, manufacturing plants, assembling plants and distribution centres. To solve the overall supply chain problem, we apply a metaheuristic algorithm based on genetic algorithm.

Given that commercially available software find it hard to optimally solve medium to large multi-stage SCD problems, such as the one we tackle in this study, we use a power transformer numerical example as a case study. The main conclusions emanating from our study are that: i) the proposed SCD is robust to variations in real-world conditions (e.g. changes in holding costs), ii) the model design is versatile enough to deal with both fixed/deterministic and real-time data, iii) the real-time partner costs can be incorporated at the selection of product variant stage, and iv) a cost-efficient supply chain is achieved.

We believe that the proposed SCD is an intelligent and expert management system, which can facilitate effective decision-making support by taking into account real-time cost data. This is particularly important when there are uncertain and volatile market conditions. Thus, it can aid managers to achieve higher efficiency, as they would have a managerial tool, which yields an optimal SCD. Higher efficiency in turn can give firms competitive edge in our increasingly globalized world.

Developing effective frameworks to solve optimal supply chain problems have real world implications, as we have argued throughout this study. Therefore, future research could consider real case studies to characterize the solution behaviour of our proposed model. Nonetheless, our work is versatile enough that it could be adopted in multi-objective optimisation contexts in which risks and environmental benefits can be explicitly addressed. Also, our proposed model does not consider uncertainty in more detail. Therefore, other efficient stochastic and robust solution techniques can also be considered (e.g. Tirkolaee et al. 2020; Babaee Tirkolaee et al. 2020;Mardani et al. 2020; Tang & Gong, 2019; Liu et al. 2019; Sangaiah et al. 2019; Tirkolaee et al. 2019). Taken together, our study goes some way in demonstrating how optimal SCD can be achieved using cloud-computing technology in which real-time data is a reality.

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Appendix

Table A1

Reference	Features			Objectives	Solution Method	Case study	Application industry	Problem characteristics
	Multi-echelon	Multi-product	BOM					
(ElMaraghy & Mahmoudi, 2009)	*	*	*	Single	MILP	*	Automotive	Single integer decision support model using Lingo by concurrent design of product module structure and supply chain configuration
(Nepal et al., 2012)	*	*	*	Multiple	ILP	*	Automotive	Multi-objective weighted goal programming optimisation using genetic algorithm by integrating product architecture decisions with manufacturing supply chain decisions
(Yang et al., 2015)	*	*	*	Single	MINLP	*	Power Transformer	Single objective MINLP optimisation using nested genetic algorithm by joint configuration of product family and supply chain as leader-follower Stackelberg game
Afrouzy et al., 2016)	*	*	*	Single	ILP			Single objective ILP priority-based genetic algorithm optimisation using LINGO by joint new product development and design of supply chain network to maximise total profit.
(Wang et al., 2016)	*	*	*	Single	MINLP	*	Power Transformer	Single objective MINLP optimisation using nested genetic algorithm by joint decision making of product family and supply chain as leader-follower Stackelberg game
(Zhang et al., 2016)	*	*	*	Single	MINLP	*	Bicycle	Single objective MINLP optimisation using artificial bee colony by joint configuration of product family and supply chain
(Pham & Yenradee, 2017)	*	*	*	Single	MIP	*	Toothbrush	Single objective MIP optimisation using CPLEX by optimal supply chain design with process network under uncertainties
(Du et al., 2019)	*	*	*	*	MINLP	*	Gear Reducer	Single objective MINLP optimisation using nested genetic algorithm by joint decision making of product family and supply chain as quartet grid
(Liu et al., 2020)	*			Multiple	MILP	*	Consumer goods	Multiple objective MILP using AIMMS by optimal design of low-cost supply chain network for new products
(Mohammed & Duffuaa, 2020)	*	*		Multiple	MILP			Multiple objective MILP using tabu search based algorithm by the optimal design of multi-product supply chain network
Current study	*	*	*	Single	MILP		Power Transformer	Single integer decision support model using genetic algorithm by the optimal supply chain design with product family on *real-time costs* viz. echelons

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