A decision support system for integrating manufacturing and product design into the reconfiguration of the supply chain networks

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ABSTRACT

A supply chain needs to meet its customers’ requirements (CRs) in terms of delivery lead times, total costs and product quality. The objective of this article is to improve the level of integration in all aspects of supply chain reconfiguration, such as the inventory allocation and manufacturing process involved, by incorporating manufacturing and product design into logistic design. The effect of uncertain customer demand, production and supply lead times are studied. An optimum supply chain network is configured by combining optimization at the strategic and tactical level. A system dynamic based computer simulation model is used to validate the operations of the supply chain. The performance of the system is measured in terms of backorders and inventory level. The results and analysis indicate that fewer stockholding points and a shorter review period of demand can improve performance in this respect. In addition, a proposal for improving the performance of supply chain in terms of lower safety stocks is presented. Finally, management decision-making is discussed, among other concluding remarks.

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1. Introduction

This paper examines the optimal supply chain configuration for customized products. Our intent is to develop a Decision Support System (DSS) for integrating manufacturing and product design into the design of the logistic process, since the supply chain must be reconfigured before determining the product design, manufacturing technologies and vendors. We use assembly to represent manufacturing, since it is inherently integrative and should be composed to meet the Functional Requirements (FRs) of the product. The result is that the supply chain can be reconfigured with full knowledge of the way in which the product is supposed to work. Supply chain reconfiguration involves creating a suitable assembly sequence, identifying subassemblies, integrating inventory control, and designing supplier–buyer coordination so that the performance in terms of backorders and inventory levels is compatible with the assembly method [40].

The liaison between manufacturing and product design, and the logistic process design should make a tradeoff between a higher unit of manufacturing cost with a more responsive supply chain or a lower manufacturing cost with a less responsive supply chain. While the FRs on this point have already been determined, there are several manufacturing options available for manufacturing or assembling the product. The supply chain configuration chooses a manufacturing option in terms of make-to-stock (MTS), make-to-order (MTO) or assemble-to-order (ATO) for each stage of the supply chain, so as to achieve the product functionality at minimum manufacturing cost and with higher supply chain responsiveness.

The supply chain reconfiguration frameworks consider three areas which are relevant to choosing a manufacturing option for each stage of the supply chain: assembly planning, demand planning, and inventory allocation. A better quality of demand planning leads to optimum inventory allocation [15,17,19,28]. The optimum further assists the supply chain with decision methods for responding to demands and improving the supply chain delivery performance [7,8,11,33,36]. The optimum assembly planning provides knowledge to the supply chain so as to realize the product with minimum lead times without impairing its functioning.

The frameworks of supply chain reconfiguration change the expectations regarding the DSS associated with the liaison between manufacturing and product design and the logistic process design, with the following challenges.

(a) Assembly redundancy: Whitney [40] mentions that a well-designed product is a predictable product. This implies that product FRs analysis helps a designer to manufacture a product with minimum manufacturing effort without impairing its functioning. Thus, the product designer must consider the Product Key Characteristics (P-KCs). P-KCs are the FRs of a
product to satisfy the Customer Requirements (CRs). P-KCs need support from the lower level of FRs to deliver CRs, which are called the Assembly Key Characteristics (A-KCs). Optimizing the assembly sequence according to the P-KCs and A-KCs hierarchy avoids redundant coupled assembly [39]. The optimum assembly sequence reduces the content of information within the product such that it also minimizes the information content within the product so as to reduce iterative operations in manufacturing [23]. In other words, instead of reducing the interdependency of the parts, the supply chain has to explain the functional relationship between parts to properly deliver functionality in a product and minimize product failures. Product failures are defined as the non-conformity of a product to the desired FRs. A lower probability of product failure minimizes the requirement on safety stock and reduces backorders.

(b) The imprecision of demand information: safety stock costs and backorders can be minimized by providing credible demand information through the application of DSS. The quality of demand information affects the ordering process and controls the target inventory level of the buyer [3]. Some research articles [9,27,37] focus on DSS development to forecast customer demands. Yao et al. [42] suggest the application of a Vendor Managed Inventory (VMI) as a DSS to minimize the inventory costs by distributing inventory status and demand information evenly along the supply chain. While VMI does not share the inventory status, the way in which VMI responds to demand depends on variations in the manufacturing process. To deal with the imprecision of demand information and manufacturing process variation, it is necessary to understand the implications of manufacturing process variation and to characterize the way in which the variations are hedged effectively through VMI.

(c) Non optimum inventory allocation: The imprecision of demand information affects the planning of the logistic process in terms of flexibility and adaptability under the limitations of the capacity to supply with respect to the system dynamics [5]. Most of VMI is used to generate production flexibility so as to minimize the discrepancy between demand and order rate [38,39,42] without considering the production capacity and capability in terms of the variability of production lead times. In other words, instead of a decision on production and order, the DSS needs to optimize the composition of the stockinglfold points; it is possible to mix push and pull inventory systems to satisfy customer demand at various levels of production variability [41].

To this end, a DSS, called the two-level optimization of supply chain networks, is proposed, for the purpose of integrating the manufacturing and product design into the supply chain reconconfiguration in order to improve demand planning, inventory allocation and assembly planning. To deal with integration effectively, the concept of the FRs analysis of a product is put forward. On the first level, optimized assembly sequencing is developed to allocate the safety stocks and to choose the stockholding points. On the second level, optimized production and distribution control is developed to characterize the supply chain networks effectively. The merit of a two-level optimization of supply chain networks is detailed in terms of inventory levels through-out supply chains and backorders.

The rest of the paper proceeds as follows. Section 2 reviews the literature on inventory allocation in the supply chain. Section 3 highlights the scope and definition of the problem. Section 4 focuses on the features of DSS modeling, mainly aiming at supply chain reconconfiguration and safety stock allocation. Section 5 validates the supply chain model in the previous section and discusses the DSS implications for management decision-making. Section 6 concludes this article.

2. Background of the research

The integration of FR analysis into the reconconfiguration of supply chain networks extends the supply chain decisions by adding ‘how to manufacture’ to ‘how much to deliver’ and ‘how much to produce’. The integration requires an interplay between quality management (QM) and supply chain management (SCM) to coordinate and integrate the manufacturing processes [32]; however, not much research has been reported on the topic. Balachandran and Radhakrishnan [2] model the effect of supply chain coordination in terms of warranty contract to minimize product failures. Whitney [40] suggests that supply chains have to meet the design intent (FRs) to obtain a well-designed assembly. Dong and Whitney [9] use an axiomatic design approach to meet FRs at a minimum degree of integrity and information content [35]. We are aware of prior research which attempts to analyze the FRs as a tactic for assembly planning in a supply chain.

The model which we develop falls within the literature on assembly planning in a supply chain, in particular for a strategic inventory allocation of supply chain reconconfiguration. In this way, our work is related to that of Novak and Eppinger [30] and Graves and Willems [18,19]. The former authors [30] hypothesize that product complexity and vertical integration are complementary and suggest greater coordination between the product design engineer and the supply chain engineer. They use original empirical evidence from the auto industry and find that simpler product architecture can be suggested for an autonomous supply chain. Graves and Willems [18,19] develop a model for positioning safety stock in a supply chain, subject to non-stationary demand. It is suggested that optimal safety stock allocation may entail changing the service times, and thus the locations of safety stocks, as demand evolves over time. The authors [18,19] assume the same demand process for a multi-echelon system consisting of some manufacturing sites. The sites operate with an independent base-stock policy.

Our work differs from that of Novak and Eppinger [30], however, in that we consider axiomatic design, for which product complexity is reduced by first identifying the liaison between the parts of a product and then providing information about the interdependency of the parts [43]. Liaison identification helps a designer to convey a well-designed manufacturing method so as to put into action the logistic planning by minimizing the interdependency of parts and to meet FRs [9] by relating the axiomatic design to assembly sequencing [43]. Not being able to do this leads to capacity overload and yields only 80% of successful assemblies on the first try [6,14,40]. In addition, part modularization helps a logistics manager to minimize the amount of uncertain information about supply and demand within supply chains [12,37] and thus to reduce the level of safety stock [22]. While liaison identification has an important role in supporting supply chain reconconfiguration in terms of better assembly planning and production clustering, the implications for the supply chain inventory cost are ignored or at best poorly understood [25].

Our model differs from that of Graves and Willems [18,19] in that we provide an insight into the behavior of inventory allocation and benefit from information sharing to minimize uncertainty about supply and demand [4,19,29,31]; this being the case, we have structured the model to allow the greatest possible responsiveness of production–distribution and clarify where the inventory hedge should be set. Graves and Willems [18,19] allocate the safety stock by assuming that the processing times are deterministic and that no capacity constraints limit production at any stage. Furthermore, the previous contributions minimize the safety stock placement at optimum processing time by considering the service level of the vertically integrated supply chain. Conversely, we consider backorder costs rather than service level targets in order to reflect managers’ commitment to providing a 100% service level. In addition, VMI is employed to an autonomous supply chain and the service level is adjustable so as to maximize the supply chain performance.
This literature review leads on to supply chain coordination in terms of manufacturing and logistics planning. The supply chain needs to simplify the manufacturing method and minimize the content of information among the processing facilities. From the manufacturing viewpoint, assembly sequencing should minimize interdependencies between parts. From the logistical viewpoint, VMI provides a promising solution. This article covers the integration of manufacturing and logistics planning to improve the supply chain performance in terms of backorders and inventory levels by studying the effect of a review period of demand and assembly sequencing after analyzing product FRs [13].

3. Problem scope and definition

In this section, we present the assembly and distribution operations of a furniture product family for reconfiguring the supply chain and allocating the inventory at the lowest possible backorder and inventory levels. The processing facilities have limited capacity for manufacture. However, the processing facilities have storage facilities. Depending on customer orders, the production quantities at the processing facilities fluctuate over time and are not necessarily pre-determined. In addition, a processing facility has the probability of failure during the production process. The suppliers have no additional information regarding the customers’ inventory level. Indeed, forecasting matrices about demand are distributed across the supply chain, which is used by the suppliers to decide on delivery and production rates.

In considering probability of failure, we formulate the problem as a queuing model and propose a dynamic simulation method. The method uses a GI/G/1-based inventory control which considers supply and demand uncertainties. The production rate in the queue model is dynamic by allowing backorders. Distribution from suppliers to buyers is considered in our model by implementing VMI to maximize the economies of scale in transportation costs.

First, in order to illustrate the proposed DSS in supply chain reconfiguration and inventory allocation, Fig. 1 presents below a description of the strategic and tactical level optimization model.

4. DSS for tactical and operations level optimization

Fig. 1 shows that the DSS is split into a two-stage optimization, a strategic and tactical level. The optimization covers:

4.1. Strategic level optimization

The supply chain reconfiguration considers delivery lead times $L_d$ and service level $z_m$ in the supply chain against demand uncertainty $\sigma_d(t)$. The sequence should reduce part interdependency. Since most of the literature on inventory allocation considers the first two components [24,19,29], part interdependency is rarely discussed.

4.1.1. KC analysis and assembly sequencing for supply chain reconfiguration

We use the generic product structure of an office chair as an example [10]. There are six part frames (Fig. 2) comprising back, upholstery and arm rest as standard parts, and a seat frame, stand and support as three distinctive modules. The FRs of the chair includes its capability for making 360° rotations (FR 1) and choosing the quality of frame (FR 2). Both of these FRs are supported by defining P-KC. The seat frame and the seat deliver P-KC 1 by allowing the customer to choose the material of the seat frame. The support and stand of the office chair deliver P-KC 2 by allowing the customer to rotate the chair 360°. Each P-KC is supported by using A-KCs to meet the quality objective of the product.

In addition, A-KCs are presented in the form of a liaison diagram, as follows. Fig. 3 shows mate joints between upholstery and seat, between back and under frame, and between arm rest and under frame. Mate joints (dotted lines) do not affect A-KCs deliverability, but contact joints (directed lines) do so directly. Joints between the support and under frame, between under frame and stand, between seat frame and under frame, and between seat and under frame are represented as A-KCs 1 to 4. A-KCs 1 and 2 support the deliverability of P-KC 1 and A-KCs 3 and 4 for P-KC 2. The assembly sequence planning in Fig. 3 guides the supply chain reconfiguration, where the arrows signify the direction of product assembly.

The assembly sequence in Fig. 3 is used to reconfigure the supply chain networks, which are represented by the design structured matrix (DSM). DSM is used for the clustering of dependencies in a matrix [43]. The goal of DSM is to cluster closely related activities as shown in Fig. 4b so as to minimize the coupling between activities. The DSM square matrix comprises rows for representing independent variables and columns representing dependent variables. The diagonal line is blank when it is expected that either dependent or independent variables are dependent upon themselves. For instance, in Fig. 4, activity

![Fig. 1. A DSS for supply chain reconfiguration and inventory allocation.](image)
number 3 is sequentially accomplished just after activity number 1 and is recognized as the second of two activities in a series. Finally, activities number 2 and number 3 have no relationship that would signify simultaneous activities. It is shown in Fig. 1a that activities number 2 and 3 are overlapping before clustering.

The assembly sequencing can be used to answer technical challenge 1 by the following proposition 1.

**Proposition 1.** If the number of stages within the supply chain is reduced and there is no overlapping cluster in the assembly sequence planning, then the product quality of the supply chain will increase. Furthermore, higher product quality minimizes the requirement for safety stock.

**Proof.** Let \( A_1 \) and \( A_2 \) be the failure probability (e.g. lateness, inappropriate quality, etc.) for materials at stages \((n - 2)\) and \((n - 1)\) respectively, their occurrence not being mutually exclusive. Thus, the probability of creating delivery delay due to the failure of one of the two coupled materials is \( p_{f(2)} = A_1 + A_2 - (A_1 \times A_2) \) for \( A_n = 1 - z_n \) to represent the service level. Further, for \( N \) coupled materials we then have a failure probability as much as

\[
p_{f(n)} = \sum_{x=n-1}^{1} A_{(n-x)} - \left( A_{(n-1)} \cap A_{(n-2)} \cap \cdots \cap A_{(1)} \right) . \tag{1}
\]

The first component of Eq. (1) represents the probability of failure due to one of \( N \) coupled materials. The second component represents the joint probability for two or more components to fail together. We use this formulation since in a non-mutually exclusive event, material failure can occur altogether so that the entire product manufacturing breaks down. Eq. (1) shows that the coupled operations should be decoupled or be localized and manufactured integrally in the same processing site of the supply chain. Thus, it simply informs us that the buyer will reject the material even if only one part of the material fails.

The localization can be accomplished by clustering the coupled operations and supplying them from the same stage to minimize \( p_{f(n)} \). Then Eq. (1) will be changed to the joint probability of failure for a non-mutually exclusive event, as follows:

\[
p_{mf(n)} = \max(A_{(n-1)}, A_{(n-2)}, \ldots, A_{(1)}) . \tag{2}
\]

We can compare in Eq. (1) and Eq. (2) that the failure probability reduces from \( p_{f(n)} \) to \( p_{mf(n)} \) by as much as

\[
p_{f(n)} - p_{mf(n)} = \sum_{x=n-1}^{1} A_{(n-x)} - \max(A_{(n-1)}, A_{(n-2)}, \ldots, A_{(1)}) - \left( A_{(n-1)} \cap A_{(n-2)} \cap \cdots \cap A_{(1)} \right) \tag{3}
\]

Furthermore, reducing the value of \( (A_{(n-1)} \cap A_{(n-2)} \cap \cdots \cap A_{(1)}) \) supports the risk sharing effort by minimizing the number of interactions (i.e. sharing functionality, interfaces, etc) within the module. Reducing \( p_{f(n)} \) supports safety stock decoupling at stage \((n)\). Finally, the safety stock reduction \( \Delta SS_n \) at stage \( n \) due to lower failure probability is represented as follows:

\[
\Delta SS_n = z_n \left( p_{f(n)} - p_{mf(n)} \right) \sqrt{L_n} \tag{4}
\]

where \( L_n \) stands for delivery lead times at stage \( n \). In the following, we describe in more detail the inventory allocation and risk sharing to minimize the total inventory costs (cycle and safety stocks) after reconfiguring the supply chain.

### 4.1.2 Inventory allocation

If one operates a supply chain while disregarding demand volatility and capacity constraints, one may encounter unexpected stock-outs, as deliveries are delayed at system bottlenecks. However, the safety stock...
follows a non-linear pattern and arbitrarily large for demand volatility which is only slightly greater than average demand. Therefore, by characterizing the necessary safety stock levels as probability for stock out, we can determine the optimal safety stock placement in supply chains with one or many capacity constraint(s).

The inventory allocation is modeled as a GI/G/1 queue model by bearing in mind the following reasons. First, consider the demand process of the upstream stage, namely the order stream (i.e., stage n) from the downstream stage (i.e., stage n − 1). Second, the model considers that the demand inter-arrival and processing rates are sometimes in heavy traffic (1 − c) < p_d or sometimes not stationary and divergent at a certain demand level V_t at time i (i.e., i ≥ 1) for \( p_d = \frac{\text{kn}}{\text{ln}} \) (\( \text{kn} \) and \( \text{ln} \) represent demand rate and production capacity at stage n respectively). As a result, the waiting time in a queue \( W_q(n) \) at stage n depends on the demand inter-arrival rate standard deviation \( \sigma_{kn} \) and service rate standard deviation \( \sigma_{ln} \) [20]. Third, the model considers the lead time variability in some ranges: \( p_{stock} = \frac{\text{kn}}{\text{ln}} \) ≤ \( W_q(n) \) ≤ \( \frac{\text{kn}^2 + \sigma_{kn}^2}{2(1-p_d)} \). The variability of lead times \( \sigma_{kn} \) signifies that the supply chain allocates the inventory to cover the demand volatility \( \sigma_{kn} \). Thus, within T time horizon with review period j from time \( t = T - j \) to \( T \), \( \sigma_{kn} \) is stated as \( \sigma_{kn} = \frac{1}{\text{kn}} - \frac{1}{\text{kn} \sigma_{kn}} \) for \( \sigma_{kn}^{n+1} \).

The longer review period of the demand j reduces the level of sensitivity about the demand changes. Lower sensitivity creates lower demand responsiveness at \( \sigma_{kn} = \frac{1}{\text{kn}} + \frac{1}{\text{ln}} \) since \( \sigma_{kn} \) represents the standard deviation of production lead times, which is inappropriate for a non-stationary demand process. Lower demand responsiveness further suggests that the supply chain should invest in a higher level of safety stock. Thus, an analysis of demand responsiveness is required to allocate the inventory.

This article uses the order of Erlang distribution \( k_n \) and \( h_n \) to measure the operation uncertainty in non-stationary demand at stage n. The reason for using the Erlang distribution in this case is that it facilitates the calculations of a stock out that is stated by using a stock out probability formulation of Leven and Segerstedt [26] as

\[
\text{Probability for stock out } p_{stock} = 1 - \int_0^{[\text{kn}]^{-1} + \text{ln}^{-1}} l_n^k e^{-l_n x} \frac{x^{k-1}}{(k-1)!} dx = h_n^{-1} x e^{-h_n x} \sum_{i=0}^{k-1} \frac{1}{i! h_n k_n^{-1}} \]

where \( l_n \) is the inventory on hand at stage n. For calculating the distribution parameters the following formulas can be used:

\[
k_n = \left( \frac{\text{ln}}{\sigma_{kn}^2} \right)^2 \]

(6)

\[
h_n = \left( \frac{\text{kn}}{\sigma_{kn}^2} \right)^2 \]

(7)

For calculating the on hand inventory at stage n, \( l_n \), the following formulas can be used:

\[
l_n = \mu_n h_n \left( W_q(n) + \frac{1}{\text{kn}} \right). \]

Eq. (8) signifies that \( l_n \) is increased at the increasing value of the \( \sigma_{kn}^2 \) and \( W_q(n) \). This trend signifies that either the lower \( \sigma_{kn}^2 \) or the higher \( \mu_n \) can help the supply chain to minimize the amount of inventory allocation. This implies that safety stock can be allocated to nodes or stockholding points with higher \( p_{stock} \) for SL [26] for SL stands for customer service level. The inventory allocation can be used to answer technical challenge 3 by the following proposition 2.

**Proposition 2.** If the level of \( p_{stock} \) is higher than SL at stage n, the additional safety stock, \( s_{st} \), required by stage n is given by putting \( p_{stock} = \text{SL} \) in the left hand side of Eq. (5), and finding the demand standard deviation during delivery lead times, \( \sigma_{kn} \) by iterative calculation.

**Proof.** Consider a case where the level of demand variation is large and thus the probability of stock out more than the expected service level. In this situation, there are two possible outcomes for the realized demand process, i.e., the demand realization is equal to \( \text{kn} \) and a shortage does not occur or equal to \( \text{kn} + \sigma_{kn} \) if a shortage occurs after considering SL. Defining \( p_{stock} = \text{SL} \) to be the probability of having a shortage at the end of planned interval gives the safety stock of the realized order interval as an iterative calculation of Eq. (5). □

In addition to the inventory allocation problem, risk sharing is developed in Section 4.1.3 to eliminate the safety stocks in some stockholding points.

### 4.1.3. Risk sharing through safety stock allocation

Section 4.1.2 mentions that the choice of \( h_n \) also influences the demand response across the supply chain. Lower \( h_n \) represents a sluggish response and, conversely, higher \( h_n \) represents a quicker response. Thus, in providing guaranteed lead times and anticipating the forecasting error, safety stock needs to be allocated to cover demand uncertainty by as many as

\[
s_{st} = z_p \sigma_{kn} \sqrt{L_n} \]

(9)

we can see from Eq. (9) that \( s_{st} \) is the only factor for allocating safety stock across the supply chain at service level \( z_p \). Thus we have Proposition 3, as follows.

**Proposition 3.** Safety stock allocation for stockholding points can be optimized by shifting the safety stock at downstream (stage n) to upstream (stage n − 1), if \( O_{n−1} = O_{n} \) holds.

**Proof.** We can transfer safety stock at stage n to all other stages that have a direct link to stage n (\( O_{n−1} = O_{n} \)) if the safety stock after risk sharing is lower than before risk sharing. Thus, we have the following relationship:

\[
\sum_{k=n-1}^{n} O_{n−1} \frac{h_n-1}{h_n} O_{n−1} > 1
\]

(10)

\[
O_{n−1} = \left( \frac{z_p \sigma_{kn−1} \sqrt{L_{n−1}}}{z_p \sigma_{kn−1} \sqrt{L_n}} \right)
\]

(11)

where \( h_n \) and \( h_{n-1} \) are the safety stock costs at stages \( n \) and \( n-1 \) respectively.

This article provides a graph to make the analysis in Eq. (11) faster. The decision can be taken simply by multiplying the holding cost ratio \( \frac{h_n-1}{h_n} \) to \( O_{n−1} = O_{n} \) in Fig. 5. The calculation is applied to all direct links between stage n and stage k for \( k = 1 \) to \( n-1 \), such that \( O_{n−1} = O_{n} \) if there is a direct link, otherwise, \( O_{n−1} = 0 \).

Fig. 5 shows that higher demand uncertainty at stage \( n-1 \) as compared to stage (n) encourages stage (n) to decouple safety stock to stage \( n-1 \) to minimize the total of safety inventory costs between the two stages. Conversely, lower demand uncertainty at stage (n) motivates both stages to keep their own safety stocks. The supply chain can extend this relationship to many stages.
4.2. Tactical level optimization

At the tactical level, we define a node as any activity point in the supply chain (material receiving and inspection, work in process (WIP) or intermediate product processing and final product processing). Thus, in each location the supply chain has at least one activity point (i.e. material receiving and inspection for warehouse). Otherwise, the location has two activity points (i.e. material and final product processing facilities), or at most three points (i.e. material, WIP and final product processing facilities).

For stage \( n \), the replenishment time, \( L_{p(n)} \), comprising production lead time, \( L_{p(n)} \) and delivery lead times, \( L_m \), is given as follows:

\[
L_{p(n)} = L_{p(n)} + L_m. \tag{12}
\]

The delivery rate in all periods must be enough to cover the demand over the upcoming \( L_m \).

The optimization of tactical level comprises demand forecast, production and inventory control. Demand responsiveness in terms of inventory responses is optimized to minimize the backorders and inventory level.

4.2.1. Demand forecast method

We assume that in each period, \( t \), the observed demand \( D(t) \) from period \( t \) is used to issue the demand forecast from period \( t \) to \( t + 1 \) or \( F(t+1) \). We assume that it is possible to set an initial inventory level \( L_0(0) \) and that \( F(t) = \lambda \) for \( t \leq 0 \) and furthermore \( F(t) \geq 0 \).

Exponential smoothing is used to estimate the future demand. The reason has its roots in the ARIMA-based demand process model, in which the forecast demand \( F(t) \) at time \( t \) and its mean value \( \lambda \) are defined as follows \([19]\):

\[
F(1) = \lambda + \varepsilon(t), \tag{13}
\]

\[
F(t + 1) = (1 - \alpha_0)F(t) + \alpha_0D(t) + \varepsilon(t), \tag{14}
\]

\[
\varepsilon(t) = D(t) - F(t). \tag{13}
\]

Eq. (13) shows that the demand forecast, \( F(1) \), at time \( t = 1 \) depends on the mean value of customer demands, \( \lambda \), and random noise term \( \varepsilon(t) \) of the time series random variable which represents the forecast error. Eq. (14) shows that the future demand forecast, \( F(t+1) \), depends on the current demand forecast, \( F(t) \) and \( \varepsilon(t) \). The value of \( \alpha_0 \) stands for the smoothing constant that is obtained from time to adjust the demand response time \( T_\alpha \) for \( T_\alpha = 1/\alpha_0 \). When \( 0 < \alpha_0 < 1 \), the demand process is a non-stationary process. When \( \alpha_0 = 1 \), Eq. (14) shows that the demand forecast is correlated to the previous demand and the demand process resembles a random walk.

4.2.2. Production and inventory control

Production and inventory control is accomplished by adjusting the production rates \( \mu_n(t) \) at stage \( n \) to minimize final product inventory \( l_n(t) \) and the WIP inventory \( l_{WIP(n)}(t) \) at stage \( n \) and time \( t \). The adjustment requires the supply chain to fulfill the demand from product inventory according to delivery order at stage \( n \), \( q_n(t) \), and considers production capacity constraint \( K_n \) at stage \( n \) as follows:

\[
\mu_n(t) = \min[K, F(t + 1) + \Delta l_n(t) + \Delta WIP_n(t)], \tag{15}
\]

\[
q_n(t) = \min\left(l_n(t), F(t + 1) + \frac{(D(t) - q_n(t) - l_n(t))L_m}{L_{p(n)}}\right), \tag{16}
\]

\[
\Delta l_n(t) = \frac{(\mu_n(t) + L_{p(n)}) - (q_n(t) + L_m)}{t_{\beta(n)}}, \tag{17}
\]

\[
\beta(t) = \frac{D(t) - F(t)}{F(t + 1) + \Delta l_n(t) + \Delta WIP_n(t)}, \tag{18}
\]

Fig. 5. Holding cost ratio at different delivery lead times \((l_n/l_{n-1})\) and demand standard deviation ratios.

Fig. 6. Template for iteration of a genetic algorithm.
4.2.3. Optimization of the response parameters

The response parameters are optimized to minimize $BO_n(t)$ for $BO_n(t) = D_t - \mu_n(t)$, at minimum difference between $\sigma_n(t)$ and $\mu_n(t)$. Since the forecast of the demand is centralized, the optimization model can be obtained by inserting Eq. (17) to Eq. (18) into Eq. (15).

However, $BO_n(t), WIP_n(t), F(t)$ and $\sigma_n(t)$ are the four independent variables that are always changing. Here, the optimization should cover the scenario where the optimization model (in this article, 1% backorders is taken as the customer risk $\alpha = 0.01$). Manipulating Eq. (15) to Eq. (18) to get $BO_n(t)$ we then have the following optimization problem:

$$\begin{align*}
\min_{T_{W(n)}, T_q(n), T_{d(n)}, T_{b(n)}} & \sum_{n=1}^{N} \Delta BO_n = \sum_{n=1}^{N} z_n \left( \frac{1 - \frac{1}{T_{W(n)}}}{1 - \frac{1}{T_{W_{n}}}} - \frac{1 - \frac{1}{T_{d(n)}}}{1 - \frac{1}{T_{d_{n}}}} \right) \\
\text{s.t.} & \quad T_{d(n)} \leq T_{W(n)}, T_q(n), T_{b(n)} \leq 5 \\
& \quad 1 \leq T_{a}; \quad T_{b(n)} = T_{W(n)}; \quad T_{q(n)} \leq 5
\end{align*}$$

where $z_n$ represents the maximum allowable backorders and $T_{b(n)}$ represents the lead time of the production process and lowest $BO_n(t) = D_t - \mu_n(t)$ (in this article, 1% backorders is taken as the customer risk $\alpha = 0.01$). Manipulating Eq. (15) to Eq. (18) to get $BO_n(t)$ we then have the following optimization problem:

$$\begin{align*}
\min_{T_{W(n)}, T_q(n), T_{d(n)}, T_{b(n)}} & \sum_{n=1}^{N} \Delta BO_n = \sum_{n=1}^{N} z_n \left( \frac{1 - \frac{1}{T_{W(n)}}}{1 - \frac{1}{T_{W_{n}}}} - \frac{1 - \frac{1}{T_{d(n)}}}{1 - \frac{1}{T_{d_{n}}}} \right) \\
\text{s.t.} & \quad T_{d(n)} \leq T_{W(n)}, T_q(n), T_{b(n)} \leq 5
\end{align*}$$

4.2.4. GA for parameter selection to give optimum value in the response parameters

The XLBit Genetic algorithms add-in of MS-Excel spreadsheet is used to solve the non-linear supply chain dynamics in terms of inventory, production and distribution decisions. This free general-purpose simulator combines system dynamics with some aspects of discrete-event simulation, and embeds a meta-heuristic optimization engine within a Monte Carlo simulation framework, which is well-suited for modeling time-dependent conditions or processes. The Excel spreadsheet also provides easy access for the user to edit the mathematical models in Section 4.2.3.

The solution to a problem is called a chromosome, which simply represents the parameters to be optimized. A GA creates an initial population (a collection of chromosomes), evaluates this population and then evolves the population through multiple generations in the search for a good solution to the problem in hand. GA will stop the iteration process whenever the regeneration process has reached a specified value [16,23]. Basically, GA has the structure described in Fig. 6.

Table 1 shows the GA parameters for the parameters $T_d$, $T_{b(n)}$, $T_{W(n)}$ and $T_{q(n)}$. Table 2 exhibits the input parameters which are used during the simulation. The different setting of lead times are used within the supply chain to observe the effect of lead times on the performance indicators.

4.3. Results and analysis

In analyzing the proposed inventory allocation model, we benchmark the original supply chain configuration before and after the assembly sequence planning. Partial variants in Fig. 2 are used to produce eight product variants in the product family. The parts are coded into capital letters, back (A), Seat frame A (B), Seat frame B (C), Upholstery (D), Stand A (E), Stand B (F), Pad (G), Wheel (H), Armrest (I). In Table 2,
proposition 2 is applied to the decision whether or not to allocate the parts and product safety stocks to the supply chain without assembly sequencing planning. The parameters of $L_{n}$ and $\lambda_{n}$ and $\mu_{n}$ are stated in advance. The volatility is set at 40% of $\lambda_{n}$. In Table 3, the same operations are applied to the supply chain configuration which follows assembly sequencing.

4.3.1. Assembly sequencing and the supply chain reconfiguration

Each part in the product structure (Fig. 2) is represented as one stage in the supply chain. However, the two dashed line which link to the same upstream part share the same stage since those two lines are options for the customers. The DSM matrix (Fig. 7) shows that the seat and seat frame should be assembled together in one stage. Similarly, the stand and support should also be assembled together in the same stage. Two benefits of the assembly sequencing re that they reduce the number of workstations from 11 stages to 6 stages and reduce the interdependencies between them.

4.3.2. Inventory allocation

Tables 2 and 3 show that the assembly sequence planning is capable of eliminating safety stocks in some of stockholding points at stage 3 (product ABDEHI) and stage 1 (wheel, pad, stand A), and furthermore minimizes the total safety stock costs for all the activity points within the supply chain. Tables 2 and 3 summarize $p_{s(n)}$ and if $p_{s(n)}(1-SL)$, an additional safety stock will be required (in our example SL = 0.99). Placing the safety stock iteratively according to Eq. (5) will increase the inventory position which is only slightly greater than average demand. In addition, Table 3 shows that except product ACDFH, all the rest product variants are assigned as safety stock free locations. This implies that the supply chain can make a saving on those products and increase the agility and production capacities towards process standardization. Process standardization reduces the number of activity points within the supply chain by clustering the interdependence parts into one location.

4.3.3. Risk sharing in terms of safety stock allocation

Furthermore, Proposition 3 is used to share the risk within the supply chain. Risk sharing reduces the total inventory costs of the products and their supporting parts. Fig. 4 is used to decide on risk sharing by obtaining a lead time ratio between stage $n$ and stage $n - 1$, and a standard deviation ratio between stage $n$ and stage $n - 1$. Table 4 shows the application of Fig. 5 and Eq. (5). Product ACDEHI is the only stage which can share its safety stock to its parts (back, seat, under frame, upholstery and armrest). It is shown by iteratively calculating Eq. (5) that the holding costs are the determining factor in deciding on risk sharing. In addition, $\alpha_{s(n)}$ also affects the risk sharing decision. It is shown that the product or parts safety stocks are shared if the demand standard deviation at stage $n$ is lower than stage $k$ for $k = 1$ to $n - 1$.
4.3.4. Optimum value of response parameters \( T_{i(n)} \), \( T_{W(n)} \) and \( T_{q(n)} \).

The optimum inventory response parameters to minimize the backorders and inventory level are presented in Table 5. The responses are applied to the new configuration of supply chain (Fig. 7) and we have six workstations.

5. Model validation and management decision-making

We chose products ABDEHI and ABDEGI in the simulation, since both products act as stockholding (before clustering) and non-stockholding points.

5.1. Model validation

The simulation validates the amount of safety stock of the two adjacent stages in the supply chain (the final product at stage \( n \) and its direct upstream at stage \( n-1 \)). The safety stock is counted as the required safety stock for products ABDEHI and ABDEGI. In order to validate the proposed analytical model, GoldSim simulation software developed by the GoldSim Technology Group is used. This general purpose simulator combines system dynamics with some aspects of discrete-event simulation, and embeds a dynamic simulation engine within a Monte Carlo simulation framework, which is well-suited for modeling time-dependent conditions or processes. The analytical models and discrete event simulation are tested at different levels of demand volatility. All other parameters in the model follow Tables 2 to 5. Moreover, some failure rates in the assembly plants are introduced to accommodate the effect of process quality to the backorders.

The validation applies the ANOVA (Table 12). In Tables 6 and 7, the analytical models of safety stock are not statistically different from the simulation safety stocks at a significant 5% level, where average P-values are 0.843 in all stages. The results show that the analytical model is capable of hedging demand variations. However, the results also show that the product ABDEGI inventory allocation by simulation is slightly higher than the analytical model and the opposite feature applies to product ABDEHI safety stock allocation. This signifies that product ABDEHI has higher inventory variance than product ABDEGI because of a higher number of stockholding points.

In addition to safety stock analysis, Tables 8 and 9 make it clear that the simulation has a different order rate at different demand volatility levels. The results imply that in non-stationary demand, the dynamic lot sizing is important in providing 100% guarantee lead times (Tables 10 and 11). Furthermore, in non-stationary demand, a more frequent demand sampling period is suggested, either for the simulation or the analytical model.

5.2. Management decision-making

In addition to the DSS model validation, Tables 6 and 7 illustrate that either at lower demand volatility \((\sigma_{VA} = 0.2)\) or higher demand volatility \((\sigma_{VA} = 0.4)\), the product ABDEHI inventory allocation for the downstream stage \((n)\) is always higher than for the upstream stage \((n-1)\). This implies that the proposed analytical and simulation models are capable of sharing the risk in terms of safety stock allocation and improving the quality of information about demand. Tables 8 and 9 summarize that the magnification of the order is eliminated without creating excessive backorders (Tables 10 and 11). Thus, the proposed DSS model contributes to current DSS commercial software (i.e. SAP APO, I2 Rhythm) [1.2.3.4] by optimally designing supply chain networks, and at the same time allocating the inventory with the fewest possible backorders.

### Table 5

<table>
<thead>
<tr>
<th>Product</th>
<th>Stage</th>
<th>( T_a )</th>
<th>( T_i )</th>
<th>( T_w )</th>
<th>( T_q )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>Back</td>
<td>4.9</td>
<td>3.4</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Underframe</td>
<td>4.9</td>
<td>3.4</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Arm rest</td>
<td>4.9</td>
<td>2.5</td>
<td>2.5</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>Upholstery</td>
<td>4.9</td>
<td>2.5</td>
<td>2.5</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>Seat frame</td>
<td>4.9</td>
<td>3.2</td>
<td>1.6</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>Underframe</td>
<td>4.9</td>
<td>3.4</td>
<td>1.2</td>
<td>0.6</td>
</tr>
</tbody>
</table>

### Table 6

<table>
<thead>
<tr>
<th>Demand process</th>
<th>Product ABDEHI safety stock</th>
<th>Simulation</th>
<th>Analytical model</th>
<th>Difference</th>
<th>Demand process</th>
<th>Product ABDEHI safety stock</th>
<th>Simulation</th>
<th>Analytical model</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma_{VA} = 0.4; \lambda_a = 200 )</td>
<td>Stage-n</td>
<td>200</td>
<td>191</td>
<td>9</td>
<td>( \sigma_{VA} = 0.2; \lambda_a = 200 )</td>
<td>Stage-n</td>
<td>102</td>
<td>96</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Stage-k</td>
<td>190</td>
<td>235</td>
<td>-45</td>
<td></td>
<td>Stage-k</td>
<td>95</td>
<td>118</td>
<td>23</td>
</tr>
<tr>
<td>( \sigma_{VA} = 0.4; \lambda_a = 250 )</td>
<td>Stage-n</td>
<td>240</td>
<td>239</td>
<td>-1</td>
<td>( \sigma_{VA} = 0.2; \lambda_a = 250 )</td>
<td>Stage-n</td>
<td>166</td>
<td>120</td>
<td>46</td>
</tr>
<tr>
<td></td>
<td>Stage-k</td>
<td>190</td>
<td>244</td>
<td>-54</td>
<td></td>
<td>Stage-k</td>
<td>133</td>
<td>122</td>
<td>11</td>
</tr>
<tr>
<td>( \sigma_{VA} = 0.4; \lambda_a = 275 )</td>
<td>Stage-n</td>
<td>259</td>
<td>263</td>
<td>4</td>
<td>( \sigma_{VA} = 0.2; \lambda_a = 275 )</td>
<td>Stage-n</td>
<td>117</td>
<td>131</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>Stage-k</td>
<td>235</td>
<td>248</td>
<td>13</td>
<td></td>
<td>Stage-k</td>
<td>128</td>
<td>124</td>
<td>4</td>
</tr>
<tr>
<td>( \sigma_{VA} = 0.4; \lambda_a = 310 )</td>
<td>Stage-n</td>
<td>270</td>
<td>296</td>
<td>26</td>
<td>( \sigma_{VA} = 0.2; \lambda_a = 310 )</td>
<td>Stage-n</td>
<td>106</td>
<td>105</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Stage-k</td>
<td>236</td>
<td>254</td>
<td>18</td>
<td></td>
<td>Stage-k</td>
<td>105</td>
<td>109</td>
<td>4</td>
</tr>
<tr>
<td>Average difference</td>
<td></td>
<td>9</td>
<td></td>
<td></td>
<td>Average difference</td>
<td></td>
<td>7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
We need to be cautious about the analytical model, since it assumes that increasing demand volatility should be responded to linearly by providing extra safety stock. However, the simulation shows that the trend is not linear. Furthermore, with higher demand volatility, the backorder level of the simulation is a little higher than that of the analytical model. We suggest a shorter sampling period of demand to reduce this difference, or using simulation to investigate the true pattern of the demand process. We can validate our suggestion by measuring order rates in the three stage supply chain (Tables 10 and 11). Furthermore, a shorter sampling period implies that a lower number of stockholding points in the supply chain make the supply chain more autonomous. The reason is that the length of the supply chain is reduced and the supply chain configuration becomes simpler than before. The simpler supply chain brings the opportunity to meet the production and distribution decisions in terms of economies of scale of transportation cost. Below, the contributions of the DSS to current commercial DSS are summarized (Table 13).

6. Concluding remarks

The proposed DSS model improves supply chain efficiency through supply chain reconfiguration and inventory allocation [18,19]. Furthermore, risk sharing adds benefit to the supply chain by reducing the safety stock investment. Proposition 1 endorses the importance of product functional analysis and assembly sequencing to supply chain reconfiguration [22]. Proposition 2 suggests a condition for safety stock allocation, and Proposition 3 guides us to decide on the conditions in which the safety stock can be decoupled. The safety stock decoupling can minimize the effect of demand uncertainty and inventory cost [4,31]. The model validation benchmarks the proposed analytical model against the simulation model, at the same model parameters. The statistical analysis for stockholding and non-stockholding points shows that the analytical and simulation models are not statistically different in terms of safety stock levels, order rates and backorders.

The supply chain reconfiguration reduces safety stock distribution at a lower number of stockholding points. Furthermore, the new supply chain configuration makes the supply chain more autonomous. The level of autonomy is higher when the interdependencies among stages in the supply chain are minimized. In addition, autonomy encourages supplier and buyer coordination. Finally, the value of the demand forecast is higher at a higher level of supplier and buyer coordination [3].

However, our model has two drawbacks: first, the smoothing constant of the demand forecast is not related to supply and demand uncertainty. However, this relation is important in deciding the level of responsiveness at which the safety stock can be eliminated. The second drawback is the limitation of the analytical model in being sensitive to backorders. It is shown in Tables 10 and 11 that the simulation yields a variety of results on backorders. In the future, the
Table 11
Backorders between analytical model and simulation for product ABDEGI.

<table>
<thead>
<tr>
<th>Demand process</th>
<th>Product ABDEGI order rate</th>
<th>Simulation</th>
<th>Analytical model</th>
<th>Difference</th>
<th>Demand process</th>
<th>Product ABDEGI order rate</th>
<th>Simulation</th>
<th>Analytical model</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{VA} = 0.4; \lambda_{VA} = 200$</td>
<td>Stage-n</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>$\alpha_{VA} = 0.2; \lambda_{VA} = 200$</td>
<td>Stage-n</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Stage k</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td></td>
<td>Stage k</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$\alpha_{VA} = 0.4; \lambda_{VA} = 250$</td>
<td>Stage-n</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>$\alpha_{VA} = 0.2; \lambda_{VA} = 250$</td>
<td>Stage-n</td>
<td>1</td>
<td>2</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>Stage k</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td></td>
<td>Stage k</td>
<td>1</td>
<td>2</td>
<td>-1</td>
</tr>
<tr>
<td>$\alpha_{VA} = 0.4; \lambda_{VA} = 275$</td>
<td>Stage-n</td>
<td>3</td>
<td>4</td>
<td>-1</td>
<td>$\alpha_{VA} = 0.2; \lambda_{VA} = 275$</td>
<td>Stage-n</td>
<td>2</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Stage k</td>
<td>3</td>
<td>4</td>
<td>-1</td>
<td></td>
<td>Stage k</td>
<td>1</td>
<td>2</td>
<td>-1</td>
</tr>
<tr>
<td>$\alpha_{VA} = 0.4; \lambda_{VA} = 310$</td>
<td>Stage-n</td>
<td>4</td>
<td>4</td>
<td>0</td>
<td>$\alpha_{VA} = 0.2; \lambda_{VA} = 310$</td>
<td>Stage-n</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Stage k</td>
<td>4</td>
<td>4</td>
<td>0</td>
<td></td>
<td>Stage k</td>
<td>2</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 12
ANOVA test of analytical model and simulation differences.

<table>
<thead>
<tr>
<th>System parameter</th>
<th>F</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safety stock difference (analytical model and simulation model)</td>
<td>0.107</td>
<td>0.746 0.939</td>
</tr>
<tr>
<td>Order rate (analytical model and simulation model)</td>
<td>0.312</td>
<td>0.578 0.896</td>
</tr>
<tr>
<td>Backorders (analytical model and simulation model)</td>
<td>3.253</td>
<td>0.081 0.612</td>
</tr>
</tbody>
</table>

Table 13
Comparison of other operational level Supply Chain Optimization software.

<table>
<thead>
<tr>
<th>Demand Planning</th>
<th>F</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAP APO [23]</td>
<td>I2 RHYTIM [23]</td>
<td>The proposed DSS</td>
</tr>
<tr>
<td>1. Promotional planning, causal analysis</td>
<td>Forecasting process through statistical methods and multiple inputs from different organization units</td>
<td>1. Centralized forecast</td>
</tr>
<tr>
<td>2. Life cycle concept</td>
<td></td>
<td>2. Supply chain reconfiguration</td>
</tr>
<tr>
<td>3. Collaborative forecasting</td>
<td></td>
<td>3. Aligning product and supply chain reconfiguration</td>
</tr>
<tr>
<td>Available to Promise (ATP)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>User friendly product catalog and product configuration</td>
<td>1. Inventory allocation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Risk sharing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Implement APIOBPCS</td>
</tr>
<tr>
<td>Distribution Planning</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Use transportation modeler, optimizer and manager order by customer service and financial settlement</td>
<td>1. VM application, 2. The application of APIOBPCS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Optimal response on demand and supply synchronization</td>
</tr>
<tr>
<td></td>
<td>1. Transportation planning and vehicle scheduling to multi-site optimization by GA and additional heuristic components</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. VMF Support</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. Demand–supply synchronization</td>
<td></td>
</tr>
</tbody>
</table>

References

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