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Design of agile supply chains including the trade-off between number of partners and reliability

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Abstract: The reliability of supply partners is particularly vital in agile supply chains as it is vulnerable to the inability of a supply partner to meet its high responsiveness and flexibility requirements resulting in the disruption of the whole network. Disruption can have expensive and extensive results for the entire agile supply chain. To mitigate the risk of disruption and improve the reliability of the whole agile supply chain, decision-makers need to pay more attention to supply chain design and construction, whilst simultaneously taking into account the sourcing strategy decisions. This paper proposes a series of models for the design of agile supply chains using dynamic programming modelling. These provide decision-makers with a systematic way of analysing one of the key decisions of sourcing strategy, namely the trade-off between the number of supply partners and reliability. The efficacy of the models is demonstrated through their application to a Chinese bus and coach manufacturer by way of an empirical illustration. The results show that this approach is effective for this application and it can be applied in other related decision-making scenarios. The methods offered in this paper provide managers with a practical tool to design their agile supply chains while considering the trade-offs between the number of partners and the reliability of the entire agile supply chain.

Keywords: Supply chain design; Supply chain reliability; Agile supply chain; Partnership; Dynamic programming

1. Introduction

Supply chain disruption is one of the most common problems in supply chain management (Purvis et al. 2016). Veysey (2011) found that approximately 85% of companies have experienced supply disruption at least once. Even if all of the key parameters of a supply chain are known with certainty, disruptions may still be experienced from time to time (Miao et al. 2009; Gualandris and Kalchschmidt 2015). Disruptive events may happen anywhere and at any time, affecting any point in the supply chain from raw materials to end-products (Diallo et al. 2017). Their causes can include extreme events, such as natural disaster, financial crisis, war, terrorism and political instability, or other more routine, but nonetheless serious causes, such as fires, labor strikes, system breakdowns, and material supply delays (Ruiz-Torres and Mahmoodi 2007). For instance, Hurricanes Harvey and Irma in 2017 on the US Gulf Coast caused extensive disruptions to many supply chains, including production, processing, warehousing, transportation and retailing. Furthermore, disruptive events may sometimes last for an extended period of time, as for example in 2010, when disruptions in flight schedules due to the unpredictable spread of volcanic ash from Iceland had a significant impact on supply chains of European companies for many months (Banker 2010). The earthquake and subsequent tsunami in northeast of Japan in 2011, disrupted the auto supply chains of Toyota, Honda and Nissan, and continued to have impacts for several years.

Disruption can have expensive and extensive adverse consequences (Arasteh et al. 2014). Thus, reliability has been a key factor in supply chain decisions as any supply chain requires high reliability to ensure both its effectiveness and efficiency (~~Burkovskis 2008;~~ de Oliveira e Silva et al. 2016). This is because disruption risks are fundamentally different from other types of risk, such as customer demand uncertainties. Supply disruption will completely halt material and production flows and cause irreparable loss to the whole supply chain. Therefore, designing reliability into the supply chain is one of the most effective ways to mitigate disruption risk. Supply chain design is central to a supply chain's reliability (Purvis et al. 2016). There are two widely used strategies which can be applied to mitigate the risk of supply chain disruption within the literature, namely:

a) Buyers reduce the partner base to build a long-term relationship and invest in improving their partners' processes, with the aim of achieving improvements in their reliability, quality of coordination, delivery performance, innovation, etc. (Meena and Sarmah, 2016). For instance, manufacturers such as Volkswagen, Ford, and GM have recently been working very closely, in China, with the tiers of their supply chains in order to improve the reliability of the entire supply chain in a country with a rapidly developing supply base. Yet, a reduced partner base may expose the buyers and the entire supply chains to the risks of supply disruption and increase interdependency. Any failure of a single partner can affect the performance of the whole supply chain dramatically (Zhang et al. 2016).

b) Buyers source from multiple partners to improve supply chain reliability, using multi-sourcing, backup sourcing, and emergency purchases (Tang et al. 2014) to mitigate the risk of supply chain disruption. For example, in a multi-stage supply chain, there are disruption risks at every stage (e.g. raw materials and semi-finished products supply, manufacturing and assembly, distribution and retail). If there is only one single partner at each stage, there is much higher risk of supply disruption for the whole supply chain than there would be the case with multiple partners at each stage.

Agile supply chain (ASC) construction involves a commitment to fulfilling customer demand promptly (Wu and Barnes 2010, 2012). It is highly important to design a reliable ASC by considering the risks and reliability of supply whilst constructing a supply chain with great responsiveness and flexibility. The inability of a partner to stick to the delivery schedule could result in the disruption of the whole network (Van Nieuwenhuyse and Vandaele 2006). This is because when pursuing the quick response and high flexibility needed to meet market changes, there is normally very short lead time and low inventory to “buffer” any interruptions between every stage in ASCs (Wu and Barnes 2011; Zhang et al. 2016). Therefore, the reliability of partners is vital to ASCs. In addition, besides considering which partners are capable and reliable, designers of supply chains also need to determine how many partners should be included in ASCs. This is an important and fundamental issue to make the ASC both reliable and responsive (PrasannaVenkatesan and Kumanan 2012; Wu and Barnes 2016). The selection of the optimal number of partners has received much attention both from academics and practitioners (Meena and Sarmah, 2016). However, in the literature, very little attention has been paid to incorporating an analysis of the trade-off between the number of partners and the reliability into the design of agile supply chains as a simultaneous exercise. This paper aims to address this problem and so help organizational decision-makers considering the reliability of a given supply chain as a whole, to construct ASCs and analyse the trade-off between the number of partners and reliability of ASCs, with limited managerial resources and potential options through dynamic programming modelling, simultaneously.

This study draws on data from a Chinese bus & coach manufacturer, Company K (a pseudonym). Since its establishment, Company K has achieved an annual average sales growth of 30%, producing over 400,000 buses in total. Currently, Company K has three manufacturing bases on the southeast coast of China. Their products have been delivered to customers in 130 countries on all five continents. As the majority of its products are made-to-order or engineered-to-order, Company K needs to build an ASC with high responsiveness and flexibility to fulfil fast changing demand for highly customized products. It cannot stock any finished goods and also tries to minimize its raw materials inventory. Therefore, Company K is dedicated to building an ASC that can fulfil customers demand whilst maximizing its total reliability within limited resource constraints. However, determining how to design the ASC as well as how to balance the numbers of partners and the reliability of the whole ASC is a big issue for Company K. This study aims to construct an effective model for this kind of problem and so help Company K to solve their issue. Further sensitivity analyses are performed to show the trade-offs between the number of partners and the reliability of the entire supply chain in more details.

The paper is organized as follows. The next section reviews the literature on reliability, supply chain design and ASCs. Section 3 proposes models for ASC design with exogenous supply reliability. Section 4 provides an empirical illustration with sensitivity analysis. Section 5 discusses the managerial implications of the proposed model. Concluding remarks in Section 6 close the paper.

2. Literature Review

Significant progress has been made in understanding how to design supply chains that are cheaper, faster to respond and more flexible. For example, Azad et al. (2014) shows that successfully reducing operational costs, enhancing responsiveness and agility increases the vulnerability of the whole supply chain. To mitigate the risk of supply disruption and construct reliable supply chains, researchers have proposed a number of approaches, such as multiple sourcing versus single sourcing, local sourcing versus global sourcing, performance based supply contracts, and optimization of the order allocation among partners (PrasannaVenkatesan and Kumanan 2012; Behzadi et al. 2017). This study focuses on multiple versus single sourcing accordingly. The literature review is organised into three sub-sections: (1) reliability and supply disruption, (2) supply chain design models considering reliability, and (3) agile supply chain construction and design.

2.1 Reliability and supply disruption

Reliability engineering belongs to one of the well-developed fields of engineering. It has been widely applied to mechanical reliability, software reliability, and transportation network reliability widely (~~Hsu and Li 2011;~~ Wiengarten et al. 2016). However, while there is a growing literature on supply disruption, up to now there has not been a widely-acknowledged definition of supply chain reliability (Tang et al. 2014).

Definitions of supply chain reliability can be divided into two categories: qualitative and quantitative definition. In the qualitative category, Miao et al. (2009) defined supply chain reliability as a supply chain performing well when parts of the chain fail. They classify five types of factors that may influence supply chain reliability. Accordingly, it is helpful to identify and measure these key factors as they may affect the reliability of the whole supply chain. Feng et al. (2014) assumed that each member of the supply chain has an imperfect production process which will result in imperfect products or even supply disruption. In the quantitative category, Lin (2009) defined system reliability as the probability that the maximum flow from the start node to the end node is not less than the demand. Sana (2010) defined reliability as the proportion of defective products that can be influenced by the cost of development. Oh et al. (2010) used a trust value to evaluate the reliability of supply chain partners in collaborative fractal-based supply chains. In this paper, we will follow the quantitative category of literature to define reliability as a probability. This will be discussed further in Section 3.

As to reliability measurement, Hsu and Wen (2002) proposed a reliability evaluation method for airline network planning under demand variations. The main contribution of their research is in providing a post evaluation method in answer to fluctuations in demand and thereby improve the decision-making flexibility on airline flight frequency. Van Nieuwenhuyse and Vandaele (2006) measured delivery reliability as the predictability of the arrival times of the sub-lots and the arrival times of the entire order in case of a lot splitting policy. Their analysis proved that lot splitting improves the delivery reliability of the supplier and hence improves the production schedule stability of the buyer. The decision-making tool they proposed is helpful for supply chain managers in predicting the delivery reliability of any given lot splitting policy. Furthermore, Miao et al. (2009) tried to divide supply chain reliability into six grades: ideal, superior, satisfy, inferior, crisis and disruption. However, using only qualitative evaluation does not seem adequate for decision-making in ASC design. This research aims to measure whole supply chain reliability quantitatively.

Supply disruption emerges as a bigger problem as supply chains becoming longer and more complex. Adenso-Diza et al. (2012) pointed out that increasing the total number of partners in the supply chain has the strongest negative effect on supply chain reliability, whilst the level of redundancy of partners has the strongest positive effect. Encompassing uncertain supply and random demand, Wang et al., (2014) built a two-stage model in the one supplier and two manufacturers situation. Their research found that manufacturers may not necessarily benefit from improvements in supplier reliability when there is a spill-over effect. Chowdhury and Quaddus (2016) identified that supply chain flexibility and disaster preparation have the highest importance for supply chain readiness, whilst recovery capability has the highest importance to response-recovery. In addition, studies by He et al. (2016) and Xu et al. (2016) have considered the impact of the reliability of suppliers on supply disruptions. He et al. (2016) propose the application of reliability threshold values on buyer pricing and ordering decisions, while Xu et al. (2016) build a flexibility production-inventory model to balance the demand and production disruptions.

More recently, Yan (2018) complements the study by Burke et al. (2009) to show the closed form solution can serve as an effective heuristic for the optimal order quantities from multiple unreliable suppliers when the salvage value is small or the demand is low. Considering interdependencies between suppliers, Hagspiel (2018) discusses the reliability improvement mechanisms by using the cooperative game theory. One of the main contributions is that the research provides the Shapley value as the unique consistent reliability allocation rule. In short, current research has reached a consensus that enhancing reliability of the entire supply chain is an effective and important way to solve the problem of supply disruption.

2.2 Supply chain design models considering reliability

Whilst a large number of optimization based models have been built for the design of supply chain configurations (Wu and Barnes 2011; Sharma et al. 2017), more and more researchers have paid attention to the topic of reliability.

Lin (2009) studied systems reliability and applied network methods to improve the reliability of a complex supply chain system by applying a performance index to evaluate the quality level of the supply network. ~~Considering both economies of scale and demand fluctuation, Hsu and Li (2011) proposed two programming models to determine production reallocation among different plants.~~ PrasannaVenkatesan and Kumanan (2012) proposed a mixed-integer linear programming model and applied particle swarm optimization technology to design and evaluate supply chain sourcing strategies. Feng et al. (2014) constructed an N-stage supply chain model, accounting for member reliability. Their analysis found that improving the reliability of individual supplies can decrease the number of extra supplies needed whilst keeping the same level of reliability of the whole supply chain. Consequently, fewer members of the supply chain can decrease management costs, transaction costs and the complexity of the supply chain as a whole.

Marley et al. (2014) concluded that interactive complexity has an important role in predicting the likelihood of supply chain disruptions. They demonstrated that increased buffers lead to an increased likelihood of disruptions at downstream nodes. Dubey et al. (2015) developed a hybrid solution approach for multi-period multi-product closed-loop sustainable supply chain design problem under uncertainty. Three robust counterpart optimization formulations have been applied and compared comprehensively. Fridgen et al. (2015) proposed Petri Net methodology to model the impacts of exogenous shocks on supply chains. The proposed approach is good at simulating different intensities of an exogenous shock. However, the model was not tested in a real business case. To mitigate the negative impacts of disruptions and minimize total supply chain costs, Kamalahmadi and Mellat-Parast (2016) constructed a two-stage programming model which integrates supplier selection and order allocation decisions. The model can help decision-makers get an insight into supplier selection under the risk of supplier and regional disruptions. Yet, only two sources of disruption in a supply chain were examined.

Modelling the sources of risk as a set of scenarios, Nooraie and Parast (2016) constructed a multi-objective model for supply chain construction. The proposed model and algorithm are very useful for evaluating the investments in improving supply chain capabilities and reducing supply chain risks. However, it is unable to solve the supply chain design problem when considering supply chain disruptions. Kanagaraj et al. (2016) established a model based on both reliability and cost aspects of supplier selection for a product with the objective of the minimum total cost of ownership. This model balances cost factors and risks in an effective way. Yet, it would be more realistic in practical applications, if more factors affecting supply chain design (such as delivery performance, capacity, etc.) could be included.

The organization of a supply chain also influences supply chain reliability management. On the one hand, the effectiveness of decentralized supply chain partners depends on the decision-making of coordination of production and purchasing to match real demand with supply, and mitigate their own risk of disruption individually (Tang et al. 2014). On the other hand, the success of centralized supply chain partners depends on supply chain planning and configuration decisions made by considering the reliability of the supply chain as a whole. Tang et al. (2014) summarized two basic incentive mechanisms for buyers to improve their suppliers' reliability, namely a quantity only contract and a subsidy contract. The former is an indirect incentive mechanism, whilst the latter is a direct incentive mechanism. In their dual sourcing model, supply reliability was assumed as endogenous reliability. In contrast, the environment for ASCs is more sensitive to exogenous supply reliability. However, there is a paucity of research of this kind. Consequently, this research will focus on exogenous supply reliability.

2.3 Agile supply chain construction and design

There are fruitful research works that focus on the relationships between supply chain agility and supply chain performance. Based on the dynamic capability view, Eckstein et al. (2015) found that supply chain agility and adaptability (2As) positively affect both cost performance and operational performance. Incorporating supply chain alignment as a third dimension and utilizing the resource-based view, Dubey et al. (2018)'s research suggests that information sharing and supply chain resources influence supply chain visibility which enhances supply chain agility, adaptability and alignment (3As). Tarafdar and Qrunfleh (2017) suggest an information system capability for agility can strengthen the positive relationship between ASC strategy and supply chain performance, based on the information processing view. In addition, based on four U.K. organizational case studies, Gunasekaran et al. (2018) present a framework for the role of big data and business analytics within agile manufacturing. Their qualitative case research found that big data and business analytics play a major role in the agility of an organization.

Whilst resilience and agility are different ideas, they do have in some things in common. On the one hand, resilience is a multi-disciplinary and multi-dimensional concept (Ponomarov and Holcomb, 2009). Supply chain resilience requires organizations to prepare, respond and recover from disturbances and maintain a positive steady state operation in an acceptable time and cost (Ribeiro and Barbosa-Povoa 2018). On the other hand, supply chain agility is the capability to adapt or respond in a speedy manner to a changing marketplace environment (Lotfi and Saghiri 2018). Considering the above definitions, although supply chain resilience and supply chain agility are two distinct terms, they also have some commonality. Ponomarov and Holcomb (2009) present agility as a formative element of resilience. Wieland and Wallenburg (2012) pointed out that resilience is formed by agility, which is reactive, and robustness which is proactive. Carvalho et al. (2012) view agility and resilience as constructs which both help to improve supply chain performance. By constructing a Structural Equation Modeling model, Lotfi and Saghiri (2018) demonstrate that agility brings about resilience. Therefore, ASC needs to consider resilience very carefully.

ASCs, as well as agile manufacturing construction and design have been receiving increased attention (Christopher 2000; Gligor et al. 2015; Fayezi et al. 2017; Ciccullo et al. 2018). Wu and Barnes (2012) proposed a four-phase dynamic feedback conceptual model for ASC construction and design systematically. This model divides the whole process of ASC construction and design into (1) Partner selection preparation, (2) Pre-classification, (3) Final selection, and (4) Application feedback steps.

At phase one - Partner selection preparation, Wu and Barnes (2010) applied Dempster-Shafer theory and mathematic optimization method to develop a set of customized partner selection criteria based on different industry requirements and different companies demands. At phase two - Pre-classification, Luo et al. (2009) used an RBF-ANN model to reduce the numbers of potential partners to a more manageable level by segmenting potential partners into different categories by using the criteria developed in phase one. The proposed model enables the potential partner base to be classified in a way that simplifies the partner selection problem by reducing the solution space. At phase three - Final selection, Wu et al. (2009) utilised an ANP-MIMOP model to choose the most appropriate partners from within one of the appropriate categories provided in phase two. Furthermore, their model can also allocate the optimal order quantities to each selected partner while considering the performance of the whole ASC. At phase four - Application feedback, Wu and Barnes (2009) developed an application feedback and continuous improvement model for partner selection in ASCs. This model can be used in practice to evaluate whether the most appropriate partners only were selected during the whole process of ASC construction and design.

Samantra et al. (2013) proposed a fuzzy mathematical method to quantify the overall degree of agility for ASCs and to evaluate the extent of successful performance of the key elements which could stimulate agility. Their methodology is also useful for benchmarking of different ASCs. Wu and Barnes (2014) also applied fuzzy set theory and integrated it with artificial neural network technology to help decision-makers to select the most appropriate partners for ASCs. The combination of these two approaches could be an effective way to classify potential partners in the qualification phase which contains large amounts of both qualitative and quantitative data.

Dubey and Gunasekaran (2015) developed an agile manufacturing framework which includes six constructs. Supplier relationship management is one of the six constructs and an important enabler of agile manufacturing. Their research pointed out that risk sharing is regarded as one of the important ingredients of supplier relationship management and a cornerstone of success in the agile environment. However, although the above literature identifies different approaches to the design of ASCs, few of them take into account supply disruption and reliability of the entire supply chain in mind, which is critical for the design and construction of ASCs.

2.4 Summary of literature review and the research gaps

From the above detailed literature review, we can summarise and identify the following research gaps: (1) Whilst there is a wealth of research on the topics of both ASC design and supply chain reliability, there is a shortage of research where these two topics intersect, namely the topic of reliable ASC design. (2) In addition, design of ASCs and sourcing strategy are always interdependent decisions, as these two decisions influence each other. However, there is also a shortage of research which take these two key decisions into account simultaneously. (3) Current research on supply chain reliability mostly applies qualitative approaches (e.g. Miao et al. (2009)'s six grades of reliability). There is a need to adopt more quantitative approaches to the measurement of supply chain reliability. In particular, there is a need to develop a method to identify optimal ASC configuration based on rigorous quantitative measurements. (4) The existing supply chain reliability literature focuses on endogenous reliability, where the risk of supply disruption can be forecasted and then effectively mitigated and managed. However, in ASCs exogenous reliability is critical. This is because exogenous supply risk cannot be forecasted as the source of supply risk outside supply chain itself. There is little existing literature that considers this decision-making environment (Tang et al. 2014; Fridgen et al. 2015). (5) Many models have been proposed for ASC design and construction. However, few of these apply a dynamic programming methodology. This is a significant omission as dynamic programming methodology has previously been successfully applied to supply chain design (Wu and Barnes 2011; Lima-Junior and Carpinetti 2017).

This paper aims to bridge the above research gaps and consequently, will propose a series of models for the simultaneous design of ASCs and analysis of the trade-off between the number of partners and reliability through dynamic programming modelling.

3. Dynamic programming models for agile supply chain design

There are two basic approaches to achieve supply chain reliability. The one is to improve the reliability of individual suppliers. The other is to increase the numbers of suppliers, using multi-sourcing as back-up, during unpredictable supply disruptions (Feng et al. 2014). This research, accordingly, focuses on multiple versus single sourcing. The main reason for applying multiple sourcing is to lower the costs of supply disruption and avoid even worse situations, such as the disruption of the whole supply chain when just one single sourcing partner at any stage is incapable of supplying in time if unforeseeable disruptive events happen (exogenous reliability). In addition, if demand for raw materials and/or semi-finished products is high, the risk of dependence on the single partner will be much higher. A partner diversification strategy is extensively accepted to be the best solution for this challenge (Anupindi and Akella, 1993). However, involving more partners in the supply chain may result in a more complicated supply-demand relationship, higher communication and transaction costs, lower benefits scale and the weakening of the bonds of cooperation. Therefore, it is very important to trade-off and find an optimal configuration for the supply chains by considering the above influencing factors, such as reliability of the whole supply chain, the costs of the supply chain configuration, etc.

Dynamic Programming (DP) is a widely-used technique to tackle optimization decision-making problems (Bautista and Pereira 2009). It has been successfully applied to many fields of operations management (~~Li and Cheng 2004;~~ Hsu and Wang 2004; Astaraky and Patrick 2015), especially in solving optimization problems. DP can be traced to the optimality principle of Bellman (1957), which argues that an optimal policy needs to be built by applying optimal policies to every stage of the decision chain (Bautista and Pereira 2009; Tang et al. 2014). In other words, any given decision-making problem can be divided into smaller sub-problems, which are solved sequentially until the original problem is solved. Therefore, DP is a useful mathematical technique for making a sequence of interrelated decisions (Hsu and Wang 2004), as is the case in the supply chain design problem. The DP technique can be used to address the ASC design problem because on the one hand, DP has the ability to maintain solution feasibility (Rong et al. 2008), which is the basis for ASC design, whilst on the other hand, the solutions to already solved sub-problems are stored (Blum 2007), which can give very clear information for decision-makers for the hard decision-making on the trade-offs between the number of partners and reliability of ASCs. Thus, DP is one of the best options to solve this problem.

Following the existing work of Tang et al. (2014), this research defines reliability as the probability that the supply chain will operate effectively to fulfil the customer demand when unpredictable disruptive events happen. In more detail, supply is subject to a random exogenous disruption: for a given production quantity *z*, the output is $z\delta$, where δ has the following distribution:

$$\delta = \begin{cases} 1, & \text{with probability } r \\ \alpha, & \text{with probability } 1 - r \end{cases} \tag{1}$$

In equation (1), $0 \le r < 1$ indicates the perfect-yield probability and $0 \le \alpha < 1$ indicates the imperfect yield rate. Thus, parameter *r* can be seen as the partner's reliability.

This research proposes risk-based dynamic programming decision-making models for partner selection and ASC design. Firstly, it proposes a basic model for general and simple decision-making situations. Then, it develops the basic model into two extended models by including more specific decision-making constraints (the logic framework of the proposed models and its application is shown as Figure 1). The basic model and the extended models are now discussed in turn.

[Take in Figure 1 about here.]

Notations:

i	is the index for the stage of supply chains, $i = 1, 2, \dots, I$
j	is the index for the stage of supply chains, $j = 1, 2, \dots, J$
k	is the index for the options of different solutions, $k = 1, 2, \dots, K$

Decision variables:

x_i	the number of partners at stage i
x_{jk}	a 0-1 variable indicating whether option k is selected at stage j ($x_{jk} = 1$) or not ($x_{jk} = 0$)

Model parameters:

X	is the designed total number of partners in the network
r_i	is the reliability of supply at stage i of the network
r_{jk}	is the reliability of option k at stage j of the network
y	is the reliability of the whole supply chain
c_i	is the resources asked for stage i of the network
c_{jk}	is the resources asked for option k at stage j of the network
C	is the total resources threshold level of the whole supply chain

3.1 Construction of Basic Model

Considering the most fundamental impact factors, this research proposes a *Basic Model* for ASC design with exogenous supply reliability. It is shown below:

$$\textbf{Max} \quad y = \prod_{i=1}^{I} R_i \tag{2}$$

$$s.t. \quad \sum_{i=1}^{I} x_i = X \tag{3}$$

$$R_i = 1-(1-r_i)^{x_i}, \quad \forall i \tag{4}$$

$$x_i \geq 0 \qquad \forall i \text{ , } x \text{ is integer} \tag{5}$$

Eqs. (2) to (4) and Ineq. (5) constitute the *Basic Model* for ASC design with exogenous supply reliability. The objective function shown in Eq. (2) aims to maximize the reliability of the whole ASC. The constraint in Eq. (3) guarantees that the total numbers of partners in the ASC equals to the designed total number of partners in the network. This constraint guarantees the reasonable and acceptable total complex level of the whole supply chain. The constraint in Eq. (4) states the reliability of different stages of the ASC. The constraint in Ineq. (5) defines the types of variables values. The fundamental idea of the *Basic Model* is a trade-off viewpoint. At any stage of the ASC, the more partners, the higher reliability as they are backing up for each other. The probability that they disrupt at the same time is much lower compared to if there was only one partner at this stage. However, the more partners in the network, the more complicated for communication, for lot-sizing, and for closer relationship bond building. Therefore, it is necessary to find an optimal solution to balance these conflicts.

3.2 Construction of Extended Model I with resource constraint

Based on the *Basic Model*, *Extended Model I*, shown below, aims to include resources constraints during the decision-making process:

$$\textbf{Max} \quad y = \prod_{i=1}^{I} R_i \tag{6}$$

$$s.t. \quad \sum_{i=1}^{I} x_i = X \tag{7}$$

$$R_i = 1-(1-r_i)^{x_i}, \quad \forall i \tag{8}$$

$$\sum_{i=1}^{I} c_i x_i \leq C \tag{9}$$

$$x_i \geq 0, \quad \forall i, \ x \ \text{is integer} \tag{10}$$

Eqs. (6) to (8) and Ineqs. (9) to (10) constitute *Extended Model I* for ASC design with exogenous supply reliability. The objective function shown in Eq. (6) aims to maximize the reliability of the whole ASC. The constraint in Eq. (7) guarantees that the total number of partners in the ASC equals the designed total number of partners in the network. The constraint in Eq. (8) states the reliability of different stages of the ASC. The constraint in Ineq. (9) ensures that the total resources required for each stages of the network are less than the total resources threshold level of the whole network. The constraint in Ineq. (10) defines the types of variables values. To make the model simpler and clear, the *Basic Model* does not take resources into consideration during ASC design. However, there are always resources constraints in decision-making for ASC design. Thus, the *Extended Model I* is an effective way to extend the *Basic Model* nearer to practical decision-making scenarios.

3.3 Construction of Extended Model II with resource constraint and potential options

Based on the *Extended Model I*, *Extended Model II* aims to include both resource constraints and potential practical solutions at different stages in the decision-making model. It is shown as below:

$$\textbf{Max} \quad y = \prod_{j=1}^{J} \left(\sum_{k=1}^{K} x_{jk} r_{jk} \right) \tag{11}$$

$$s.t. \quad \sum_{j=1}^{J} \left(\sum_{k=1}^{K} x_{jk} c_{jk} \right) \le C \tag{12}$$

$$\sum_{k=1}^{K} x_{jk} = 1, \quad \forall j \tag{13}$$

$$x_{jk} = 0 \ or \ 1, \quad \forall j, \ \forall k \tag{14}$$

Eqs. (11) and (13), Ineqs. (12) and (14) constitute the *Extended Model II* for ASC design with exogenous supply reliability. The objective function shown in Eq. (11) aims to maximize the reliability of the whole ASC. The constraint in Ineq. (12) ensures that the total resources required for each stage of the network are less than the total resources threshold level of the whole network. The constraint in Eq. (13) restricts selection at each stage of ASC to only one potential option. The constraint in Eq. (14) defines the types of variables values. Besides the resources constraints, the *Extended Model II* aims to take more detailed potential options into account during the network design process. This gives decision-makers more confidence as it excludes impractical options from decision-making. Furthermore, by including the potential options into the model, the results of the model will be more practical and closer to the real business context.

To solve the above models, this research proposes to apply dynamic programming methodology. The start point is to define the key concepts of the dynamic programming model based on the above theoretical models. They are discussed respectively as follows:

a) Stages: The programming stages (i) are designed as the stages of agile supply chain, $i = 1, 2, \dots, I$.
b) States: The states (y_i) are the limited numbers of partners (*Basic Model* and *Extended Model I*) or the numbers of available resources at stage i (*Extended Model II*).
c) Decisions: The decisions (u_i) are the numbers of partners at stage i (*Basic Model* and *Extended Model I*) or the potential options at stage i (*Extended Model II*).
d) Cost function: The cost function can be defined as $v_i(y_i, u_i) = 1 - (1 - r_i)^{u_i}$.
e) Transition function: The transition function can be defined as $y_{i+1} = y_i - u_i$.

This research applies the Matlab® environment and platform which is a mature product of MATH WORKS Co. as the programming environment and tool.

4. Empirical illustration and sensitivity analysis

In this section, the proposed models for ASC design are applied to an empirical illustration, namely Company K (a pseudonym), which operates in the Chinese Bus & Coach Manufacturing Industry in order to illustrate their practical operability. Founded in 1980s, Company K has three manufacturing bases on the southeast coast of China. Since its establishment, Company K has achieved an annual average sales growth of 30%, producing over 400,000 buses in total. It has been listed amongst the “Top 100 Most Valuable Chinese Brands”. Products from Company K have been delivered to customers on all five continents. As the majority of its products are made-to-order or engineered-to-order, Company K does not stock any finished goods and tries to minimize its raw materials inventory, and builds the quick response capability to the fast-changing demands for customization. Company K is dedicated to building an ASC that can fulfil this kind of market demand whilst maximizing its total reliability within limited resource constraints. Section 4.1, 4.2 and 4.3 describes the application of the proposed models within the decision-making environment of Company K.

4.1 Basic Model

In the basic decision-making situation, decision-makers collect the information about the reliability of each supply chain partner (shown as Table 1). From Table 1 we can see that different partners at different supply chain stages have different levels of reliability. The decision-makers need to make a trade-off between the scale of the supply chain (i.e. the total number of partners in the supply chain) and the whole supply chain reliability. By applying the proposed *Basic Model*, Eq. (2) to Ineq. (5), decision-makers can get the optimal results from the dynamic programming process (shown in Table 2). From Table 2 we can see that, if the scale of the supply chain is limited to twelve partners, the total reliability of the supply chain is 0.8763. From Table 2, we can also see the reliability and scale of each stage of the constructed supply chain. It is easy to identify that stage 3 (manufacturing) has the highest reliability while stage 1 (tier 2 suppliers) has the lowest reliability in comparison with the other stages. These results give valuable information to decision-makers for continuous improvement and further resource allocation.

[Take in Tables 1 and 2 about here.]

The dynamic programming result is also shown in Figure 2 in a more intuitive way.

[Take in Figure 2 about here.]

By varying the numbers of partners in the supply chain, decision-makers can compare the reliability of the whole supply chain under the different decision-making scenarios. Table 3 shows the results of the dynamic programming with respect of different partners scale.

Table 3 also shows the calculation time for the dynamic programming for further sensitive analysis. The variation tendency of both the reliability of the whole supply chain and the calculation time are shown in Figure 3. From Table 3 and Figure 3 we can see that as the number of partners in the supply chain increases, both the reliability of the whole supply chain and the calculation time are increasing. However, their rates of increase are different. Compared to the calculation time, the reliability of the whole supply chain increases faster. This phenomenon indicates two points. Firstly, it is easier to enhance the reliability of the whole supply chain while the number of partners is smaller (we might refer to this as *partner economies of scale*). After reaching a certain level, in this case more than sixteen partners, increasing of number of partners has little benefits on increasing the reliability of the whole supply chain (we might refer to this as *partner dis-economies of scale*). Secondly, the increasing rate of calculation time is lower which means the proposed model and the dynamic programming methodology is robust. The calculation efficiency is high and acceptable whilst the problem scale is increasing.

[Take in Table 3 and Figure 3 about here.]

Table 4 shows the comparative growth of reliability both on a moving base and a fixed base ~~(of 5)~~. The comparative growth of reliability on a moving base can be defined as how much the percentage of supply chain reliability would be increased for every additional number of partners; while the comparative growth of reliability on a fixed base can be defined as how much the percentage of supply chain reliability would be increased compared with the supply chain reliability of a fixed initial number of partners (e.g. the fixed numbers of partners and its corresponding reliability are 5 and 0.2988 in Table 4). Their variation trend can be seen in Figure 4. Table 4 also shows the cost benefit ratio of the reliability of the whole supply chain (the number of partners was seen as a resource here; the *cost benefit ratio* could be defined as how much supply chain reliability would be increased for every additional unit of resource required, which equals to the *comparative growth on fixed base* divided by the *resources requirement* increased). Figure 5 describes the decreasing trend of the cost benefit ratio. Based on the above key indicators and the in-depth analysis and comparisons on their different variation trend, decision-makers can draw important conclusions which could support them make the best possible decisions.

[Take in Table 4, Figures 4 and 5 about here.]

From Table 4 and Figure 4 we can see the phenomenon of “partner economies of scale” more easily. The blue line in Figure 4 represents the comparative growth on a moving base. It decreases very fast. When the number of partners is bigger than twelve, the comparative growth on a moving base of the reliability of the whole supply chain drops to less than 5% from more than 30% at the very beginning. In contrast, the red line which represents the comparative growth on a fixed base, increases faster in the beginning but much slower after reaching the “ceiling”. From Table 4 and Figure 5 we can also see a very similar phenomenon. The cost benefit ratio drops rapidly after the number of partners becomes greater than twelve. This information provides a very effective way for decision-makers in balancing the reliability of the whole supply chain with the numbers of partner in the ASC.

4.2 Extended Model I with resource constraint

In most decision-making situations, resources, such as managerial resources, financial resources, and time resources, are always a constraint which cannot be neglected. *Extended Model I* incorporates the resource constraints into the decision-making process. Table 5 shows the reliabilities of each of the supply chain partners and their related resources requirements. In the Bus and Coach Industry, relationship management with partners is vital and very difficult for the whole ASC because of the need for high variety and small batch sizes of semi-finished products. From the Table 5 we can see that the Tier 1 and Tier 2 suppliers have relatively lower reliability whilst having higher resources requirements. Decision-makers need to find an optimal configuration of the whole supply chain to maximize supply chain reliability with limited the total resources requirements. Table 6 shows the detailed process of the dynamic programming given the available resources are no more than 140. From Table 6 we can also see that Tier 2 and Tier 1 suppliers (Stage 1 and 2) have the largest numbers of partners, whilst requiring more than half of total resources. This result is in line with the industry’s current characteristics. Figure 6 shows the results of the designed ASC configuration in a more visual way.

[Take in Table 5, Table 6 and Figure 6 about here.]

Table 7 shows the effect of varying the available resources on supply chain reliability and calculation time. Figure 7 describes the variation trend of the results shown in Table 7. From Table 7 and Figure 7 we can see that both the reliability of the supply chain and the calculation time increases with increasing available resources. The rate of increase of reliability of the supply chain is bigger than the rate of increase of the calculation time.

[Take in Table 7 and Figure 7 about here.]

Table 8 shows a more in-depth analysis of the relationship between supply chain reliability and different resource requirements. It shows comparative growth both on a moving base and a fixed base. Figure 8 shows them in a more visual way. From Figure 8, it is easy to see that there is a sharp drop for comparative growth on a moving base from 45% to 5% when resources increase from 40 to 70. Beyond this interval, the comparative growth on a moving base fluctuates between 1% and 5%. These findings will help decision-makers identify the most effective interval for resources allocation and utilization. In addition, Figure 9 describes the cost benefit ratio in Table 8. We can also identify the most effective and efficient resources quantity (resources requirement = 60) with the highest cost benefit ratio (5.21%). The above decision-making support information can help decision-makers to balance the number of partners as well as resource allocation with the reliability of the whole supply chain and make a good trade-off between them.

[Take in Table 8, Figures 8 and 9 about here.]

4.3 Extended Model II with resource constraint and potential options

Besides considering the resource constraints, for most of decision-making situations, not all combinations of potential partners are feasible and practical due to many different limitations and constraints. Therefore, it is more practical and efficient to exclude those unfeasible and impractical combinations. *Extended Model II* excludes the unfeasible and impractical options and only makes decisions on feasible and practical potential options. This will improve the decision-making efficiency as the results of the decision-making process can be implemented without further modification or adjustment, thereby avoiding any re-calculations and ineffective decision-making.

After carefully sourcing research, decision-makers of Company K collect the feasible potential options for each different stage for their ASC design and construction (shown as Table 9). By applying the proposed *Extended Model II*, Eq. (11) to Ineq. (14), decision-makers will get the optimal result which is shown in Table 10. From Table 10 we can see that more resources are allocated to the previous stage, tier 2 and tier 1 suppliers, as they have lower reliability. To enhance the whole supply chain reliability, more resources need to be utilized at the "bottleneck process".

[Take in Tables 9 and 10 about here.]

For sensitivity analysis, decision-maker can also vary the available resources to evaluate the corresponding ASC reliability. Table 11 shows the programming results and their calculation times. Figure 10 depicts their increasing trend. It is easy to see, from Figure 10, in the first half interval (allocated resources from 30 to 80), the reliability of the whole supply chain increases much faster than in the second half interval (allocated resources from 90 to 140). At the same time, the calculation times increase smoothly. Based on the above increasing trends, we can draw the following two conclusions. Firstly, there are high partner economies of scale of resource allocation interval. At this interval, increasing resource allocation will produce higher returns on reliability improvement. Secondly, the dynamic programming methodology is efficient in solving this optimal problem. The calculation time will not increase sharply when the calculation amount increases.

[Take in Table 11 and Figure 10 about here.]

To evaluate and balance the scale and corresponding reliability of the whole supply chain, decision-makers can analysis the comparative growth both on a moving base and a fixed base (shown in Table 12). Figure 11 describes the variation trends for both of them. As the available resources increases, the comparative growth on a moving base and a fixed base have total different variation trends. The comparative growth on a moving base decreases very fast at the first half interval and then continuously decreases but more smoothly at the second half interval. In contrast, the comparative growth on a fixed base increases very quickly at the first half interval and continuously increases but much slowly at the second half interval. There seems to be a “ceiling” for supply chain reliability improvement after the available resources reach a certain amount. Decision-makers need to take this economic phenomenon into consideration when making their final decisions. Whilst more resources do lead to higher reliability, any supply chain should simultaneously consider its resources utilization efficiency. In addition, Table 12 and Figure 12 provides more information on the cost benefit ratio. Figure 12 clearly shows both the reducing impact of additional resources on the cost benefit ration and the decreasing rate of the impact.

[Take in Table 12, Figures 11 and 12 about here.]

5. Comparative analysis and managerial implications

Section four applied the three proposed models in a specific case by way of empirical illustration. This section of the paper will consider the applicability of the different models by comparing and contrasting the programming processes and results in a systematic way.

~~First of all, the calculation times are collected and compared in Table 13 and Figure 13. (As for the programming processes and programming results of the three proposed models, the *Basic Model* has a bigger data set. In order to make the comparison on the same basis (i.e. similar number of partners), this section extracts the data from the last twelve rows from Table 3 and Table 4 only.) From Table 13 and Figure 13 we can see that there are two different variation trends. The one is shown as the *Basic Model*, the other is shown as the other two extended models. In comparison to the calculation time of the *Basic Model*, the calculation times of the extended models increase much more quickly as the number of partners increases. This finding shows the advantage of the *Basic Model* on its~~

~~programming process. In other words, the *Basic Model* needs for less calculation ability and time to solve the ASC design and construction problem. However, we should also point out that the *Basic Model* is only an elementary decision-making tool. It considers the most fundamental decision-making impact factors only and excludes other constraints and limitations. Therefore, the *Basic Model* is more applicable for an early phase of decision-making when data and information is limited. Application of the *Basic Model* can provide an initial picture for decision-makers and can also indicate the data and information required for further decision-making.~~

~~[Take in Table 13 and Figure 13 about here.]~~

First of all, the comparative growth on a fixed based of different models are collected and compared in Table 13 and Figure 13 (As for the programming processes and programming results of the three proposed models, the *Basic Model* has a bigger data set. In order to make the comparison on the same basis (i.e. similar number of partners), this section extracts the data from the last twelve rows from Table 4 only). Although all of the lines in Figure 14 have an increasing trend, it is very interesting to see that all three proposed models show different variations in both range and speed. The *Basic Model* has the smoothest variation trend (blue line), while the two other models have a much larger variation. This finding indicates that these three have different sensitivities with regard to the allocated resources, with the *Basic Model* having a lower sensitivity to resource allocation than the other two. In addition, in comparison to *Extended Model II* (red line), *Extended Model I* (green line) has a higher sensitivity to resource allocation in the first half interval. This phenomenon shows that it will be more efficient for decision-makers to allocate more limited resources in the decision-making scenario of *Extended Model I* at this interval. The above information can help decision-makers to understand that the same amount of resources may have different impacts on different decision-making scenarios. The key issue here is how limited resources can be invested in the most efficient way. The proposed models and the above comparative analysis can help decision-makers to better understand decision-making situations and make the right decisions.

[Take in Table 13 and Figure 13 about here.]

Secondly, comparative growth figures, on a moving base, for the different models are collected and shown in Table 14 and Figure 14. The variation trends of comparative growth on a moving base merely reverse in comparison to comparative growth on a fixed base. All of the lines in Figure 14 decline, but with different speeds and to different extents. In more detail, the comparative growth on a moving base of the *Basic Model* declines with a very smooth speed and extent. This variation trend corresponds to the variation trend of the *Basic Model* in Figure 13. These smooth variation trends give evidence of the insensitivity of the decision-making scenario of the *Basic Model* compared to the other two decision-making scenarios. When comparing the decision-making scenarios of the two extended models, it is very interesting to see the two different rates of decrease in speed and extent. When resources are very limited, as in the first half of the interval, supply chain reliability in the decision-making scenario of *Extended Model II* (red line) improves more slowly than in the decision-making scenario of *Extended Model I* (green). When total resource increases in the second half interval, things change and the situation reverses. Supply chain reliability in the decision-making scenario of *Extended Model II* (red line) improves faster than the decision-making scenario of *Extended Model I* (green). Again, these findings would help decision-makers to evaluate and assess the number of partners and their resource allocation while considering the ASC design and its entire reliability.

[Take in Table 14 and Figure 14 about here.]

Thirdly, data on the cost benefit ratio are collected and compared in Table 15 and Figure 15. In this research, the cost benefit ratio has been defined as the percentage of reliability improvement per unit of allocated resources increased. For instance, in Table 8, the first cost benefit ratio (4.74%) is the comparative growth on a fixed base (47.42%) divided by the difference of allocated resources between 30 and 40. The same calculation method for the cost benefit ratio is used in Table 14. Thus, we get the green and red lines in Figure 15. The situation is different for the *Basic Model*. As there are no resources to take into consideration, we take the number of partners in Table 4 as a proxy for “resources”. The first cost benefit ratio (34%) is the comparative growth on a fixed base (34%) divided by the difference of partner numbers between 6 and 5. Therefore, we plot the blue line in Figure 15 with a different vertical axis (right axis). From Table 15 and Figure 15 we can see that, generally speaking, all of the cost benefit ratio lines decline as the available resources increase. This finding shows the traditional economic law of diminishing marginal returns, here. The application of this type of analysis could help decision-makers to understand ASC design and the related sourcing strategy more clearly and visually.

[Take in Table 15 and Figure 15 about here.]

Last but not least, it is also helpful to compare the proposed models and findings with the existing research. There are four interesting comparisons to note. Firstly, the proposed models are quantitative in comparison to the previous qualitative ones, such as Miao et al. (2009)'s six grade reliability research. Use of detailed quantitative analysis would enable decision makers not only to quantify their decisions but also to make better strategic sourcing decisions (qualitative decision) as well. Secondly, the proposed models focus on exogenous supply reliability compared to the majority of existing work, which considers only endogenous reliability (Tang et al. 2014; Hagspiel 2018). Yet, as discussed in section 2.4, exogenous reliability is critical in ASCs. Thirdly, this research proposes a series of models considering different decision-making scenarios, in comparison to some of current literature which provides for a single one only (e.g. Nooraie and Parast 2016; Kanagaraj et al. 2016). Specially designated models for specific decision-making scenarios would give greater flexibility and convenience to supply chain managers and enhance their decision-making effectiveness. Finally, compared to the recent works by Dubey et al. (2015), the calculation time (CPU time) of the proposed model is less sensitive to the scale of the problem. In other words, the proposed model and the application of the DP methodology is robust whilst increasing of the scale of the problem.

6. Conclusion

Decision-making for ASC design is both important and challenging (Wu and Barnes 2014;

Derwik and Hellstrom 2017). It is important because the reliability of partners is especially vital as ASCs aim to achieve a supply chain with greater responsiveness and flexibility. This makes them particularly vulnerable to the inability of a supply partner to meet its delivery schedule, resulting in the disruption of the whole network (Peng and Lu 2017). It is challenging because decision-makers need to understand whether it is better to invest their scarce resources in improving the reliability of partners or in increasing the number of partners, multi-sourcing, in order to reduce their exposure to less reliable individual partners (PrasannaVenkatesan and Kumanan 2012; Yousefi-Babadi et al. 2017). This research proposed a series of models to solve the supply chain design problem in response to supply disruption. It provides valuable flexibility for ASC managers to choose and apply the most appropriate model for different decision-making scenarios. This study also proposed a scientific and effective way to analyse the trade-off between the number of partners and reliability. ASC professionals will find it extremely useful to consider the trade-off between the number of partners and the reliability of the entire supply chain using a systematic approach. It will also help ASC managers to rethink their sourcing strategy at the same time. By using Company K and its supply chain as an example, this research demonstrates the efficacy of the application of the proposed models.

The contribution of this research can be summarised as follows. Firstly, it incorporates the consideration of supply reliability within ASC design. Although there is plenty of research into ASC and supply reliability and disruptions, their consideration is separate and isolated. There is little research that considers them simultaneously. In addition, whilst considering reliability within the design of ASCs, this paper also proposes a systematic way of analysing the strategic trade-off between the number of partners and the reliability of ASCs at the same time. Secondly, the proposed models are quantitative but also practical. Using these quantitative measurements and evaluations, it is easy and practical for decision-makers to find the optimal configurations of ASCs. Furthermore, the series of models proposed in this study are closely related but have different applicability. Decision-makers can apply any one or more of them, based on their specific decision-making situations and requirements. This characteristic provides sufficient flexibility for decision-makers. In return, this flexibility can improve both the efficiency and effectiveness of their decision-making. Thirdly, the proposed models investigate exogenous reliability which is critical, but has had little attention in ASC design, there being little published research focusing on this aspect of decision-making. Last but not least, this is the first time that the dynamic programming methodology has been applied in the case of ASC. The attempt to apply this mature methodology to the ASC design has been successful. Dynamic programming offers solutions that are feasible and visible, providing very clear information for decision-makers on the trade-offs between the number of partners and reliability of ASCs.

There are also several limitations of this research. The first is its application in only one case. The specific decision-making environment of a single case may conceal potential application problems that might only become apparent in other decision-making contexts. Secondly, as there is no standard model for dynamic programming, the modelling process could appear complex and opaque to practical decision-makers in comparison to other more visualized methodologies, such as AHP/ANP, Fuzzy Set Theory, etc. Thirdly, some important impact factors are not included in the proposed models, for instance, lead time variation, stock levels and capacity constraints, etc.

Further work is required to overcome the limitations discussed above. In particular, further research needs to concentrate on the application of the models to different decision-making scenarios and contexts. This would strengthen both the generalizability of the research and provide the feedback needed to refine the models and their application. It would be particularly helpful to gather data from organizational decision-makers on both the usability of the models in practice and the extent to which their application leads to successful performance from the resulting supply chain design. Further work is also needed to validate the computationally feasibility of the proposed models for more realistic problems.

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Figures

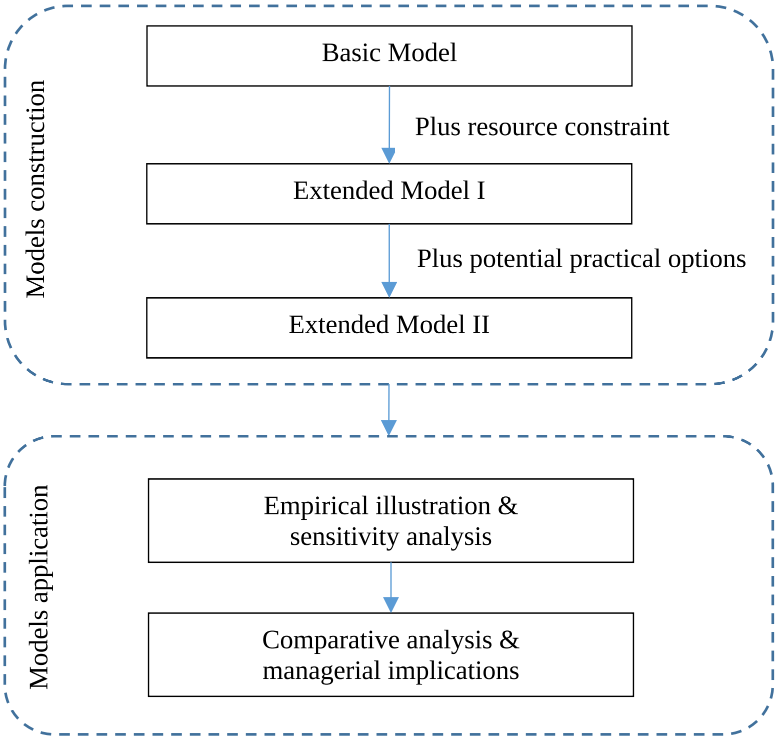

Figure 1: The logic framework of the proposed models and its application

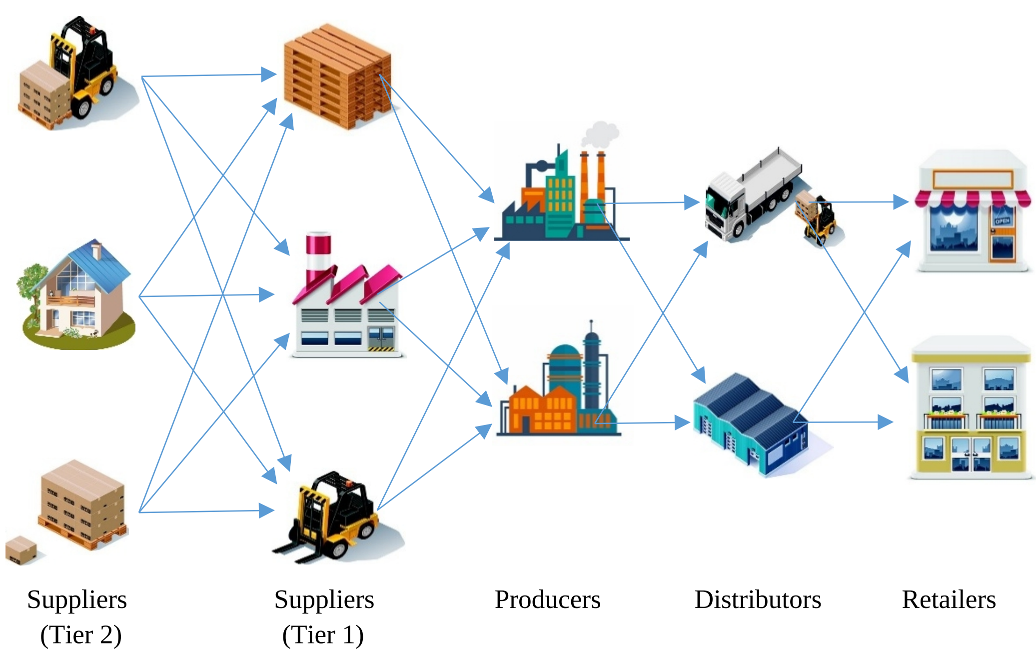

Figure 2: Construction of the agile supply chain (No. of Partners = 12)

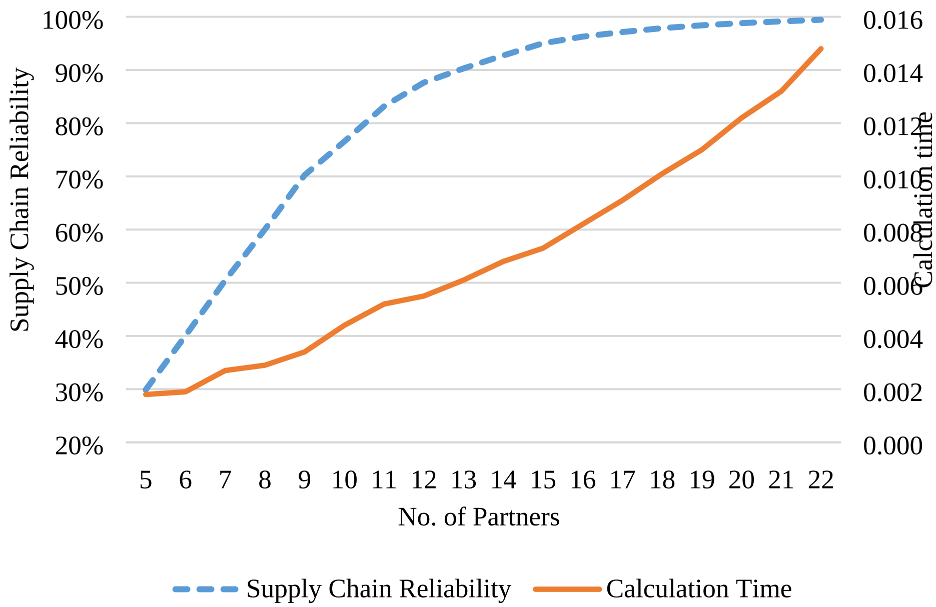

Figure 3: Reliabilities of the whole supply chain and calculation time with respect of different numbers of partners

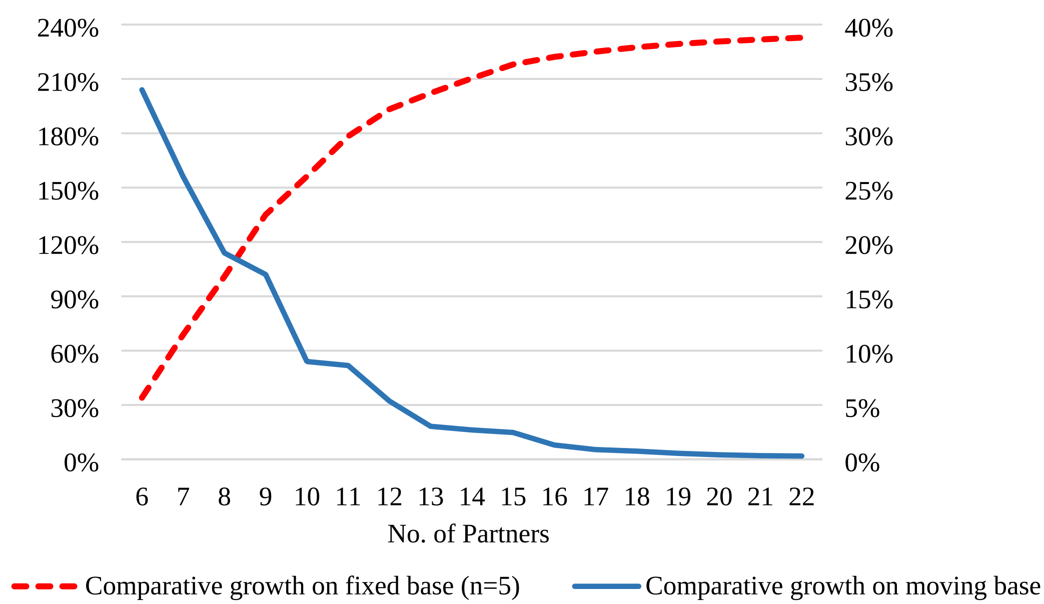

Figure 4: The comparative growth of supply chain reliability with respect of different nos. of partners

Note: *n* represents the number of partners.

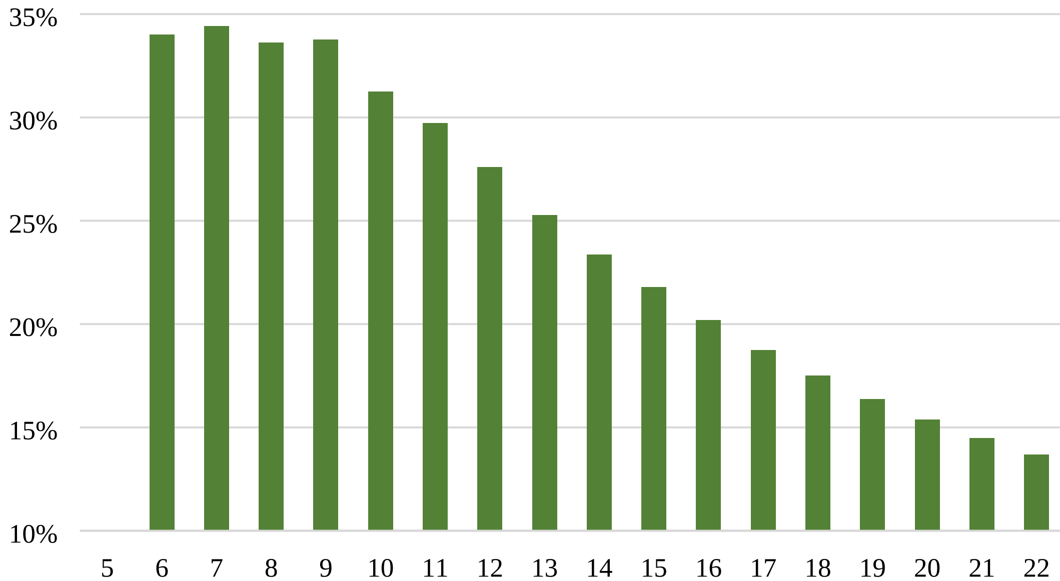

Figure 5: The cost benefit ratio with respect of different nos. of partners (*Basic Model*)

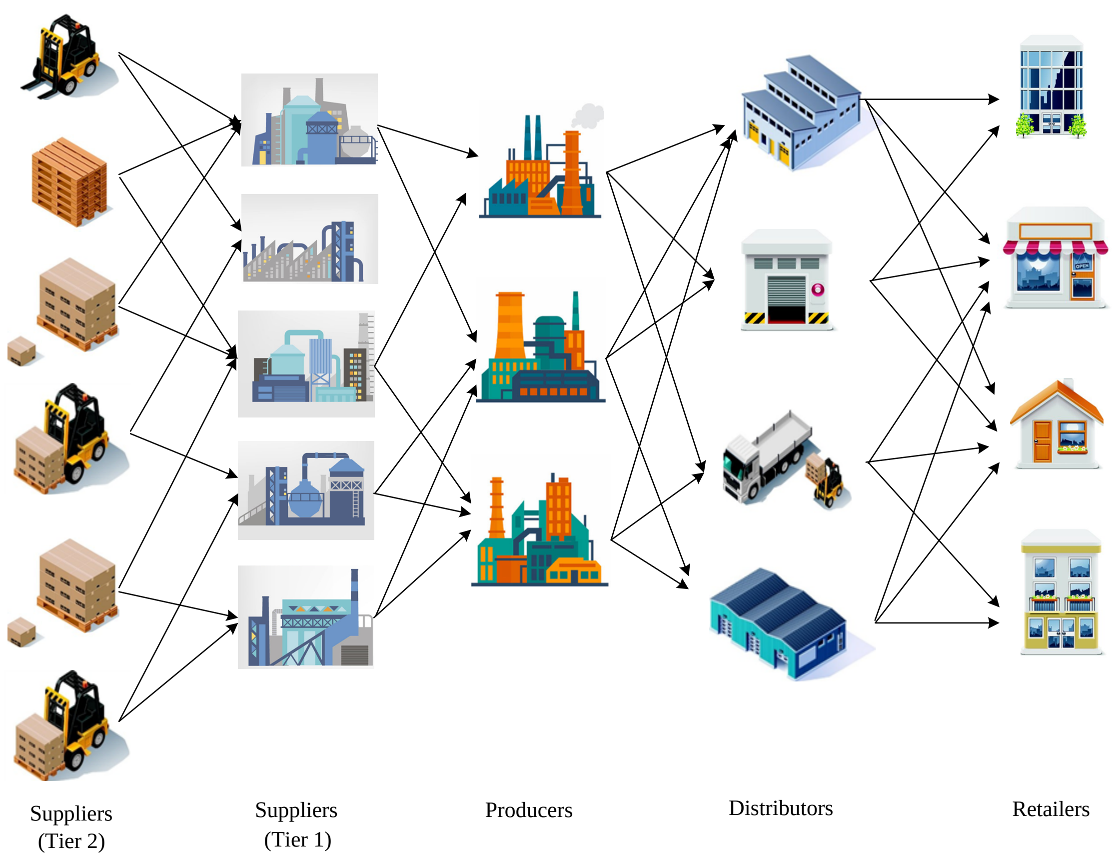

Figure 6: The configuration of the designed agile supply chain (*Extended Model I*)

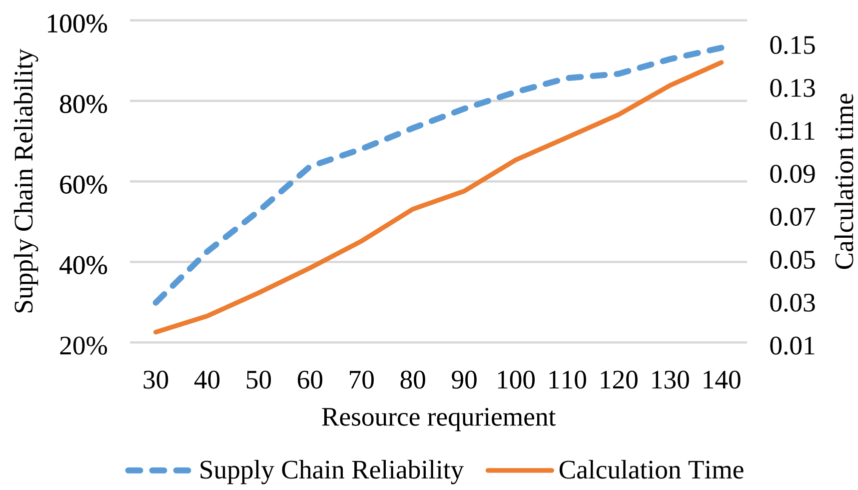

Figure 7: Reliabilities of the whole supply chain and calculation time with respect of different resource requirement (*Extended Model I*)

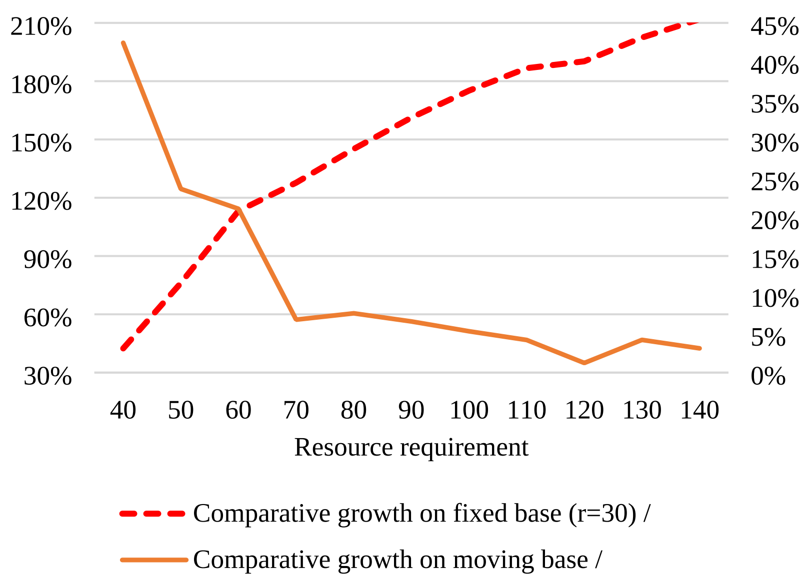

Figure 8: The comparative growth of supply chain reliability with respect of different resource requirement (*Extended Model I*)

Note: r represents the resource requirement.

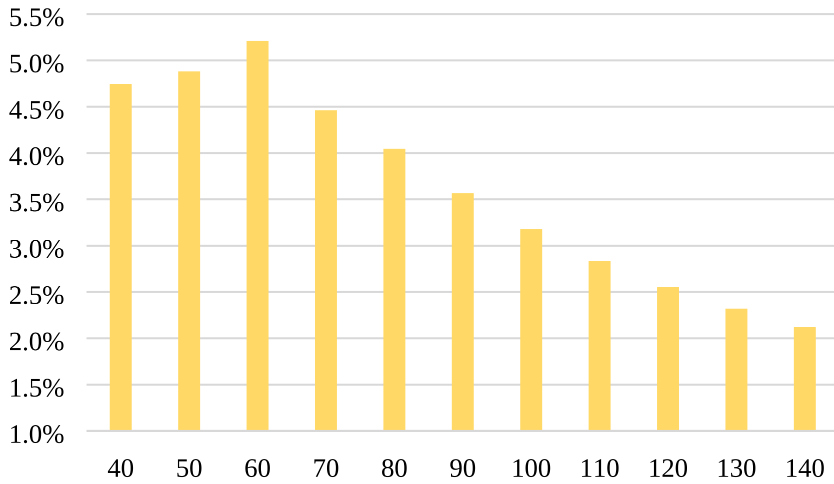

Figure 9: The cost benefit ratio with respect of different resource requirement (*Extended Model I*)

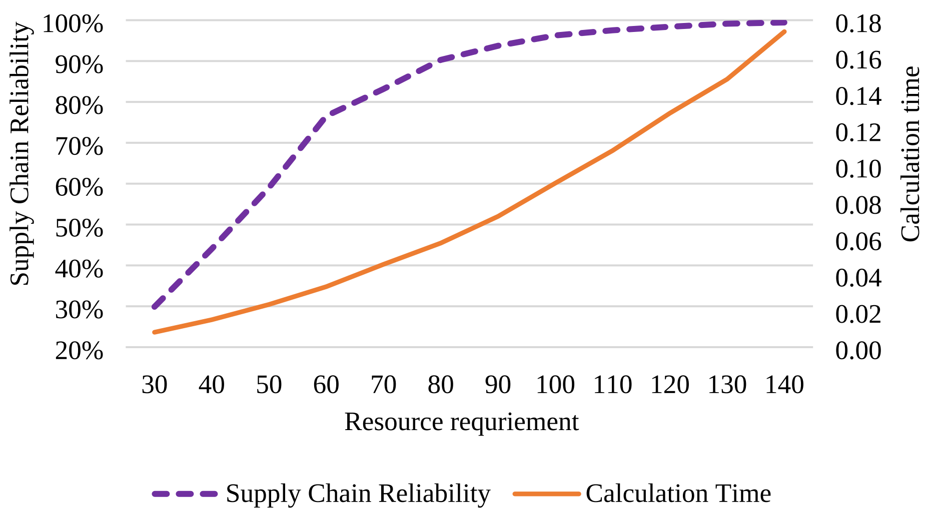

Figure 10: Reliabilities of the whole supply chain and calculation time with respect of different resource requirement (*Extended Model II*)

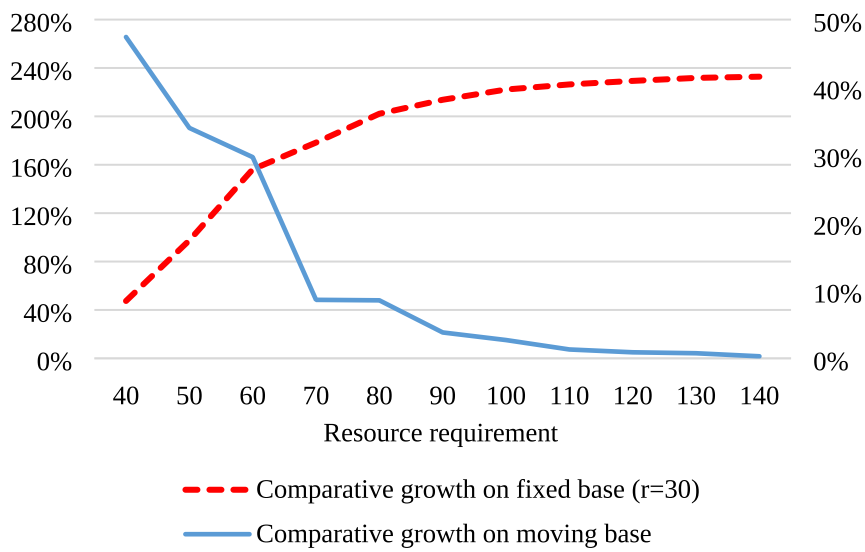

Figure 11: The comparative growth of supply chain reliability with respect of different resource requirement (*Extended Model II*)

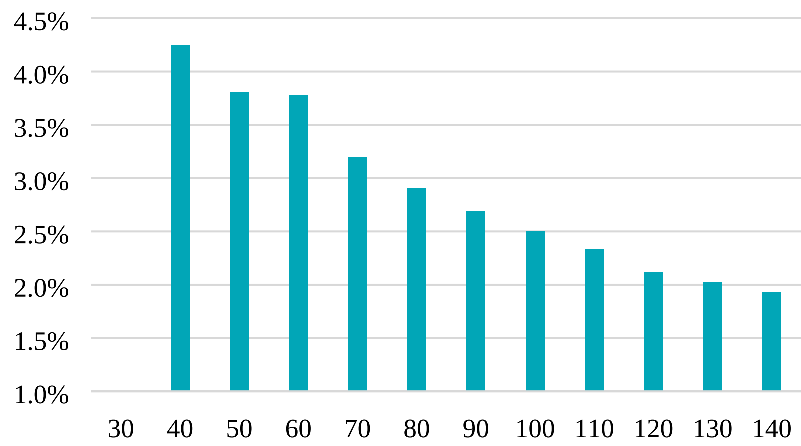

Figure 12: The cost benefit ratio with respect of different resource requirement (*Extended Model II*)

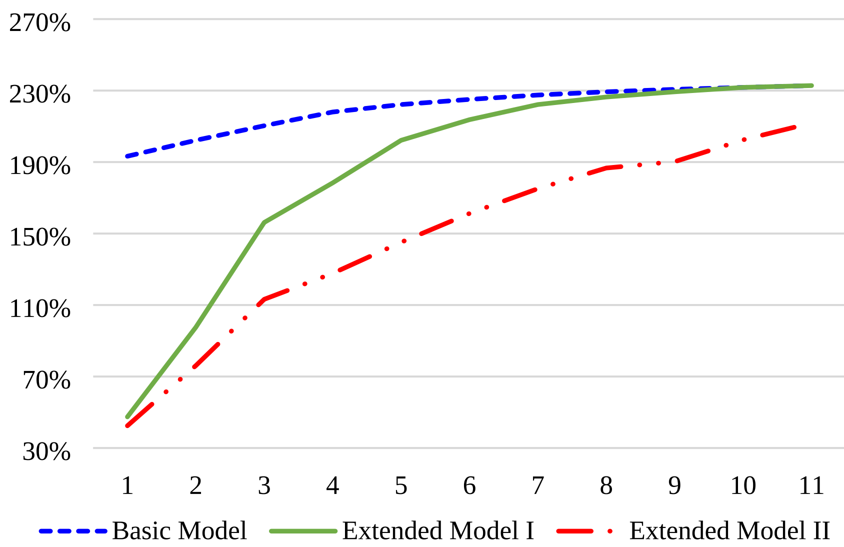

Figure 13: Comparison of comparative growth on fixed base of different models

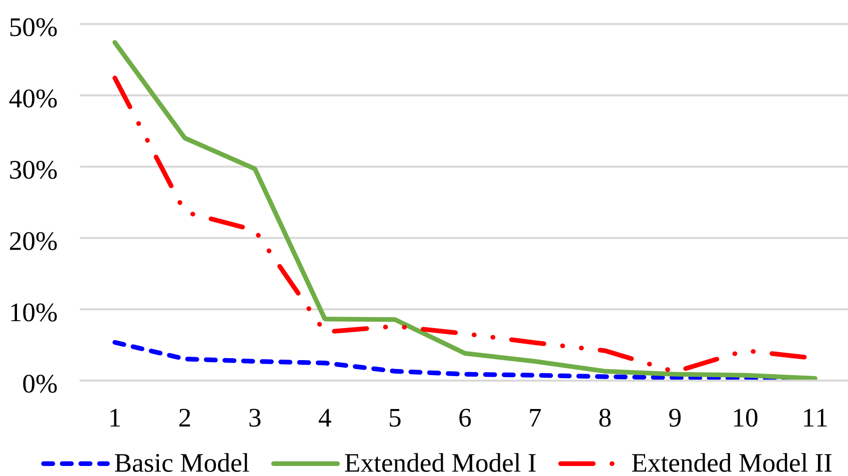

Figure 14: Comparison of comparative growth on moving base of different models

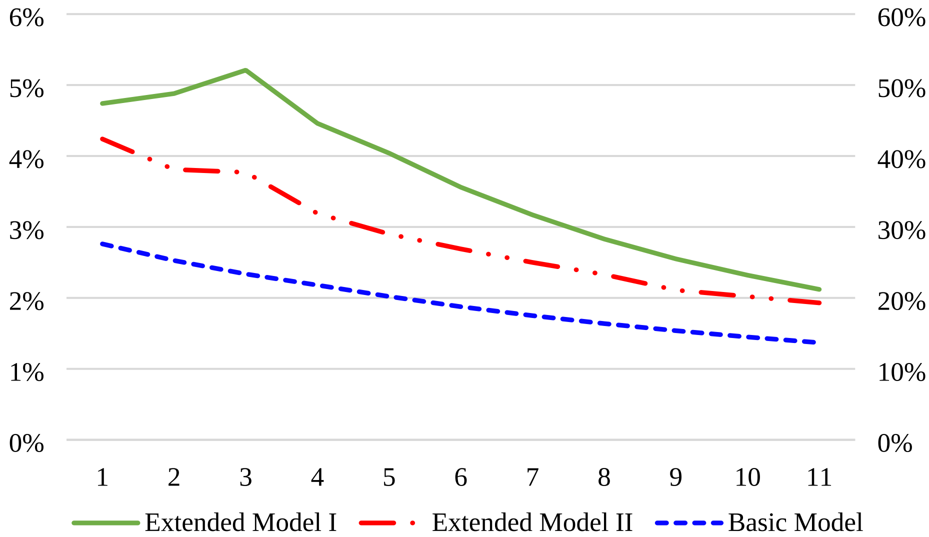

Figure 15: Comparison of cost benefit ratio of different models

Tables

Table 1: The reliabilities of each supply chain partners

Supply Chain Partners	Suppliers (Tier 2)	Suppliers (Tier 1)	Producers	Distributors	Retailers
Reliability	0.66	0.74	0.91	0.81	0.83

Table 2: The process of dynamic programming for *Basic Model*

Stages	Resources	No. of partners	Reliability
1	12	3	0.9607
2	9	3	0.9824
3	6	2	0.9919
4	4	2	0.9639
5	2	2	0.9711

Note: The reliability of the whole supply chain = 0.8763

Table 3: Reliabilities and calculation time of supply chain with respect of partners scale

No. of Partners	Supply Chain Reliability	Calculation Time
5	0.2988	0.0018
6	0.4004	0.0019
7	0.5045	0.0027
8	0.6003	0.0029
9	0.7024	0.0034
10	0.7656	0.0044
11	0.8317	0.0052
12	0.8763	0.0055
13	0.9029	0.0061
14	0.9273	0.0068
15	0.9502	0.0073
16	0.9627	0.0082
17	0.9713	0.0091
18	0.9786	0.0101
19	0.9840	0.0110
20	0.9881	0.0122
21	0.9914	0.0132
22	0.9944	0.0148

Table 4: The comparative growth and cost benefit ratio of supply chain reliability with respect to different numbers of partners

No. of partners	Reliability	Comparative growth on moving base	Comparative growth on fixed base (n=5)	Cost benefit ratio
5	0.2988	-	-	-
6	0.4004	34.00%	34.00%	34.00%
7	0.5045	26.00%	68.84%	34.42%
8	0.6003	18.99%	100.90%	33.63%
9	0.7024	17.01%	135.07%	33.77%
10	0.7656	8.998%	156.22%	31.24%
11	0.8317	8.634%	178.35%	29.72%
12	0.8763	5.363%	193.27%	27.61%
13	0.9029	3.035%	202.18%	25.27%
14	0.9273	2.702%	210.34%	23.37%
15	0.9502	2.470%	218.01%	21.80%
16	0.9627	1.316%	222.19%	20.20%
17	0.9713	0.893%	225.07%	18.76%
18	0.9786	0.752%	227.51%	17.50%
19	0.9840	0.552%	229.32%	16.38%
20	0.9881	0.417%	230.69%	15.38%
21	0.9914	0.334%	231.79%	14.49%
22	0.9944	0.303%	232.80%	13.69%

Table 5: The reliabilities of each supply chain partners

Supply Chain Partners	Suppliers (Tier 2)	Suppliers (Tier 1)	Producers	Distributors	Retailers
Resources requirements	9	7	6	5	3
Reliability	0.66	0.74	0.91	0.81	0.83

Table 6: The process of dynamic programming for the *Extended Model I*

Stages	Resources	No. of partners	Reliability
1	140	6	0.9985
2	86	5	0.9988
3	51	3	0.9993
4	33	4	0.9987
5	13	4	0.9992

Note: The reliability of the whole supply chain = 0.9944

Table 7: Reliabilities of supply chain with respect of different resources requirement (*Extended Model I*)

Resources	Supply Chain Reliability	Calculation Time
30	0.2988	0.0082
40	0.4405	0.0151
50	0.5903	0.0235
60	0.7656	0.0333
70	0.8317	0.0456
80	0.9029	0.0573
90	0.9374	0.0720
100	0.9627	0.0903
110	0.9753	0.1082
120	0.9840	0.1288
130	0.9914	0.1475
140	0.9944	0.1737

Table 8: The comparative growth and cost benefit ratio of supply chain reliability with respect of different resource requirement (*Extended Model I*)

Resource Requirement	Supply Chain Reliability	Comparative growth on moving base	Comparative growth on fixed base (*r*=30)	Cost benefit ratio
30	0.2988	/	/	/
40	0.4256	47.42%	47.42%	4.74%
50	0.5262	34.01%	97.56%	4.88%
60	0.6371	29.70%	156.22%	5.21%
70	0.6805	8.634%	178.35%	4.46%
80	0.7324	8.561%	202.18%	4.04%
90	0.7806	3.821%	213.72%	3.56%
100	0.8221	2.699%	222.19%	3.17%
110	0.8566	1.309%	226.41%	2.83%
120	0.8672	0.892%	229.32%	2.55%
130	0.9037	0.752%	231.79%	2.32%
140	0.9319	0.303%	232.80%	2.12%

Table 9: The reliabilities and resource requirement of each potential options

Options	Suppliers (Tier 2)		Suppliers (Tier 1)		Producers		Distributors		Retailers	
	c_{1i}	r_{1i}	c_{2i}	r_{2i}	c_{3i}	r_{3i}	c_{4i}	r_{4i}	c_{5i}	r_{5i}
1	6	0.66	7	0.74	9	0.91	5	0.81	2	0.83
2	9	0.75	11	0.80	17	0.92	11	0.88	7	0.89
3	15	0.87	13	0.91	27	0.95	20	0.94	10	0.93
4	17	0.94	20	0.96	33	0.97	26	0.97	15	0.97
5	24	0.98	27	0.99	38	0.99	31	0.98	19	0.99

Table 10: The process of dynamic programming for the *Extended Model II*

Stages	Resources	Options	Reliability
1	130	5	0.9800
2	106	5	0.9900
3	79	5	0.9900
4	41	4	0.9700
5	15	4	0.9700

Note: The reliability of the whole supply chain = 0.9037

Table 11: Reliabilities of supply chain with respect of different resource requirements (*Extended Model II)*

Resources	Supply Chain Reliability	Calculation Time
30	0.2988	0.0148
40	0.4256	0.0223
50	0.5262	0.0331
60	0.6371	0.0447
70	0.6805	0.0572
80	0.7324	0.0721
90	0.7806	0.0805
100	0.8221	0.0950
110	0.8566	0.1055
120	0.8672	0.1161
130	0.9037	0.1297
140	0.9319	0.1404

Table 12: The comparative growth and cost benefit ratio of supply chain reliability with respect of different resource requirement (*Extended Model II*)

No. of Partners	Supply Chain Reliability	Comparative growth on moving base	Comparative growth on fixed base (*r*=30)	Cost benefit ratio
30	0.2988	/	/	/
40	0.4405	42.44%	42.44%	4.24%
50	0.5903	23.64%	76.10%	3.81%
60	0.7656	21.08%	113.22%	3.77%
70	0.8317	6.812%	127.74%	3.19%
80	0.9029	7.627%	145.11%	2.90%
90	0.9374	6.581%	161.24%	2.69%
100	0.9627	5.316%	175.13%	2.50%
110	0.9753	4.197%	186.68%	2.33%
120	0.9840	1.237%	190.23%	2.11%
130	0.9914	4.209%	202.44%	2.02%
140	0.9944	3.121%	211.88%	1.93%

Table 13: Comparison of comparative growth on moving base of different models

Scenario	Basic Model	Extended Model I	Extended Model II
1	/	/	/
2	5.36%	47.42%	42.44%
3	3.04%	34.01%	23.64%
4	2.70%	29.70%	21.08%
5	2.47%	8.63%	6.81%
6	1.32%	8.56%	7.63%
7	0.89%	3.82%	6.58%
8	0.75%	2.70%	5.32%
9	0.55%	1.31%	4.20%
10	0.42%	0.89%	1.24%
11	0.33%	0.75%	4.21%
12	0.30%	0.30%	3.12%

Table 14: Comparison of comparative growth on fixed base of different models

Scenario	Basic Model	Extended Model I	Extended Model II
1	/	/	/
2	193.27%	47.42%	42.44%
3	202.18%	97.56%	76.10%
4	210.34%	156.22%	113.22%
5	218.01%	178.35%	127.74%
6	222.19%	202.18%	145.11%
7	225.07%	213.72%	161.24%
8	227.51%	222.19%	175.13%
9	229.32%	226.41%	186.68%
10	230.69%	229.32%	190.23%
11	231.79%	231.79%	202.44%
12	232.80%	232.80%	211.88%

Table 15: Comparison of cost benefit ratio of different models

Scenario	Basic Model	Extended Model I	Extended Model II
1	/	/	/
2	27.61%	4.74%	4.24%
3	25.27%	4.88%	3.81%
4	23.37%	5.21%	3.77%
5	21.80%	4.46%	3.19%
6	20.20%	4.04%	2.90%
7	18.76%	3.56%	2.69%
8	17.50%	3.17%	2.50%
9	16.38%	2.83%	2.33%
10	15.38%	2.55%	2.11%
11	14.49%	2.32%	2.02%
12	13.69%	2.12%	1.93%