Hybrid simulation optimisation modelling for integrated planning of cash and material flows in supply chains

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Abstract

Supply chains are composed of suppliers, manufacturers, distributors, and retailers that are integrated with regard to the physical, financial, and information flows across the supply chain networks. Considering the financial flow within supply chain models is of paramount importance as implementing the supply chain decisions relies on the availability of the financial resources. For instance, opening a new facility in the supply chain network is impossible unless the funding mechanism is explicit.

This research aims to incorporate financial flow modelling into the supply chain models to ensure that the financial resources are available to the supply chain members at the right time while the profitability of the supply chain is maximized. It provides new insights into the methods to monitor the flow of cash within supply chain networks. It further provides a more realistic view to supply chain total cost by considering the cash holding cost as a constituent of the total cost. To analyse and optimise the performance of the studied supply chains in this research, Hybrid simulation optimisation modelling is used as the modelling approach as it is an effective tool to accommodate uncertainties in internal and external factors to the supply chains, conflicting objectives related to the responsiveness and efficiency of the supply chain, and delays in the supply chain product, information, and cash flows.

To distribute the financial resources fairly among supply chain members, two simulation-based optimisation (SBO) models are developed. The first model is a multi-objective model which contains the minimization of the cash cycle for supply chain members and the second model is a single-objective model that considers the cash cycle of the supply chain as objective function. The two models are optimised through finding the optimal values to the inventory and financial decisions parameters. The results indicated that the cash cycle of the supply chain members and the cash cycle of the supply chain can be decreased significantly by identifying the optimal values to the inventory and financial decisions parameters.

To minimize the inventory of the products at supply chain facilities and match the flow of cash with the demand of the supply chain members under economic uncertainty, an SBO model is developed. The developed model aims to minimize the bullwhip effect, cash flow bullwhip, and supply chain total cost through finding the optimal values to the inventory and financial decisions parameters. The results showed that the SBO model is an effective tool in managing the trade-offs between objective functions as it significantly improved the values of the objective functions compared to the simulation modelling.

To manage the trade-off between profitability and cash cycle in a manufacturing supply chain under economic uncertainty, an SBO model is developed. The developed model aims to minimize cash conversion cycle and maximize economic value-added through finding the optimal values to the production, inventory, and financial decisions parameters. The results showed the superiority of the SBO approach over simulation modelling.

Finally, to maximize the profitability of a manufacturing supply chain in an integrated supply chain network design, supplier selection, and asset-liability management problem under economic uncertainty, a hybrid analytical-SBO model is developed. The developed model aims to maximize the economic value added through finding the optimal values to the manufacturing, inventory, financial, and distribution decisions. The results showed that the hybrid approach outperforms the individual analytical and SBO approaches.

Chapter 1. Introduction

1.1. Research Motivation

Severe competition in the marketplace and the increased expectations of the customers have prompted the firms to search for solutions which help them to create competitive edge in order to survive in the highly competitive market. Developing supply chain networks which can respond quickly to the customer demands and deliver the right products at the right time at the minimal price is a preferred way to retain competitive edge. A supply chain network composed of all the parties which are involved in the process of providing a good or service for a customer. The parties include raw material suppliers, producers, distributors, wholesalers, and retailers which are linked through flows of material, money, and information (Gupta and Dutta, 2011). The material flows downstream to the customers, whereas the funds flow upstream, and information moves in both directions. Supply chain management (SCM) is the active streamlining of business supply-side activities to match the supply of products with the consumers' demand and the supply of funds with the demand of supply chain members at a minimum cost. The activities regarding the supply of products include the procurement of raw material, production, distribution, transportation, and so on. While, the activities associated with the supply of funds contain issuing the invoices, payment, securing loans, equity issuance, and so on.

To improve the business supply-side activities many decisions relating to the flow of information, products, and money are required to be made. These decisions are grouped into strategic, tactical, and operational decisions. The strategic decisions have a long-lasting effect on the supply chain performance and are reviewed anywhere between yearly and once every five years. These include the decisions regarding the location and capacity of the supply chain entities. The tactical decisions have a medium-term effect on the supply chain performance and are updated anywhere between quarterly and yearly. These contain the decisions related to procurement, production planning, inventory planning, and so on. The operational decisions have a short-term effect on the supply chain performance and are reviewed anywhere between daily and weekly. These include decisions such as production scheduling, transportation scheduling and so on.

In addition to the supply-side activities which relate to supply chain responsiveness, the supply chain networks are required to be efficient. Although, efficiency and responsiveness do not move at the same direction. An efficient supply chain strives to eliminate waste and maximize performance at a minimum cost. While, a responsive supply chain aims to shorten the product distribution lead time and payment lead time. Therefore, a trade-off is required to be made between efficiency and responsiveness in the supply chain networks.

Supply chain networks may confront uncertainties in external factors which may have detrimental effects on both supply chain efficiency and responsiveness. For instance, uncertainty in demand may result in bullwhip effect. The bullwhip effect occurs when the variations in the demand of supply chain members are amplified when moving upstream of the supply chain (Lee et al., 1997). This phenomenon causes many inefficiencies in supply chain product flow such as excessive inventory, stock-outs and inefficiencies in supply chain cash flow such as increased total cost and higher cost of capital.

In addition to the uncertain external factors, there are some delays in the downstream flow of products, upstream flow of funds, and two-sided flow of information in the supply chain networks. The distribution lead times, trade credits, and information delays are the examples for delays exist in product flow, cash flow, and information flow, respectively.

The existence of conflicting efficiency and responsiveness objectives, delays and uncertainties cause supply chain networks to be complex systems. Computer simulation has been described as the most effective tool for analysing the complex systems. Although the simulation is a powerful tool in representing the complex systems, it is not able to optimise the performance of the systems due to its incapability in identifying the optimal values to the controllable design variables. Incorporating optimisation tools into simulation transform it into a prescriptive tool rather than a descriptive one. On the other hand, optimisation tools may not be able to efficiently accommodate the uncertainties rooted in supply chain networks, due to their inability to depict stochastic behaviours and complex relationships between supply chain entities that exist in real world problems (Mele et al., 2006). Therefore, to optimise the performance of a complex system such as supply chain, the optimisation and simulation tools are required to be integrated. Such an integrated framework is knowns as hybrid simulation optimisation modelling. The hybrid simulation optimisation modelling is divided into simulation-based optimisation (SBO) modelling and hybrid analytical-simulation modelling. The SBO includes the integration of simulation and optimisation algorithms and the hybrid analytical-simulation contains the integration of independent simulation and optimisation models.

Financial factors have a major impact on supply chain planning. Implementing all the supply chain operational decisions rely directly on the availability of the financial resources. A supply chain cannot achieve its desired performance, unless the operational decisions are in accordance with its financial decisions. Moreover, the operational and financial decisions have mutual effect on each other. For instance, investing in production increases production capacity and may affect the production amount. On the other hand, reducing the inventory levels increases the profitability and may affect the amount of cash holding.

The SBO methodology has been frequently applied to address supply chain problems related to planning of product flow. For instance, inventory planning (Mele et al., 2006; Duggan, 2008), capacity planning (Georgiadis and Athanasiou, 2013; Sudarto et al., 2017). While, it has been applied in a limited number of studies to address a supply chain problem concerned with integrated planning of financial and product flows. For instance, Puigjaner and Laínez (2008) applied the SBO to address an integrated supply chain network design, production planning, distribution planning, and cash management problem. The research on the application of hybrid analytical-simulation approach for supply chain modelling is still in its infancy as the approach is new. Therefore, more studies on the application of hybrid analytical-simulation approach for solving the supply chain problems are required to be conducted. Supply chain planning models predominantly focus on the planning of physical flow, while the studies considered the planning of financial flow are very limited in proportion to the relevant literature (Yousefi and Pishvaee, 2018; Chauffour and Malouche, 2011). To conclude, supply chain planning literature requires the SBO and hybrid analytical-simulation models which integrate the planning of cash and material flows to address supply chain problems.

1.2. Research objectives and methodologies

This thesis aims to integrate planning of the cash and material flows within supply chain networks. The integration is performed through four case studies. As shown in Figure 1.1, all four case studies incorporate the stock management problem which refers to the issue of optimally regulating stock variables in a system to meet some system objectives. For instance, supply chain managers seek to minimize the inventory levels whilst providing 100% service levels in fulfilling the orders.

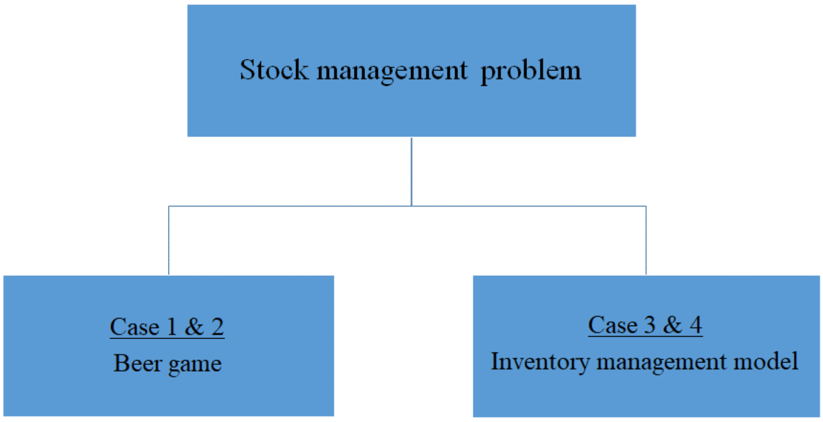


Figure 1.2.1. Case studies incorporating the stock management problem.

Case study 1 and 2 are based on the beer distribution game introduced by Sterman (1989) and replicate a four echelon beer supply chain with the objective of fulfilling customer demand while minimizing the inventory levels. In both case studies, the beer game is further extended through incorporating the financial flow modelling and relaxing the initial assumptions of the game including deterministic demand and distribution lead times. In case study 1, minimizing the cash conversion cycles, which is a metric for working capital performance, of the supply chain members are considered as objective functions. In case study 2, the existence of the cash flow bullwhip which relates to the bullwhip effect in the cash flow is illustrated and it is minimized. In case study 3, the inventory management model developed by Sterman (2000) is extended through incorporating the flow of cash within the supply chain network. The objective of the original model is to balance production rate and inventory levels for a manufacturer in order to fulfil the customer demand. While, the extended model in addition to the product flow decisions such as production rate seeks to determine the optimal financial decisions such as collection policy from the customer and the payment policy to the supplier in order to minimize the cash to cash cycle of the supply chain while fulfilling the customer demand. In case study 4, the developed inventory and cash management model in case study 3 is integrated with an optimisation model in which the optimal network structure and the optimal values to the stock variables such as inventory and cash are determined considering the capacity constraints. To put it in a nutshell, the principal objectives of the research are enumerated as follows:

1. Managing the trade-offs between conflicting cash conversion cycle minimizations for supply chain members

2. Reducing the bullwhip effect and cash flow bullwhip in a supply chain under deterministic demand and lead times, stochastic demand and deterministic lead times, and stochastic demand and lead times
3. Managing the trade-offs between the financial performance and liquidity in a supply chain network under economic uncertainty
4. Addressing an integrated supply chain network design, supplier selection, inventory planning, and asset-liability planning

To achieve the first three research objectives, the SBO methodology in which system dynamics simulation and genetic algorithms (GA) are integrated is applied. The GA determines the optimal values to the controllable decision parameters in the system dynamics model. The fourth objective is addressed using the hybrid analytical-SBO methodology in which an SBO model and a mixed integer linear programming (MILP) model are integrated. The MILP model identifies the optimal values to the decision variables of the simulation model, while the optimal values to the decision parameters of the simulation model are determined by the SBO model.

1.3. Summary of contributions

The primary contributions of this thesis are as follows:

A methodology for working capital management in a supply chain using the SBO is provided. The employed methodology identifies the optimal values to the inventory and financial decision parameters. This work has been published at IEEE conference on intelligent systems, Portugal, 2018. (Badakhshan et al., 2018).

A methodology for reducing the bullwhip effect and cash flow bullwhip in a supply chain using the SBO is presented. The efficiency of the methodology for various stages of complexity including deterministic demand and lead times, stochastic demand and deterministic lead times, and stochastic demand and lead times is investigated. This work has been published at International Journal of Production Research (IJPR), Volume 58, Issue 17. (Badakhshan et al., 2020).

A methodology for managing the trade-offs between financial performance and liquidity in a supply chain under economic uncertainty using the SBO is presented. The applied methodology determines optimal values to the inventory and financial decisions parameters in three probable economic scenarios. This work will be submitted to an international journal in the near future.

A methodology for integrating supply chain network design, supplier selection, inventory planning, and asset-liability planning under economic uncertainty by employing the hybrid analytical-SBO approach is provided. The applied methodology determines the optimal supply chain network structure, the suppliers to work with, the optimal values to the current and fixed assets, and the optimal inventory parameters such as inventory adjustment time and financial decisions parameters such as payment policy. This work will be submitted to an international journal in the near future.

1.4. Thesis outline

This thesis contains eight chapters and a brief summary of each chapter is provided as follows:

Chapter 1 presents an introduction to the research carried out in this project. The research objectives, methodologies employed, and contributions are discussed.

Chapter 2 provides a comprehensive literature review on applications of simulation-based optimisation modelling and hybrid analytical-simulation modelling in supply chain management. Moreover, a literature review on the supply chain models with financial aspects is given.

Chapter 3 presents an introduction to the system dynamics and the genetic algorithms. The integration of the system dynamics simulation and the genetic algorithms in the form of simulation-based optimisation framework is also discussed. The integration of the SBO and MILP in the form of the hybrid analytical-simulation framework is also elaborated.

Chapter 4 provides the proposed SBO approach to manage the working capital within supply chain networks. The cash conversion cycle is defined and the SBO approach is applied to manage the trade-offs between conflicting cash conversion cycle minimizations for supply chain members in the beer distribution game through finding the optimal values to the inventory and financial decisions parameters.

In chapter 5 the concept of cash flow bullwhip is explained and the proposed SBO approach is applied to reduce the bullwhip effect, cash flow bullwhip, and supply chain total cost in the beer distribution game supply chain. This chapter concludes with two experiments designed to investigate the ability of the SBO reduced the bullwhip effect, cash flow bullwhip, and supply chain total cost when facing stochastic demand and deterministic lead times and stochastic demand and lead times.

In Chapter 6 the same SBO methodology is employed to manage the trade-offs between financial performance and liquidity under economic uncertainty in a real case study from the recent literature. The economic value added and the cash conversion cycle represent the financial performance and liquidity, respectively. The scenario tree approach is also applied to formulate the economic uncertainty. The performance of the SBO methodology is also compared with the performance of the system dynamics simulation in each defined scenario.

Chapter 7 provides the proposed hybrid analytical-SBO methodology that integrates physical and financial flows in a supply chain. The proposed methodology is applied to address an integrated supply chain network design, supplier selection, and inventory and asset-liability planning problem under economic uncertainty. The scenario tree approach is also applied to formulate the economic uncertainty. The performance of the hybrid analytical-SBO methodology in each defined scenario is also compared with the performances of the analytical and SBO approaches.

Chapter 8 draws a conclusion to the thesis where the major achievements of this research are discussed and some potential direction for future research are suggested.

Chapter 2. Literature review

2.1. Introduction

Supply chain management (SCM) is the management of product, information, and financial flows among supply chain members in order to deliver superior customer value at the lowest cost to the supply chain. In this chapter, firstly an overview of SCM is provided. A discussion on the two important paradigms in the SCM, i.e. efficiency and responsiveness, and the drivers of the supply chain are presented. The necessity of incorporating financial flow into supply chain planning is discussed. A taxonomy on supply chain modelling and a comprehensive literature review on simulation-based optimisation and hybrid analytical-simulation modelling is provided to identify the gaps in the literature. Finally, the areas which require further research are recognized and the need for applying the simulation-based optimisation and hybrid analytical-simulation techniques to model the supply chain models with financial aspects is justified.

2.2. Overview of supply chain management

A supply chain is a network of organizations which cooperatively work together in order to manage and improve the flow of products, information, and cash within the network (Christopher, 2005). A supply chain is characterized by a forward flow of products, a backward flow of cash, and a two-sided flow of information. It is composed of a series of inter-organizational and intra-organizational business processes in order to procure raw materials from suppliers, promote these raw materials into the finished products, distribute them to distributors, wholesalers, and retailers, and finally deliver them to the end customers. Brewer et al. (2001) classify key supply chain processes into: customer relationship management, customer service management, demand management, customer order fulfilment, manufacturing flow management, procurement, product development and commercialization, and return. It is imperative for a supply chain to continuously control and improve these processes.

The core objective of a supply chain is to fulfil customer needs while optimizing the total cost including procurement cost, production cost, inventory holding cost, distribution cost, etc (Christopher, 2005). A successful supply chain provides the right product, at the right price, at the right time to the customer. Therefore, customer satisfaction is at the heart of supply chain management. To achieve the customer satisfaction several tasks are required to be carried out within the supply chain networks. The three main tasks of the supply chains are design, planning, and execution. Supply chain design is related to the strategic decisions such as facility location, supply relationships, logistics strategy and so on. Supply chain planning deals with tactical decisions such as production and distribution planning. Supply chain execution corresponds to the operational decisions such as order management and production management (Davis, 1993; Buurman, 2002). Supply chain event management is an additional major task in supply chain management that includes reactive risk management activities such as announcing plan changes and initiating corrective measures (Otto, 2003).

Supply chain tasks including design, planning, execution, and event management are required to be performed in a way that not only result in customer satisfaction through fulfilling the customer demand at the right time and at the right price, but also maintain the supply chain total cost at the lowest possible level. In other words, supply chain tasks aim to improve the efficiency and responsiveness of the supply chain.

Supply chain efficiency is defined as the ability of a supply chain to fulfil the customer demands at the lowest cost (Chopra and Meindl, 2007). An efficient supply chain focuses on lowering various costs which are incurred by supply chain members. These costs include production cost, inventory holding cost, transportation cost to name a few. A supply chain is efficient when the use of resources is optimised and the waste at all costs is avoided.

Supply chain responsiveness is concerned with the ability of the supply chain to respond quickly to the changes in the marketplace (Kilger et al., 2015). These changes might be related to the end customer demand, lead times within the supply chain network and any other internal or external factor which necessitates updating the supply chain plans. A supply chain is responsive when the products move quickly through the supply chain network from suppliers to the manufacturers to the distributors to the retailers and finally to the end customers (Perry et al., 1999).

A responsive supply chain concentrates on shortening the lead times such as manufacturing lead times and distribution lead times which prolong the amount of time that takes to deliver the products or services of the supply chain to the end customers. To reduce the lead times various tools such as electronic data interchange, automated warehousing, and improved manufacturing methods might be applied. Although implementing the solutions for lead time reduction impose extra costs on the supply chain members, in the long-term they result in reducing supply chain costs. For instance, the cost of holding inventory and the cost of lost sales are diminished as a result of lead time reduction.

The characteristics of efficient and responsive supply chains are described in Table 2.1. An efficient supply chain sets decision strategy regarding the product design, pricing, manufacturing, inventory holding, lead time, and supplier selection to minimize the total cost of the supply chain network. While, a responsive supply chain overlooks the cost savings opportunities and focuses on solutions which maximize the speed of responding to customer demands.

Christopher et al. (2016) describe the differences between efficient and responsive supply chains from five perspectives:

1. *Core objective.* The core objective of an efficient supply chain is to reduce the waste. While, the responsive supply chain aims to fulfil customer demand immediately.
2. *Supply chain structure.* The efficiency is related to the developing long-term supply chain partnerships that are reinforced over time. Although, the responsiveness involves reconfiguring the supply chains based on new market opportunities.
3. *Measuring the performance*. Efficient supply chains strive to improve productivity measures such as profit margins. Although, responsive supply chains endeavour to improve responsiveness metrics such as order fulfilment ratio.
4. *Organizing the workflow*. An efficient supply chain concentrates on developing the procedures to standardise the workflow within the supply chain. Whereas, the responsive supply chain focuses on developing the flexible workflows that enable the supply chain members to respond quickly to the market changes.
5. *Planning and controlling of the workflow*. Efficient supply chains plan and control the workflow in fixed time periods, e.g., monthly, while the responsive supply chains emphasise on immediate interpretation of market changes and quick response to the customer demands

Table 2.1. Comparing of efficient and responsive supply chains (Chopra and Meindl, 2007).

	Efficient supply chain	Responsive supply chain
Primary goal	Demand fulfilment at the lowest cost	Quick response to the demand
Product design strategy	Maximize performance at a minimum product cost	Maximize product differentiation
Pricing strategy	Lower margins as price is a primary customer driver	Higher margins as price is not a primary customer driver
Manufacturing strategy	Lower costs through utilizing the benefits of economy of scale	Maintaining the capacity flexibility to hedge against demand/supply uncertainty
Inventory holding strategy	Minimizing the inventory level	Maintaining safety stock inventory to hedge against demand/supply uncertainty
Lead time strategy	Reduce but not at the expense of cost increase	Reduce aggressively regardless of cost increase
Supplier selection strategy	Supplier selection based on cost and quality	Supplier selection based on expedition, quality, flexibility, and reliability

Real world supply chains are neither fully efficient nor fully responsive. According to the Fig 2.1 which illustrates the cost-responsiveness efficient frontier, increasing supply chain responsiveness will cost more, thus lowering the efficiency. Chopra and Meindl (2007) state that demand uncertainty plays a pivotal role in designing an efficient or responsive supply chain. As the uncertainty of customer demand increases the supply chain is required to be more responsive.

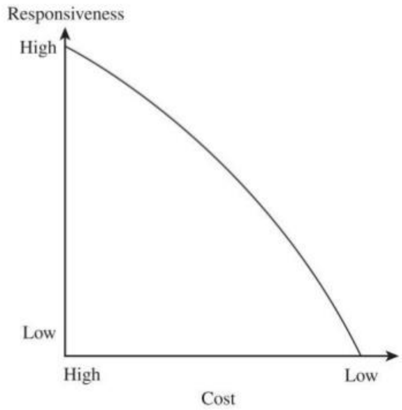


Figure 2.1. Cost-responsiveness efficient frontier (Chopra and Meindl, 2007)

2.2. Drivers of supply chain performance

A supply chain is defined as a chain that links supply chain members through flows of products, cash, and information across the chain. Effective supply chain management is related to the effective management of the products, cash, and information flows across the supply chain to make a trade-off between efficiency and responsiveness that best satisfies the needs of a competitive strategy of a supply chain. The performance of the supply chain could be streamlined through improving its drivers. Chopra and Meindl (2007) classified supply chain performance drivers into six categories: facilities, transportation, inventory, sourcing, information, and pricing. For each individual driver, a trade-off between responsiveness and efficiency is required to be made by supply chain managers. The interplay between these drivers determines whether the supply chain is efficient, responsive or both.

The structure of the supply chain decision making process is illustrated in Fig 2.2. Inventory, facilities, and transportation known as logistical drivers are related to the physical flow in the supply chain. Information, sourcing, and pricing known as cross functional drivers relate to cash and information flows in addition to the physical flow. The performance of the supply chain is contingent on the decisions which are made regarding these drivers. It is worth noting that the framework should not be viewed from top down as the study of the logistical and cross-functional drivers may suggest updating the structure of the supply chain and supply chain strategy. The detailed discussion on each driver and its impact on supply chain performance are provided below.

2.2.1. Facilities

Facilities refer to the locations where a product is manufactured, assembled or stored (Chopra and Meindl, 2007). Facilities are known as the “where” of the supply chain. Two major types of facilities are production and storage sites. Decisions on the location, capacity, and flexibility of the facilities can have a major impact on supply chain performance as they determine the degree of efficiency and responsiveness of the supply chain. For instance, a supply chain is more efficient if multiple retailers across a wide area are supplied by a single centralized storage facility and is more responsive if the retailers are supplied by various storage facilities that increases cost but diminishes the delivery time (Pochampally et al., 2004; Huang et al., 2005). Therefore, when making decisions with regard to facilities, supply chain managers should assess the impact of their decisions on efficiency and responsiveness of the supply chain (Chopra and Meindl, 2007; Kilger et al., 2015).

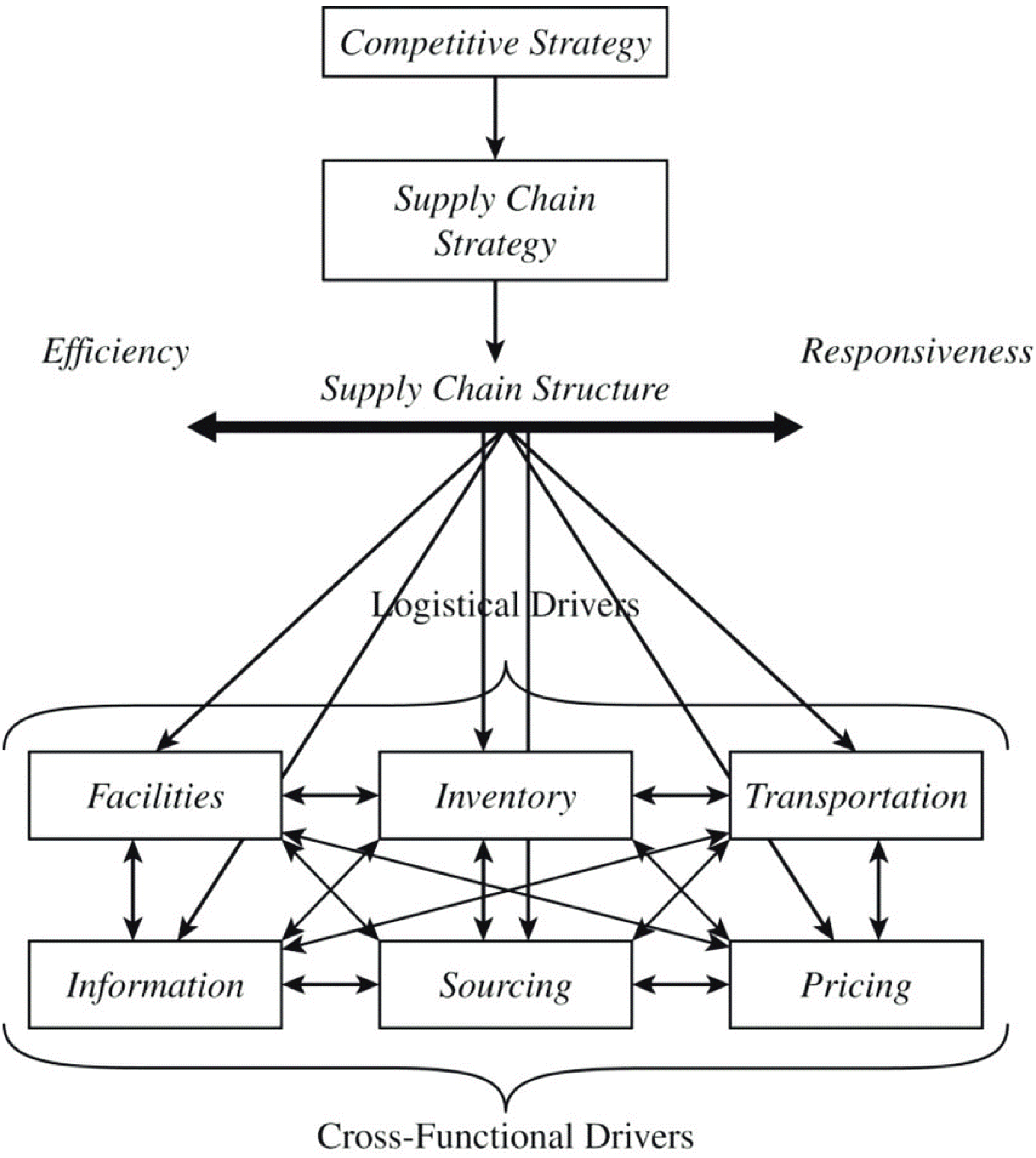


Figure 2.2. supply chain decision making framework (Chopra and Meindl, 2007).

2.2.2. Transportation

Transportation refers to the movement of the products between supply chain facilities (Chopra and Meindl, 2007). Rail, motor, water, and air are basic modes of transportation which have different characteristics and provide different qualities of transport service with regard to expedition, shipment size, shipment cost, and flexibility (Stank and Goldsby, 2000). Transportation decisions can have a major impact on supply chain performance as they determine the degree of efficiency and responsiveness of the supply chain. Faster transportation modes such as air improve supply chain responsiveness while decreasing its efficiency. On the other hand, slower transportation modes such as water shipment improve supply chain efficiencies while limiting its responsiveness. Therefore, the challenge for the transportation decision is to find the right balance between the transportation time and the transportation cost. The transportation decisions must be made in line with customer requirements. Faster transportation modes are preferred when serving customers who seek high level of responsiveness. Whereas, efficient transportation modes are selected when serving cost-sensitive customers. Moreover, transportation mode impacts other supply chain drivers. For instance, transportation model directly impacts on inventory holding cost, stock out cost, and operating costs of the facilities. Therefore, the impact of transportation decisions on other supply chain drivers should be examined while making transportation decisions (Chopra and Meindl, 2007).

2.2.3. Inventory

Inventory refers to the raw materials, work in progress (WIP), and finished goods which are held in production and storage sites within the supply chain (Chopra and Meindl, 2007). Inventory is the main source of cost to the supply chain and it is held because the supply cannot be matched to the demand. Companies are continuously seeking solutions to bridge the gap between the supply and demand to reduce the inventory and thus the cost. Inventory decisions have a decisive influence on supply chain performance (Magnanti et al., 2006). A responsive supply chain entails large quantity of stock to fulfil the orders quickly. While, an efficient supply chain holds small quantity of stock to decrease the costs. The size of safety stock, cycle inventory, and seasonal inventory are inventory related decisions that determine whether a supply chain is more responsive or more efficient. As inventory is a major element of supply chain cost, the inventory decisions should be determined in line with supply chain strategy.

2.2.4. Sourcing

Sourcing in the supply chain refers to the selection of the suppliers, design of contracts with the suppliers, collaboration in product design, procurement of the raw materials, and evaluation of the suppliers' performances (Chopra and Meindl, 2007). Supplier failure is known as one of the top supply chain risks which results in increased acquisition costs, excessive downtime of production resources, poor customer service, loss of revenue, and market share (O'Marah, 2009). Various strategies such as single versus multiple sourcing, local versus global sourcing, optimizing order allocation among multiple suppliers, and performance-based supply contracts have been suggested by the researchers to mitigate the negative impacts of the supplier failure (Swink and Zsidisin, 2006; O'Marah, 2009). Global sourcing includes making a trade-off between reliable high-cost local suppliers and unreliable low-cost offshore suppliers (Ravindran et al., 2010). Multiple sourcing improves the responsiveness of the firms in responding to the customers' demands. Optimizing order allocation among multiple suppliers improves the efficiency of the supply chain in terms of supply chain procurement costs. Performance-based supply contracts assure that during the supply contract the quality of the raw materials/products which are supplied by the supplier remains unchanged and the firms are able to terminate the supply contracts if there is deviation from the committed quality levels.

2.2.5. Information

Information is one of the flows that connects supply chain members. Increased global competition has raised the need for an intimate relationship between the supply chain partners (Flynn et al., 2010). Information sharing is one of the solutions for establishing the intimate relationships among supply chain members. Information sharing refers to distributing useful information between organizational units within supply chain networks. There are various types of information that could be shared among supply chain members. Some familiar types of information which are shared within supply chain networks are: inventory information, sales data, sales forecasting, order information, product ability information, and information about new products (Lotfi et al., 2013). Information sharing may bring several benefits to the supply chain members such as inventory reduction, cost reduction, bullwhip effect reduction and improved resource utilization (Lee, So and Tang, 2000; Mourtzis, 2011). Therefore, supply chain members are required to employ advanced information technologies to share information between them to increase the competitive advantage of the supply chain network in today's global economy (Goodman and Darr, 1998; Lotfi et al., 2013).

2.2.6. Pricing

Pricing refers to the process of determining the amount a company should charge its customers in exchange for its products. A variety of factors such as manufacturing cost, market place, market competition, market condition, and the quality of the product influence the price of a product (Christopher and Gattorna, 2005). Pricing is one of the major elements of the marketing strategy which not only affects the behaviour of the products or services customers but also influences the performance of the supply chain (Voeth and Herbst, 2006). Pricing impacts on the buying decision of the customers as: (1) price is the most flexible marketing variable that can be adjusted to respond to or stimulate customer demand; (2) price is the trigger of the first impression through which the customers make their purchasing decision. Proper pricing is crucial as it has been shown that the customers may stop learning more about the product when the price is higher than expected; (3) sales promotions which are implanted through price adjustment are capable of stimulating demand for a particular product (Christopher and Gattorna, 2005). From a supply chain perspective, the pricing decisions are made with the objective of the increasing the profitability of the supply chain. Chopra and Meindl (2007) argue that the supply chain members should employ a pricing strategy which either increases revenue or reduces cost, or preferably both. The pricing process which conforms to the dynamic behaviour of the customers can help to absorb the customer demand and improve the supply chain profitability (Panda et al., 2015).

As discussed earlier, the essence of supply chain management is to make a trade-off between responsiveness and efficiency through decisions which are made regarding the supply chain drivers, i.e., facilities, transportation, inventory, sourcing, information, and pricing. For each individual driver, a trade-off between responsiveness and efficiency is required to be made by supply chain managers. The interplay between these drivers determines whether the supply chain is efficient, responsive or combined. In this study, decisions on facilities, inventory, sourcing, information, and pricing are made to manage the trade-off between the efficiency and responsiveness.

2.3. Supply chain finance

Supply chain management integrates suppliers, manufacturers, distributors, and customers with regard to the physical and financial flows across the supply chain network (Comelli et al., 2008). Considering the financial flow within supply chain networks is of paramount importance as implementing the supply chain decisions relies on the availability of the financial resources. For instance, opening a new facility in the supply chain network is impossible unless the funding mechanism is explicit. Moreover, the financial and physical flows have a mutual effect on one another. For example, inventory optimisation leads to savings in the financial resources which can in turn provide the required resources for implementing other operational decisions such as production capacity expansion. Therefore, it is imperative to incorporate the financial flow into supply chain models in addition to the physical flow.

The financial flow within supply chain networks is usually considered from two perspectives: (1) cost and (2) flow of funds (Yousefi and Pishvaee, 2018). The cost perspective is related to attributing fixed or variable costs to supply chain activities such as holding inventory and transportation and then deducting these costs from the revenue generated in the supply chain to measure the profitability. The flow of funds perspective is related to considering the financial flow dynamics by studying the dynamics of the assets and liabilities.

Supply chain finance which is described as the intersection of the supply chain management and finance integrates the planning of the financial and physical flows within the supply chain networks considering the financial flow dynamics (Stemmler, 2002; Hofmann, 2005). Supply chain finance focuses on a collaborative inter-organizational financing approach, whereby the financial situations of the supply chain members are optimised by integrating all the financing processes (Pfohl and Gomm, 2009). The objective of supply chain finance is to decrease the cost of capital for supply chain members and accelerate cash flow within the supply chain networks through applying financing solutions on assets and liabilities that are either offered by the financial service providers such as banks to the supply chain members or by the supply chain members to their suppliers and customers (Gomm, 2010; Wuttke et al., 2013).

The financing solutions offered by the financial service providers include short-term solutions on receivables and payables and long-term loans for fixed assets financing. For instance, reverse factoring is a financing solution provided by a financial service provider and initiated by a buyer, in which the financial service provider pays the buyers payables to its suppliers at an accelerated rate in exchange for a discounted price (Camerinelli, 2009). The financing solutions offered by the supply chain members to their suppliers and customers include solutions on optimizing the working capital elements including cash, receivables, payables, and inventories (Gelsomino et al., 2016). The trade credit, advance payment, and vendor-managed inventory are examples of the financing solutions on working capital optimisation.

Working capital optimisation comprises reducing the current assets including inventory, and receivables whilst increasing the current liabilities or payables in order to minimize the capital tied up in the company's turnover process (Hofmann and Kotzab, 2010). Working capital optimisation can be achieved through minimizing cash conversion cycle (CCC) which is a metric that integrates inventory, receivables, and payables and indicates the efficiency of working capital management. The CCC is defined as the average days that it takes for a company to convert a dollar invested in raw material into a dollar collected from customer (Stewart, 1995) is one of the widely used key performance indicators to measure the efficiency of a firm's working capital management. This study focuses on working capital optimisation by using the financing solutions that are provided by the supply chain members to their customers and suppliers in presence of economic uncertainty. Among various solutions, this study focuses on trade credit and advance payment.

- ***Trade credit*** is an agreement between the buyer and the supplier in which the buyer is permitted to postpone the payment for the received goods or services to a scheduled later time. Trade credit can be defined as a type of 0% financing offered by the supplier to the buyer.
- ***Advance payment*** is an agreement between the supplier and the buyer in which the supplier is paid for the goods or services which have not been received by the buyer. Advance payment can be defined as a type of 0% financing offered by the buyer to the supplier.

There are cases in which the buyer is allowed to postpone part of the value for the received goods or services known as partial trade credit and the supplier is paid for part of the received order known as partial advance payment. In this study, each supply chain member offers either full or partial trade credit to its customers and either partial or full advance payment to its suppliers.

Economic uncertainty refers to microeconomic, macroeconomic, financial, and market conditions that impact profitability and working capital performance within supply chain networks (Longinidis and Georgiadis, 2013). In this study, the economic value added (EVA) and the cash conversion cycle (CCC) are used to measure the profitability and working capital performance, respectively. The EVA is a widely used index which indicates the economic performance of a firm and considers the real costs associated with the main sources of capital, i.e., equity and liabilities, used by the firm (Ogier, Rugman and Spicer, 2004). Therefore, it provides a more realistic representation of a firm’s profitability.

Considering the uncertainties in economic parameters that are used in calculating the profitability and working capital performance indicators, i.e., CCC and EVA, provides a more realistic representation of the profitability and working capital performance within supply chains. In this study, the concept of economic cycle in which it is assumed that the economic condition between the economic cycles remains unchanged is applied to model the uncertainties in five economic parameters including demand, risk free rate of interest, expected return of the market, short-term interest rate, and long-term interest rate.

- ***Risk free rate of interest*** is the reward for placing the capital in an investment without taking any risks such as the interest rate of a treasury bill.
- ***Expected return of the market*** is the return of the most representative stock market index.

Moreover, this study focuses on asset-liability optimisation. The asset-liability optimisation includes optimizing fixed assets, current assets, current liabilities, long-term liabilities, and equity. In other words, the asset-liability optimisation involves optimizing fixed assets, long-term liabilities, and equity in addition to the working capital. The objective of the asset-liability optimisation is to ensure that assets are available to cover liabilities and is achieved through using the equations of the balance sheet. The balance sheet is a financial statement that reports a firm's assets, liabilities and equity at a given point in time. The core notion behind balance sheet is that the assets are financed by liabilities and/or equity. Therefore, at any given time the value of the assets equals to the value of the liabilities plus value of the equity that is known as the fundamental equation of the balance sheet. The other equations of the balance sheet include equality of the assets, liabilities, and equity with the sum of their elements. In this study, the optimal values to the assets, liabilities, and equity is achieved through maximizing the economic value added (EVA) index.

2.4. Supply chain modelling

Modelling is an extremely powerful tool for analysing complex systems such as supply chains. Various modelling approaches such as optimisation and simulation have been applied to deal with supply chain problems. Giannoccaro and Pontrandolfo (2001) classified approaches for supply chain modelling into: analytical approaches, approaches based on artificial intelligence, simulation approaches, and hybrid simulation optimisation approaches. In this thesis, an overview of the literature on applying analytical, artificial intelligence, and simulation approaches for supply chain modelling is provided to show the application of these modelling approaches for addressing the supply chain problems. Moreover, a thorough review of the literature on applying hybrid simulation optimisation approaches for supply chain modelling is presented to identify the gaps in this area. The literature on hybrid simulation optimisation modelling is divided into simulation-based optimisation modelling and hybrid analytical-simulation modelling and the gaps in both areas are identified.

2.4.1. Analytical modelling

Analytical approaches refer to the approaches such as linear programming, mixed-integer linear programming, stochastic programming, and robust optimisation (Giannoccaro and Pontrandolfo, 2001). A summary of previous works on analytical approaches is provided in Table 2.2. To provide an overview of the studies which applied analytical approaches for supply chain modelling a literature search in web of science database using the keywords such as “stochastic programming” or “robust optimisation” and “supply chain” was conducted and some of the papers which were published in highly reviewed operations and production management journals such as International Journal of Production Economics (IJPE) and International Journal of Production Research (IJPR) were selected and included in Table 2.2.

Table 2.2. Analytical approaches for supply chain modelling

Article	Research scope	Analytical approach
Yu and Li (2000)	Stochastic logistic problems	Robust optimisation
Agrawal et al. (2002)	SC capacity and inventory planning	Stochastic programming
Lababidi et al. (2004)	SC production and inventory planning	Stochastic programming
Guillén et al. (2005)	SC network design	Stochastic programming
Spitter et al. (2005)	SC production planning	Linear programming
Leung et al. (2006)	SC production planning	Stochastic programming
Snyder et al. (2007)	SC facility location	Stochastic location model with risk pooling
Aalaei and Davoudpour (2017)	SC network design	Robust optimisation
Nindyasari et al. (2018)	SC distribution planning	Mixed integer linear programming
Brunaud et al. (2019)	SC inventory planning	Linear programming
Bertsimas and Youssef (2019)	SC inventory planning	Robust optimisation
Ganji et al. (2020)	SC production and distribution scheduling	Mixed integer non-linear programming

2.4.2. Artificial intelligence modelling

Approaches based on artificial intelligence consists of approaches such as fuzzy multi-objective programming, fuzzy linear programming, fuzzy goal programming, evolutionary programming, reinforcement learning, and genetic algorithms (Giannoccaro and Pontrandolfo, 2001). Table 2.3 summarises the studies that applied artificial intelligence approaches. To provide an overview of the studies which applied artificial intelligence approaches for supply chain modelling a literature search in web of science database using the keywords such as "fuzzy linear programming" or "reinforcement learning" and "supply chain" was conducted and some of the papers which were published in highly reviewed operations and production management journals such as International Journal of Production Economics (IJPE) and International Journal of Production Research (IJPR) and highly reviewed journal in the area of fuzzy logic such a "Fuzzy Sets and Systems" were selected and included in Table 2.3.

Table 2.3. Approaches based on artificial intelligence for supply chain modelling

Article	**Research scope**	**Artificial intelligence approach**
Sakawa et al. (2001)	SC production and transportation planning	Fuzzy linear programming
Giannoccaro and Pontrandolfo (2002)	SC inventory planning	Reinforcement learning
Giannoccaro et al. (2003)	SC inventory planning	Fuzzy numbers
Lin and Chen (2003)	SC inventory planning	Genetic algorithm
Kumar et al. (2004)	SC supplier selection	Fuzzy multi-objective programming
Chen and Lee (2004)	SC production and distribution planning	Fuzzy numbers
Deshpande et al. (2004)	SC task assignment	Fuzzy multi-objective programming
Wang and Shu (2005)	SC inventory planning	Fuzzy numbers and genetic algorithms
Truong and Azadivar (2005)	SC network design	Genetic algorithm

Amid et al. (2006)	SC supplier selection	Fuzzy multi-objective programming
Xie et al. (2006)	SC inventory planning	Fuzzy numbers
Kumar et al. (2006)	SC inventory planning	Evolutionary programming
Selim et al. (2008)	SC production and distribution planning	Fuzzy goal programming
Jiang and Sheng (2009)	SC inventory planning	Reinforcement learning
Sun and Zhao (2012)	SC inventory planning	Reinforcement learning
Oroojlooyjadid et al. (2017)	SC bullwhip effect	Reinforcement learning
Yousefi and Pishvaee (2018)	Global SC planning	Fuzzy mixed integer linear programming

2.4.3. simulation modelling

Simulation modelling composed of approaches such as discrete-event simulation and system dynamics (Giannoccaro and Pontrandolfo, 2001). Table 2.4 provides a summary of the studies which employed the simulation approaches. To provide an overview of the studies which applied simulation approaches for supply chain modelling a literature search in web of science database using the keywords such as “system dynamics” or “discrete-event simulation” and “supply chain” was conducted and some of the papers which were published in highly reviewed operations and production management journals such as International Journal of Production Economics (IJPE) and International Journal of Production Research (IJPR) and highly reviewed journals and conferences in the area of simulation modelling such a “Simulation Practice and Theory” and “Winter Simulation Conference” were selected and included in Table 2.4.

Table 2.4. Simulation approaches for supply chain modelling

Article	**Research scope**	**Simulation approach**
Towill et al. (1992)	Bullwhip effect	System dynamics
Towill and del Vecchio (1994)	Bullwhip effect	System dynamics
van der Vorst (2000)	SC network design	Discrete event simulation
Minegishi and Thiel (2000)	SC production and inventory planning	System dynamics
Jansen et al. (2001)	SC distribution planning	Discrete event simulation
Zhao and Xie (2002)	SC information sharing	Discrete event simulation
Hung et al. (2006)	SC production and inventory planning	System dynamics
Nair and Closs (2006)	SC inventory and distribution planning	Discrete event simulation
Chatfield et al. (2007)	SC architecture	Agent-based simulation
Chiang and Feng (2007)	SC information sharing	Discrete event simulation
Chaerul et al. (2008)	SC waste management	System dynamics
Van Der Vorst et al. (2009)	SC network design	System dynamics
Persson and Araldi (2009)	SC production and inventory planning	Discrete event simulation
Ferreira and Borenstein (2011)	SC planning	Agent-based simulation
Das and Dutta (2013)	Closed loop SC	System dynamics
Vidalakis (2013)	SC distribution planning	Discrete event simulation
Long and Zhang (2014)	SC production, inventory and transportation planning	Agent-based simulation
Tian et al. (2014)	Green SC	System dynamics
Cigolini et al. (2014)	SC network design	Discrete event simulation

Bautista et al. (2019)	SC sustainability assessment	System dynamics
Prinz et al. (2019)	SC energy efficiency	Discrete event simulation
Yazan and Fraccascia (2020)	SC waste management	Agent-based simulation
Tipmontian et al. (2020)	SC block chain	System dynamics

2.4.4. Hybrid simulation optimisation modelling

Hybrid simulation optimisation models are constructed through integrating analytical and simulation approaches. Integrating mixed-integer linear programming (MILP) and discrete-event simulation is an example of hybrid simulation optimisation approaches. Simulation-based optimisation is a hybrid simulation optimisation approach which refers to integrating simulation models such as system dynamics and optimisation algorithms such as genetic algorithms. In this thesis, the hybrid simulation optimisation models except for simulation-based optimisation are called hybrid analytical-simulation models. Although, in some studies, the hybrid analytical-simulation modelling was called simulation-based optimisation. To conduct a systematic literature review on applying simulation-based optimisation and hybrid analytical-simulation approaches for supply chain modelling, a literature search in web of science database using the keywords “simulation-based optimisation” and “supply chain” was conducted. The generated papers were then reviewed and classified into (1) the studies which applied simulation-based optimisation approach, i.e., integrating simulation and optimisation algorithms, and (2) studies which employed hybrid analytical-simulation approach, i.e., i.e., integrating simulation and optimisation models**.**

2.4.4.1. Simulation-based optimisation modelling

Tables 2.5 presents a summary of the previous works on the simulation-based optimisation modelling. Table 2.5 is divided into five sections; Article showing the article’s author(s) reference; Research scope presents the article’s main field of study; optimisation algorithm shows the algorithm which was employed to determine the optimal values to the decision parameters; simulation model displays the modelling approach which was used to simulate the supply chain problem; optimisation objective shows the objectives which were considered in the studied supply chain model. The full list of the papers presented in Table 2.5 is given in appendix.

The literature review on simulation-based optimisation (SBO) modelling for supply chain management, shown in Table 2.5, demonstrates that discrete-event simulation is the most applied simulation technique in the SBO models (Jiang and Ruan, 2008; Aydogan-Cremaschi et al., 2009; Ding, Benyoucef and Xie, 2009; Dong and Leung, 2009; Li, Sourirajan and Katircioglu, 2010; Maliki, Sari and Souier, 2013; Kulkarni and Niranjan, 2013; Fischer et al., 2014; Essoussi, 2015; Woerner, Laumanns and Wagner, 2016; Yang, Arndt and Lanza, 2016; Chavez, Castillo-Villar and Webb, 2017; Keramydas et al., 2017; Afshar-Bakeshloo et al., 2018). While, the share of system dynamics simulation in the SBO models is considerably lower than the share of the discrete-event simulation. In terms of research scope, the inventory planning problem which corresponds to the planning of the material flow within supply chain networks has been addressed in a significant number of studied papers (Mele et al., 2006; Schwartz, Wang and Rivera, 2006; Amodeo, Chen and El Hadji, 2007; Gao and Wang, 2008; Veeraraghavan and Scheller-Wolf, 2008; Diaz and Bailey, 2011; Essoussi, 2015). Although, the working capital planning problem which relates to the integrated planning of inventory, cash, accounts receivable, and accounts payable has remained under investigated (Puigjaner and Laínez, 2008; Bandaly, Satir and Shanker, 2016).

The cost minimization has been widely considered as objective function in the supply chain planning models (Beyer, 2006; Chunxu, Feifei and Jianbing, 2007; Yoshizumi and Okano, 2007; Jiang and Ruan, 2008; Aydogan-Cremaschi et al., 2009; Duan and Liao, 2013; Pitzer and Kronberger, 2015; Kara and Dogan, 2018). While the literature on supply chain planning lacks studies that focus on managing the trade-off between financial performance, i.e., cost minimization or profit maximization, and working capital management through developing the multi objective models. Working capital management focuses on minimizing the inventory levels, while financial performance metrics i.e., cost minimization or profit maximization aim to minimizing the backlog cost that is higher than the inventory holding cost.

To fill the gap in the literature of supply chain planning using SBO modelling, in chapters 4-6 of this study, three SBO models which integrate system dynamics simulation and genetic algorithm are developed to address three working capital planning problems. To manage the trade-offs between conflicting objectives in the working capital planning models, multi-objective models are presented in chapters 5 and 6. The model presented in chapter 5, aims to minimize the total cost of the supply chain while minimizing the bullwhip effect and cash flow bullwhip. The model presented in chapter 6, aims to manage the trade-off between profit maximization and CCC minimization which represents the working capital performance. The

CCC is minimized through minimizing the inventory levels. While the profit is maximized through minimizing the lost sale or backlog that is achieved by maximizing the inventory levels.

Table 2.5. Simulation-based optimisation approaches for supply chain modelling

Article	Research scope	Optimization algorithm	Simulation model	Optimization objective
Mele et al. (2006)	SC inventory planning	Genetic algorithms (GA)	Agent-based simulation (ABS) Monte Carlo	Max: Total profit
Schwartz et al. (2006)	SC inventory planning	simultaneous perturbation stochastic approximation (SPSA)	Internal model control (IMC) Model predictive control (MPC)	Max: Profit
Beyer (2006)	SC inventory planning and demand forecasting	NA	Object-oriented Simulation	Min: Total cost
Georgiadis et al. (2006)	SC capacity planning	Proposed MOO methodology	System dynamics (SD)	Min:sustainability dimensions performance cost Min: remanufacturing
Amodeo et al. (2007)	SC inventory planning	NSGA-II	Petri nets	Min: Inventory cost Max: service level
Chunxu et al. (2007)	SC supplier selection and inventory planning	GA	Disperse-event simulation	Min: Total cost
Yoshizumi and Okano (2007)	SC network design	Lagrangian relaxation algorithm Steepest descent method	Not available (NA)	Min: Total cost
Gao and Wang (2008)	SC inventory planning	Particle Swarm optimization (PSO)	NA	Min: Total cost
Jiang and Ruan (2008)	SC inventory planning	PSO	Discrete-event simulation (DES)	Min: Total cost
Sundar Raj and Lakshminarayanan	SC performance assessment and	GA	NA	Min: Total Cost
Veeraraghavan and Scheller-Wolf (2008)	SC inventory planning	Framework proposed by authors	NA	Min: Total Cost
Puigjaner and Laínez (2008)	SC network design, production and distribution planning, and cash management	Two stage shrinking horizon (SHT) approximation	MPC	Max: Change in equity Min: Environmental impact
Duggan (2008)	SC inventory planning	GA	SD	Min: Wholesaler cost Min: Retailer cost
Ding et al. (2009)	SC network design, distribution and inventory planning	NSGA-II	DES	Min: Total cost Max: Service level
Aydogan-Cremaschi et al. (2009)	Life-support system design	NA(deterministic algorithm)	DES	Min: Total cost
Dong and Leung (2009)	SC inventory planning	GA	DES	Max: Production balance Min: Lost sales
Li et al. (2010)	SC inventory planning	Bisection search	DES	Min: Total cost
Georgiadis and Athanasiou (2010)	SC capacity planning	Proposed MOO methodology	SD	Min:sustainability dimensions performance cost Min: remanufacturing capacity expansion

2.4.4.2. Hybrid analytical-simulation modelling

Tables 2.6 presents a summary of the previous works on the hybrid analytical-simulation modelling. Table 2.6 is divided into five sections; Article showing the article's author(s) reference; Research scope presents the article's main field of study; optimisation model shows the optimisation approach which was used for modelling the supply chain problem; simulation model displays the modelling approach which was used to simulate the supply chain problem; optimisation objective shows the objectives which were considered in the studied supply chain model.

The literature review on hybrid analytical-simulation modelling for supply chain management, shown in Table 2.6, indicates that discrete-event simulation is the most commonly applied simulation technique in the hybrid analytical-simulation models (Wan et al., 2003; Jung et al., 2004; Almeder and Preusser, 2007; Chen et al., 2010; Durand, Mele and Bandoni, 2012; Diabat et al., 2013; Frazzon, Albrecht and Hurtado, 2016; Ziarnetzky and Mönch, 2016; Chiadamrong and Piyathanavong, 2017). While, limited number of studies conducted on applying an SBO model in a hybrid analytical-simulation framework. Moreover, from our analysis of the literature there is no study that has employed system dynamics simulation in a hybrid analytical-simulation model. In terms of research scope, the integrated planning problems such as distribution and inventory planning problem has been addressed in a significant number of the studied papers (Jung et al., 2004; Almeder and Preusser, 2007; Chen et al., 2010; Gu and Rong, 2010; Varthanan, Murugan and Kumar, 2012; Diabat et al., 2013).

Addressing the strategic supply chain planning problem, which includes integrating the strategic decisions such as network design and planning decisions such as inventory planning, using the hybrid analytical-simulation framework has remained under investigated. Although, a significant number of the hybrid analytical-simulation models were developed to address the integrated planning problems (Jung et al., 2004; Almeder and Preusser, 2007; Chen et al., 2010; Gu and Rong, 2010; Durand, Mele and Bandoni, 2012; Varthanan, Murugan and Kumar, 2012; Diabat et al., 2013). Cost minimization has been the dominant objective function in the hybrid analytical-simulation models (Truong and Azadivar, 2003; Wan et al., 2003; Jung et al., 2004; Chen et al., 2010; Nikolopoulou and Ierapetritou, 2012; Sahay, Ierapetritou and Wassick, 2014; Boulaksil, 2016). While, the literature on supply chain hybrid analytical-simulation modelling lacks the sufficient number of studies which consider the profit maximization as the objective function.

To fill the gap in the supply chain hybrid analytical-simulation modelling literature, in chapter 7 of this study, a hybrid analytical-simulation framework which integrates an SBO model and a mixed-integer linear programming (MILP) model is developed to address a strategic supply chain planning problem which integrates supplier selection, network design, inventory planning, and asset-liability planning problems. The SBO model integrates a system dynamics simulation model and a genetic algorithm. The developed MILP and SBO models aim to maximize the profit of the supply chain and are connected through an iterative process. The detailed description of the connection between the SBO and MILP models is elaborated in the next chapter.

Table 2.6. Hybrid analytical-simulation approaches for supply chain modelling

Article	Research scope	Optimization model	Simulation model	Optimization objective
Truong and Azadivar (2003)	SC network design	Mixed integer linear programming (MILP) GA	NA	Min: Aggregate costs Max: Service level
Wan et al. (2003)	SC inventory planning	MILP GA	DES	Min: Total cost
Elmahi et al. (2004)	SC transport scheduling	Linear programming (LP) GA	PN	Min: Delivery time
Jung et al. (2004)	SC production and inventory planning	LP Gradient-based stochastic search	DES Monte Carlo	Min: Total cost Max: Customer satisfaction level
Almeder and Preusser (2007)	SC production and distribution planning	MILP	DES	Min: Total cost
Chen et al. (2010)	SC production and distribution planning	MILP	DES	Min: Total cost
Gu and Rong (2010)	SC production and inventory planning	MILP	NA Monte Carlo	Max: Customer satisfaction level
Varthanan et al. (2012)	SC production and distribution planning	MILP Discrete particle swarm optimization (DPSO)	NA	Min: Total cost
Durand et al. (2012)	Equipment location and production scheduling	MILP GA	DES Monte Carlo	Max: Expected demand satisfaction
Nikolopoulou and Ierapetritou (2012)	SC production and distribution planning	MILP	Agent-based simulation (ABS)	Max: Total cost
Diabat et al. (2013)	SC inventory and distribution planning	LP	DES+ Simulated Annealing	Min: Total cost (translation of all KPIs into an overall cost function)
Sahay and Ierapetritou (2013)	SC distribution and inventory planning	Multi-objective MILP	ABS	Min: Total cost Min: Environmental impact
Singh et al. (2014)	SC network design	GA MILP	ABS	Max: Total net present value
Sahay and Ierapetritou (2014)	SC distribution and inventory planning	LP	ABS	Min: Total Cost
Sahay and Ierapetritou (2015)	SC distribution and inventory planning	MILP	ABS	Max: Profit Min: Downside risk Max: service level
Frazzon et al. (2016)	SC production and transportation scheduling	LP GA	DES	Min: Tardiness
Boulaksil (2016)	SC inventory planning	LP	NA	Min: Total cost Max: Service level
Ziarnetzky and Mönch (2016)	Production planning and capacity expansion	LP Simulated Annealing	DES	Max: Profit
Chiadamrong and Piyathanavong (2017)	SC network design	MILP	DES+OptQuest	Max: profit

2.5. Research gaps

2.5.1. Gap 1. working capital management and supply chains

Working capital management (WCM) seeks to improve the efficiency of a firm's operation through managing its inventory, accounts receivable, and accounts payable. Cash conversion cycle which is defined as the average days that it takes for a company to convert a dollar invested in raw material into a dollar collected from customer is one of the widely used key performance indicators to measure the efficiency of a firm's working capital management (Hofmann and Kotzab, 2010). Supply chain entities, e.g. suppliers, manufacturers are willing to decrease their financial cost through diminishing CCC, however, CCC may be fallen for a company at the expense of CCC increase for either their upstream or downstream partners or both. Consequently, single company perspective toward working capital management appears to be inefficient in supply chain perspective.

Several works studied the CCC in supply chain. For instance, Zhang et al. (2017) considered the minimization of the supply chain CCC as an objective in a multi-objective mixed integer linear programming model that was developed to address a supply chain network design problem. Lind et al. (2012) used an empirical approach to measure the CCCs for the members of an automotive supply chain during 2006-2008. The results showed that during the studied period there was no considerable change in the CCC of the supply chain members. Banomyong (2005) used the balance sheet of the members in a global shrimp supply chain to measure their CCCs. Theodore Farris and Hutchison (2002) applied a descriptive research and argued that the lower the CCC of the supply chain members the more successful the supply chain is. They suggested extending the average accounts payable, reducing the average accounts receivable, and shortening the production cycles as the strategies to reduce the cash conversion cycle for the supply chain members.

Hofmann and Kotzab (2010) applied conceptual model building approach and argued that the CCC metric should be considered from supply chain perspective rather than single company perspective. They introduced a new metric called collaborative cash conversion cycle (CCCC) to measure the efficiency of the working capital management in a supply chain. Ruyken et al. (2011) applied an empirical approach and argued that the minimizing of the CCCs for supply chain echelons are in conflict, as one firm's payable conversion period is another firm's receivable conversion period. They inferred that the right CCC for every single supply chain member should be determined considering the extent of responsiveness or efficiency of the supply chain, supply chain design configuration, and risk aspect rooted within the supply chain network. Talonpoika et al. (2014) used the empirical approach and argued that for supply chains such as ICT and publishing, in which the supply chain members receive advance payments, CCC may not be an effective tool for measuring the efficiency of working capital. They introduced modified cash conversion cycle (CCC) as a new metric for measuring the cycle time of working capital in industries which receive advanced payments.

Much of the literature on working capital management in the supply chain applied the empirical approaches to measure the CCCs for supply chain members (Theodore Farris and Hutchison, 2002; Ruyken et al., 2011; Lind et al., 2012). Although, modelling approaches such as simulation and optimisation are under-represented. Moreover, it has been argued that supply chain members may reduce their cash conversion cycle at the expense of increasing it for their upstream and/or downstream members (Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011). The literature lacks the studies which applied a practical modelling approach to manage the trade-offs between conflicting CCC minimizations for supply chain members by finding the optimal values to the financial and inventory decisions parameters. Finally, the literature lacks the studies that applied the collaborative CCC (CCCC) as the metric for measuring the efficiency of the working capital management in supply chains.

To fill the gap in the literature, in chapter 4 of this study, simulation-based optimisation approach which integrates system dynamics simulation and genetic algorithms is applied to manage the trade-offs between conflicting cash conversion cycle minimizations for supply chain members and to minimize the collaborative CCC (CCCC) of the supply chain through finding the optimal values to the financial decisions parameters including price and unit cost and inventory decisions parameters including desired inventory, desired supply line, inventory adjustment parameter, and supply line adjustment parameter.

Table 2.7. Working capital management and supply chains literature

Gap 1	**Current literature**	**Focus of approach/SC issues**	**Parameters/variables considered**	**Approaches**
Working capital management and supply chain	Lack of simulation and optimisation modelling (Theodore Farris and Hutchison, 2002; Ruyken et al., 2011; Lind et al., 2012) Lack of quantitative approach for modelling the trade-offs in CCCs minimization (Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011) Lack of CCCC application for measuring the working capital management in supply chains (Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011; Lind et al., 2012)	Managing the trad-offs between conflicting CCCs Minimization for supply chain members Minimizing the CCCC of the supply chain	Desired Inventory Desired Supply line Inventory adjustment parameter Supply line adjustment parameter Price Unit cost	System dynamics Multi-objective optimisation Genetic algorithms Simulation-based optimisation

2.5.2. Gap 2. Bullwhip effect and cash flow bullwhip

Beer distribution game which first was introduced by Sterman (1989) is a simplified but still realistic representation of a four-echelon beer supply chain consisting of a retailer, wholesaler, distributor, and factory. Using the SD simulation, it is illustrated that variations in end customer demands cannot be handled by the supply chain members which results in excessive inventory levels for the supply chain members. The inventory levels for upstream members of the supply chains, i.e., distributor and manufacturer are several of magnitudes larger than the end customer demand (O'donnell et al., 2006). This undesirable phenomenon is called bullwhip effect which leads to inefficiencies such as excessive inventory and stock-outs (Lee et al., 1997; Chen et al., 1999). Demand forecasting, lead times, and ordering policies were identified as the main contributors to the bullwhip effect (Dejonckheere et al., 2003).

Supply chains are mostly forecast-driven rather than demand-driven (Barlas and Gunduz, 2011). In other words, supply chain members control and replenish inventory based on historical data. The impact of forecasting methods on the bullwhip effect has been investigated in several studies. Alwan et al. (2003) study the bullwhip effect in a periodic review inventory control and replenishment system in which mean squared forecasting method is used for demand forecasting. They conclude that the bullwhip effect could be mitigated using the mean squared forecasting method. Zhang (2004) investigated the impacts of three forecasting methods including moving average, exponential smoothing, and minimum mean squared error on bullwhip effect in a periodic inventory review system with a first order autoregressive (AR1) demand process. The findings showed that all the three forecasting methods lead to the bullwhip effect. Luong (2007) studied the bullwhip effect in a periodic review inventory system with a first order autoregressive (AR1) demand process in which minimum mean squared method was used for demand forecasting. He concluded that the bullwhip effect could be diminished through increasing the value of the demand autocorrelation.

The impact of the lead time on the bullwhip effect was investigated in several studies. Chatfield et al. (2004) studied the bullwhip effect under stochastic lead time and found that lead time variability exacerbates variance amplification in the supply chain. Kim et al. (2006) measured the impact of stochastic lead times in a k-stage supply chain and found that the lead time variability increases the bullwhip effect. Much of literature regarding the impact of lead time on the bullwhip effect point out that the lead time and the lead time variability should be minimized as the longer lead times and larger lead time variations have an adverse effect on the supply chain performance (Chen et al., 2000; Agrawal et al., 2009).

Ordering policy is another main contributor to the bullwhip effect which was investigated by the researchers. Dejonckheere et al. (2004) showed that in an order up to (OUT) inventory system in which the demand is forecasted using exponential smoothing or moving average, the bullwhip effect is unavoidable. They proposed a general replenishment rule for order smoothing. Balakrishnan et al. (2004) emphasize the importance of proposing new replenishment policies that are able to generate smooth order patterns which in turn can reduce the demand amplification. Hosoda and Disney (2006) introduced the Generalized order-up-to policy to mitigate the bullwhip effect in a three-echelon supply chain in which minimum mean square error method was applied for demand forecasting. The proposed ordering policy added a proportional controller to the simple order-up-to (OUT) policy. They showed that the proposed replenishment policy reduces the inventory costs by 10%. Boute et al. (2007) investigate the impact of ordering policy in a two-echelon supply chain including a retailer and a manufacturer with independent and identically distributed (I.I.D) customer demand. They showed that smoothing the ordering pattern at the retailer's level mitigates the replenishment lead time and the bullwhip effect.

Previous research on the bullwhip effect has highlighted the existence of this phenomenon and identified its main causes to mitigate its adverse effects (Alwan et al., 2003; Zhang, 2004; Luong, 2007). However, there is lack of studies that focus on minimizing the bullwhip effect by finding the optimal values to the controllable decisions of the supply chain members. Moreover, previous research does not consider the flow of cash in the bullwhip effect modelling. To fill the gap in bullwhip effect literature, in chapter 5 of this study, the bullwhip effect is minimized through finding the optimal values to the inventory decisions of the supply chain members. In the developed model the flow of cash is considered in addition to the flow of products.

In addition to the high volatility in inventory levels, the bullwhip effect results in high volatility in the number of days that it takes for supply chain members to convert resource inputs into the cash flows collected from the customers known as cash conversion cycle (CCC). In such circumstances, supply chain members may confront liquidity constraints, as they are not able to predict the amount of time that it takes to get access to the cash. Tangsucheeva and Prabhu (2013) named this undesirable phenomenon "cash flow bullwhip" (CFB), which is caused by variations in the CCC that occurs throughout financial flows in the supply chain. Cash flow bullwhip was quantified as the ratio of variability in CCC to variability in the end customer demand and the bullwhip effect and lead time were identified as its most significant contributors in an inventory system with the order up to (OUT) replenishment policy (Tangsucheeva and Prabhu, 2013). Goodarzi et al. (2017) identified rationing and shortage gaming as the main cause of the CFB in inventory systems with OUT policy, while it was identified as the least significant contributor to the CFB in Tangsucheeva and Prabhu (2013) study. Tangsucheeva and Prabhu (2014) argue that the existence of the CFB in the supply chain networks indicates the need for improving the cash flow forecasting. They presented a stochastic model to improve the accuracy of cash flow forecasting models within supply chain networks. The proposed model was developed by integrating Markov chain model in which payment probabilities were calculated by accounts receivable (AR) aging report (Corcoran, 1978) and Bayesian model whereby the payment probability was extracted from payment behaviour of every single customer (Pate-Cornell et al., 1990). Sim and Prabhu (2017) developed a mathematical model to measure the CFB in a two-echelon supply chain including a supplier and a manufacturer. It was shown that the financing of the supplier by the manufacturer reduces the CFB in the supply chain.

Previous research on the CFB has identified the causes of this phenomenon (Tangsucheeva and Prabhu, 2013; Goodarzi et al., 2017). There is a lack of studies that focus on minimizing the CFB through finding the optimal values to the inventory bullwhip contributors including the desired inventory, the desired supply line, the inventory adjustment parameter, and the supply line adjustment parameter. Furthermore, price and unit cost are two decision parameters that assist the decision maker in controlling variations in the CCC. To fill the gap in CFB literature, in chapter 5 of this study, the CFB is minimized through identifying the optimal values to the price, unit cost, and inventory decisions that cause the inventory bullwhip.

Table 2.8. Bullwhip effect and cash flow bullwhip literature

Gap 2	**Current literature**	**Focus of approach/SC issues**	**Parameters/variables considered**	**Approaches**
Bullwhip effect and cash flow bullwhip	Lack of studies which minimize the bullwhip effect through finding the optimal values to the controllable decisions (Alwan et al., 2003; Zhang, 2004; Luong, 2007) Lack of cash flow consideration into bullwhip effect modelling(Balakrishnan, et al., 2004; Hosoda and Disney, 2006) Lack of research on minimizing the CFB through finding the optimal values to the bullwhip effect contributors (Tangsucheeva and Prabhu, 2013, 2014; Goodarzi et al., 2017; Sim and Prabhu, 2017)	Bullwhip effect Cash flow bullwhip (CFB)	Desired Inventory Desired Supply line Inventory adjustment parameter Supply line adjustment parameter Price Unit cost	System dynamics Multi-objective optimisation Genetic algorithms Simulation-based optimisation

2.5.3. Gap 3: Inventory planning and working capital management under economic uncertainty

Inventory planning refers to making a trade-off between efficiency and responsiveness. The inventory levels at the stock keeping units need to be adequate to meet customer demands and simultaneously at the minimum level to minimize the inventory holding cost. Inventory planning includes controlling the inventory levels and replenishing the inventory to respond to the customer demands quickly while minimizing the inventory levels.

Several studies applied system dynamics to simulate the inventory planning systems. These studies aim to explore the dynamics of the inventory planning to evaluate system improvement strategies. Ashayeri and Lemmes, (2006) developed a SD model to investigate how various demand forecasting methods, different logistics routes, and alternative inventory planning methods may increase the profitability of a supply chain. Peng et al. (2014) proposed a SD model for inventory and logistics planning in a post-seismic supply chain. They investigated the effects of three inventory planning strategies and four demand forecasting methods under different lead time uncertainties on the system performance. Umeda, (2007) proposed an integrated simulation framework which combined SD and discrete-event simulation to examine the efficiency of three inventory planning strategy including push, pull, and hybrid push-pull and two production planning strategy including make to order and make to stock in a manufacturing supply chain model presented by Sterman (2000).

Verwater-Lukszo and Christina (2005) developed a SD model to improve inventory and production management in a batch-wise plant. The developed model aimed to assess the impact of four inventory and production management tactics including increasing production capacity, eliminating safety stock, reducing safety stock, and reducing desired service level on the system performance indicators which were inventory level and service level. Poles and Cheong (2009) applied SD approach to model and simulate an inventory control system for a remanufacturing process in a closed-loop supply chain. The study aimed to analyse the impacts of residence time which was defined as the time period that products stay with customers and changes in level of company incentives for recycling on total inventory costs in an inventory system with pull strategy. Belhajali and Hachicha (2013) employed SD simulation to determine the safety stock for a single-stage inventory system with order-up-to (OUT) policy.

Reyes et al. (2013) employed SD simulation to improve the management of the inventory in a disaster relief system. They found that the transhipment strategy in which supply chain members at the same echelon exchange inventory could reduce inventory costs and improve service to the disaster victims. Cannella et al. (2015) applied SD simulation to quantify the impact of inventory record inaccuracy in collaborative supply chains. The results showed that the detrimental effects of the inventory record inaccuracy in terms of supply chain costs and service level in upstream supply chain is higher than the downstream supply chain. Schuh et al. (2015) developed the manufacturing supply chain model introduced by Sterman (2000) to investigate the impacts of the disturbances on the manufacturing supply chains. Minnich and Maier (2007) developed a SD model to compare the efficiency and responsiveness of the pull-based and push-based inventory systems in the high-tech electronics industry. The results showed that the pull-based inventory planning systems are more efficient and responsive than the push-based systems providing higher fluctuations in capacity utilization upstream in the supply chain.

Sánchez et al. (2016) developed a SD model to improve the performance of a production and inventory control in an automotive supply chain. Applying sensitivity analysis on model parameters including cycle time, production adjustment time, delivery time, desired raw material inventory, and desired finished good inventory, the order fulfilment ratio was raised to 1. Mehrjoo (2014) used SD to assess the risks of delays, forecasting, and inventory in fast fashion apparel industry. Mashhadi et al. (2015) presented a SD model to evaluate the impacts of additive manufacturing on configuration of supply chains. The simulation results showed that the inventory levels for supply chain members in additive manufacturing systems is lower than the traditional systems. Campuzano-Bolarín et al. (2015) integrated SD and optimisation to reduce the bullwhip effect and inventory costs in a perishable product supply chain using different E-business scenarios.

Sheehan et al. (2016) applied SD simulation to mitigate the waste of raw material and finished good inventory in closed-loop supply chains. Lot size, product variety, process choice, and throughput were identified as the driving factors in industrial waste production and waste reduction policies were sought through modifying the values to the driving factors. Schmelzle and Tate (2015) employed SD modelling to investigate the impact of macroeconomic factors including interest rate, exchange rate, and inflation rate on inventory management policies. They concluded that keeping low levels of inventory in supply markets with high currency devaluation rates decreases the total cost of the supply chain. Shahi (2016) integrated SD simulation and OptQuest optimisation solver to determine the minimum and the maximum inventory levels in an order-up-to inventory control and replenishment system.

Much of the literature on the application of the SD modelling for inventory control and replenishment focuses on evaluating the impacts of various policies on improving the system's performance in terms of efficiency and responsiveness. The effects of the improvement policies on the system's performance are measured through modifying the values to the decision parameters of the model. In other words, by applying SD modelling, the modeller is solely able to compare the effects of varied policies, i.e., different values of the controllable parameters, through performing what-if analysis which may not be an effective strategy particularly, when the decision parameters are continuous such as inventory decisions. Therefore, incorporating optimisation algorithms into the SD simulation is inevitable when the modeller aims to identify the optimal values to the continuous decision parameters.

To fill the gap in inventory planning using SD simulation, In chapter 6 of this study, the genetic algorithm which is a metaheuristic and is an effective tool for optimisation of the continuous parameters (Mühlenbein and Schlierkamp-Voosen, 1993) is applied to identify the optimal values to the inventory decisions parameters such as inventory and supply line adjustment parameters.

Working capital management from supply chain perspective relates to managing accounts receivable, accounts payable, and inventories through cooperation and coordination among supply chain members (Gelsomino et al., 2016). Several studies incorporated receivables and payables into inventory planning problem by using the trade credit policy. Ravichandran (2007) developed a dynamic programming model to address an inventory planning problem. The proposed model considered the constraints on receivables and payables in addition to the inventory and order fill rate constraints. Due to the complexity of the model, the simulation was applied to determine the optimal ordering policies for supply chain members so as to maximize the profit of the supply chain, minimize the inventory levels of the members, and minimize the working capital for the supply chain members. Teng (2009) developed a mathematical model which integrated receivables and payables management into an inventory planning problem. The objective of the developed model was to identify the optimal ordering policy for a retailer who received trade credit by its supplier and offered either partial trade credit or full trade credit to its customer depending on their debt payment history.

Huang (2007) developed a mathematical model to identify the optimal inventory cycle time and order quantity for a retailer which was offered partial permissible delay in payment by its supplier when its order quantity was smaller than a predetermined quantity. Huang and Hsu

(2008) developed a mathematical model to determine the optimal ordering policy for a retailer that had access to the full trade credit offered by its supplier while he offered partial trade credit to his customer. Moussawi-Haidar and Jaber (2013) presented a mathematical model that incorporated the management of receivables, payables, and cash into an inventory planning problem in a two-echelon supply chain including a retailer and a supplier where the delayed payment was allowed by the supplier. The objective of the developed model was to determine the optimal order size, payment time, and maximum cash level to keep in account for the retailer to minimize the inventory and financial costs.

Ho et al. (2008) presented a mathematical model to address an integrated supplier-buyer inventory planning problem in which the supplier offered the retailer a two-part trade credit policy. If the buyer paid within a specified time period, he was offered cash discount, otherwise he needed to pay the full purchasing price before another specified period which was larger than the first specified period. The objective of the developed model was to identify the optimal pricing, ordering, shipping and payment policy to maximize the total profit of the supply chain. Teng and Chang (2009) developed a mathematical model to determine the optimal replenishment decisions for a retailer in presence of two-level trade credit which implied that the trade credit offered by supplier to the retailer differed from the trade credit offered to the customer by the retailer. Liao (2008) developed a mathematical model based on economic order quantity model to identify the optimal replenishment policy for a retailer that received trade credit from its supplier and provided trade credit to its customer. Mahata (2012) developed an economic order quantity-based inventory model to determine the optimal inventory policy for a retailer that was provided with full trade credit by its supplier and offered partial trade credit to its customers.

Much of the literature on inventory planning under trade credit applied mathematical modelling approaches, and the simulation-based modelling remains underrepresented. Moreover, cost minimization or profit maximization are the dominant objective function in the developed models in the literature, while the literature lacks the studies that manage the trade-off between profitability and liquidity through developing the multi objective models. Finally, the literature lacks the studies that consider uncertainties in economic parameters such as demand and interest rates. To fill the gap in the inventory planning under trade credit literature, in chapter 6 of this study, a simulation-based optimisation model which integrates SD simulation and a genetic algorithm is developed to manage the trade-off between profitability and liquidity under economic uncertainty.

Table 2.9. Inventory planning and working capital management literature

Gap 3	**Current literature**	**Focus of approach/SC issues**	**Parameters/variables considered**	**Uncertain parameters**	**Approaches**
Inventory planning and working capital management under economic uncertainty	Inability of SD modelling in identifying the optimal inventory parameters (Reyes et al, 2013; Peng et al., 2014; Cannella et al., 2015) Lack of simulation-based modelling for integrated inventory planning under trade credit problem (Liao, 2008; Teng, 2009; Mahata, 2012) Lack of multi-objective models which manage the trade-offs between profitability	Managing the trade-offs between economic value-added (EVA) maximization and cash conversion cycle (CCC) minimization	Desired Inventory Desired Supply line Inventory adjustment parameter Supply line adjustment parameter Price Unit cost Collection policy Payment policy	Demand Risk-free rate of interest Expected return of the market Short-term interest rate Long-term interest rate	System dynamics Multi-objective optimisation Genetic algorithms Simulation-based optimisation

	and liquidity in inventory planning under trade credit models (Huang, 2007; Huang and Hsu, 2008; Teng and Chang, 2009) Ignoring the economic uncertainty in the inventory planning under trade credit problem (Ravichandran, 2007; Liao, 2008; Teng, 2009)				

2.5.4. Gap 4: Strategic supply chain planning and supply chain finance under economic uncertainty

As explained in section 2, supply chain design refers to strategic decisions such as network design and supplier selection. While, supply chain planning is related to the tactical decisions such as production and inventory planning. Strategic supply chain planning integrates the strategic and tactical decisions. For instance, integrating a network design and an inventory planning problem is considered a strategic supply chain planning problem. Strategic supply chain planning models show more realistic viewpoint of supply chain decisions; as different decisions in the supply chain are related to each other and deciding on them in an integrated manner results in better performance. Besides, application of the strategic supply chain planning models reduces unexpected events such as increased cost through the supply chain network (Laínez et al., 2008; Gupta and Dutta, 2011).

Several works incorporated financial flow modelling into the strategic supply chain planning problem. Melo et al. (2006) developed a MILP model to address an integrated supply chain network design and inventory planning problem considering budget constraints. The developed model aimed to identify the optimal network structure, flow of goods in the network, inventory levels held at the facilities, and the amount of capacity transferred between the facilities. Naraharisetti et al. (2008) developed a MILP model to address a strategic supply chain planning problem considering budget constraints. The objective of the developed model was to maximize the net present value of the total assets through determining the optimal values to the flow of products in the network, inventory decisions, open/close decisions of the facilities, and the loans.

Zhang et al. (2017) presented a multi-objective MILP model to formulate a strategic supply chain planning problem for a multi-source, multi-product, multi-stage supply chain. The developed model considered minimizing the cash conversion cycle in the supply chain network in addition to minimizing the total cost and maximizing the customer service level. The developed model aimed to identify the optimal network structure, flow of products in the network, and the inventory levels at the facilities. Puigjaner and Laínez, (2008) presented an SBO framework to incorporate financial flow planning into a supply chain network design and distribution planning problem under demand, price, and interest rate uncertainties. The objectives of the developed model were to maximize the change in equity and minimize the environmental impact through identifying the optimal level of current assets, fixed assets, and liabilities in addition to the network design and distribution planning decisions such as the location of the facilities and the flow of products in the network.

Longinidis and Georgiadis (2011) developed a MILP model to incorporate balance sheet equations and financial ratios constraints into a strategic supply chain planning problem under demand uncertainty. The proposed model aimed to maximize economic value added of the supply chain network through determining the optimal values to the number, location and capacity of the warehouses and distribution centres in the supply chain network, the flows of materials in the network, the inventory levels at facilities, and the production rates at the plants. Nickel et al. (2012) developed a MILP model to incorporate financial flow modelling in a strategic supply chain planning problem under demand and interest rates uncertainties. The objective of the developed model was to identify the optimal values to the location of the facilities in the network, investment choices, loans, inventory levels at the facilities, and the flow of products within the network to maximize the total financial benefit.

Longinidis and Georgiadis (2013) presented a mixed integer nonlinear programming (MINLP) model to make a trade-off between financial performance and credit solvency within a strategic supply chain planning problem under economic uncertainty. Economic value added (see Stewart Iii (1994)) and Z-score (see Altman (1968)) were applied to measure the financial performance and credit solvency, respectively. The developed model determined the optimal values to the level of fixed assets, current assets, liabilities, and equity in addition to the optimal number, location and capacity of the warehouses and distribution centres in the supply chain network, the flows of materials in the network, the inventory levels at the facilities, and the production rates at the plants.

Ramezani et al. (2014) developed a MILP model which considered the financial aspects of the supply chain in addition to the operational aspects to address a strategic supply chain planning problem. The developed model aimed to find the optimal values to the short-term liabilities, optimal level of current assets, fixed assets, and liabilities in addition to the location of the facilities, inventory levels at the facilities, and the flow of products in the network so as to maximize the change in equity. The results showed that the change in equity in the developed model was higher than in the traditional model in which the financial decisions are made after deciding on the operational decisions. Cardoso et al. (2016) developed a bi-objective MILP model which incorporated financial risk measures into the design and planning of closed-loop supply chains under demand uncertainty. The objectives of the developed model include maximizing the supply chain expected net present value and minimizing the financial risk. The financial risk is measured through applying four different risk measures including VaR, CVaR, variability index, and down-side risk. The ε-constraint model was used to solve the developed model.

Yousefi and Pishvaee (2018) presented a MILP model which integrated physical and financial flows within a strategic supply chain planning problem under exchange rate uncertainty. The developed model aimed to maximize the profitability of the supply chain through identifying the optimal financial flow decisions including the level of current assets, fixed assets, and liabilities in addition to the optimal physical flow decisions including the number of required suppliers and distribution centres in the supply chain network, the amount of raw material to be purchased by the manufacturer, the flow of material in the network, and the optimal inventory levels should be held at each supply chain entity. The profitability of the supply chain was measured by the economic value added (EVA).

Previous research on integrated strategic supply chain planning and supply chain finance mostly applied MILP modelling, while the hybrid analytical-simulation approach which are more efficient than the analytical approaches in capturing the nonlinearities, delays, and feedback loops exist in such problems have remained underrepresented. Previous studies take into account a limited number of uncertainties, mostly uncertainty in demand, while there is lack of studies that consider a wide range of uncertainties in the economic parameters. To fill the gap in the literature, in this study, a hybrid analytical-simulation model is developed to address a strategic supply chain planning problem under economic uncertainty. The strategic supply chain planning problem includes supplier selection, network design, inventory planning, and asset-liability optimisation.

Table 2.10. Strategic supply chain planning and supply chain finance literature

Gap 4	**Current literature**	**Focus of approach/SC issues**	**Parameters/variables considered**	**Uncertain parameters**	**Approaches**
Strategic supply chain planning and supply chain finance under economic uncertainty	Lack of hybrid analytical-simulation modelling for strategic supply chain planning problem (Yousefi and Pishvaee, 2018; Melo et al., 2006; Ramezani et al., 2014; Cardoso, et al., 2016; Zhang et al., 2017)	SC network design Supplier selection Inventory planning Working capital management Cash management	Desired Inventory Desired Supply line Collection policy Payment policy Desired Cash Price Fixed and current assets Short-term and long-term liabilities Equity	Demand Risk-free rate of interest Expected return of the market Short-term interest rate Long-term interest rate	System dynamics Genetic algorithms Simulation-based optimisation Hybrid analytical-simulation

	Ignoring the economic uncertainty in the strategic supply chain planning problem (Melo et al., 2006; Naraharisetti et al., 2008; Ramezani et al., 2014; Zhang et al., 2017)				

Chapter 3. Simulation-based optimisation and hybrid analytical-SBO

3.1. Introduction

As the literature reviews presented in the previous chapter concluded, there is a great lack of research involving the integration of system dynamics and the genetic algorithms in the SBO literature and there is also a considerable need for integration of the SBO and MILP in the hybrid analytical-simulation literature. In this chapter, firstly, an introduction to the system dynamics and optimisation techniques are provided and the selection of the genetic algorithm as the optimisation technique in this study is justified. Later on, the integration of the system dynamics simulation and the genetic algorithm in the form of simulation-based optimisation framework is discussed. Finally, the integration of the SBO and MILP in the form of the hybrid analytical-simulation framework is elaborated.

3.2. System Dynamics

System dynamics (SD) is a simulation technique for modelling complex, non-linear, and dynamic systems developed by Jay W. Forrester during the mid-1950s. According to Richardson (1991), SD is a computer-aided approach to policy analysis and design of any dynamic system characterized by independence, mutual function, information feedback, and circular causality. SD captures the dynamical behavior of the system through considering information feedbacks and delays of the model (Angerhofer and Angelides, 2000). SD modelling enables users to evaluate the behaviour of the system and its response to various policies. Supply chain processes, information, strategies, and organizational limits can be qualitatively described by the SD modelling. Supply chains are complex systems comprise multiple autonomous entities which can be characterized by a stock and flow structure for acquisition, storage, converting inputs into outputs, and the decision rules governing these flows (Sterman, 2000). SD is an applicable approach for modelling and analysing the supply chains as the existing flows in the supply chain networks, e.g. information, material, and cash flows, create important feedbacks among the supply chain agents (Georgiadis, Vlachos and Iakovou, 2005). SD modelling process can be subdivided into three steps. First, the generation of a causal loop diagram, which is translated into a stock and flow diagram in the second step. The final step includes the formulation of a mathematical system of differential equations (Bießlich et al., 2014). In order to transfer the causal loop diagram into a simulation-capable stock and flow diagram, five central building blocks, namely; stocks, flows, auxiliaries, feedbacks, and time delays, are defined. The stocks indicate the current state of the system and are only changed through their in-and outflows. The flows, on the other hand, are determined by various model variables that change the flows and consequently the stocks. The auxiliary is attributed to all other model variables which cannot be defined as stocks and flows. The corrective measures taken by the system to bridge the gap between the actual value and the desired value of a variable are known as feedback loops (Campuzano and Mula, 2011). The time delay is defined as a process whose output lags behind its input (Sterman, 2000). An SD stock and flow model representing a simple capital injection process, utilizing the building blocks is depicted in Figure 3.1.

The stock in this process is the system's cash level where the inflow of cash which is as the result of products selling and the outflow of cash triggers by purchasing costs increase and decrease the cash level.

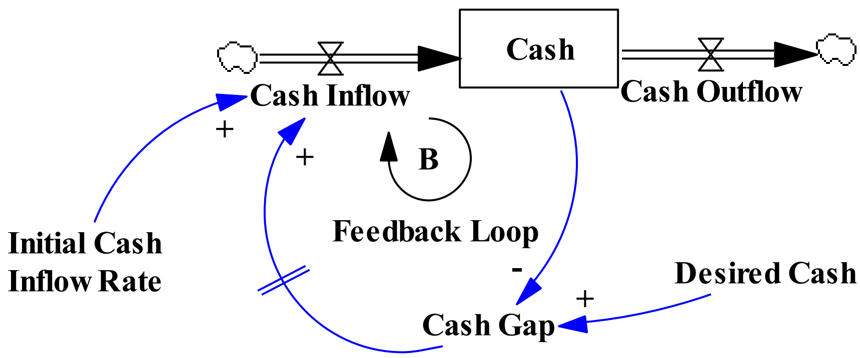


Figure 3.1. A simple SD stock and flow model with feedback loop and delay

The initial cash inflow rate and the cash gap variable constitute the flow of cash injection into the cash pool, by defining the cash inflow variable. The cash gap variable is part of the feedback loop which takes corrective measures to keep the cash at a desired level, by increasing or decreasing the cash gap. There is a delay between identifying the cash gap and bridging the gap through the cash inflow rate. As explained, the stocks accumulate their flows where the net flow, e.g., the inflow less the outflow, into the stock is the rate by which the stock is changed. The cash stock is defined by integral Equation 3.1, where Cash_{t-1} represents the cash level in the previous time period, and Cash_t , $\mathrm{Cash\ inflow}_t$, $\mathrm{Cash\ outflow}_t$ represent the variable values at current time t.

$$Cash_t = Cash_{t-1} + (Cash\ inflow_t - Cash\ outflow_t) \tag{3.1}$$

In chapters 4-7 of this study, the stock and flow structure of the system dynamics simulation modelling is applied to represent the flow of products, information, and cash within distribution and manufacturing supply chains. The state of each supply chain system is indicated by stocks such as the inventory of the raw material, the inventory of the products, and the inventory of cash. The change in the stocks is represented by flows such as order delivery, and order payment. The parameters that remain unchanged during the simulation time such as payment policy, i.e., the amount of cash payment at the time of order placement, and desired level of inventory are shown as auxiliaries. The corrective measures that are taken by the supply chain systems to bridge the gap between the auxiliaries such as the desired inventory and the desired cash with their actual values are indicated by feedback loops. Finally, the time delays exist in the supply chain systems such as the time delay between placing an order and receiving of the order known as the distribution lead time and the time delay between shipping of an order and receiving of the payment are shown by delay functions.

3.3. optimisation techniques

Optimisation is defined as the determination of optima which is maxima or minima in a search space using a fitness function (cost function). The main objective of the optimisation is to identify the singular global optimum in a search space that may contain multiple local optimal. There main approaches to the optimisation include analytical optimisation, exhaustive searching and natural optimisation.

3.3.1. Analytical optimisation

Analytical optimisation includes using differential calculus to minimize a cost function (fitness function) and to find the global optimum. If the cost function contains one variable, the first derivative of the cost function is set to zero and the variable value is determined. If the second derivative of the cost function in the determined point is less than zero, the determined point is a maximum. Otherwise, it is a minimum (Lawden, 2006).

3.3.2. Exhaustive searching

Exhaustive searching approach determines the global optimum by extensively investigating the cost function surface (Aliev and Larin, 1998). In other words, the extensive searching approach performs an extensive survey of the surface to gain an overall perspective on the entire topological layout of the cost function surface. Using this approach, each possible solution within the entire search area is evaluated the global optimum is identified after complete analysis. As in the exhaustive searching approach, all possible solutions need to be examined, this method requires a considerable amount of time to identify the global optimum. To make the exhaustive approach more effective in terms of solving time, a variation of this approach that uses branch and bound heuristics, is applied which is called semi-exhaustive search approach. This approach considers the positions of neighbouring solutions and requires less evaluation. Heuristic methods are employed to determine the number and proximity of the neighbours to be used in the semi-exhaustive search approach (Yoo, 2006).

3.3.3. Natural optimisation

Natural optimisation approaches use the mechanisms that exist in our natural surroundings to identify the global optimum in the search space. There are many nature inspired algorithms such as genetic algorithms (GAs), particle swarm optimisation (PSO), ant colony optimisation (ACO), and simulated annealing (SA) to name a few. Some of widely applied nature inspired algorithms are explained as follows.

3.3.3.1. Simulated annealing

Simulated annealing algorithm is inspired from annealing process whereby metal is heated to melting point and is then very slowly cooled. The slow cooling allows the atoms to line up and form a crystal that is the state of minimum energy in the system. The rate by which cooling occurs is of paramount importance as a rapid cooling results in a non-crystalline meta-stable glass. The formation of the perfect crystal is analogues to finding the global optimum in an optimisation problem and the formation of non-crystalline meta-stable glass is analogous to mistake a local minimum for the global optimum. Similar to the annealing process in which the temperature is set to high in the early stages of the process for faster melting, simulated annealing algorithm initially wanders toward a broad region of the search space that contain good solutions. Similar to the annealing process in which after the melting the temperature is slowly reduced for greater stability, simulated annealing algorithm thoroughly examines the sections of the search space that provide better solutions than the other sections to identify the global optimum. This approach guides the optimisation to find the best valley in the search space before searching for the lowest point within the specific valley which is the global optimum. Simulated annealing approach is used for solving combinatorial optimisation problems in which the search space is discrete (Van Laarhoven and Aarts, 1987).

3.3.3.2. Particle swarm optimisation

Particle swarm optimisation is inspired from the swarming behaviour of birds and fish. It solves an optimisation problem by having a population of candidate solutions knowns as particles and moving these particles in the search space according to their best known positions and the best known position of the entire swarm. When improved positions are discovered, they guide the movements of the swarm. By repeating the process it is hoped but not guaranteed that a satisfactory solution will be identified (Kennedy and Eberhart, 1995). Particle swarm optimisation algorithm does not require the optimisation problem to be differentiable as opposed to the classic optimisation methods. Although, it cannot guarantee an optimal solution is ever discovered. As the decision parameters that are required to be optimised in this study are continuous, particle swarm optimisation can be used to obtain the optimal values to the decision parameters.

3.3.3.3. Ant colony optimisation

Ant colony optimisation algorithm is inspired by ants behaviour. In the natural world, ants walk randomly in search of food and upon finding it go back to their colony while laying down pheromone trails. Other ants that find such a path are likely to follow the trail in an attempt for finding food rather than travelling randomly. If the ants which followed the trail are successful at finding the food, they reinforce the pheromone trail while returning to their colony. Over time the pheromone trail will start to evaporate, thus reducing its attractiveness. The longer it takes for an ant to travel down the path and back again, the longer it takes for the pheromones to evaporate. The evaporation of the pheromone avoids the convergence to a locally optimal solution. Ant colony optimisation algorithm is used for solving combinatorial optimisation problems. As the decision parameters that are required to be optimised in this study are continuous, ant colony optimisation is not a viable method for obtaining the optimal values to the decision parameters.

3.3.3.4. Genetic algorithms

Genetic algorithms (GAs) are computational algorithms inspired by Darwinian evolutionary theory which can be called in short as “survival of the fittest” (Darwin, 1859). In GAs it is assumed that fittest solutions survive and their characteristics are transferred from one generation to the next (Duggan, 2008). GAs do not require derivative information found in analytical optimisation, work well with numerically generated data, experimental data or analytical functions, possess the ability to jump out of local minimum, and are able to optimise continuous and discrete parameters, particularly the continuous parameters (Lu et al., 2009). Consequently, GAs are an efficient and robust method of obtaining global optimisation in complex optimisation problems (Johnson and Vonk, 1997). GAs are able to optimise conflicting objectives simultaneously; the population is composed of individuals from different sectors of the cost function surface that enables the GA algorithm to search over large areas of the search space in parallel. This attribute makes the Gas a perfect fit for multi-objective optimisation problems (Streichert, 2002).

The GA is a well-suited optimisation algorithm for this study as the decision parameters that are required to be optimised in this study are continuous and the studied optimisation problems are multi-objective. In chapters 4-7 of this study, the GA is applied to find the optimal values to the decision parameters, i.e., auxiliaries, of the system dynamics simulation models such as inventory and financial decisions parameters while making trade-offs between conflicting supply chain objectives such as simultaneous bullwhip effect and total cost minimization.

To optimise SD models using GAs, each solution known as chromosome is represented by an array of elements, where each position in the array pertains to a possible parameter value. A solution pool named population is formed by a set of chromosomes. The algorithm starts with setting up a population of random possible solutions. Then, the chromosomes are evaluated based on the objective function to obtain the fitness of the solution. A fitness value shows that how good each solution is in satisfying objective functions. Applying the rule of survival of the fittest, strongest solutions are selected from the population. Subsequently, solutions with higher fitness are combined to produce new solutions by performing crossover operator. These solutions are known as parent solutions. To ensure maintaining variety in the overall population, new solutions may then be subjected to small variations from parent solutions called mutation operator. Each population then represents a generation, and the process continues until predefined stopping criteria is met, such as convergence of fitness over generations or reaching maximum number of generations (Lu et al., 2012). A brief outline of how GA derives optimal parameter values is illustrated in Figure 3.2 and outlined below.

Initialization. Initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

Evaluation. Every solution is then evaluated through simulation based on an objective(s), e.g. total cost of the supply chain, and is assigned a fitness value. The fitness value for the solution is computed using the objective function(s) value(s), e.g. the lower the total cost of the supply chain, the higher the fitness value of the solution.

Selection. During each successive epoch, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as this process may be very time-consuming. Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection.

Reproduction. This process includes generating a new population of solutions from those selected through genetic operators: crossover and mutation. Crossover operator is used to take two solutions from the mating pool, and combines elements of those solutions to produce two new solutions: the procedure for this contains: (1) identifying a random crossover point on the two selected parent chromosomes and mark the two solutions at this point, (2) joining the first half of the first solution with the second half of the second solution also the first half of the second solution with the second half of the first solution to produce first and second child, respectively, and finally (3) replace parent solutions with the newly defined solutions (Duggan, 2008). Mutation operator is another genetic operator makes random changes to the solutions to deter stuck on a local optimum. Mutation operator generates a new solution by randomly changing one or more elements of the selected solution, namely, the value of one of the control parameters. The procedure for mutation involves: (1) selecting a small number of solutions for each generation by random, (2) selecting one or more elements of that solution randomly, and (3) generating a new value for the chosen elements considering the highest and lowest possible values for each parameter (Duggan, 2008).

Iteration and termination. The old population is replaced with the new population and cycle repeats until an optimal or near optimal solution to the problem appears in the population. Common terminating conditions are: a solution is found that satisfies minimum criteria, fixed number of generations reached, allocated budget (computation time/money) reached, the highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results, or combinations of the aforementioned conditions. To put it in a nutshell, the overall solution set becomes fitter through each generation and finally converges to an optimum.

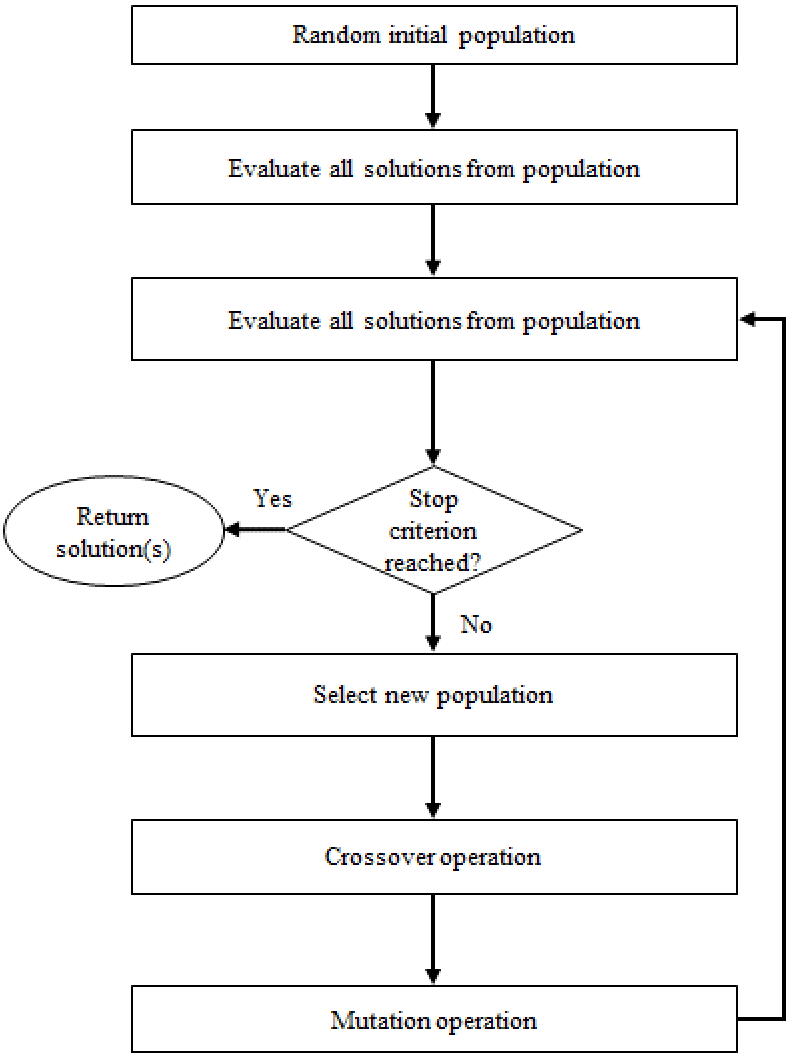


Figure 3.2. General GA process

3.4. Simulation-based optimisation

SBO is the process of obtaining optimal control parameters, i.e., input parameters, where the objective functions are examined through the output results of the simulation model (Ólafsson and Kim, 2002). The SBO process has been depicted schematically in Figure 3.3. The optimisation model encompasses optimisation algorithms, optimisation objectives, and constraints, whereas the simulation model depicts the system environment and considers governing dynamics such as uncertainties, time delays, feedback loops, and complex relationships (Aslam, 2013). The two models are related through defined input and output parameters. SBO is an iterative process which mostly is launched during the optimisation modeling process by generating initial values for the input parameters in the simulation model (supply chain decision variables). The simulation model is then run using inputted values to evaluate system performance. The performance measures are then fed back into the optimisation model. Based on this feedback a new set of decision variables are generated and inputted into the simulation model for evaluation (Aslam, 2013). This iterative process continues until a stop criterion has been met, such as performing a defined number of evaluations, elapsing a specific amount of time or any user-specified criterion (Syberfeldt, 2009). The SBO integrates the advantages of the simulation and optimisation modelling. Simulation models are powerful tools to model the complexities and incorporate the dynamic behaviour of supply chains. However, they are not able to determine optimal values to the decision parameters (Abo-Hamad and Arisha, 2011). On the other hand, optimisation models can identify the optimal values to the decision parameters. Although, they are not as efficient as simulation models in capturing the dynamics exist in supply chain networks including the uncertainties, time delays, feedback loops, and complex relationships. In the SBO framework, firstly a supply chain network is represented through simulation modelling to take into account its dynamic behaviour, and then integrated with optimisation methods to acquire optimal solution sets (Aslam, 2013).

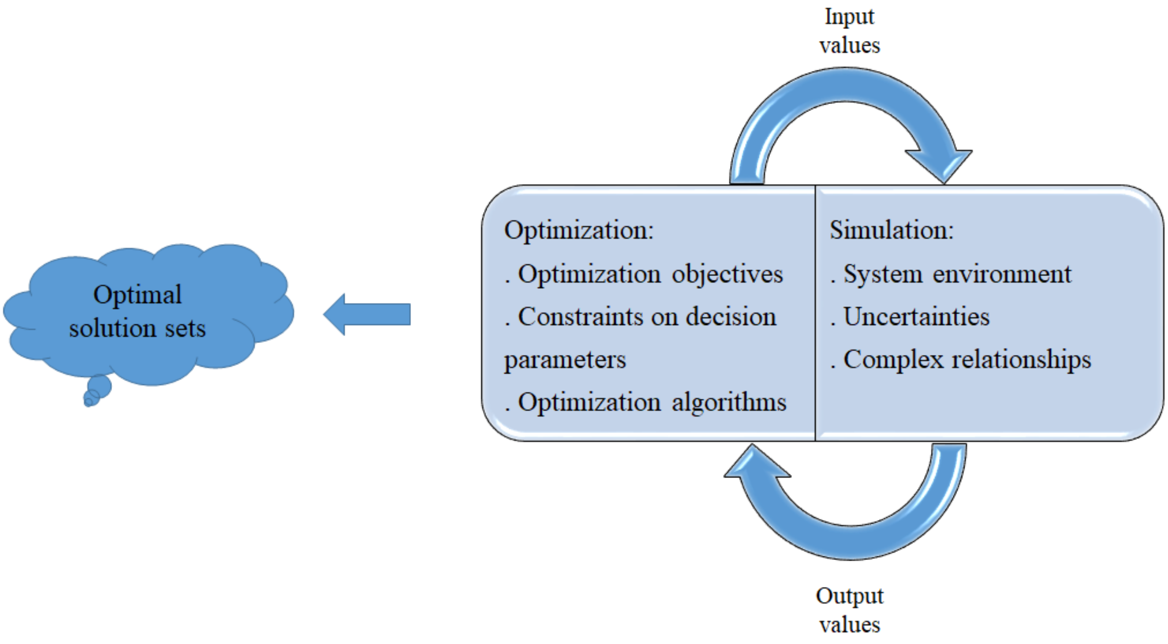


Figure 3.3. Simulation-based optimisation process

In chapters 4-6 of this study, the simulation-based optimisation (SBO) methodology is employed to integrate system dynamics simulation models and optimisation models. The system dynamics simulation models represent the dynamic behaviours of the studied supply chains and the optimisation models include the optimisation objectives such as total cost minimization, the constraints on the decision parameters i.e., auxiliaries, of the system dynamics models, and the genetic algorithm that is applied for identifying the optimal values to the decision parameters.

3.5. Hybrid analytical-SBO

The SBO technique merely enables the modeller to identify the optimal values to the decision parameters which are the input parameters to the simulation model. Although, it is not able to determine the optimal values to the decisions such as production level which cannot be formulated as input parameters to the simulation model. These decisions are states and flows in the simulation model. The analytical-simulation modelling enables the modeller to identify the optimal values to the decision variables, i.e., states and flows, in addition to the decision parameters, i.e., input parameters or auxiliaries. The hybrid analytical-simulation modelling consists of constructing independent optimisation and simulation models and then integrating the solution strategy through connecting the independent models. In this study, the SBO is the simulation model. Therefore, the hybrid analytical-simulation modelling is called hybrid analytical-SBO modelling. The process of the hybrid analytical-SBO modelling is illustrated in Figure 3.4. The optimisation model encompasses optimisation objectives and constraints on decision variables, while the SBO model contains the simulation model, constraints on decision parameters, and optimisation algorithms. The two models are connected through defined input and output parameters. The hybrid analytical-SBO modelling is an iterative process which is launched by considering initial values for the capacities in the optimisation model. The optimisation model is then solved and the optimal values to the decision variables are determined and inputted into the SBO model. The SBO model is then run and the optimal values to the capacities in the optimisation model, which are the input parameters to the SBO model, are identified and outputted into the optimisation model to generate a new set of decision variables. This iterative process continues until the difference between the value of the objective function(s) obtained from the optimisation model and the value of the objective function(s) obtained from the SBO model is less or equal to a user-specified difference tolerance level.

The hybrid analytical-SBO integrates the advantages of the SBO and optimisation modelling. SBO models are powerful tools to incorporate the dynamic behaviour of supply chains and to determine the optimal values to the decision parameters. Although, they are not able to determine the optimal values to the decision variables.

On the other hand, optimisation models are capable of identifying the optimal values to the decision variables. While, they are not as efficient as SBO models in capturing the dynamics exist in supply chain networks including the uncertainties, time delays, feedback loops, and complex relationships and also identifying the optimal values to the decision parameters. Optimizing the decision parameters in the optimisation models converts them into non-linear models and increases the computational time. In the hybrid analytical-SBO framework, firstly the optimal values to the decision variables are determined by optimisation modelling which takes into account the constraints on the decision variables and then integrated with the SBO modelling which incorporates dynamics in the supply chain network to identify the optimal decision parameters.

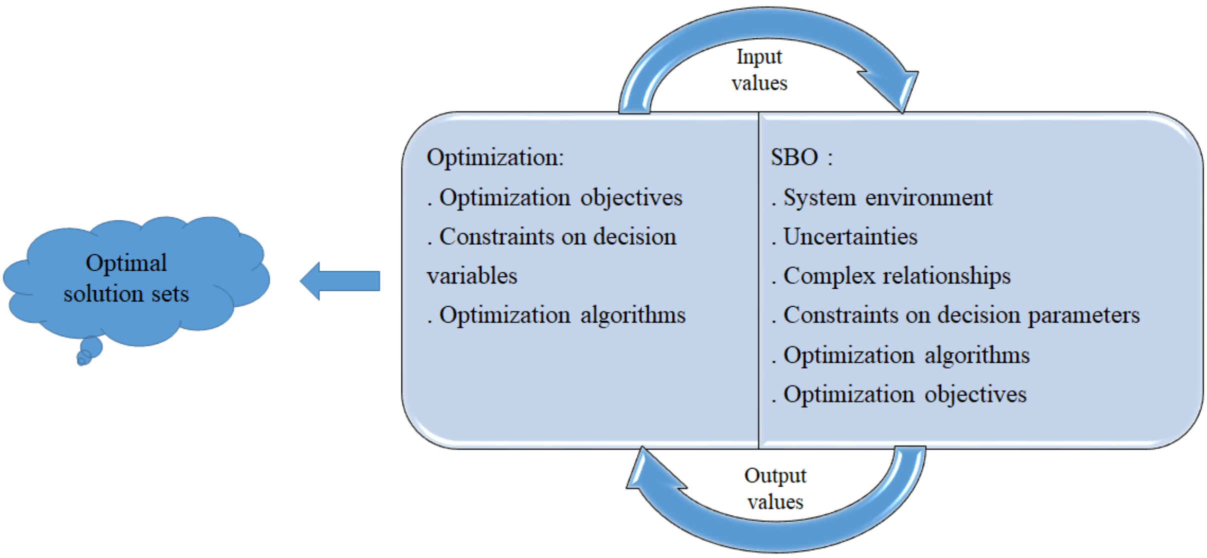


Figure 3.4. Hybrid analytical-SBO process

In chapter 7 of this study, the hybrid analytical-SBO approach is applied to integrate a mixed-integer linear programming (MILP) model and an SBO model. The MILP contains the optimisation objective that is maximizing the economic value added (EVA) and the constraints on the decision variables, i.e., flows and stocks, of the SBO model. The SBO model includes the system dynamics simulation model, which represents the dynamic behaviour of the studied supply chain and the genetic algorithm that is applied for identifying the optimal values to the decision parameters such as the desired inventory.

3.6. Conclusions

This chapter presents an introduction to the simulation approach that was used in this study, i.e., SD, and justifies the selection of the GA as the optimisation algorithm, i.e., for solving multi-objective optimisation problems in this study. Thereafter, the integration of simulation models and optimisation algorithms within the SBO framework and the integration of the optimisation and SBO models within the hybrid analytical-simulation framework are clarified. The SBO framework is merely capable of identifying the optimal decision parameters. While, using the hybrid analytical-SBO framework the optimal decision variables are determined in addition to the optimal decision parameters.

Chapter 4. Simulation-based optimisation of collaborative working capital management within supply chain

4.1. Introduction

Working capital management (WCM) integrates the product and cash flows for supply chain members. The WCM seeks to improve the efficiency of a firm's operation through managing its inventory, accounts receivable, and accounts payable. Cash conversion cycle (CCC) which is defined as the average days that it takes for a company to convert a dollar invested in raw material into a dollar collected from customer is one of the widely-used key performance indicators to measure the efficiency of a firm's working capital management. A low CCC implies that the company has lower financial cost to fund its business operation. Supply chain entities, e.g. suppliers, manufacturers are willing to decrease their financial cost through diminishing CCC, however, CCC may be fallen for a company at the expense of CCC increase for either their upstream or downstream partners or both. Consequently, single company perspective toward working capital management appears to be inefficient in supply chain perspective.

In this chapter to manage the working capital from supply chain perspective two optimisation models are developed. The first optimisation model is a multi-objective model that aims to minimize the cash conversion cycle (CCC) of supply chain members and the second optimisation model is a single-objective model that aims to minimize the collaborative cash conversion cycle (CCCC) of the supply chain. A simulation-based optimisation approach, which integrates system dynamics (SD) simulation and the genetic algorithm (GA), is applied to fulfill the objectives by identifying the optimal values to the inventory and financial decisions parameters.

The rest of the chapter is organized as follows. Section 4.2 describes the model that was developed to measure the CCC for the supply chain members, the CCCC of the supply chain, and the proposed SBO methodology for reducing the CCC of the members and the CCCC of the supply chain. In section 4.3, the beer distribution game that is the studied supply chain is elaborated and two optimisation models for minimzing the CCC and the CCCC are developed. Section 4.4 illustrates the applicability of the proposed SBO approach and compares its performance with system dynamics simulation. Finally, concluding remarks are presented in section 4.5.

4.2. Methodology

4.2.1. Ordering policy

Amongst various types of replenishment policies (see Silver et al., 1998; Zipkin, 2000), Order-Up-To (OUT) policy and reorder point-order quantity or (r,Q) model are the most commonly used replenishment policies. In this study OUT policy is considered as the ordering policy. In this system, the inventory position is determined by (= amount on-hand + inventory on-order – backlog). The inventory position is reviewed periodically (e.g. daily, weekly, monthly) and an order is placed to enhance inventory level to an OUT level (S) that defines order quantities (Towill, 1982). Therefore, the values to the two decision variables need to be recognized: (1) inventory position review period, and (2) the OUT level (S). The OUT level is determined by the sum of expected demand during risk period (= lead time+ review period) and a safety stock to satisfy higher than expected demands during the risk period. To simplify, in this study, the review period is assumed to be equal to one week. Therefore,

$$S_t = \widehat{D}^{T_p+1} + K.\sigma^{T_p+1} \tag{4.1}$$

T_p represents lead time, $\widehat{D}^{T_p+1}$ is an estimate of mean demand over $T_p + 1$ periods, K is a constant chosen to meet a desired service level, and σ^{T_p+1} is an estimate standard deviation of forecast error over $T_p + 1$ periods.

The exponential smoothing method used to forecast the demand. Accordingly, the ordering policy is defined as follows:

$$O_t = S_t - \ inventory\ position_t \tag{4.2}$$

The order at the end of period t (O_t) equals to the difference between OUT level and inventory position. The inventory position is determined by the sum of net inventory (NI) and inventory on order (SL). The net inventory equals to the value of inventory on hand (INV) minus backlog (B). The safety stock level is replaced with desired net inventory (DNI). Subsequently, (4.2) can be rewritten as follows:

$$O_t = \overbrace{DF_t\left(T_p+1\right)+DNI}^{S_t} - \overbrace{\left(NI_t+SL_t\right)}^{inventory\ position},$$

$$O_t = \underbrace{DF_t}_{Demand\,forecast} + \underbrace{(DNI - (INV_t - B_t))}_{AINV}\ \underbrace{(T_p DF_t - SL_t)}_{ASL},$$
$$where\ DF_t = SMOOTH(D_t, \gamma),$$
$$\gamma = 1 \tag{4.3}$$

The $T_p DF_t$ is assumed to be desired supply line or DSL. As the gap between the OUT level (S_t) and the current inventory is not replenished entirely in a review period, smoothing replenishment rules should be used to give an appropriate weight (i.e.,α and β) to the gap terms (Disney et al., 2007).

$$O_t = DF_t + \alpha(DNI - (INV_t - B_t)) + \beta(DSL - SL_t),$$
$$O'_t = MAX(0, O_t) \tag{4.4}$$

In (4.4), desired net inventory (DNI), desired supply line (DSL), inventory proportional parameter (α), and inventory on order proportional parameter (β) which are known as controllable parameters; allow us to amend the dynamic behavior of the supply chain. Moreover, it is ensured that the place orders by supply chain members are non-negative.

4.2.2. Working capital management

Working capital management involves managing inventories, accounts receivable, and accounts payable to ensure capability of a firm to continue its operation. The objective of working capital management is to reduce current assets and also extend current liabilities in order to minimize the capital tied up in the company's turnover process (Hofmann and Kotzab, 2010). To manage working capital effectively, firstly metrics which are used for measuring its efficiency should be identified. Cash conversion cycle (CCC) is one of the key indicators for measuring the efficiency of working capital management which is defined by (4.5) through adding days inventory outstanding (DIO) and days sales outstanding (DSO) minus days payable outstanding (DPO). The days inventory outstanding (DIO) is measured by dividing average inventory value into daily cost of goods sold (COGS). The days sales outstanding (DSO) is defined as average accounts receivable divided by daily revenue and the days accounts payable outstanding (DPO) is the ratio of average accounts payable and daily COGS. CCC indicates the length of time that it takes for a company to convert resource inputs into cash flows collected from customers.

$$CCC = \underbrace{\frac{Average\ Inventory}{COGS/_{365}}}_{DIO} + \underbrace{\frac{Average\ Account\ receivable}{Revenue/_{365}}}_{DSO} - \underbrace{\frac{Average\ Account\ Payable}{COGS/_{365}}}_{DPO} \qquad (4.5)$$

To determine DIO (4.6), the value of average inventory which is the product of inventory position (I) and sales price per unit (sp) is divided by daily cost of goods sold (COGS) which is measured by multiplying unit cost (uc) and the average demand (D). Dividing COGS by 365 assures the expression of DIO in days since both average inventory and COGS are expressed in currency unit (£). Therefore, DIO can be calculated as:

$$DIO = 365\left(\frac{sp}{uc}\right)\left(\frac{I}{D}\right) \qquad (4.6)$$

In (4.7), account receivable (AR) can be expressed in terms of demand, backlog (B) and inventory level (I) as follows:

$$AR = m\,min(sp(D+B), spI) \qquad (4.7)$$

Where m indicates the collection policy of the firm; $0 \leq m \leq 1$. It would be equal to 1 if all sales is in the form of credit and would be zero if all value of sales is in the form of advanced payment. Replace (4.7) in DSO, obtain

$$DSO = m\left(\frac{min(sp(D+B), spI)}{spD/_{365}}\right) = 365\,m\ \left(\frac{\min(D+B, I)}{D}\right) \qquad (4.8)$$

Lastly, consider (4.9) in which accounts payable (AP) can be calculated by order quantity (q) and unit cost (uc) as follows:

$$AP = nucq \qquad (4.9)$$

Where $0 \leq n \leq 1$, shows the payment policy of the company. It would be equal to 1 for all credit purchases and zero for all purchases the price must be paid before delivery. In this study both m, n is assumed to be equal to one.

Replace (4.9) in DPO, we get

$$DPO = \frac{nucq}{ucD/_{365}} = 365\ n\ \left(\frac{q}{D}\right) \tag{4.10}$$

Given (4.5), CCC can be obtained as follows:

$$CCC = 365\left(\frac{sp}{uc}\right)\left(\frac{I}{D}\right) + 365\ m\ \left(\frac{min(D+B,I)}{D}\right) - 365\ n\ \left(\frac{q}{D}\right) \tag{4.11}$$

The lower the CCC, the lower financial cost for a company to fund its business operation. The cash to cash cycle (CCC) can be diminished through lowering days inventory outstanding (DIO), reducing days sales outstanding (DSO), and extending days payable outstanding (DPO) (Tangsucheeva and Prabhu, 2013).

Hofmann and Kotzab (2010) argue that the “leading” and most powerful companies in a supply chain are often able to degrade their own cash conversion cycle at the expense of CCC increase for either their upstream or downstream partners or both. Hence, a single company perspective on working capital management appears to be inefficient in the supply chain perspective. They suggest collaborative CCC as an indicator for measuring efficiency of the working capital management in supply chain networks. The collaborative CCC in a supply chain can be obtained by adding up all inventory periods of the members, adding accounts receivable period (DSO) of the last member of the chain (retailer) and deducting accounts payable period (DPO) of the first member of the chain (supplier) (Hofmann and Kotzab, 2010).

4.3. Experiments

4.3.1. Beer distribution game

The beer game (BG) is a role playing simulation game was originally developed in (Sterman, 1989). The main objective of the game was to demonstrate the existence of the bullwhip effect within supply chain networks. In this study, a four-agent BG consists of a manufacturer, a distributor, a wholesaler, and a retailer is modelled and cash flow between supply chain members is taken into account, in addition to material and information flows, to measure the collaborative CCC of the supply chain network. Each member strives to maintain a dynamic equilibrium between inflows (arriving goods from upstream member) and outflows (goods being sent to downstream member). According to the assumptions of the beer game (BG), customer demand starts by ordering 4 crates of beer during the first four week and then suddenly, in week 5, the customer demand rises to 8 crates per week for the rest of the simulation (Joshi, 2000). The distribution lead time is constant and equals to 2 weeks. The initial values of the variables at each entity at $t = 0$ are extracted from (Joshi, 2000). The simulation model is run for 120 weeks and the values of the CCCC are illustrated in Fig.2.

4.3.2. Optimisation model

4.3.2.1. Optimisation model I

As discussed earlier, the objective of the first optimisation model is to manage the trade-offs between the CCC minimizations for the supply chain members through identifying the optimal values to the decision parameters (e.g. $\alpha, \beta, DNI, DSL, SP, UC$). The optimisation model is formulated as:

$$\begin{aligned} Min\ MCCC &= Min\ \mu_{MCCC} = \sum_{t=0}^{T} \frac{MCCC}{T} \\ Min\ DCCC &= Min\ \mu_{DCCC} = \sum_{t=0}^{T} \frac{DCCC}{T} \\ Min\ WCCC &= Min\ \mu_{WCCC} = \sum_{t=0}^{T} \frac{WCCC}{T} \\ Min\ RCCC &= Min\ \mu_{RCCC} = \sum_{t=0}^{T} \frac{RCCC}{T} \end{aligned} \tag{4.12}$$

Subject to:

$$0 \le \alpha^i \le 1,\ 0 \le \beta^i \le 1,\ 0 \le DNI^i \le 12,\ 0 \le DSL^i \le 15, 1 \le SP^i \le 4,$$
$$0.5 \le UC^i \le 3.5 \tag{4.13}$$

The objective functions are related to minimizing the cash conversion cycle (CCC) of the supply chain entities which is measured by the mean of cash to cash cycle for each entity over the simulation period. The lower and upper bounds for the decision parameters of entity *i* (e.g., manufacturer, distributor, wholesaler, and retailer) are defined by Eq. (4.13).

4.3.2.2. optimisation model II

As discussed earlier, the objective of the second optimisation model is to minimize the collaborative CCC (CCCC) or supply chain CCC (SCCC) through identifying the optimal values to the decision parameters (i.e.α, β, DNI, DSL, SP, and UC). The optimisation model is formulated as:

$$Min\ SCCC = Min\ \mu_{SCCC} = \sum_{t=0}^{T} \frac{SCCC}{T} \tag{4.14}$$

$$0 \le \alpha^i \le 1, \qquad 0 \le \beta^i \le 10,$$
$$0 \le DNI^i \le 12, \qquad 0 \le DSL^i \le 15,$$
$$1 \le SP^i \le 4, \qquad 0.5 \le UC^i \le 3.5 \qquad (4.15)$$

The objective function is related to minimizing the supply chain cash conversion cycle (SCCC) which is measured by the mean of supply chain cash conversion cycle over the simulation period. The lower and upper bounds for the decision parameters of entity i (e.g., manufacturer, distributor, wholesaler, and retailer) are defined by (4.15).

4.4. SBO implementation

SD simulation approach and the GA as optimisation engine are integrated in the form of an SBO model to derive optimal values to the controllable parameters (i.e. α, β, DNI, DSL, SP, UC) so as to make trade-offs between conflicting CCC minimizations in the optimisation model I and minimize collaborative CCC (CCCC) of the supply chain in the second optimisation model. To solve the optimization model I that is a multi-objective model the weighted sum method which is one of the widely used methods for addressing multi- objective optimization problems is applied. In this method, the multi-objective optimisation problem is transformed into a single objective optimisation problem through multiplying each objective function by a weighting factor and aggregating all weighted objective functions (Marler and Arora, 2010). The weight of an objective is chosen in proportion to the relative importance of the objective (Gass and Saaty, 1955) and the aggrgated weights of objectives needs to add up to 1. In the optimization model I all objective functions are given the same importance and consequently the same weight. Therfore the multi-objective model presenyted in Eq. (4.12) is transformed into a single-objective model as follow that is used the fitness function of the GA for identifying the optimal values to the decision parameters.

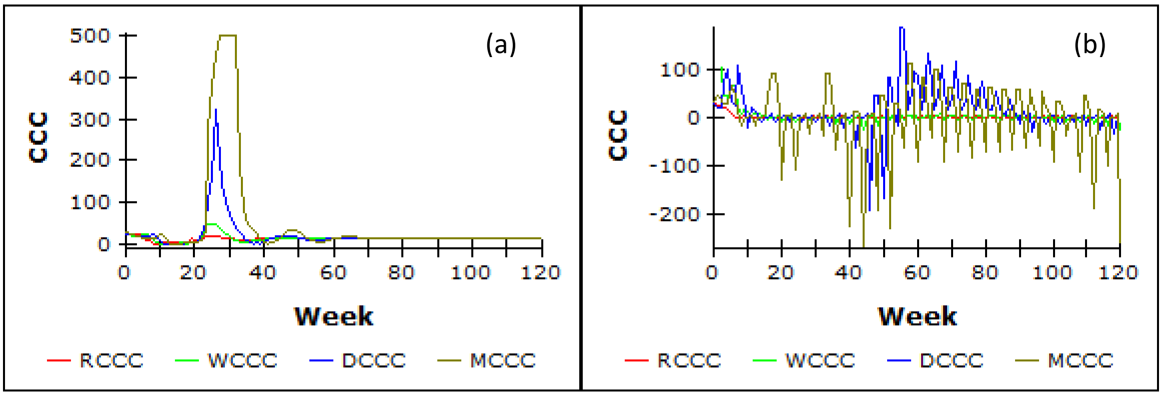
$$new\ objective = w1 \times \text{Min}\ \mu_{MCCC} + \text{w2} \times \text{Min}\ \mu_{MCCC} + \text{w3} \times \text{Min}\ \mu_{MCCC} + \text{w4} \times \text{Min}\ \mu_{MCCC}\ ;$$
$$\text{w1=w2=w3 =w4= 0.25} \qquad (4.16)$$

The genetic algorithm parameters are set as follows. Population size is set to be 200, crossover rate is set to be 0.8, and the mutation rate is set to be 0. The fitness function for the optimization model I is as follows.

$$Fitness\ Function = \frac{1}{w1 \times \text{Min}\ \mu_{MCCC} + \text{w2} \times \text{Min}\ \mu_{MCCC} + \text{w3} \times \text{Min}\ \mu_{MCCC} + \text{w4} \times \text{Min}\ \mu_{MCCC}}\ ;$$
$$\text{w1=w2=w3 =w4= 0.25} \qquad (4.17)$$

With the defined constraints for the decision parameters in the optimisation model I and the set values for the GA parameters, the SBO is run.

Figure 4.1 illustrates the CCC of the supply chain members before and after employing the SBO methodology. According to the results demonstrated in Figure 4.1(a), before applying SBO methodology, cash conversion cycle (CCC) of the manufacturer in week 30 arrived at 500 days, almost 72 weeks, while employing optimal parameter values not only results in significant decrease in cash to cash cycle of upstream members, i.e. distributor and manufacturer, but also improves CCC of the downstream members, i.e. wholesaler and retailer (see Figure 4.1(b)). The CCC of the manufacturer and the distributor in some weeks is negative that implies they are collecting money from their customers before providing any service. The optimal values to the decision parameters also objective functions values are displayed in Table 4.1.



Retailer cash conversion cycle (RCCC), Wholesaler CCC (WCCC), Distributor CCC (DCCC), Manufacturer CCC (MCCC)

Figure 4.1. System performance before and after applying the SBO methodology

Table 4.1. Optimal parameter values

α^M	0.74	UC^M	1.24
α^D	0.12	DNI^R	4.07
α^W	0.76	DSL^R	5.48
α^R	0.52	SP^R	2.75
β^M	0.72	UC^R	2.89
β^D	0.88	SP^S	1.09
β^W	0.97	DNI^W	11.62
β^R	0.94	DSL^W	9.68
DNI^D	4.29	SP^W	2.74
DSL^D	7.42	UC^W	2.38
SP^D	2.05	DCCC	0.12
UC^D	1.76	MCCC	-263.47
DNI^M	3.59	RCCC	-0.46
DSL^M	0.82	WCCC	-31.32
SP^M	1.56		

With the defined constraints for the decision parameters in the optimisation model II and setting the GA parameter values as population size 200, crossover 0.8, and mutation 0.1, the SBO is run. The fitness function for the optimization model II is defined as follows.

$$Fitness\ Function = \frac{1}{SCCC} \quad (4.17)$$

Figure 4.2 depicts the collaborative CCC (CCCC) of the supply chain members before and after employing the SBO methodology. According to the results demonstrated in Figure 4.2(a), before applying SBO methodology, collaborative cash conversion cycle (CCCC) in week 30 arrived at 600 days, almost 86 weeks, while employing optimal parameter values results in negative cash conversion cycle for the supply chain in most of the weeks (see Figure 4.2(b)). The optimal values to the decision parameters also objective function value are displayed in Table 4.2.

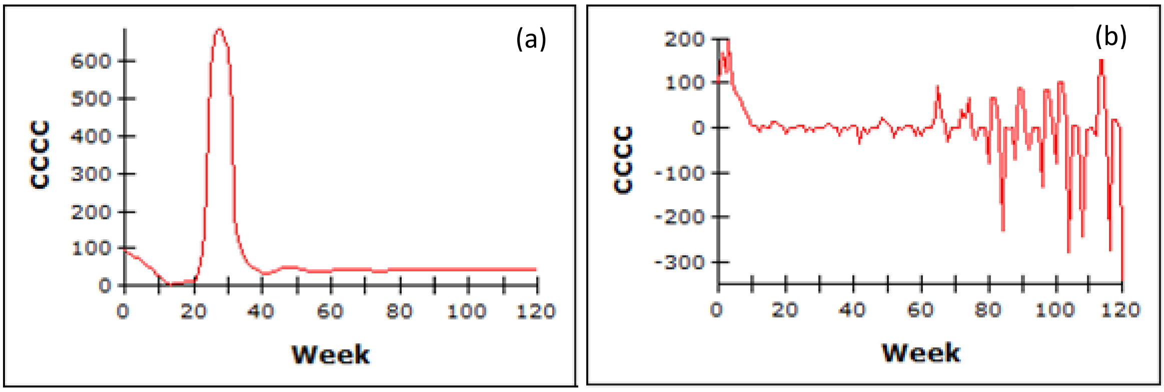


Figure 4.2. Collaborative cash conversion cycle (CCC) before and after employing the SBO

Table 4.2. Optimal parameter values

α^M	0.68	DSL^M	5.83
α^D	0.13	SP^M	1.54
α^W	0.9	UC^M	1.13
α^R	0.17	DNI^R	10
β^M	0.48	DSL^R	9.22
β^D	0.61	SP^R	2.96
β^W	0.83	UC^R	2.57
β^R	0.68	SP^S	1.03
DNI^D	7.8	DNI^W	11.01
DSL^D	5.12	DSL^W	6.43
SP^D	1.99	SP^W	2.52
UC^D	1.82	UC^W	2.37
DNI^M	2.94	CCCC	-343.75

4.5. Conclusions

In addition to matching the supply of products with the demand of customers within supply chain networks, the supply of cash is also required to be matched with the demand of supply chain members. Single company perspective on working capital management results in heterogeneous distribution of cash among supply chain entities. Therefore, working capital management should be considered from supply chain perspective in which each company is aware of the impact of its corrective measures for managing the working capital on its suppliers and customers.

As discussed in section 2.5.1 and is illustrated in Table 4.3, much of the literature on working capital management in the supply chain applied the empirical approaches to measure the CCCs for supply chain members (Theodore Farris and Hutchison, 2002; Ruyken et al., 2011; Lind et al., 2012). Although, modelling approaches such as simulation and optimisation are under-represented. Moreover, it has been argued that supply chain members may reduce their cash conversion cycle at the expense of increasing it for their upstream and/or downstream members (Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011). The literature lacks the studies which applied a practical modelling approach to manage the trade-offs between conflicting CCC minimizations for supply chain members by finding the optimal values to the financial and inventory decisions parameters. Finally, the literature lacks the studies that applied the collaborative CCC (CCCC) as the metric for measuring the efficiency of the working capital management in supply chains.

To fill the gap in the literature, in this chapter, a simulation-based optimisation model which integrates system dynamics simulation and genetic algorithms is developed for working capital management in a supply chain. In this model financial flow modelling is incorporated into the system dynamics simulation of the beer distribution game and minimizing the cash conversion cycle for supply chain members and minimizing the collaborative CCC of the supply chain are considered as optimisation objectives. This contribution extends the previous research on working capital and supply chain management by using the SBO modelling for managing the trade-offs between conflicting CCCs minimization for supply chain members and minimizing the collaborative CCC of the supply chain (Theodore Farris and Hutchison, 2002; Ruyken et al., 2011; Lind et al., 2012; Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011). The genetic algorithm is applied to identify the optimal values to the financial decisions parameters including price and unit cost and inventory decisions parameters including desired inventory, desired supply line, inventory adjustment parameter, and supply line adjustment parameter so as to mange the trade-offs between conflicting CCCs minimization for supply chain members and minimize the collaborative CCC of the supply chain.

Table 4.3. Working capital management and supply chains literature

Current literature	**Parameters considered**	**Managing the trad-offs between conflicting CCCs Minimization for supply chain members**	**Minimizing the collaborative CCC (CCCC) of the supply chain**	**Approaches**
(Theodore Farris and Hutchison, 2002; Ruyken et al., 2011; Lind et al., 2012; Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011)	-	×	×	Empirical Conceptual modelling
This study	Inventory control parameters Price Unit cost	✓	✓	Simulation-based optimisation (System dynamics and genetic algorithms)

The results indicated that the CCC of the supply chain members and the collaborative CCC of the supply chain (CCCC) can be decreased significantly by identifying the optimal values of inventory and financial decision parameters. Given the results of our study, supply chain managers should measure Collaborative CCC rather than CCC. In other words, this research provided the supply chain managers with a novel view to shift from the common paradigm of single perspective toward working capital management to collaborative cash flow management.

As it was shown in Figure 3, volatility of CCC for upstream members of the supply chain is significantly higher than that of the downstream members. This phenomenon is called cash flow bullwhip and relates to the bullwhip effect in the cash flow of the supply chain. In the next chapter an SBO model is developed to minimize the cash flow bullwhip in supply chains.

Chapter 5. Minimizing bullwhip effect and cash flow bullwhip in a supply chain using simulation-based genetic algorithms optimisation

5.1. Introduction

To remain responsive to uncertain demand conditions, supply chain members carry inventory to prevent orders being lost and also try to update orders placed to their upstream member according to the volatility in demand of their downstream member. However, there is a delay between the order placement time and the receiving of the order by the upstream member. In other words, the volatility in demand is not concurrently perceived by the upstream members such as the manufacturer and distributor. This unwanted phenomenon is called the Bullwhip Effect (BWE) and is mostly attributed to the lack of coordination between participants, distorted information, and information delays in the supply chain (Coppini et al., 2010).

In addition to the inefficiencies in product flow within a supply chain, such as excessive inventory, stock-outs, distorted demand forecasting (Chen et al. 2000; Lee, Padmanabhan, and Whang 1997), the BWE also negatively affects the financial flow through heterogonous distribution of cash among supply chain members. The cash conversion cycle (CCC) is one of the pivotal metrics used to measure supply chain efficiency in cash flow management (Zhao et al., 2015). The CCC is defined as the length of time that it takes for a company to convert resource inputs into cash flows collected from customers (Stewart, 1995). The lower the CCC, the more successful the firm is in managing cash flow. For example, Amazon is a role model in the effective management of cash flow possessing a CCC of -51 days in 2009 (Kumar, Eidem and Perdomo, 2012). Indeed, Amazon collects cash from customers before providing any service. Reducing the number of days inventory held at a firm is one of the actions that can be taken to reduce the CCC (Randall and Theodore Farris, 2009).

Volatility in inventory levels, which is caused by the BWE, results in variability in the number of days inventory outstanding, and accordingly causes variations in the CCC (Tangsucheeva and Prabhu, 2013). In such circumstances, supply chain members may face liquidity constraints, as they are not able to predict the amount of time that it takes to get access to the cash. The term “cash flow bullwhip” (CFB) was first introduced by Tangsucheeva and Prabhu (2013) to name this undesirable phenomenon, which is caused by variations in the CCC that occurs throughout financial flows in the supply chain. In this chapter, a simulation-based optimisation (SBO) framework including genetic algorithm (GA) and SD is developed to minimize the CFB, BWE, and supply chain total cost through identifying the optimal values to the inventory and financial decisions.

The rest of the chapter is organized as follows. Section 5.2 describes the model that was developed to measure the CFB within the supply chain and the proposed SBO methodology for mitigating the CFB. The beer distribution game which is the studied supply chain is elaborated in section 5.3. Section 5.4 illustrates the applicability of the proposed SBO approach and compares its performance with information sharing starategy in mitigating the CFB. Finally, concluding remarks are presented in section 5.5.

5.2. Supply chain model for cash flow bullwhip effect

Simulation stages of our case study model are outlined as follows. First, nomenclatures are demonstrated. Second, ordering policies applied by supply chain members are introduced and causes of the inventory bullwhip are identified in the ordering policy. Then, the impact of the ordering policy on CCC is investigated. To measure variations of the CCC and CFB, the SD simulation model of the studied supply chain composed of one manufacturer, one distributor, one wholesaler, and one retailer is developed. Causes of the inventory bullwhip and CFB are part of inputs and outputs of the simulation model, respectively. The validity of the SD model is assessed through implementing an extreme condition test. Furthermore, the capability of the model in showing the bullwhip effect within the supply chain network is another proof of its validity. Thereafter, feasible intervals of the input parameters, including causes of inventory bullwhip, price, and unit cost, are defined and the SBO approach is applied to derive optimal combination of the parameters to minimize CFB, BWE, and SCTC. Nomenclatures are presented in Table 5.1.

Table 5.1. Nomenclatures

Symbol	Definition
OP_t	Ordering decision made at the end of period t;
DF_t	Demand forecast at period t;
NI_t	Net inventory at time t;
SL_t	Supply line at time t;
γ	Smoothing parameter;
$COGS$	Cost of goods sold;

DIO	Days inventory outstanding;
DSO	Days sales outstanding;
DPO	Days payable outstanding;
q	Order quantity;
D	Demand;
I	Level of average inventory;
B	Backlog;
m	Collection policy;
n	Payment policy;
$SCTC$	Supply chain total cost;
$MBWE$	Manufacturer bullwhip effect;
$MCFB$	Manufacturer cash flow bullwhip;
TC_i	Total cost of entity i;
MPO	Manufacturer placed orders;
$MCCC$	Manufacturer cash conversion cycle;
${\sigma^2}_{MPO}$	Variance of manufacturer placed order;
${\sigma^2}_{\mathrm{DD}}$	Variance of distributor demand;
${\sigma^2}_{MCCC}$	Variance of manufacturer cash conversion cycle;
α_i	A fraction of the gap between desired on-hand inventory and current level of on-hand inventory of entity i;
β_i	A fraction of the gap between desired supply line and current level of supply line of entity i;
DI_i	Desired inventory of entity i;
DSL_i	Desired SL of entity i;
SP_i	Sales price per unit of entity i;
UC_i	Unit cost of entity i;
RPO	Retailer placed orders;
WPO	Wholesaler placed orders;
DPO	Distributor placed orders;
RI	Retailer inventory;
WI	Wholesaler inventory;
DI	Distributor inventory;
MI	Manufacturer inventory;
$RCCC$	Retailer cash conversion cycle;
$WCCC$	Wholesaler cash conversion cycle;
$DCCC$	Distributor cash conversion cycle;
i	Supply chain member index;

5.2.1. Ordering policy

In this study we have applied the ordering policy developed by Mosekilde et al. (1991) to calculate the amount to order (OP) for each member of the supply chain. The placed order which must be non-negative is calculated as:

$$OP_t = MAX\,(0, DOP_t) \tag{5.5}$$

Where the desired amount to order (DOP) is defined as follows:

$$DOP_t = DF_t + \alpha \underbrace{\left(DI - \overbrace{(INV_t - B_t)}^{NI} \right)}_{\text{INV Gap}} + \beta \underbrace{(DSL - SL_t)}_{\text{SL Gap}} \tag{5.6}$$

To determine the desired amount to order (DOP), each member endeavours not only to meet the forecasted demand of its downstream member but also bridge the inventory and supply line gaps. The exponential smoothing method with a smoothing parameter (γ) that equals to one is used to forecast the demand forecast (DF) as follows:

$$DF_t = SMOOTH\,(D_t, \gamma) \tag{5.7}$$

The inventory gap is the difference between the desired inventory (DI) and net inventory (NI) which is calculated by subtracting the unfulfilled orders (B) from the inventory (INV). The supply line (SL) gap is defined as the gap between the desired and actual supply line. The supply line represents the previous orders which have been sent by the upstream member but still have not been delivered. The desired inventory and the desired supply line are constant values which are specified by each member and represent the inventory levels which are desired to be held or to be on order for each member. As the inventory and supply line gaps are not replenished entirely in a review period, smoothing replenishment rules should be used to give an appropriate weight (i.e., α and β) to the gap terms (Disney et al., 2007).

α and β represent the discrepancy of units needed in the form of on-hand inventory (INV) and the supply line (SL) respectively. A high α value indicates an aggressive policy to bridge the gap between the desired inventory and the current net inventory. In the case of β, a high value shows that all the orders in the supply line have been considered, when deciding on the amount of orders to be placed with the upstream member.

In Expression (2), desired inventory (DI), desired supply line (DSL), inventory proportional parameter (α), and inventory on order proportional parameter (β) which are known as controllable parameters allow us to amend the dynamic behaviour of the supply chain. Indeed, changing these exogenous factors results in a set of ordering patterns ranging from order variance amplification (bullwhip) to dampening (smoothing) (Disney et al., 2007). In the next section, it is explained how Expression (5.2) may lead to a fluctuation in the CCC known as CFB.

5.2.2. Impact of ordering policy on CCC and CFB

According to Eq. (4.11) that defines the CCC using its three constituents: days sales outstanding (DSO), days inventory outstanding (DIO), and days payable outstanding (DPO) the CCC is a function of order quantity (q), inventory (I), demand (D), sales price per unit (SP), upstream sales price (USP), and unit cost (UC). Each supply chain member applies the replenishment rule presented in Eq. (5.1) to determine its order quantity. The variability of CCC is used to measure the cash flow bullwhip (CFB) for supply chain members as follows (Tangsucheeva and Prabhu, 2013):

$$\text{CFB} = \frac{\text{Variance of CCC}}{\text{Variance of downstream demand}} = \frac{\text{VAR(CCC)}}{\text{VAR(D)}} \tag{5.4}$$

To decrease CFB, the variability of CCC needs to be diminished through determining the optimal values for the inventory decision parameters (e.g., α, β, DNI, DSL), sales price per unit (SP), and unit cost (UC). To measure CFB through the supply chain, a system dynamics (SD) structure of the Beer distribution game is developed. In this case, inputs are inventory decisions parameters, price, and unit cost (i.e., control parameters) and outputs are variations of cash to cash cycle and CFB for participants. Simulation models that are developed by the SD approach are considered to be more robust than other types of simulation models, even though there are robustness tests that can be used to test the validity of the model. To show the robustness of our developed simulation model, the extreme condition test (Sterman, 2000) is applied. The extreme condition test deals with a test accompanied by a reasonable expected behaviour according to its inputs values (Sterman, 2000). e.g., dramatic increase in price of a product results in converging the demand function to zero (Sterman, 2000). To run the extreme condition test in our developed model, sales price per unit of product which is a model input is increased significantly. As a result, the CCC rises dramatically. Hence, it can be concluded that the behaviour of the model is reasonable.

5.2.3. Simulation-based optimisation (SBO)

After simulating the supply chain's cash flow and observing the CFB across the supply chain network, we need to manage its adverse effects through recognizing optimal values for the controllable parameters. As was indicated in the previous section, the CCC is a function of order size which is affected by ordering parameters including demand forecast updating (α), and rationing and shortage gaming (β) given in Eq. (5.2). That is to say, the CCC is influenced by factors that contribute to inventory bullwhip, hence our objective is to minimize CFB by recognising optimal values to the ordering parameters, inventory decisions, price, and unit cost. These are input parameters for the simulation model. Moreover, minimizing supply chain total cost and the BWE are other objective functions that will be taken into account. Here, simulation-based optimisation (SBO) is used to determine the optimal decision variables through integrating system dynamics (SD) and a Genetic algorithm (GA). SBO is an emerging field which consolidates simulation analysis by integrating optimisation methods into it. In other words, SBO transforms simulation model from a descriptive tool toward a prescriptive method. Regardless of the optimisation algorithm used, the process of optimizing an SD model involves four steps: (1) Developing the stock and flow diagram, (2) Selecting control parameters by which performance of the system is adjusted, (3) Specifying the lower and upper bounds of control parameters, and (4) Identifying model variables for optimisation. These variables represent the values that need to be optimised (Duggan, 2008).

After following these steps, the optimisation algorithm can be implemented. In all cases, SBO involves an iterative process between the optimiser and the simulation model, where firstly the optimisation algorithm inputs a set of parameter values to the simulation model and the simulation model then outputs performance measurements of the model to the optimiser. The optimisation algorithm then compares the performance of the system with the performance produced by previous permutations of the parameters in order to generate a new set of parameter values. This process continues until a stop criterion has been met, such as performing a defined number of evaluations, elapsing a specific amount of time or any user-specified criterion (Syberfeldt, 2009). The framework of the SBO approach in this study is shown in Figure 5.1.

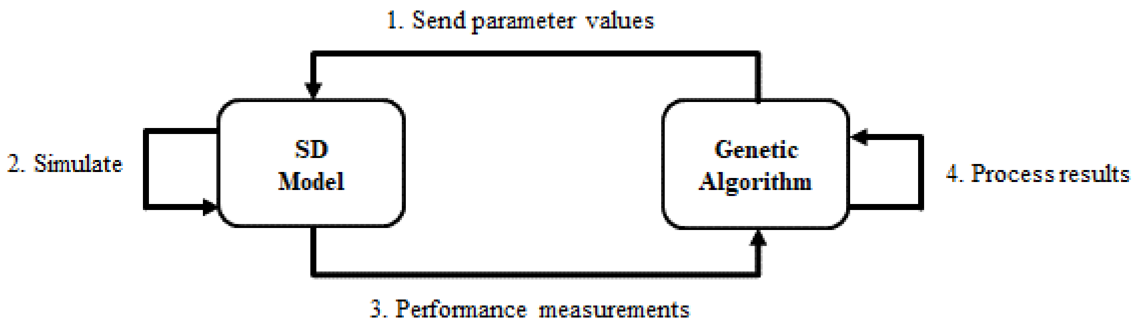


Figure 5.1. SBO process

5.2.4. Genetic algorithms (GAs)

Genetic algorithms (GAs) are computational algorithms inspired by Darwinian evolutionary theory which can be called in short as "survival of the fittest" (Darwin, 1859). In GAs it is assumed that fittest solutions survive and their characteristics are transferred from one generation to the next (Zaman et al. 2012). To optimise SD models using GAs, each solution known as a chromosome is represented by an array of elements, where each position in the array pertains to a possible parameter value. A solution pool named population is formed by a set of chromosomes. The algorithm starts with setting up a population of random possible solutions. Then, the individuals are evaluated based on the objective function to obtain the fitness of the solution. A fitness value shows how good each solution is in satisfying objective functions. Applying the rule of survival of the fittest, fittest solutions are selected from the population. Subsequently, solutions with higher fitness are combined to produce new solutions by performing a crossover operator. These solutions are known as parent solutions. To ensure maintaining variety in the overall population, new solutions may then be subjected to small variations from parent solutions called a mutation operator. Each population then represents a generation, and the process continues until predefined stopping criteria are met, such as convergence of fitness over generations or reaching the maximum number of generations (Lu et al., 2012). GAs are well suited for parameter optimisation and can also be extended to multiple objective optimisation (MOO) (Streichert, 2002). Therefore, in this research, a GA is employed to specify optimal values to the control parameters (e.g. $\alpha, \beta, DNI, DSL, SP, UC$). As it was explained in section 3.3.3.4 and shown in Figure 3.2, the GA derives the optima values to the control parameters as follow.

Representation. The first step in applying GA is to encode a solution of the problem into appropriate array representation. The length of the array is 25 (four supply chain members with 6 element each participant plus supplier sales price).

Initialization. The population size is set to be 200 solutions, each of which consists of 25 random elements, i.e. 6 elements for each member plus supplier sales rice. The values to the elements are randomly generated within their feasible intervals defined by the modeller. The lower and upper bounds of these intervals must be large enough to ensure that the optimal settings are inside the searching boundary (Chiadamrong and Piyathanavong, 2017). The process of generating random solutions continues until the population of 200 solutions is reached.

Evaluation. Every solution is then evaluated through simulation based on the supply chain total cost (SCTC), bullwhip effect (BWE), and cash flow bullwhip (CFB) and is assigned a fitness value. The fitness value for the solution is computed using the objective functions values, i.e. the lower the SCTC, BWE, and CFB, the higher the fitness value. Supply chain total cost (SCTC) includes inventory cost and backorder (backlog) cost. Bullwhip effect (BWE) and cash flow bullwhip (CFB) are minimized for manufacturer, as this member experiences the highest demand fluctuations and CCC variability compared to other supply chain members.

Selection. The roulette wheel principle (Goldberg, 1994) is applied to select chromosomes from the solution pool into a mating pool for generating offspring. Firstly, solutions are given a range between [0, 1] according to their fitness function value. The higher the fitness of the solution, the greater the assigned range. Then, random numbers between [0, 1] are generated and based on the range they are in the solutions are inserted into the mating pool. For example, one solution may be in the range of [0, 0.30], if the random number generated is within this range, this solution would be selected to enter the mating pool.

Reproduction. This process includes generating a new population of solutions from those selected through genetic operators: crossover and mutation. Crossover operator is used to take two solutions from the mating pool, and combines elements of those solutions to produce two new solutions: the procedure for this contains: (1) identifying a random crossover point on the two selected parent chromosomes and mark the two solutions at this point, (2) joining the first half of the first solution with the second half of the second solution also the first half of the second solution with the second half of the first solution to produce first and second child, respectively, and finally (3) replace parent solutions with the newly defined solutions (Duggan, 2008). The crossover operator in this study is set to be 0.8. Mutation operator is another genetic operator makes random changes to the solutions to deter stuck on a local optimum. Mutation operator generates a new solution by randomly changing one or more elements of the selected solution, namely, the value of one of the control parameters. The procedure for mutation involves: (1) selecting a small number of solutions for each generation by random, (2) selecting one or more elements of that solution randomly, and (3) generating a new value for the chosen elements considering the highest and lowest possible values for each parameter (Duggan, 2008). The mutation operator in this study is set to be 0.1.

Iteration and termination. The old population is replaced with the new population and cycle repeats until an optimal or near optimal solution to the problem appears in the population. GA tries to determine the optimal control parameters for each member. It applies a fitness function to determine the best chromosomes (solutions) in all generations also decide when to stop evolution. The proposed fitness function is defined as the inverse of the SCTC, BWE, and CFB as shown in Eq. (5.5), where a lower TC, BWE, and CFB results in a higher fitness value. SCTC aggregates inventory holding cost and backlog cost of all the members. The BWE is quantified through the ratio between the variance of orders and the variance of demand (Chen et al., 2000). Finally, the CFB is measured through Eq. (5.4).

$$\text{Fitness Function}=\frac{1}{\text{SCTC}+\text{MBWE}+\text{MCFB}} \tag{5.5}$$

As the initial population in GA, i.e. solution set, is randomly selected within the solution space and also that the optimisation process is stochastic, the exact same results will not be replicated every time. To obtain a wide range of optimal results, the optimal parameter sets are gained by defining various initial population. Thereafter, non-dominated optimal solutions are chosen from generated optimal solutions. Finally, the most ideal solution is selected by the decision maker based on higher level information (Duggan, 2008). In this work, MATLAB GA toolbox was used to perform the simulation with the fitness function of Eq. (5.5) with the restriction set on the ranges of the control parameters (e.g. α, β, DNI, DSL, SP, UC).

5.3. The beer distribution game

In this study, a four-agent Beer distribution game consisting of a manufacturer, a distributor, a wholesaler, and a retailer is modelled and cash flow between supply chain members is taken into account, in addition to the material and information flows, to measure the CFB for each supply chain member.

The studied supply chain model is shown in Figure 5.2., As in the case of the original BG, there is no information sharing between the supply chain entities and each entity places orders with its upstream member using the ordering policy outlined in section 5.2.1. The stock and flow structure of the material flow is shown in Figure 5.3. Joshi (2000) provides a complete description of the BG stock and flow model. Another relevant variable in this model, in addition to the orders placed to the upstream members, is the supply chain total cost (SCTC) (5.6), which is calculated by aggregating the total cost of the supply chain members. Total cost (5.7) for each agent is composed of the inventory holding cost and backlog cost. Inventory holding cost (5.8) is the product of inventory level and unit holding cost. However, the backlog cost (5.9) is determined by multiplying the backlog level into the unit stock out cost.

Supply chain total cost = $TC_M + TC_D + TC_W + TC_R$	(5.6)
Total cost = Inventory holding cost + backlog cost	(5.7)
Inventory holding cost = Inventory × unit holding cost	(5.8)
Backlog cost = Backlog × unit stock out cost	(5.9)

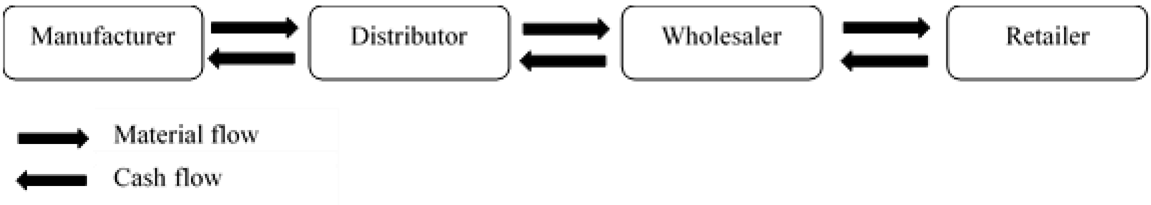


Figure 5.2. A four-echelon supply chain

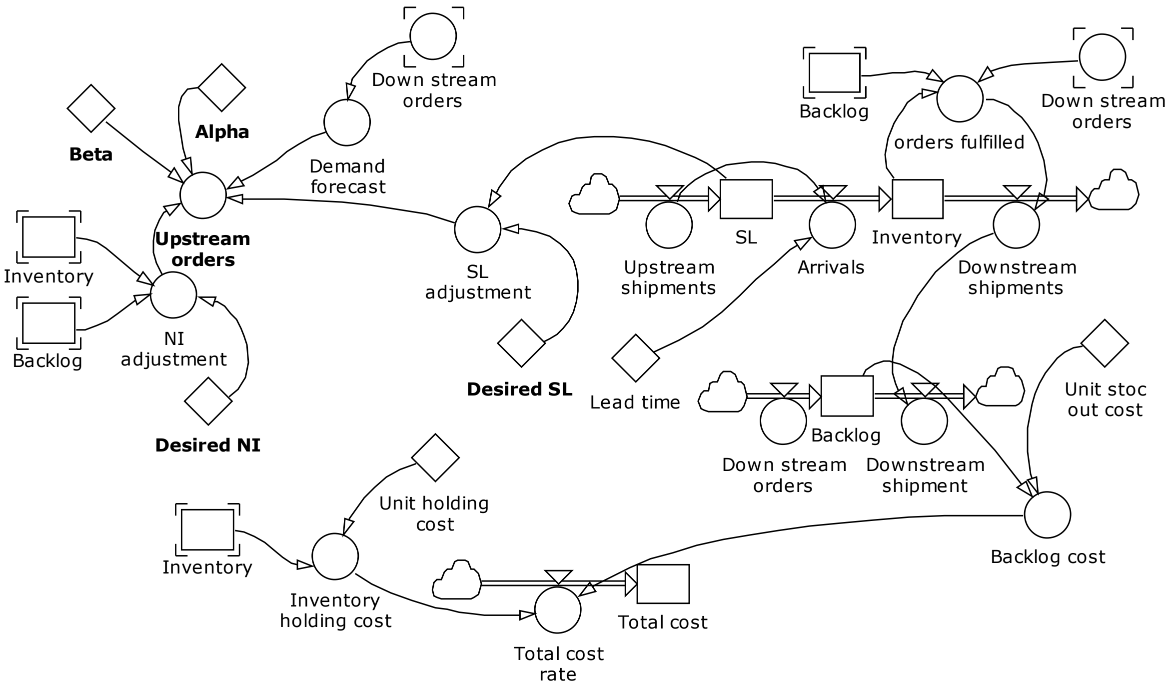


Figure 5.3. Generic structure of material stock and flow diagram for a member

The financial stock and flow model is shown in Figure 5.4 Each member pays for the orders placed to its upstream member and is paid for the orders received from its downstream member. The variable of interest in this model is the CCC which is determined by Eq. (4.11). The detailed description of the financial stock and flow model are presented as follows. The accounts receivable for each agent (5.10) is the product of downstream shipments and unit sales price of the product. The sales price of each member's product is determined by (5.11) -(5.14).

The revenue of each agent (5.15) is defined as the product of unit sales price and downstream orders. The days sales outstanding (DSO) (5.16) is defined as average accounts receivable divided by the daily revenue. As the simulation model is run weekly, the revenue is divided by seven to determine daily revenue. To measure inventory value (5.17), the inventory level is multiplied by the product unit sales price. The cost of goods sold (COGS) (5.18) is measured by multiplying downstream orders and unit product cost. The unit product cost is composed of all the costs that the members incur for unit of product, such as the production cost for the manufacturer and purchasing cost for the distributor. The unit product cost for each member is defined by (5.19) - (5.22).

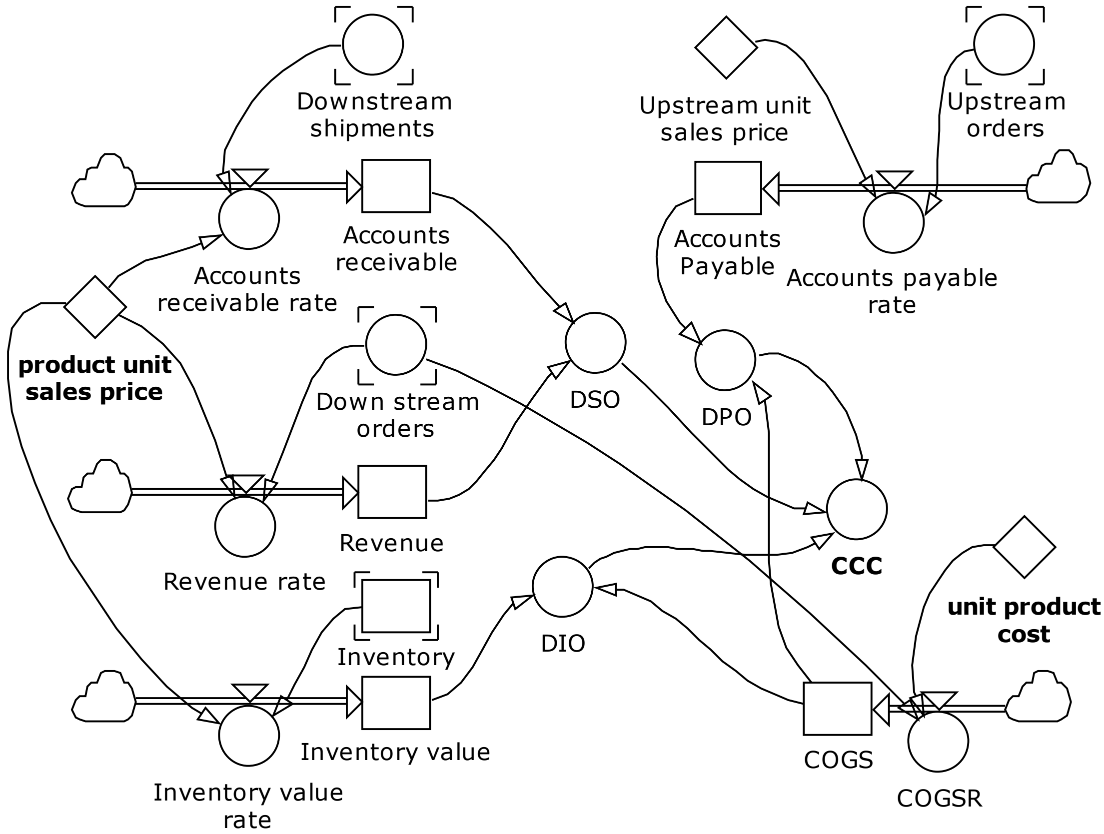


Figure 5.4. Generic structure of financial stock and flow diagram for a member

$\frac{d(\text{Accounts receivable})}{dt} = \text{downstream shipments} \times \text{product unit sales price}$	(5.10)
Manufacturer unit sales price = 1.5	(5.11)
Distributor unit sales price = 2	(5.12)
Wholesaler unit sales price = 2.5	(5.13)
Retailer unit sales price = 3	(5.14)
$\frac{d(\text{Revenue})}{dt} = \text{downstream orders} \times \text{product unit sales price}$	(5.15)
$\text{DSO} = \frac{\text{Average(accounts receivable)}}{\text{Revenue}/7}$	(5.16)
$\frac{d(\text{Inventory value})}{dt} = \text{Inventory} \times \text{product unit sales price}$	(5.17)
$\frac{d(\text{COGS})}{dt} = \text{downstream orders} \times \text{unit product cost}$	(5.18)
Manufacturer unit product cost = 1.25	(5.19)
Distributor unit product cost = 1.75	(5.20)

Wholesaler unit product cost = 2.25	(5.21)
Retailer unit product cost = 2.75	(5.22)

The days inventory outstanding (DIO) (5.23) is measured by dividing the average inventory value into the daily COGS. To measure the amount of payables (5.24), product unit sales price of the upstream member is multiplied by orders. The days accounts payable outstanding (DPO) (5.25) is the ratio of average accounts payable and daily COGS. Cash conversion cycle (CCC) (5.26) for each supply chain member is the summation of DSO, and DIO minus DPO.

$\mathrm{DIO} = \dfrac{\text{Average (inventory value)}}{\mathrm{COGS}/7}$	(5.23)
$\dfrac{d(\text{Accounts payable})}{dt} = \text{orders} \times \text{upstream unit sales price}$	(5.24)
$\mathrm{DPO} = \dfrac{\text{Average(accounts payable)}}{\mathrm{COGS}/7}$	(5.25)
$\mathrm{CCC} = \mathrm{DSO} + \mathrm{DIO} - \mathrm{DPO}$	(5.26)

5.3.1. MOO of the BG

To determine the optimal decision parameters for the supply chain members, an optimisation problem which contains the objective functions and constraints on parameter values should to be formulated. The objective functions for the optimisation problem are denoted as (5.27):

$$\begin{cases} \text{Min SCTC} = \text{Min } \mu_{SCTC} = \sum_{t=0}^{T} \frac{SCTC}{T} \\ \text{Min MBWE} = \text{Min } \sigma^2{}_{MPO} / \sigma^2{}_{DD} \\ \text{Min MCFB} = \text{Min } \sigma^2{}_{MCCC} / \sigma^2{}_{DD} \end{cases} \tag{5.27}$$

Decision variables: α_I, β_I, DI_I, DSL_I, SP_I, UC_i

Subject to:

$$0 \le \alpha_I \le 1,\ 0 \le \beta_I \le 1,\ 0 \le DI_I \le 12,\ 0 \le DSL_I \le 15,\ 1 \le SP_I \le 4,$$

$$0.5 \le UC_i \le 3.5 \tag{5.28}$$

The first objective function is related to minimizing the SCTC which is measured by the mean of supply chain total cost over the SBO period. The second objective is to minimize the BWE for the manufacturer which is formulated as the ratio of variation in manufacturer's order to variation in its downstream demand. The third objective function pertains to CFB minimization for the manufacturer quantified by the ratio of variation in the manufacturer's CCC to variation in its downstream demand. The lower and upper bounds for the decision parameters of entity i (e.g., manufacturer, distributor, wholesaler, and retailer) are defined by Eq. (5.28). The manufacturer, as the final upstream member of the supply chain, endeavours to manage variations in the order quantity, and cash conversion cycle (CCC) in order to reduce the BWE, and CFB respectively. It would be interesting to know whether minimizing the order quantity and CCC fluctuations for the manufacturer results in volatility reduction in order quantity and CCC for other supply chain members. The premise for this model is that the decision maker aims to minimize SCTC and also minimize the BWE and CFB throughout the supply chain network.

To solve the multi-objective optimisation problem indicated in Eq. (5.27) and Eq. (5.28) the weighted sum method which is one of the most widely used methods for solving multi-objective optimisation problems is applied. In this method, the multi-objective optimisation problem is transformed into a single objective optimisation problem through multiplying each objective function by a weighting factor and aggregating all weighted objective functions (Marler and Arora, 2010). The weight of an objective is chosen in proportion to the relative importance of the objective (Gass and Saaty, 1955). Considering a multi-objective optimisation problem with m objectives, where w_i $(i = 1, \ldots, m)$ represents the weighting factor for the ith objective function. If $\sum_{i=1}^{m} w_i = 1$ and $0 \leq w_i \leq 1$, the weighted sum is a convex combination of objectives (Kim and De Weck, 2006). As the objective functions in Eq. (5.27) have the same importance for the decision maker, they are given equal weights that add up to one and Eq. (5.27) is transformed into a single-objective function as follows.

$$\text{new obj} = \text{w1} \times \text{Min}\, \mu_{SCTC} + \text{w2} \times \text{Min}\, {\sigma^2}_{MPO} / {\sigma^2}_{DD} + \text{w3} \times \text{Min}\, {\sigma^2}_{MCCC} / {\sigma^2}_{DD} \quad \text{w1} = \text{w2} = \text{w3} = 0.33 \qquad (5.29)$$

5.4. Experiments

This section outlines the results of the tests conducted on the beer distribution game using the SBO methodology and information sharing, which are two common techniques for bullwhip effect reduction. The SBO aims to minimize the total cost of the supply chain in addition to the

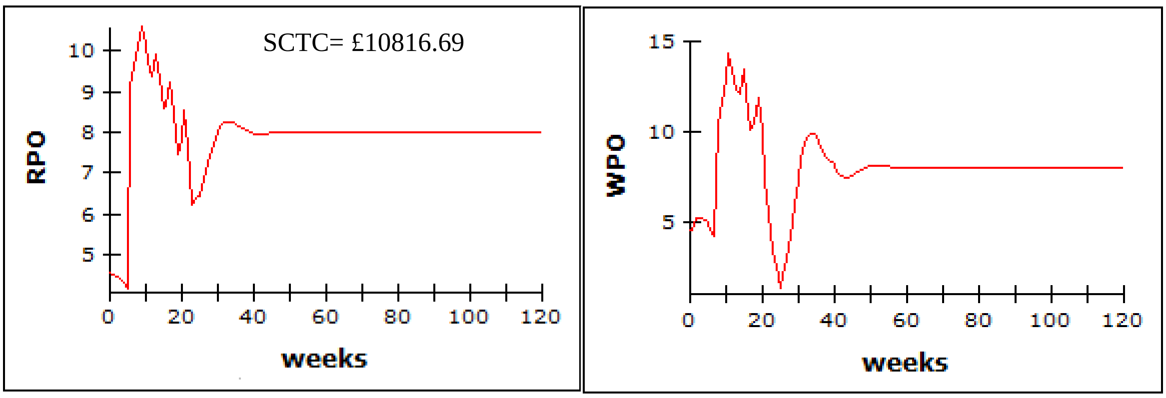
BWE and CFB for the manufacturer by obtaining the optimal price, unit cost, and inventory decision parameters for all members. The information sharing strategy involves supply chain members being informed about end customer demand.

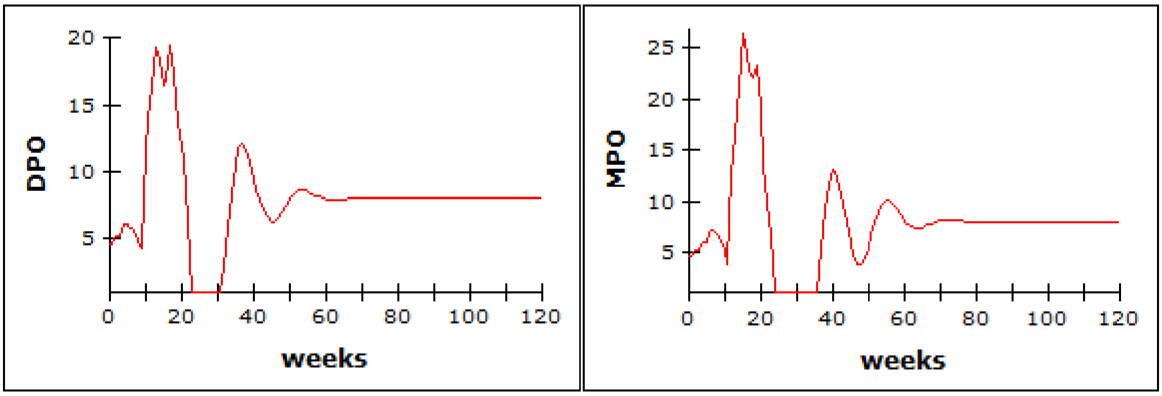
5.4.1. Experiment 1

The first experiment was designed to test the performance of the SBO and information sharing under the assumptions of the original beer game, which included deterministic demand and lead times. According to the assumptions of the beer game (BG), customer demand starts by ordering 4 crates of beer during the first four weeks and then suddenly, in week 5, the customer demand rises to 8 crates per week for the rest of the simulation (Joshi, 2000). Aslam and Ng (2016) provides the initial values for material flow variables and parameters at each entity at t = 0. The values for cash flow parameters, unit cost and price, are shown in Table 5.2. As expected from running the SD-BG model, Figure 5.5 clearly demonstrates the existence of the BWE. The placed orders by upstream members is several orders of magnitude larger than the end customer demand. The manufacturer placed order (MPO) is 3.4 times more than the end customer demand at week 12. This oscillating effect shows how an increase in the customer demand, from four to eight in week 5, has resulted in a huge oscillating effect at the final upstream member, manufacturer.

Table 5.2. Sales price and unit cost of supply chain members

Manufacturer		Distributor		Wholesaler		Retailer	
SP	*UC*	*SP*	*UC*	*SP*	*UC*	*SP*	*UC*
1.5	1.25	2	1.75	2.5	2.25	3	2.75





Retailer placed orders (RPO)
Wholesaler PO (WPO)
Distributor PO (DPO)
Manufacturer PO (MPO)

Figure 5.5. The bullwhip effect

The inventory levels for entities is shown in Figure 5.6. The inventory level for the manufacturer between weeks 25 and 35 remains at 60, which is 7.5 times larger than the customer demand.

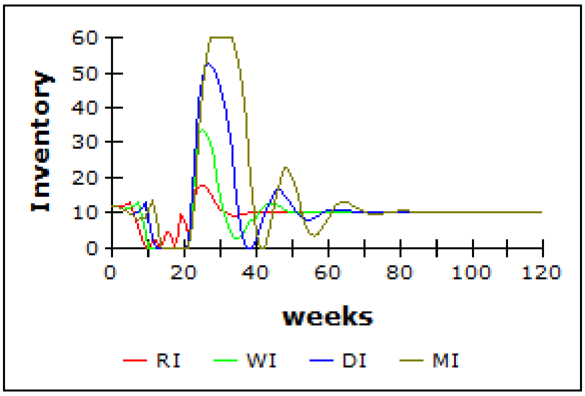
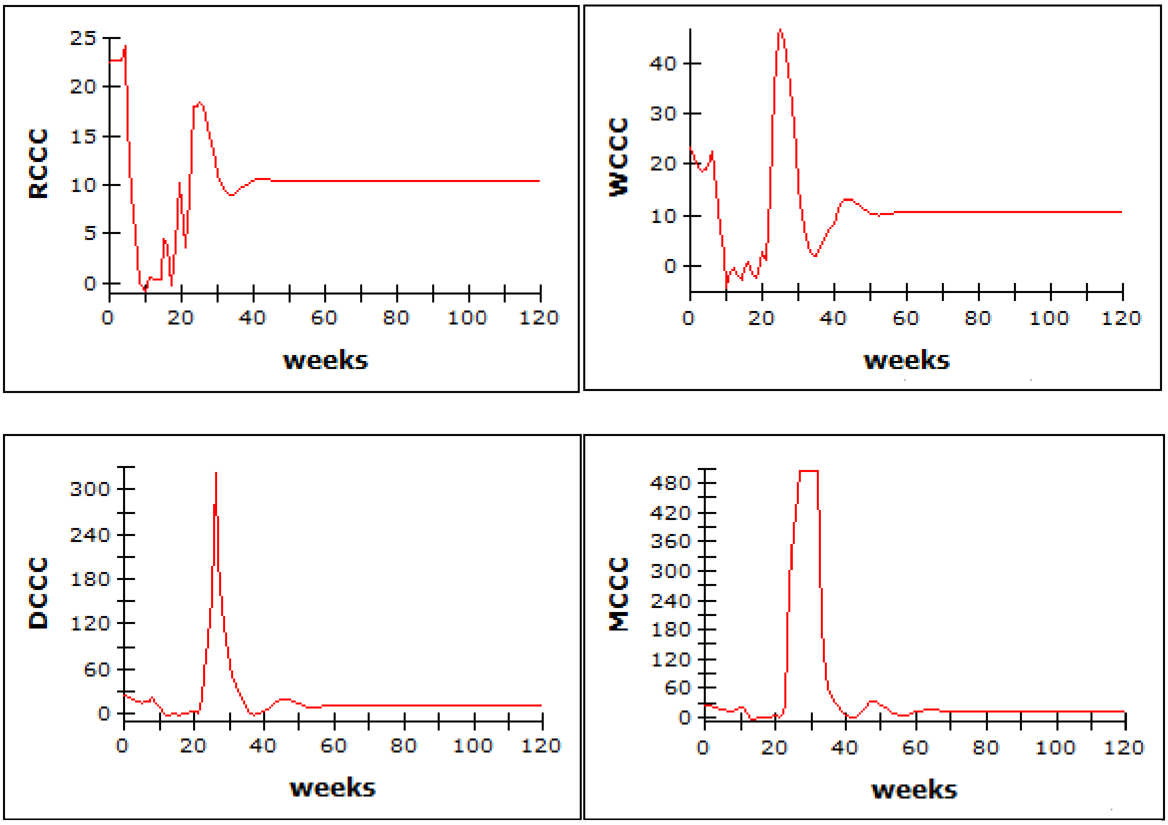


Figure 5.6. The inventory of supply chain members

The variability of the cash conversion cycle (CCC) for supply chain members is shown in Figure 5.7. The existence of the BWE results in an increase in inventory levels which subsequently leads to a rise in days inventory outstanding (DIO). An increase in DIO also results in CCC growth. The oscillations in CCC rises significantly as we move toward upstream members of the chain so that CCC for the final entity, manufacturer, ranges from 30 to 500 days. Hence, it can be concluded that the existence of the BWE prolongs the cash to cash cycle for the upstream members.



Retailer cash conversion cycle (RCCC), Wholesaler CCC (WCCC), Distributor CCC (DCCC), Manufacturer CCC (MCCC)

Figure 5.7. The cash flow bullwhip

5.4.1.1 Impact of information sharing

Considering the assumption that SC members do not share the demand information, each entity forecasts the end customer demand based on the previous orders of its downstream member. Most companies amplify the demand of their downstream member which leads to information distortion throughout the supply chain that is one of the main drivers of the BWE. Information sharing is a mechanism which eliminates information distortion and reduces the BWE through sharing the end customer demand between the SC members (Yu et al .2001).

To illustrate the impact of information sharing on diminishing the BWE, CFB and SCTC, the results of the original SD model in which the demand information are not shared among the SC members are compared with the results obtained from the SD model in which there is information sharing between the entities. According to the results shown in Figure 5.8(a)-(c), the information sharing among the SC members reduces the variability in the placed orders by the customers, variability in inventory levels of the entities, and variability in cash conversion cycles of the entities. According to the results shown in Figure 5.5, the placed orders by the SC members in the original SD model has a scale of 0-27. While, after the information sharing the placed orders by the SC members vary in the range of [1, 12] (see Figure 5.8(a)). According to the results shown in Figure 5.6, the inventory levels of the SD members in the original SD model has a scale of 0-60. While, after the information sharing the inventory levels of the SC entities vary in the range of [0, 20] (see Figure 5.8(b)). According to the results illustrated in Figure 5.7, the CCCs of the members has a scale of 30-500. Although, after the information sharing the CCCs of the SC entities vary in the range of [0, 27] (see Figure 5.8(c)).

As explained, the DIO volatility is caused by increasing the inventory levels. Therefore, mitigating the inventory levels through information sharing reduces the CFB in addition to the BWE. Although the BWE and CFB decrease dramatically as a result of implementing the information sharing strategy, the impact of the strategy on reducing the SCTC is not significant. The SCTC decreases by 8 percent, from £10816 to £9915.65. The reason is that the information sharing strategy does not identify the optimal values for the inventory decision parameters which affect the inventory levels of the SC members and consequently the SCTC.

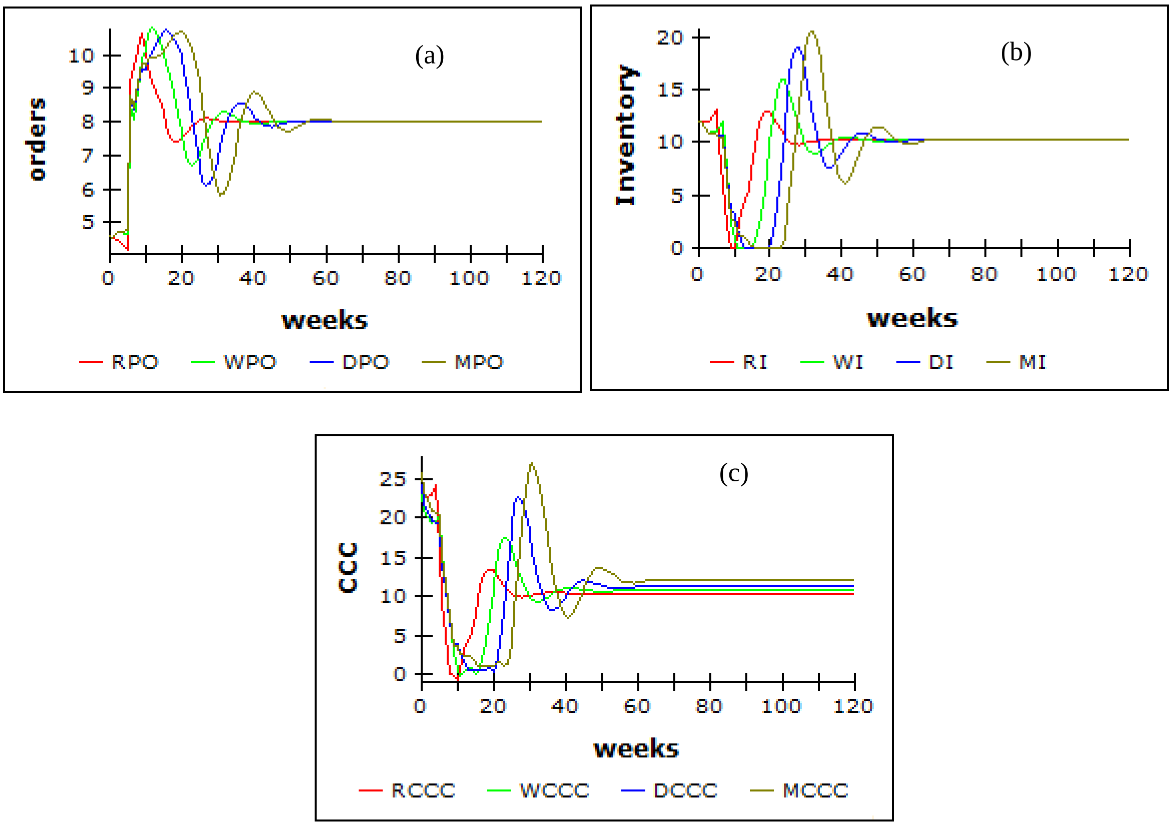


Figure 5.8. Impact of information sharing for experiment 1

Although, information sharing may bring several benefits to the supply chain members such as inventory reduction, cost reduction, bullwhip effect reduction and improved resource utilization (Lee, So and Tang, 2000; Mourtzis, 2011). Some of the supply chain members are not willing to share their information including sales data, sales forecasting, order information, inventory information and so on with other members of their supply chains, unless those members are part of their own company. It goes without saying that partial information sharing is not as effective as full information sharing in reducing the bullwhip effect, cash flow bullwhip, and supply chain total cost. Although, it should be noted that the partial information sharing particularly when the order information is shared with the upstream members of the supply chains that are hardest hit by bullwhip effect and cash flow bullwhip, the partial information sharing may have a significant impact in reducing the bullwhip effect, cash flow bullwhip, and supply chain total cost (Zhang and Chen, 2013).

5.4.1.2 SBO implementation

The execution of the SBO methodology is based on the process referred to in section 5.2.3. In order to implement the SBO, a number of specific values need to be decided on, including:

- The range of values for decision parameters which are defined by Eq. (18).
- The parameters for the GA which are set as follows: the population size is 200, the crossover and mutation rates are set to be 0.8 and 0.1, respectively. To specify an appropriate population size, a number of population sizes are selected, and the algorithm is run 15 times for each population size. The results are reported in Table 5.3. Increasing the population size improves the mean and the standard deviation of the fitness function. The population size of 200 is an appropriate population size as the population size of 250 does not improve the best fitness value. Although, it slightly reduces the standard deviation of the fitness function.

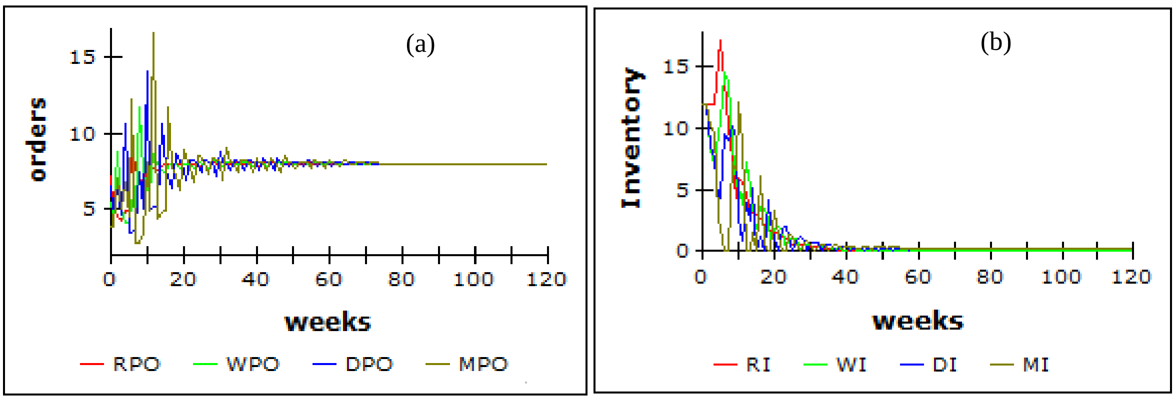
Table 5.3. Impact of population size on fitness function

Population size	Reverse fitness value			
	Best (Min)	Worst (Max)	Mean	Standard deviation
50	*7055.64*	*7116.68*	*7072.37*	*28.68*
100	*7049.38*	*7136.38*	*7050.40*	*25.26*
150	*7046.29*	*7073.51*	*7047.80*	*14.62*
200	*7035.64*	*7053.38*	*7043.72*	*5.50*
250	*7035.64*	*7052.23*	*7041.52*	*5.21*

The optimal solution recommends a non-aggressive strategy toward bridging the gap between the desired inventory and current net inventory, i.e., the value of α for all members is less than

0.5, and a cautious approach to order quantity for distributor and retailer, i.e., the value of β for distributor and retailer is more than 0.5.

To illustrate the effectiveness of the SBO methodology in minimizing the BWE, CFB, and SCTC, the results of the SBO model in which the end customer demand is not shared among the members are compared with the results obtained from the SD model in which there is information sharing between the entities. According to the results shown in Figure 5.9(a), order quantities of all supply chain members converge with customer demand (8 crates/week) at week 40. Whilst, before applying the SBO notwithstanding sharing the demand information within the SC network, the placed orders adjust to customer demand at week 60 (see Figure 5.8(a)). SC members are not required to hold inventory from week 60 until the end of the simulation in the SBO model (see Figure 5.9(b)) , while in the SD model with information sharing at the same period the SC members hold 10 crates/week in inventory (see Figure 5.8(b)). Similarly, optimal controllable parameters lead to a 0 day cash conversion cycle for all the members at week 30 (see Figure 5.9(c)). However, the non-optimal parameter values result in an 11 day cash cycle for the retailer at week 40 (see Figure 5.8(c)). In addition to the BWE and CFB reduction, implementing the SBO methodology leads to a 29% decrease in the SCTC due to the lower inventory levels which is held by the SC members. The SCTC reduced from £9915.65 obtained from the SD model with information to £7017.94 after employing the SBO methodology.



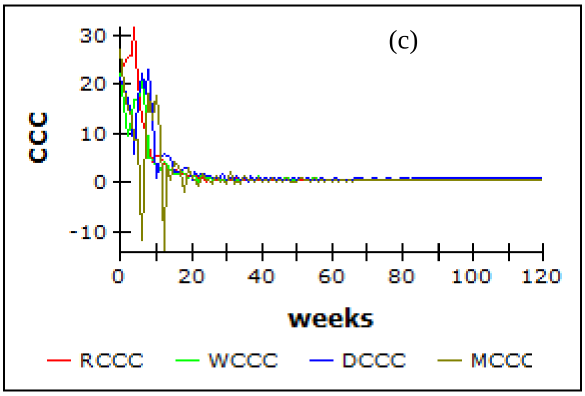


Figure 5.9. Impact of employing SBO for experiment 1

5.4.2 Experiment 2

The second experiment examines the performance of the SBO and information sharing under stochastic demand where it is assumed that the customer demand fluctuates in the range of [0,15] (Kimbrough et al. 2002). Figure 5.10(a) illustrates the ordering quantities for each member of the supply chain before applying the SBO and information sharing. It demonstrates the amplifications occurring in the orders and the customer's orders cannot be easily tracked. The manufacturer placed order (MPO) is 3.4 times more than the highest orders could be placed by the end customer at week 12. As expected, the performance of the members in tracking the customer's demand is inferior to their performance in experiment 1. Therefore, the inventory levels of the members that are shown in Figure 5.10(b) are higher than the inventory levels in experiment 1 (see Figure 5.6). In experiment 2 before employing the information sharing and SBO, the highest inventory level which held by the SC members is 110 which held by the distributor at week 30 of the simulation (see Figure 5.10(b)). While, in experiment 1 the highest inventory level held by the SC members before employing the information sharing and SBO is 60 which was held by the manufacturer between weeks 25 and 35 (see Figure 5.6). Figure 5.10(c) depicts the oscillations in cash cycles of the members which are higher than the cash cycle oscillations in experiment 1. The highest CCC for the SC members before information sharing and SBO in experiment 2 is 1432 days. While, the highest CCC for the SC members before information sharing and SBO in experiment 1 is 27 days. The accumulated cost of the supply chain in this experiment before applying BWE reduction techniques is £14283.42 that is higher than the total cost in experiment 1.

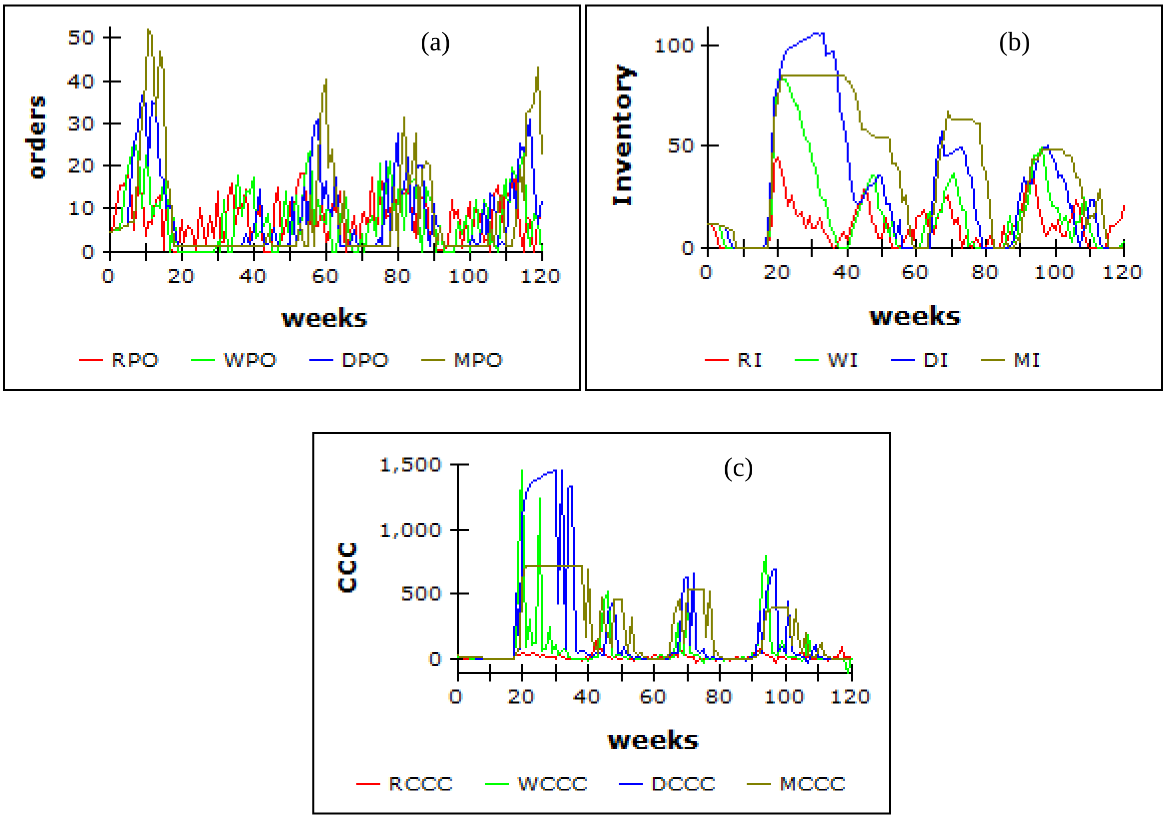


Figure 5.10. Results for experiment 2 before using information sharing and SBO

5.4.2.1 Impact of information sharing

The impact of information sharing on reducing the BWE, CFB, and SCTC is shown in Figure 5.11(a)-(c). The ordering quantity of all members is given in Figure 5.11(a), which has a scale of 0-27. While before information sharing, the placed orders by the SC members has a scale 0-51 (see Figure 5.10(a)). According to the results shown in Figure 5.10(b), the inventory levels of the SC members before information sharing has a scale of 0-110. While, after the information sharing the inventory levels of the SC entities vary in the range of [0, 83] (see Figure 5.11(b)). According to the results illustrated in Figure 5.10(c), the CCCs of the members before information sharing has a scale of 0-1432. Although, after the information sharing the CCCs of the SC entities vary in the range of [0, 712] (see Figure 5.11(c)). In addition to the BWE and CFB reductions, the SCTC decreased dramatically as a result of implementing the information sharing strategy. The SCTC reduced by 23 percent, from £14283.42 before information sharing to £10947.54 after information sharing.

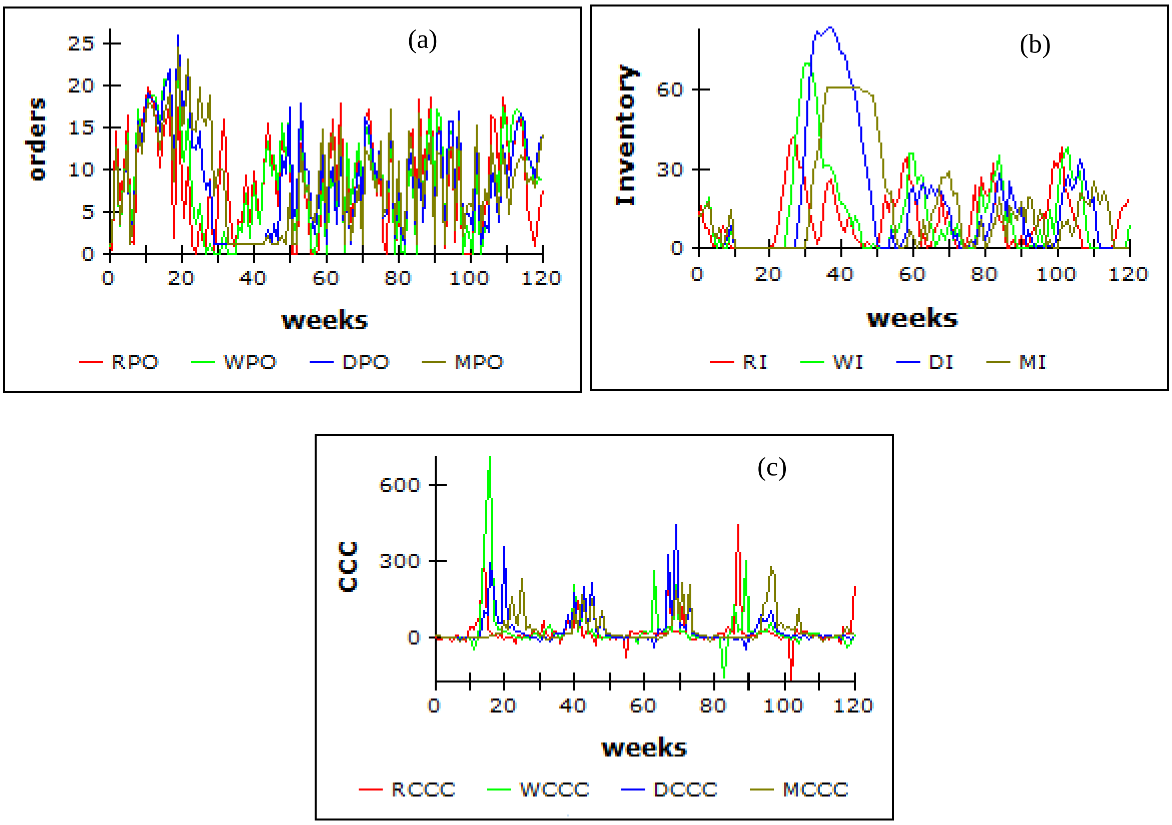
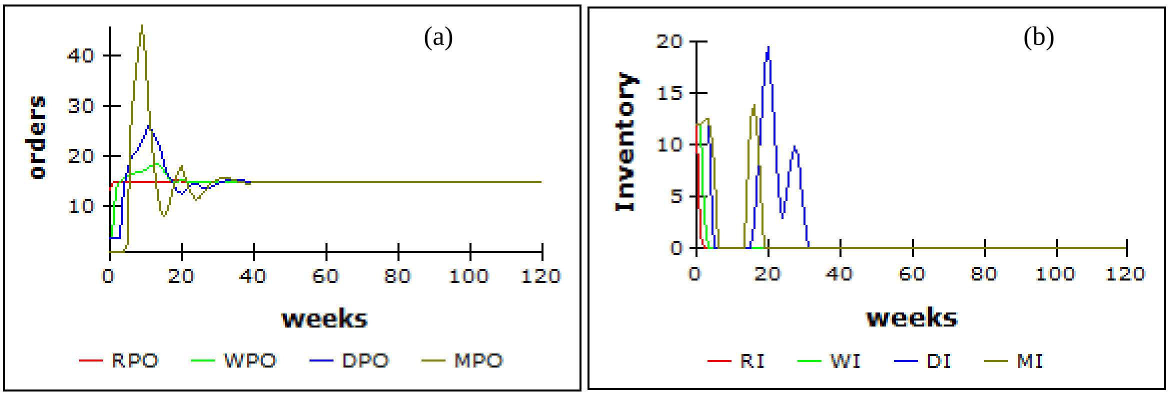


Figure 5.11. Impact of information sharing for experiment 2

5.4.2.2 Impact of SBO

Using the values for the GA parameters presented in the previous section, i.e., population size 200, crossover 0.8, and mutation 0.1, the SBO is run for 15 times. The standard deviation of the obtained fitness values is 6.71 and the best fitness value is 8332.83. The order quantities of the members are shown in Figure 5.12(a), which has a scale of 0-45. The largest order placed by a member in the SBO method is higher than the largest order placed in the case of information sharing, i.e., 27(see Figure 5.11(a)). While, the inventory levels of the members, as illustrated in Figure 5.12(b), are significantly lower than the inventory levels in the information-sharing scenario. The inventory levels of the SC members in the SBO model reaches to 0 at week 30 and remains unchanged until the end of the simulation. While, in the SD model with information sharing the inventory of the retailer who possess the lowest volatility among the SC members fluctuates in the range of [0, 38] from week 30 until the end of the simulation (see Figure 5.11(b)). The cash cycle of the members after using the SBO method is indicated in Figure 5.12(c) that proves the cash flow bullwhip is significantly reduced comparing the SD model with information sharing. After employing the SBO method, the CCC of the all members remains at 0 day from week 40 until the end of the simulation. While, after employing the information sharing strategy, the CCC of the manufacturer who possess the lowest volatility in cash to cash cycle among the SC members varies in the range of [0, 225] (see Figure 5.11(c)).

The SBO method proposes an aggressive approach toward bridging the gap between the desired inventory and current net inventory for the manufacturer and retailer. This implies that the value of α for the manufacturer and retailer is less than 0.5. A cautious strategy is needed for orders in the supply line for the retailer as, the value of β for the retailer is more than 0.5. Further experiments were performed to investigate if the recommended policy was robust for all random values in the range of [0-15] and deterministic lead times. 50 sets of random customer's demand were generated by MATLAB, and the SBO was run 15 times for each set to determine the fitness function. The lowest fitness function found would be the optimal solution for that specific set of random values when all 50 sets of random values are examined. The results indicate that the aggressive approach to inventory gap for the manufacturer and retailer and cautious approach to order quantity for the retailer was optimal in 45 sets. This shows that the recommended policy for inventory replenishment is an effective policy for diminishing the BWE, CFB, and SCTC when demand varies slightly [0-15], and the lead times are deterministic. The lower inventory levels held by the SC members after employing the SBO method leads to lower SCTC comparing the information sharing. The total cost of the supply chain after using the SBO method decreased by 24 percent. The SCTC reduced to £8292.74 from the total cost of £10947.54 in SD model with information sharing.



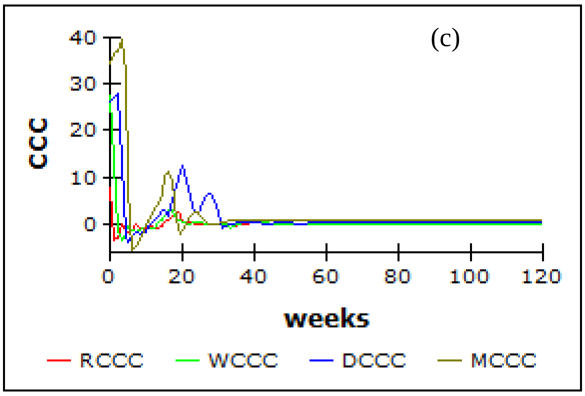


Figure 5.12. Impact of employing SBO for experiment 2

5.4.3 Experiment 3

Experiment 3 extends the experiment 2 through considering the stochastic lead times in addition to the stochastic demand. The shipping lead time varies in the range of [0, 4] in each time period. Figure 5.13(a) illustrates the ordering quantities for each member of the supply chain before applying the SBO and information sharing. It demonstrates the amplifications occurring in the orders and the customer's orders cannot be easily tracked. The manufacturer placed order (MPO) is 2.7 times more than the highest orders could be placed by the end customer at week 12. Although amplifications occurred in the placed orders, the performance of the members in tracking the customer's demand is better than their performance in experiment 2. Therefore, the inventory levels of the members that are shown in Figure 5.13(b) are lower than the inventory levels in experiment 2. In experiment 3 before employing information sharing and SBO, the highest inventory level which held by the SC members is 27 which held by the distributor at week 30 of the simulation. While, in experiment 2 the highest inventory level held by the SC members before employing the information sharing and SBO is 110 which was held by the distributor at week 35 (see Figure 5.10(b)). Figure 5.13(c) depicts the oscillations in cash cycles of the members which are lower than the cash cycle oscillations in experiment 2. The highest CCC for the SC members before information sharing and SBO in experiment 3 is 40 days. While, the highest CCC for the SC members before information sharing and SBO in experiment 2 is 1432 days. The accumulated cost of the supply chain in this experiment before applying BWE reduction techniques is £18387.96, which is higher than the total cost in experiment 2 notwithstanding the lower levels of the inventory held by the members. The reason is that uncertainty in lead times affects the on-time delivery of the products negatively and consequently the stock outs increase. As the unit stock out cost is higher than the unit inventory holding cost, the total cost of the supply chain in experiment 3 is higher than the total cost in experiment 2.

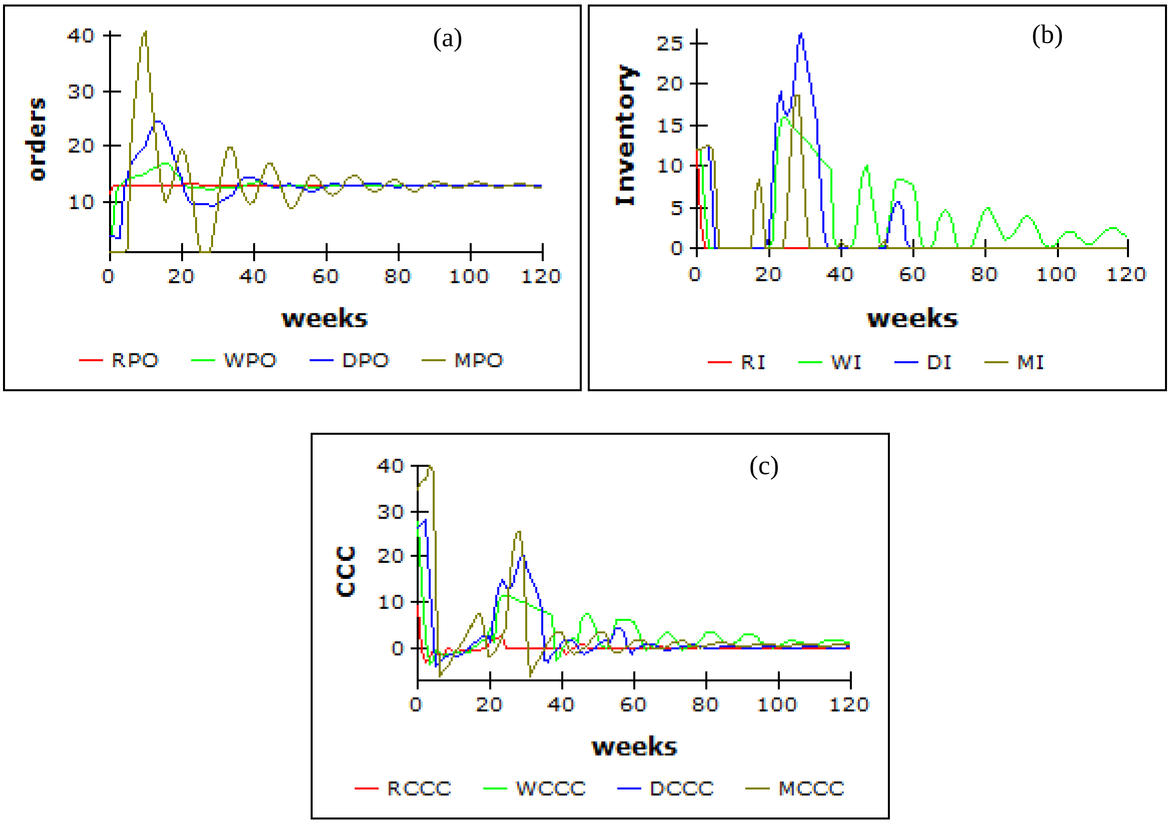


Figure 5.13. Results for experiment 3 before using information sharing and SBO

5.4.3.1 Impact of information sharing

The impact of information sharing on reducing the BWE, CFB, and SCTC is shown in Figure 5.14(a)-(c). The ordering quantity of all members is given in Figure 5.14(a), which has a scale of 0-23. While before information sharing, the placed orders by the SC members has a scale 0-40 (see Figure 5.13(a)). Although the ability of the members in tracking the customer's demand is ameliorated as a result of information sharing, the inventory levels illustrated in Figure 5.14(b) show amplifications and are higher than the inventory levels before information sharing. The inventory levels of the SC members before information sharing has a scale of 0-27(see Figure 5.13(b)). While, after the information sharing the inventory levels of the SC entities vary in the range of [0, 42] (see Figure 5.14(b)). The higher inventory levels help the members to mitigate the lost sale, which decreases the total cost to £10672.94 after information sharing, from the original cost of £18387.96 before information sharing. Figure 5.14(c) depicts the CCC of the members after information sharing that have risen compared with before information sharing. The CCC increases are caused by higher days inventory outstanding that is caused by higher inventory levels. According to the results illustrated in Figure 5.13(c), the CCCs of the members before information sharing has a scale of 0-40. Although, after the information sharing the CCCs of the SC entities vary in the range of [0, 687] (see Figure 5.14(c)).

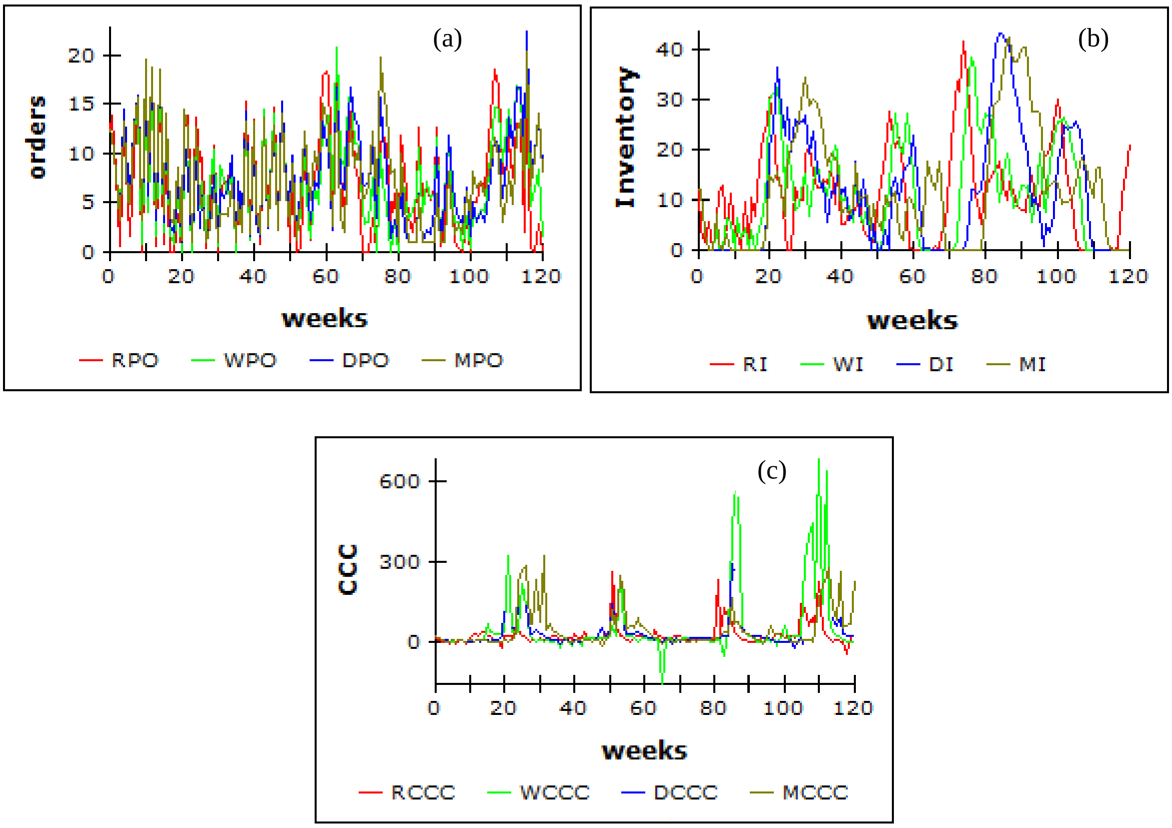


Figure 5.14. Impact of information sharing for experiment 3

5.4.3.2 Impact of SBO

Using the values for the GA parameters presented in experiment 1, the SBO is run 15 times. The standard deviation of the obtained fitness values is 8.59 and the best fitness value is 8761.54. The order quantities of the members that are shown in Figure 5.15(a) have a scale of 0-30. Similar to experiment 2, the largest order placed by a member in the SBO method is higher than the largest order placed in the case of information sharing, i.e., 23 (see Figure 5.14(a)). Whilst the inventory levels of the members, are illustrated in Figure 5.15(b), are much lower than the inventory levels in the information-sharing scenario. In the SBO model, the inventory of the retailer who possess the highest inventory level among the SC members from week 60 until the end of the simulation remains at 8 crates. While, in the SD model with information sharing the inventory of the retailer who possess the lowest volatility among the SC members fluctuates in the range of [0, 42] at the same time period (see Figure 5.14(b)). The cash cycle of the members after using the SBO method is shown in Figure 5.15(c) that proves the cash flow bullwhip is significantly reduced comparing the SD model with information sharing. After employing the SBO method, the CCC of the retailer who possess the highest cash to cash cycle among the members remains at 10 days from week 60 until the end of the simulation. While, in the SD model with information sharing the CCC of the retailer has a scale of 0-275 (see Figure 5.14(c)).

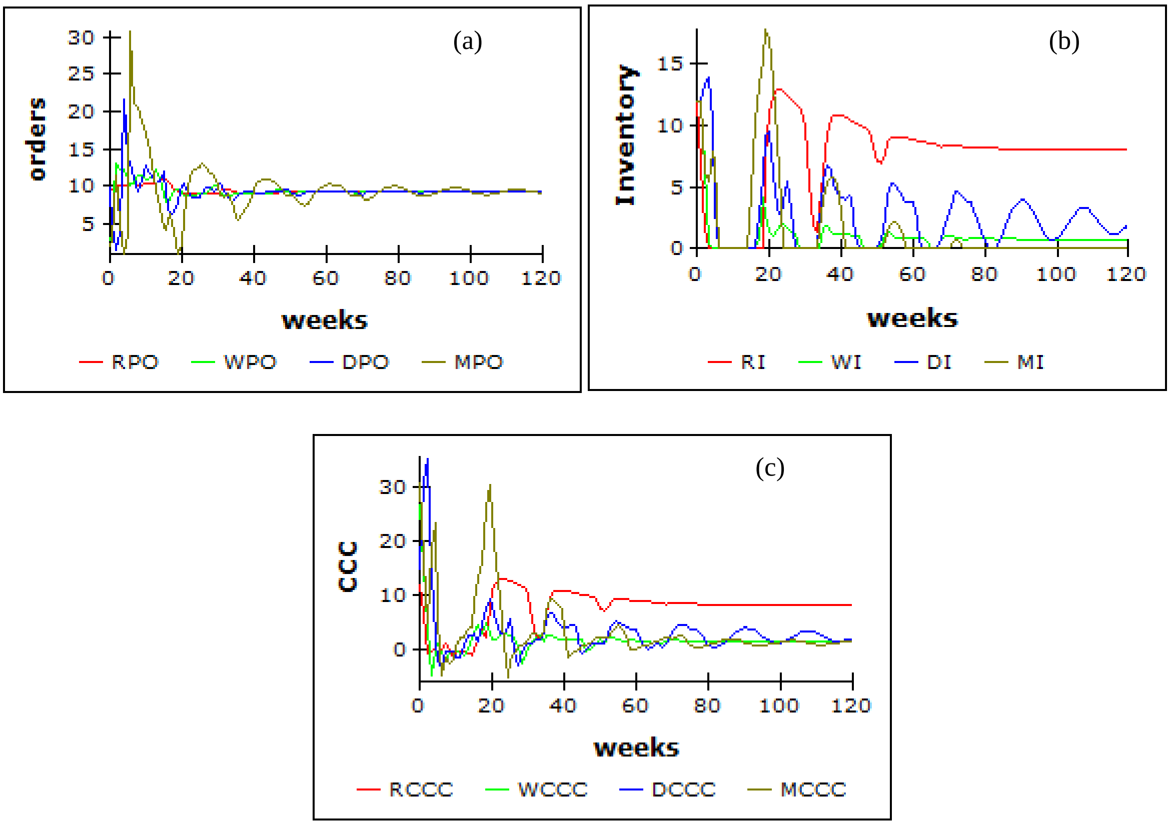


Figure 5.15. Impact of employing SBO for experiment 3

The SBO method proposes an aggressive approach to bridging the gap between the desired inventory and current net inventory for the distributor and the wholesaler. The value of α for the distributor and wholesaler is less than 0.5, and a cautious strategy is required for orders in the supply line for the distributor and wholesaler, i.e., the value of β for the retailer is more than 0.5. Further experiments were performed to investigate if the recommended policy was robust for all random values in the range of [0-15] and random lead times in the range of [0-4]. 50 random sets representing customer's demand and lead times were generated, and the SBO was run 15 times for each set to determine the fitness function. The lowest fitness function found would be the optimal solution for that specific set of random values. To identify the most frequent policy for bridging the inventory gap and supply line consideration, the recommended policies for the random sets are examined. Table 5.4 shows the replenishment policies that occurred most frequently and the associated mean fitness values.

This experiment proves that the replenishment policy is found by the SBO method. Aggressive policies by the distributor and wholesaler for inventory gap and cautious policies by the distributor and wholesaler to supply line are not robust for every set of random customer orders and lead times within the defined ranges. However, these policies occur most frequently and provide the highest fitness value. The lower inventory levels held by the SC members after employing the SBO method leads to lower SCTC comparing the information sharing. The accumulated cost of the supply chain in the SBO method amounts to £8729.90 which is 18 percent lower than the accumulated cost in the SD model with information sharing.

Table 5.4. Replenishment policies found optimal for random demand and lead times

Replenishment policy	Rate of occurrence	Mean reverse fitness value
Aggressive distributor and wholesaler to net inventory gap Cautious distributor and wholesaler to supply line	*23*	*8876.28*
Aggressive manufacturer and retailer to net inventory gap Cautious retailer to orders in supply line	*19*	*8935.61*
Non-aggressive members to inventory gap Cautious retailer and distributor	*8*	*9027.52*

5.5. Concluding discussion

Supply chain management seeks to match the supply of products with the demand of customers and the supply of money with the demand of the agents. Heterogeneous distribution of products among supply chain members known as the bullwhip effect (BWE) and heterogenous distribution of cash among supply chain members known as the cash flow bullwhip (CFB), trigger inefficiencies in operational processes of the members such as purchasing and inventory management and consequently reduce supply chain service level.

As discussed in section 2.5.2 in chapter 2 and is presented in Table 5.5, Previous research on the BWE has highlighted the existence of this phenomenon and identified its main causes to mitigate its adverse effects (Alwan et al., 2003; Lee et al., 2004; Zhang, 2004; Luong, 2007). However, there is lack of studies that focus on minimizing the BWE by finding the optimal values to the controllable decisions of the supply chain members. Moreover, previous research does not consider the flow of cash in the BWE modelling.

Previous research on the CFB has identified the causes of this phenomenon (Tangsucheeva and Prabhu, 2013; Goodarzi et al., 2017). There is a lack of studies that focus on minimizing the CFB through finding the optimal values to the inventory bullwhip contributors including the desired inventory, the desired supply line, the inventory adjustment parameter, and the supply line adjustment parameter. Furthermore, price and unit cost are two decision parameters that assist the decision maker in controlling variations in the CCC.

To fill the gap in the BWE and CFB literature, in this chapter, an SBO model is developed for reducing the bullwhip effect, cash flow bullwhip, and the total cost in a supply chain under deterministic demand and lead times, stochastic demand and deterministic lead times, and stochastic demand and lead times. In this model financial flow modelling is incorporated into the system dynamics simulation of the beer distribution game to identify the optimal financial decisions in addition to the optimal operational decisions. This contribution extends previous supply chain research on minimizing the bullwhip effect (Alwan et al., 2003; Zhang, 2004; Luong, 2007; Balakrishnan, et al., 2004; Hosoda and Disney, 2006; Tangsucheeva and Prabhu, 2013, 2014; Goodarzi et al., 2017; Sim and Prabhu, 2017) through diminishing the destructive effects of the bullwhip effect in supply chain financial flow in addition to the physical flow. Moreover, it incorporates the financial flow modelling into the inventory planning models and determines the optimal values to the financial decisions parameters, in addition to the inventory decisions. Finally, it incorporates CFB minimization as an objective function into an SBO model.

The initial model is developed as in Aslam and Ng (2016) to validate the approach by observing similar results and then extending the SBO model. The main objective of the proposed SBO model is to find the optimal values of desired inventory, desired supply line, forecasting parameter for inventory, forecasting parameter for supply line, sales price per unit, and unit cost for supply chain entities to make trade-offs between the SCTC, CFB, and BWE. Three experiments were developed to investigate the ability of the SBO model in identifying the optimal replenishment policy.

Table 5.5. Literature on bullwhip effect and cash flow bullwhip

Current literature	**Parameters considered**	**Minimizing the BWE by finding optimal parameter values**	**Minimizing the CFB by finding optimal parameter values**	**Approaches**
(Alwan et al., 2003; Zhang, 2004; Luong, 2007; Balakrishnan, et al., 2004; Hosoda and Disney, 2006; Tangsucheeva and Prabhu, 2013, 2014; Goodarzi et al., 2017; Sim and Prabhu, 2017)	Inventory control parameters	✕	✕	System dynamics Mathematical modelling
This study	Inventory control parameters Price Unit cost	✓	✓	Simulation-based optimisation (System dynamics and genetic algorithms)

The first experiment was the MIT beer distribution game, which employs deterministic demand and lead times. The SBO found the optimal replenishment policy to be non-aggressive approach to the inventory gap for all members, and a cautious approach to orders in the supply line for the retailer and distributor. The second experiment tested random demand and deterministic lead times. The SBO found the optimal replenishment policy to be an aggressive approach to the inventory gap for the retailer and manufacturer, and a cautious approach to orders in the supply line for the retailer. The third experiment extended the second experiment through considering random lead times in addition to the random customer demand. In this experiment, an aggressive approach to the inventory gap for the distributor and wholesaler and cautious approach to orders in supply line for the distributor and wholesaler was identified to be the optimal replenishment policy.

Comparing the performance of the developed SBO model with the information sharing strategy in reducing the SCTC showed that the SBO outperformed the information sharing in all three experiments. In the first experiment, after employing the SBO technique the SCTC reduced by 29 percent comparing the SCTC of the SD model with information sharing. Similarly, the SCTC in the SBO model under demand uncertainty, and demand and lead time uncertainties, i.e., experiments 2 and 3, reduced by 24 percent and 18 percent, respectively comparing the SD model with information sharing. Decreasing the gap between the SD model with information sharing and the developed SBO model as the number of stochastic parameters increase conveys the importance of the information sharing among supply chain members in mitigating the SCTC.

In this chapter, the uncertainties in economic parameters which refers to macroeconomic, financial, and market conditions are not considered. While, these uncertainties may have a tremendous impact on financial and working capital performances in supply chain networks. In the next chapter the impact of uncertain economic parameters such as short-term interest rate on working capital performance and profitability, which are measured by the CCC and economic value added (EVA) index is investigated.

Chapter 6. Managing the trade-off between financial performance and liquidity in a supply chain under economic uncertainty

6.1. Introduction

Supply chain finance that is described as the intersection of the supply chain management and finance integrates the planning of the financial and physical flows within the supply chain networks (Stemmler, 2002; Hofmann, 2005). The objective of supply chain finance is to decrease the cost of capital for supply chain members and accelerate cash flow within the supply chain networks through applying financing solutions on assets and liabilities. The financing solutions employed by the supply chain finance could be divided into two categories: (1) the "finance oriented" solutions that comprises short-term financial solutions on accounts payable and receivable offered by a third-party creditor (e.g., factoring, reverse factoring), and (2) "supply chain oriented" solutions where a financial institution such as a bank might not be involved and consists of solutions on working capital optimisation and sometimes asset-liability optimisation through cooperation and coordination among supply chain participants (e.g., VMI financing, fixed asset financing) (Gelsomino et al., 2016). Working capital optimisation involves optimizing inventories, accounts receivable, and accounts payable to ensure capability of a firm to continue its operation. The objective of working capital optimisation is to reduce the current assets and also increase the current liabilities in order to minimize the capital tied up in the company's turnover process (Hofmann and Kotzab, 2010).

Economic uncertainty which refers to macroeconomic, financial, and market conditions has a tremendous impact on financial and working capital performances in supply chain networks (Longinidis and Georgiadis, 2013). The financial performance represents the profitability of the supply chain and the working capital performance represents the accessibility of the supply chain members to necessary funds for continuing their operations. Although considered together, financial performance and working capital metrics which in this study are economic value added (EVA) and cash conversion cycle (CCC) are not necessarily moving to the same direction as each one has a different fundamental objective. The EVA, targets at maximizing the wealth, while the CCC focuses on minimizing the accumulated capital.

In this chapter, an SBO framework, including genetic algorithm (GA) and system dynamics (SD) simulation, that integrates the planning of the financial and physical flows is presented to manage the trade-off between financial performance and working capital management in presence of economic uncertainty.

The rest of the chapter is organized as follows. Section 6.2 describes the model assumptions and the stock management problem. The proposed SBO model is presented in section 6.3. Section 6.4 illustrates the applicability of the proposed model through a case study. Finally, concluding remarks are presented in section 6.5.

6.2. Problem Definition and Assumptions

The stock management problem refers to the issue of controlling a system state or stock to meet some system objectives. For instance, all supply chain participants manage their inventory and resources to balance production with the demand of their customer. Stocks are solely altered through modification in their inflow and outflow rates, thus requiring a decision maker to set the inflow of the stock so as to counteract the drainage of the stock also eliminate any discrepancy between the current and the desired state of the stock (Sterman, 2000). Sterman (Sterman, 2006) points out that there is a delay between a decision maker control actions and its effect on the stock (system state) which needs to be formulated. A firm seeking to increase its raw material inventory cannot acquire new units immediately but must await delivery of the orders by the supplier. The control of the stock management problem can be split into two parts, where the first part pertains to stock and flow structure of the stock management system, and the second part relates to the decision rules applied by the decision maker to control the inflow rate of the stock (Sterman, 2000).

The stock management structure can be found in several different application domains such as inventory management, capital investment, and human resources. In this paper, the stock management structure of inventory management model presented by Sterman (2000) is developed through considering the financial flow in addition to physical flow. Moreover, multi-objective optimisation (MOO) is integrated with the proposed model by implementing SBO approach. Figure 1 displays the stock and flow structure of an extended version of the inventory management model developed by Sterman (2000). A new stock variable namely materials supply line has been added to the original model. The production centre implements a make-to-stock production strategy, in which the products are manufactured for storage based on demand forecasts. However, two delays exist in the model: (1) the time lag in filling the inventory as the manufacturing of a product takes time, and (2) the time lag in materials shipment from suppliers known as order lead time. All the units that ordered to be manufactured but are not yet finished is represented through the work-in-process (WIP) inventory and the materials which ordered to the suppliers but not yet received is described by materials supply line. As Figure 1 depicts, the WIP inventory is defined through production start rate and production rate, while materials supply line is determined by materials order rate and materials delivery rate.

The original model seeks to specify an adequate production start rate which in time restores the expected shipments of products from the inventory and ensures the adequacy of work in process and inventory levels to provide a good customer service level (Sterman, 2006). In addition to the production start rate, the presented model aims to define a sufficient material order rate that will in time replace the material usage rate from the materials inventory as well as keeping a sufficient materials supply line and inventory to provide a good service level for production line. These objectives are achieved by identifying the optimal values for the inventory control parameters which have been highlighted in Figure 6.1. For a detailed information about the inventory management model the reader is referred to (Sterman, 2000).

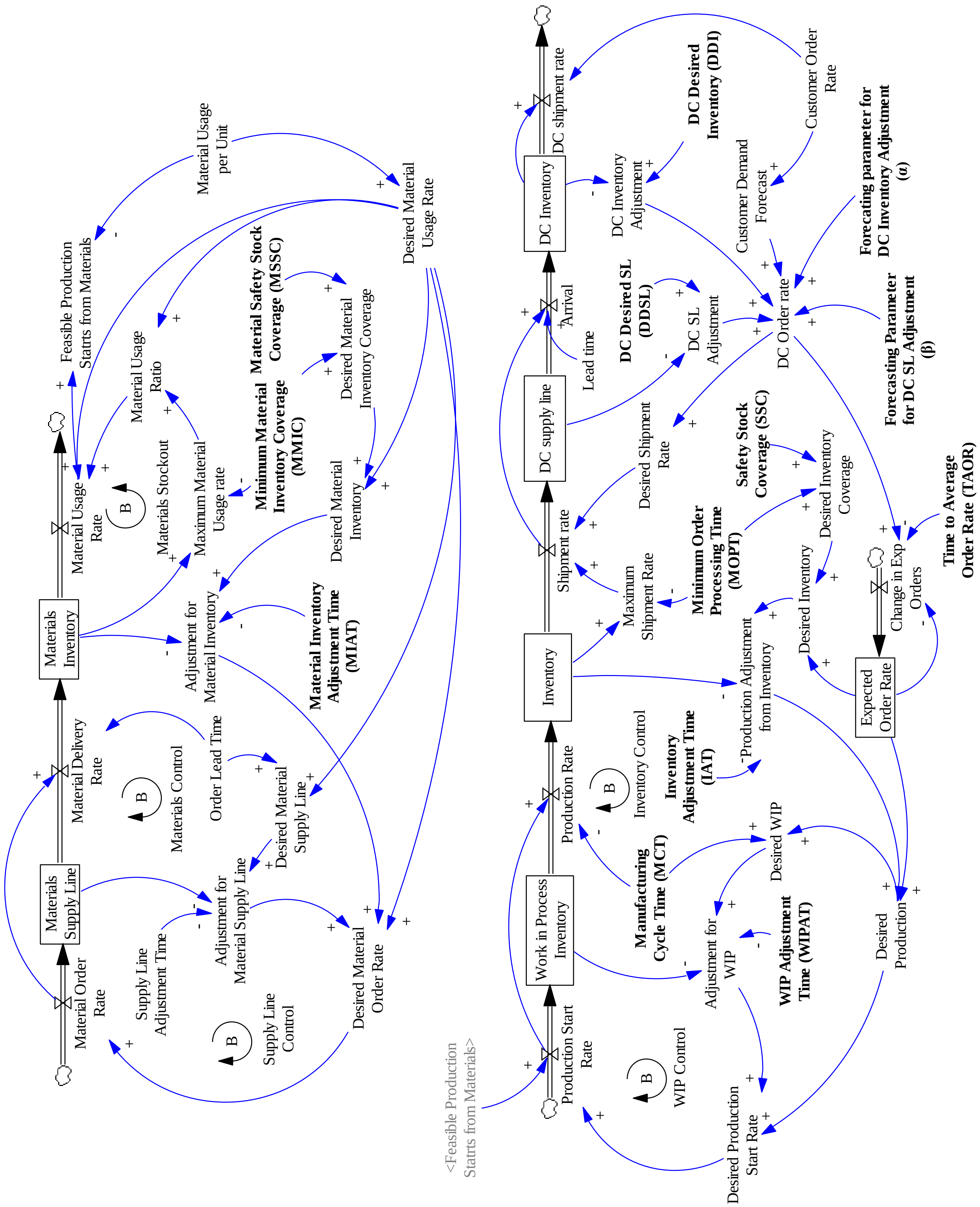


Figure 6.1. Stock and flow structure of extended inventory management model

6.2.1. Economic uncertainty

The concept of economic cycle is applied to model economic uncertainty. Stagnation, boom, and recession are categories which express the economic cycle. In our model five uncertain parameters illustrate the uncertainty in economic environment: (1) customer demand, (2) expected return of the market, (3) risk-free rate of interest, (4) short-term interest rate, and (5) long-term interest rate (Longinidis and Georgiadis, 2013). During a boom period, economic prosperity leads to increased purchasing power of customers which results in excessive demand for products and services. The expected return of the market rises, as the investors who are optimistic about the future of the companies present in the stock market increase their investment. Risk-free rate of interest, which is usually the interest rate of a governmental bond, falls as the risk of default diminishes. The risk of borrower's default decreases, therefore financial institutions charge lower short-term and long-term interest rates. On the other hand, during a recession period all the aforementioned parameters move to the opposite direction. In a stagnation period, it is assumed that the past shapes the future due to the fact that there are minor deviations in the value of parameters comparing the preceding period (Longinidis and Georgiadis, 2013).

The scenario analysis approach is applied to formulate economic uncertainty. Postulated scenarios are shown in Figure 6.2. In the current period there is no economic uncertainty resulting in a single scenario branch over the first year. In the start of the second period, there are three potential conditions, e.g. boom, stagnation, and, recession, which leads to three scenarios. Each scenario encompasses a set of constant parameter values.

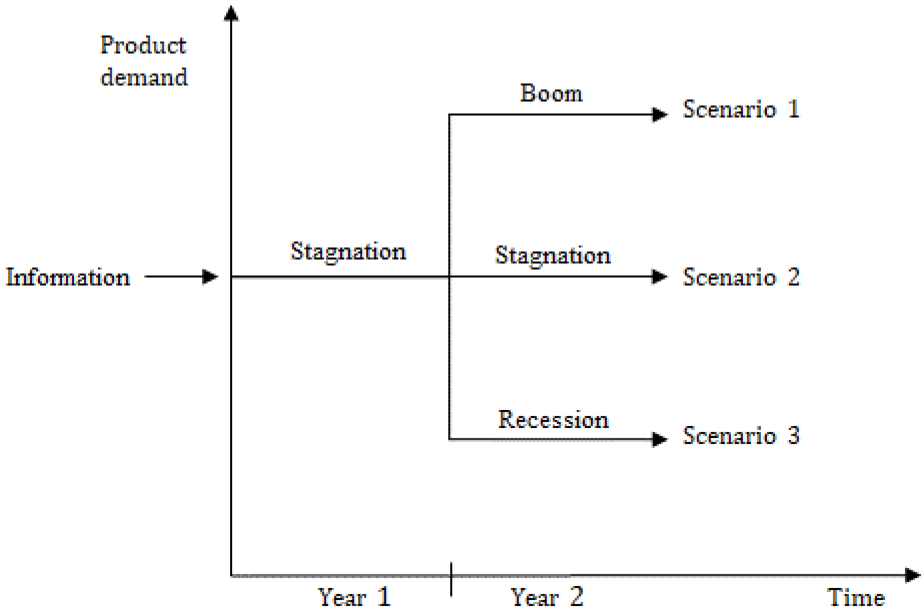


Figure 6.2. Scenarios tree for economic uncertainty

6.2.2. Economic value added (EVA)

Stewart Iii (1994) presented Economic value added (EVA) index to measure the financial performance of a company. The proposed index measures the economic value created by a business through deducting cost of capital employed from its operating profit. The calculation of the EVA index is expressed in Eq. (6.1), where NOPAT is the net operating profit after tax derived from income statement. WACC is the weighted average cost of capital which indicates the average rate of return is expected to be paid for the main sources of capital, i.e. debt and equity, leveraged by the company (Ogier et al., 2004).

$$EVA = NOPAT - WACC \times (Total\ Debt + Shareholder's\ Equity) \tag{6.1}$$

6.3. System-Dynamics Modelling

The proposed model extends the inventory management model developed by Sterman (Sterman, 2000) through incorporating financial flow modelling also considering economic uncertainty. Another novelty relates to presenting MOO structure of the model and pareto-optimal solutions set obtained from the MOO.

6.3.1 Financial Flow Modelling

To measure the efficiency of the financial flow management through the supply chain, the economic, and working capital performances of the supply chain members should be evaluated.

In this study, cash conversion cycle (CCC), and economic value added (EVA), indexes are applied to measure the economic, and working capital performances, respectively.

The financial stock and flow structure is illustrated in Figure 6.3. The end customers place orders to the manufacturer. The collecetion policy (m) (6.2) defines the amount of order value must be collected in cash. For instance, $m = 0.2$ implies that 20 percent of the order value needs to be paid in cash before the product delivery. These order values accumulate on cash (6.3). The rest of the order value is integrated in receivable accounts (6.4). To fulfill the end customer demand, the manufacturer places orders to the raw material suppliers. The payment policy (n) (6.2) indicates the share of order value paid in cash. The rest of the order cost required to be paid by the manufacturer to the suppliers is accumulated on payable accounts (6.5). The value of inventory held in the manufacturer warehouse is determined by inventory value (6.6). As the manufacturer pays some part of its order value in cash also is being paid in advance by end customers for some part of its sales revenue, CCC (4.11) may not be an effective tool for measuring the cash to cash cycle. Days of advance receivement outstanding (DAdRO) (6.7) and days of advance payment outstanding (DAdPO) (6.8) are incorporated into updated CCC metric (6.9).

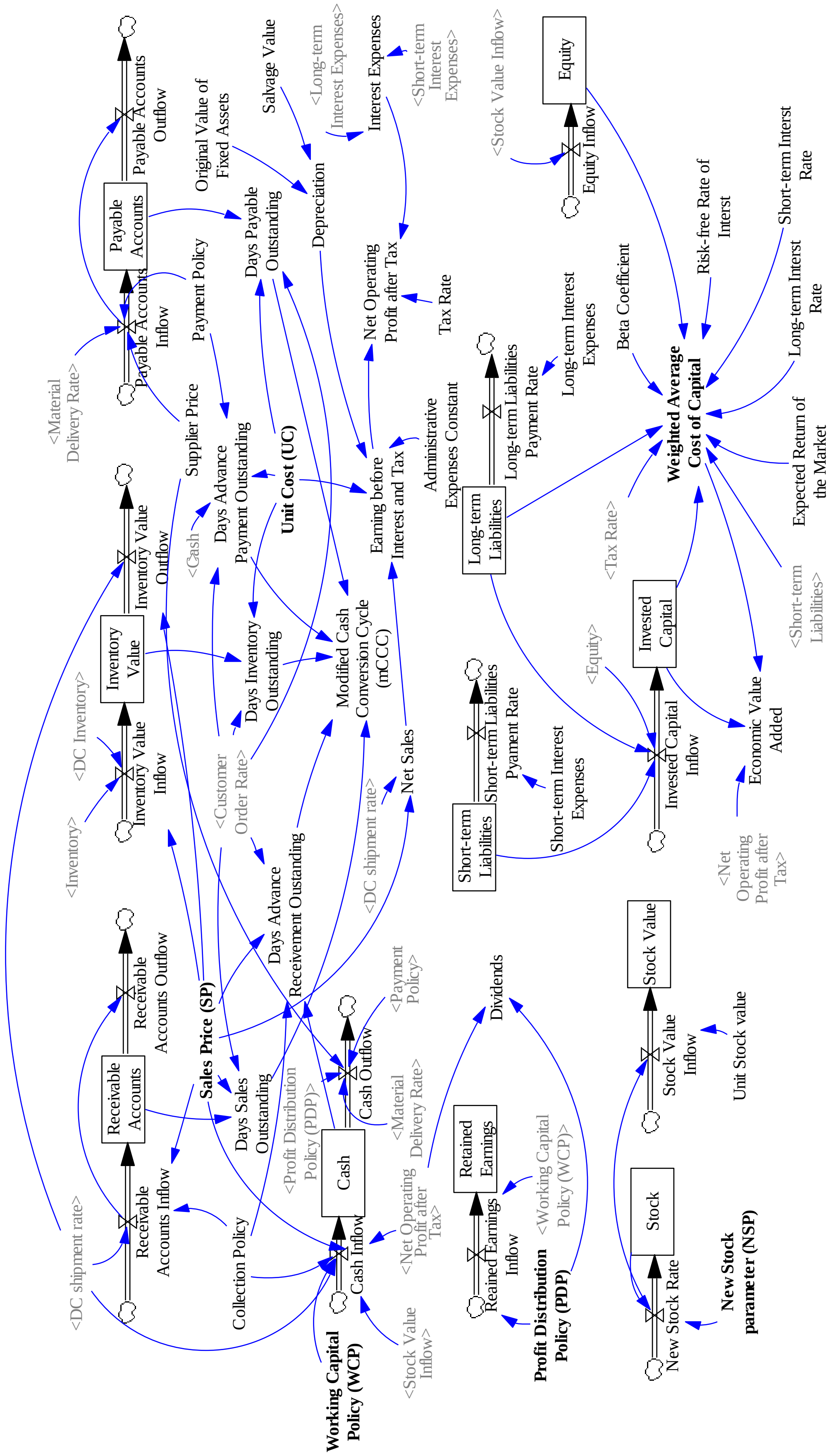


Figure 6.3. Stock and flow structure of financial flow

$0 \le m, n \le 1$	(6.2)
$Cash = INTEGRAL(Cash\ Inflow - Cash\ Outflow)$	(6.3)
$Receivable\ Accounts = INTEGRAL(Receivable\ Accounts\ Inflow - Receivable\ Accounts\ Outflow)$	(6.4)
$Payable\ Accounts = INTEGRAL(Payable\ Accounts\ Inflow - Payable\ Accounts\ Outflow)$	(6.5)
$Inventory\ Value = INTEGRAL(Inventory\ value\ Inflow - Inventory\ Value\ Outflow)$	(6.6)
$DAdRO = \frac{Average\ Cash}{Revenue/365}$	(6.7)
$DAdPO = \frac{Average\ Cash}{COGS/365}$	(6.8)
$Updated\ Cash\ Conversion\ Cycle = DIO + DSO - DPO - DAdRO + DAdPO$	(6.9)

The income statement is a fiancial statement which represents the earnings also the costs incured by a company in a fiscal year. Eq. (6.10)-(6.12) formulate the income statement. Net sales (6.10) is the product of shipment rate and sales price. Earning before interest and taxes (EBIT) (6.11) is calculated by subtracting COGS (6.12), depreciation, and administrative expenses from net sales. To calculate depreciation (6.13), the sum of years' digits method (Dhaliwal, Salamon and Smith, 1982) which is a form of accelerated depreciation is applied. It is assumed that fixed assets are depreciated within two years (104 weeks) which is the length of simulation time. Administrative Costs (6.14) is the product of administrative constants which equals to 0.01 and net sales. Net operating profit after taxes (NOPAT) (6.15) is determined by subtracting interest expenses (6.16), which includes short-term and long-term interests expenses, from EBIT and then multiplying the result with the term (1-Tax Rate). Short-term interest expenses and long-term interest expenses are constants values that are equal to the weekly payment for short-term and long-term liabilities, respectively. NOPAT is allocated between dividends, working capital, and retained earnings. Dividends (6.17) is the product of NOPAT and profit distribution policy (6.18) which is decided in board of directors meeting. Working capital policy (6.19) indicates the share of NOPAT alloted to working capital. Finally, the rest of NOPAT is added to retained earnings (6.20).

$Net\ Sales = Sales\ Price \times Shipment\ Rate$	(6.10)
$EBIT = Net\ Sales - COGS - Depreciation - Administrative\ Expenses$	(6.11)
$COGS = Unit\ Cost \times Shipment\ Rate$	(6.12)
$Depreciation = \frac{104 - Time + 1}{\underbrace{(1 + 2 + \cdots + 104)}_{5460}} \times (Original\ Value\ of\ Fixed\ Assets - Salvage\ Value)$	(6.13)
$Administrative\ Expenses = Administrative\ Constant \times Net\ Sales$	(6.14)
$NOPAT = (EBIT - Interest\ Expenses) * (1 - Tax\ Rate)$	(6.15)
$Interest\ Expenses = Short - term\ Interest\ Expenses + Long - term\ Interest\ Expenses$	(6.16)
$Dividends = NOPAT \times Profit\ Distribution\ Policy$	(6.17)
$0 \leq Profit\ Distribution\ Policy \leq 1$	(6.18)
$0 \leq Working\ Capital\ Policy \leq 1$	(6.19)
$Retained\ Earnings = INTEGRAL(Retained\ Earnings\ Inflow)$	(6.20)

The level of equity (6.21) increases by stock value inflow (6.22) which is a function of new stock rate and unit stock value. Short-term liabilities (6.23) and long-term liabilities (6.24) are depleted by payment of the short term interst expenses and long term inteerest expenses, respectively. Invested capital (6.25) accumulates the amount of financing from short term liabilities, long term liabilities, and equity. WACC (6.26) is a figure expressing the required return on the invested capital which is determined by multiplying cost of debt (6.27) and cost of equity (6.28) by their proportional weight and take the sum of the results. Unlike cost of debt, Cost of equity may not be easily calculated as there is not an explicit value on the return that the firm's equity investors required on their investments. Therefore, the capital asset pricing model (CAPM) is applied as a substitute. The CAPM model calculates expected return for assets, notably stocks through considering time value of money and risk. The risk-free rate of interest , which is usually the yield on government bonds such as U.S. Treasuries, compensates for time value of money, while the second part of the formula represents the amount of compensation for taking on additional risk. The risk measure (β) is the amount of systematic risk existing in an asset. Economic value added (EVA) (6.29) is calculated by subtracting the cost of invested capital from NOPAT.

$Equity = INTEGRAL(\ Stock\ Value\ Inflow)$	(6.21)
$Stock\ Value\ Inflow = New\ Stock\ Rate \times Unit\ Stock\ Value$	(6.22)
$Short\ term\ Liabilities = Integral(-Short\ term\ Interest\ Expenses)$	(6.23)
$Long\ term\ Liabilities = Integral(-Long\ term\ Interest\ Expenses)$	(6.24)
$Invested\ Capital = Integral(Short\ term\ Liabilities + Long\ term\ Liabilities + Equity)$	(6.25)
$WACC = \frac{Equity}{Invested\ Capital} \times Cost\ of\ Equity + \frac{Short - term\ Liabilities + Long\ term\ Liabilities}{Invested\ Capital} \times Cost\ of\ debt \times (1 - Tax\ Rtae)$	(6.26)
$Cost\ of\ Debt = \frac{Short\ term\ Liabilities}{Short\ term\ Liabilities + Long\ term\ Liabilities} \times Short\ term\ Interest\ rate + \frac{Long\ term\ Liabilities}{Short\ term\ Liabilities + Long\ term\ Liabilities} \times Long\ term\ Interest\ rate$	(6.27)
$Cost\ of\ Equity = Risk\ free\ Rate\ of\ Interest + (Expected\ Return\ of\ the\ Market - Risk\ free\ Rate\ of\ Interest) \times \beta$	(6.28)
$EVA = NOPAT - WACC \times Invested\ Capital$	(6.29)

Although SD simulation models are considered to be more robust than other type of simulation models, they are required to be validated through validation tests. The extreme conditon test (Sterman, 2000), which is one of the validation tests for SD models, is used to show the robustness of our developed simulation model. The extreme condition test assesses whether model behaves appropriately according to its inputs values (Sterman, 2000). E.g., the demand for a product converges to zero when there is a significant increase in the price (Sterman, 2000). To run extreme condition test in our developed model, sales price per unit of product that is a model input increases dramatically. Consequently, CCC and EVA grow significantly.

6.3.2. Multi-objective Modelling of the Extended Inventory Management Model

The main objective of the extended inventory management model is to provide a good customer service level by meeting customer demand through keeping a sufficient amount of inventory level. Although keeping high level of inventory ensures the capability of the firm on meeting the customer demands, it imposes significant holding costs on the manufacturing company. Thus, a trade-off is required to be made between the sufficient level of inventory and shipment rate. Furthermore, the downstream flow of material from the suppliers to the firm is required to be responded by the upstream flow of money which necessitates the availability of the working capital. Minimization of working capital metric (CCC) expedites the accessibility to cash through minimizing the inventory level. Finally, profitability is the main objective of all businesses which in this study is measured by EVA. Maximization of EVA may be achieved by increasing the shipment rate which leads to increasing the inventory level, even though CCC minimization seeks to decrease the level of inventory. Consequently, another trade-off is required to be made between the cash to cash and profitability metrics. The objective functions are denoted as follows:

$$Objective\ functions \begin{cases} Max\ EVA = Max\ \mu_{EVA} \\ Min\ CCC = Min\ \mu_{CCC} \end{cases} \quad (6.30)$$

Where $\mu_{EVA} = \frac{\sum_{t=0}^{T} EVA}{T},\ \mu_{CCC} = \frac{\sum_{t=0}^{T} CCC}{T}$

Where

$Input\ (Decision\ parameters)$
$= WIPAT, MCT, IAT, MOPT, SSC, TAOR, m, MIAT, MSSC, MMIC, NSP, n, PDP, SP, UC, WIPAT, WCP$

And $Output = \mu_{EVA}, \mu_{CCC}$

Subject to: $0.25 \le WIPAT \le 10,\ 5 \le MCT \le 15,\ 5 \le IAT \le 15,\ 0.25 \le MOPT \le 10,\ 0.25 \le SSC \le 10,\ 5 \le TAOR \le 15,\ 0 \le m \le 1,\ 5 \le MIAT \le 15, 0.25 \le MSSC \le 10, 0.25 \le MMIC \le 10, 0 \le NSP \le 1$, $0 \le n \le 1, 0 \le PDP \le 0.50, 7 \le SP \le 12, 3 \le UC \le 6, 0.25 \le WIPAT \le 10, 0 \le WCP \le 0.50,\ 0 \le \alpha \le 1$, $0 \le \beta \le 1,\ 0 \le DDI \le 30000,\ 0 \le DDSL \le 35000$ (6.31)

$\alpha = forecasting\ parameter\ for\ inventory\ adjustment$: denote the aggressiveness of the distributor in bridging the gap between the desired and current inventory.

$\beta = forecasting\ parameter\ for\ supply\ line\ adjustment$: denote the level of consideration of the distributor to the inventory on-orders at the time of order placement

$m = collection\ policy$: denotes the share of the sales is required to be collected in cash

$n = payment\ policy$: denotes the share of the raw material purchase is required to be paid in cash

DDI: denote the desired inventory by the distributor

$DDSL$: represent the desired inventory on order by the distributor

$IAT = The\ inventory\ adjustment\ time$: represents the time period over which the manufacturer seeks to bridge the gap between the desired and current inventory of finished products

$MIAT = The\ material\ inventory\ adjustment\ time$: represents the time period over which the manufacturer seeks to bridge the gap between desired and current inventory of the raw material

$MSSC = The\ manufacturer\ safety\ stock\ coverage$: represents the time period over which the manufacturer would like to maintain a safety stock coverage to hedge against volatility in distributor's demand

$SSC = The\ safety\ stock\ coverage$: represents the time period over which the distributor would like to maintain a safety stock coverage in order to meet any variations in retailers' demands

$MMIC = The\ minimum\ material\ inventory\ coverage$: represent the minimum material inventory required by the manufacturer

$MOPT = The\ minimum\ order\ processng\ time$: denotes the minimum time required by the manufacturer to process and ship a distributor order

$PDP = The\ profit\ distribution\ policy$: denotes the dividends that is required to be paid to the shareholders

$SP = The\ sales\ price$: The price per tonne of product which is paid to the retailers by the customers

$TAOR = The\ time\ to\ average\ order\ rate$: denotes the time period over which the distributor demand forecast is adjusted to actual retailers' orders

$UC = The\ unit\ production\ cost$: denotes the production cost per tonne of product at the manufacturer

$WIPAT = The\ WIP\ adjustment\ time$: represents the time required for the manufacturer to adjust its WIP inventory to its desired level

$MCT = The\ manufacturing\ cycle\ time$: represents the average delay time of the production process for the products from start until completion of the product

$NSP = New\ stock\ parameter$: represents the level of the stock that should be issued

$WCP = Working\ capital\ policy$:reprents the share of NOPAT dedicated to the working capital

The first objective relates to maximizing EVA and the second objective pertains to minimization of CCC. The objective functions are formulated as the mean of performance indicators over the simulation period.

6.3.3. Multi-objective Simulation-based Optimisation

Simulation models are descriptive tools which solely depict the current state of the studied system. On the other hand, optimisation models are prescriptive tools that are able to provide recommendations to improve the performance of the system. Therefore, integrating optimisation and simulation leads to a consolidated framework which can be both descriptive and prescriptive. Such an integrated framework is called simulation-based optimisation (SBO). SBO is the process of obtaining optimal values for the decision variables, where the objective functions are measured through the simulation model (Ólafsson and Kim, 2002). SBO is an iterative process which mostly is launched during the optimisation modeling process by generating initial values for input parameters of the simulation model, i.e., supply chain decision parameters. The simulation model is then run using inputted values to evaluate system performance. Thereafter, the performance measures are fed back into the optimisation model. Based on this feedback a new set of decision parameters are generated and inputted into the simulation model for evaluation (Aslam, 2013). This iterative process continues until a user-specified stop criterion has been met. For instance, performing a defined number of evaluations (Syberfeldt, 2009).

Multi-objective optimisation (MOO) is a method is applied to solve problems containing conflicting objectives that may not be formulated to a common scale of cost or benefit (Tabucanon, 1996). To solve problems with multiple objectives firstly, non-dominated set of optimal solutions are obtained. Secondly, the decision maker chooses the optimal solution based on its preferences (Deb, 2001). Non-dominated solutions are a set of different points in a frontier called Pareto optimal. The solutions which belong to the Pareto optimal do not have any superiority over another, however, they dominate all other solutions. A solution S^1 dominates another solution S^2, if S^1 is significantly better than S^2 in at least one optimisation objective, and where S^1 is no worse than S^2 regarding all optimisation objectives (Deb, 2001).

In this study, the weighted sum method, one of the most widely-used methods for multi-objective optimisation (Stanimirovic, Zlatanovic and Petkovic, 2011), is utilized to construct the Pareto optimal frontier. In this method, multi-objectives are transformed into a single objective through multiplying each objective function by a weighting factor and aggregating all weighted objective functions (Marler and Arora, 2010). The weight of an objective is chosen in proportion to the relative importance of the objective (Gass and Saaty, 1955). Considering a multi-objective optimisation problem with m objectives, where w_i $(i = 1, \dots, m)$ represents the weighting factor for the ith objective function. If $\sum_{i=1}^{m} w_i = 1$ and $0 \leq w_i \leq 1$, the weighted sum is a convex combination of objectives (Kim and De Weck, 2006). Therefore, the solution obtained by each single objective optimisation is a point on the Pareto optimal frontier. By changing the weighting factors (w_i), the single objective optimisation determines a different optimal solution. The obtained optimal solutions form the set of non-dominated solutions that might be represented in a two dimensional chart where each point in the Pareto optimal frontier implies a combination of inventory and financial decisions parameters.

As mentioned in chapter 3, GAs are well suited for parameter optimisation and can also be extended to multiple objective optimisation (MOO) (Streichert, 2002). Therefore, in this study, a GA is employed to specify optimal values to the inventory and financial control parameters to minimize cash conversion cycle (CCC), while maximizing economic value added (EVA). The fitness function of the GA is defined as:

$$FitnessFunction = w1 \times \mu_{EVA} - w2 \times \mu_{CCC} \qquad w1 = w2 = 0.5 \tag{6.32}$$

6.4. A case study

In order to demonstrate the applicability of the proposed model, numerical experiments are performed in this section. The data of the case study was introduced in Longinidis and Georgiadis (2011) and Longinidis and Georgiadis (2013). A manufacturing supply chain including a manufacturer which implements a make-to-stock production strategy is considered. In the forward direction, the manufacturer is supplied by raw material suppliers and ships finished products to the customer zones. To hedge against unexpected variations in customer's demand, the manufacturer preserves a certain coverage of expected demand as safety stock. The suppliers are able to satisfy the entire order of manufacturer. There is no backlog of unfilled orders, and in the case the manufacturer is not able to meet the customers' demand, the orders are lost. In the reverse direction, the manufacturer asks the end customers to prepay a fraction of their purchasing cost (i.e., collection policy) and also pays a fraction of the procurement cost (i.e., payment policy) to the supplier. The problem consists of finding the optimal values to the controllable inventory and financial parameters for the manufacturer in order to make a trade-off between the CCC, and EVA, under all economic scenarios. As the problem is multi-objective, the generated Pareto optimal frontier provides a set of optimal controllable parameters to be selected based on decision maker's preferences.

The initial data for running the simulation model are presented in Tables 6.1 and 6.2. Table 6.1 shows the five parameters that express into a large extent the economic uncertainty. These parameters are in compliance with the scenario tree structure presented in Figure 6.2. The balance sheet, at the beginning of the simulation period, is presented in Table 6.2. The original value and salvage value of fixed assets are 210,000 and 168,000, relative money units (rmu) respectively. Moreover, the administrative constant is considered to be 0.01, the tax rate is 30% per year, the beta coefficient equals to unity, and stock value is 7 rmu per stock.

Table 6.1. Customer demand and financial parameters related to economic scenarios

Scenario	Parameter									
	$CD_{t=0}^{[s]}$	$CD_{t=53}^{[s]}$	$STR_{t=0}^{[s]}$	$STR_{t=53}^{[s]}$	$LTR_{t=0}^{[s]}$	$LTR_{t=53}^{[s]}$	$r_{f_{t=0}}^{[s]}$	$r_{f_{t=53}}^{[s]}$	$r_{m_{t=0}}^{[s]}$	$r_{m_{t=53}}^{[s]}$
S_1	10000	15000	7.00	5.60	4.00	3.00	2.50	2.00	5.00	6.00
S_2	10000	10000	7.00	7.00	4.00	4.00	2.50	2.50	5.00	5.00
S_3	10000	5000	7.00	8.40	4.00	5.00	2.50	3.00	5.00	4.00

Table 6.2. Balance sheet at the beginning of simulation time (t=0)

Account	rmu[a]
$A.1. Assets$	170,000
$A.1.1. Tangible\ assets$	170,000
$A.1.2. Intangible\ assets$	0
$A.2. Current\ assets$	70,000
$A.2.1. Cash$	29,968
$A.2.2. Receivable\ accounts$	28,000
$A.2.3. Inventory$	12,032
$A. Total\ assets$	240,000
$B.1. Equity$	130,000
$B.1.1. Common\ stock$	80,000
$B.1.2. Retained\ earnings$	50,000
$B.2. Debt$	110,000
$B.2.1. Short-term\ liabilities$	45,000
$B.2.2. Long-term\ liabilities$	65,000
$B. Total\ debt\ and\ equity$	240,000

[a]Relative money units

6.4.1. Results

To assess the effect of economic uncertainty on the model performance the SD simulation model is required to initialize in a balanced equilibrium. Therefore, all the model stocks including the inventories and supply lines are set to be equal to their desired values and the expected order rate is set to be equal to the customer order rate. Figures 6.4(a)- 6.4(d) represent the inventory, cash to cash cycle, and EVA dynamics for the SC members in scenario 1 obtained from running the SD simulation model for two years, 104 weeks. The distributor increases placed orders to the manufacturer to meet the surge in customer's demand occurred at the week 53 that results in peaking its inventory level at 15000 units of product at week 55. The inventory of the distributor levels at its new equilibrium at 12700 unit of products at week 70. There is a plunge in manufacturer's inventory after the demand growth as the manufacturing cycle time is 5 weeks. At week 58 the inventory of the manufacturer starts to rise and reaches to its new equilibrium level, 41600 units of products, at week 80. The cash conversion cycle dynamics follows the pattern in the manufacturer's inventory which holds the highest levels of inventory among supply chain members. The cash conversion cycle at the start of the second-year plummets as a result of fall in the accumulated inventory in the supply chain network and reaches to its new equilibrium level, 87 days, at week 80. The EVA value added at the start of the second year increases sharply due to the reduction in inventory levels of the manufacturer and rise in sales before levelling off at £51700 at week 100.

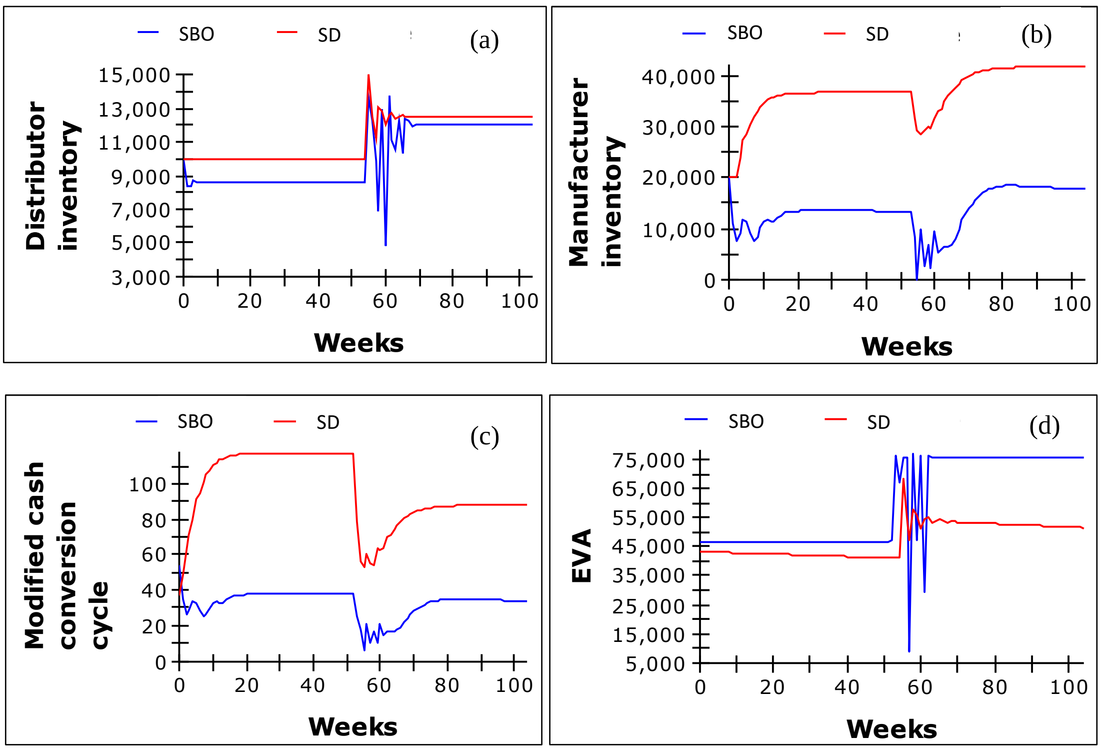


Figure 6.4. SD and SBO models performances scenario 1

To implement the presented multi-objective simulation-based optimisation model, a number of specific values need to be decided on. The range of values for the decision parameters which defined by Eq. (6.31). The parameters for the GA which are set as follows: the population size is 300, the crossover and mutation rates are set to be 0.8 and 0.1, respectively. To specify an appropriate population size, a number of population sizes were selected and the algorithm was run 15 times for each population size. The results are reported in Table 6.3. Increasing the population size improves the mean and the standard deviation of the fitness function until reaching to the population size that generates the optimal solution, i.e. 300.

Table 6.3. Impact of population size on fitness function

Population size	Fitness value			
	Worst (Min)	Best (Max)	Mean	Standard deviation
150	*59615.64*	*59723.68*	*59642.37*	*38.28*
200	*59596.38*	*59684.24*	*59625.40*	*25.36*
250	*59487.80*	*59537.51*	*59514.29*	*14.62*
300	*59422.11*	*59453.62*	*59433.72*	*6.42*
350	*59422.11*	*59448.23*	*59431.51*	*6.21*

For each scenario using the aforementioned parameters, the SBO is run 15 times and the best fitness value is identified. The simulation system is then run using the optimal decision parameters obtained from the SBO model that generated the best fitness value. Figures 6.4(a)-6.4(d) represent the inventory, cash to cash cycle, and EVA dynamics for the SC members in scenario 1 after employing the SBO methodology. The inventory level of the distributor decreases after applying the SBO methodology. From week 75 onwards the distributor inventory remained at 11800 units of products, while before SBO at the same period it levelled off at 12700 units. The fluctuation in distributor’s inventory after employing SBO is significantly higher than before SBO. The inventory of manufacturer before SBO fluctuates at the range of [10000, 15000]. While after using SBO, it is oscillating in the range of [3200, 23000]. Contrary to the distributor’s inventory, the inventory of manufacturer diminished significantly after using the SBO. The manufacturer’s inventory peaked at 20000 units of products, while it peaked at 41600 before SBO. Moreover, after SBO the inventory level of the manufacturer at week 80 is 18000 and continues to decrease, although before SBO, it remains constant at 41600 units from week 80 onwards. The significant reduction in inventory levels of the manufacturer yields the dramatic fall in cash to cash cycle. The cash conversion cycle after SBO oscillates in the range of [6, 38] and continues to decrease at week 80 onwards from 33 days. While before SBO, it fluctuates in the range of [36, 114] and remains stable at 87 days from week 80 onwards. The EVA after SBO follows the same pattern as before SBO except for more frequent and higher domain oscillations between weeks 53 and 65. Furthermore, after SBO the EVA reaches to equilibrium level of £75800, while before SBO its equilibrium level is £51700.

Figures 6.5(a)- 6.5(d) represent the inventory, cash to cash cycle, and EVA dynamics for the SC members in scenario 2 obtained from running the SD simulation model for two years, 104 weeks. As the customer's demand remains unchanged during the simulation model, the system maintains its equilibrium state during the simulation time. The manufacturer inventory and the cash conversion cycle follow a goal seeking pattern which is achieved at week 10. The EVA decreases linearly as the invested capital increases linearly.

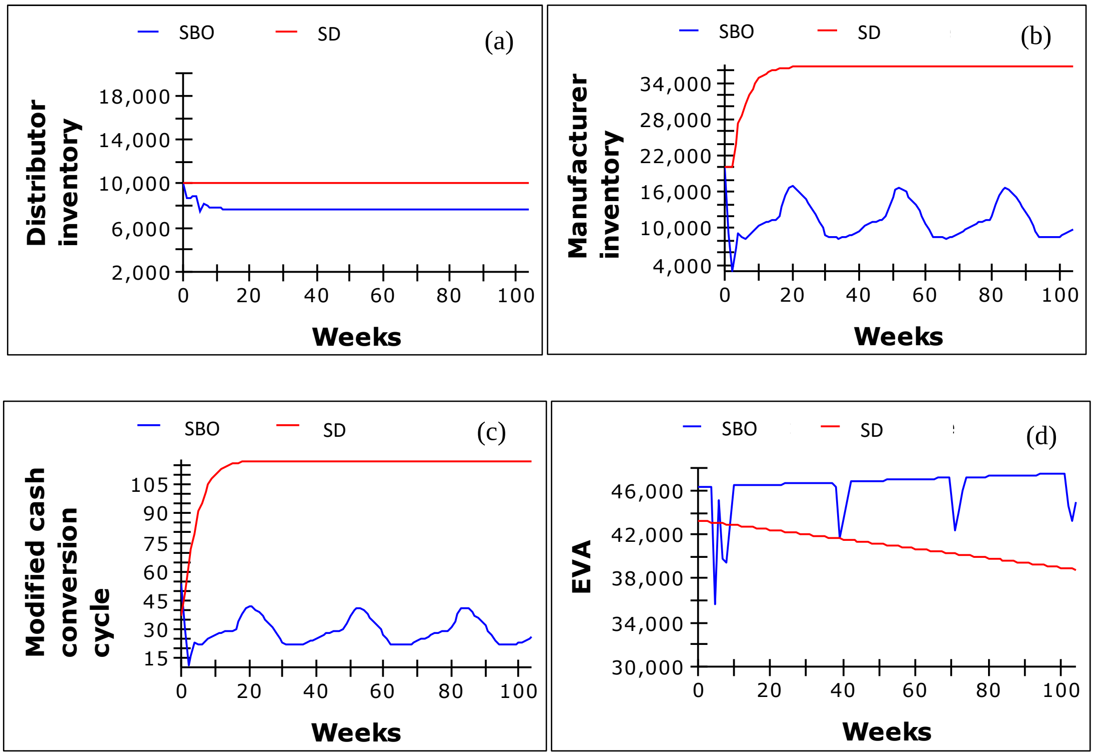
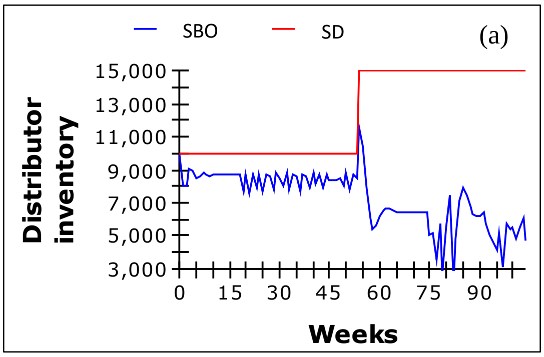


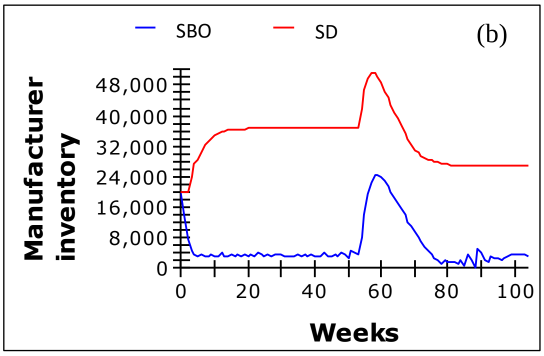
Figure 6.5. SD and SBO models performances scenario 2

Figures 6.5(a)- 6.5(d) represent the inventory, cash to cash cycle, and EVA dynamics for the SC members in scenario 2 after employing the SBO methodology. As in experiment 1, the SBO methodology reduces the inventory level of the distributor. The distributor's inventory remains at 7613 from week 10 until the end of the simulation. While, in the SD model it remains at

10,000 during the simulation time. Similar to the scenario 1, the inventory level of the manufacturer diminishes significantly after employing the SBO methodology. Before using the SBO, the manufacturer's inventory reaches to 36600 units of products at week 10 and remains stable until the end of the simulation. While, after employing the SBO, from week 10 onwards it oscillates in the range of [8500, 17200]. The significant decrease in the manufacturer's inventory level prompts reduction in cash to cash cycle. After using the SBO, the cash conversion cycle from week 10 until the end of the simulation fluctuates in the range of [22, 43] days. Although, in the SD model at the same period it remains stable at 117 days. The EVA after using the SBO, from week 10 onwards oscillates in the range of [42300, 47500] which is achieved as a result of reduction in the inventory held by the manufacturer. The EVA in the SD model is £43300 at the start of the simulation and arrives at £38900 at week 104.

Figures 6.6(a)- 6.6(d) represent the inventory, cash to cash cycle, and EVA dynamics for the SC members in scenario 3 obtained from running the SD simulation model for two years, 104 weeks. The inventory of the distributor remains unchanged at 10000 units of products until the end of the first year. At the start of the first-year distributor's inventory surges to 15000 units of products and remains stable until the ends of the simulation as a result of slump in customer's demands. The inventory of the manufacturer before the start of the second year shows a goal seeking pattern which reaches its goal, which is 36700 units of products, at week 10. At the start of the second year it grows significantly and arrives at 50400 units of products at week 60. Between weeks 60 and 80, there is a plummet in manufacturer's inventory levels before converging to the new equilibrium level at 26600 at week 80. The cash conversion cycle shows the similar pattern to the manufacturer inventory. At week 60 the cash to cash cycle peaks at 364 days and its new equilibrium level is 175 days which is achieved at week 80. The EVA at the start of the second-year plunges as a result of slump in customer's demand and reaches to £13569 at the end of the simulation.





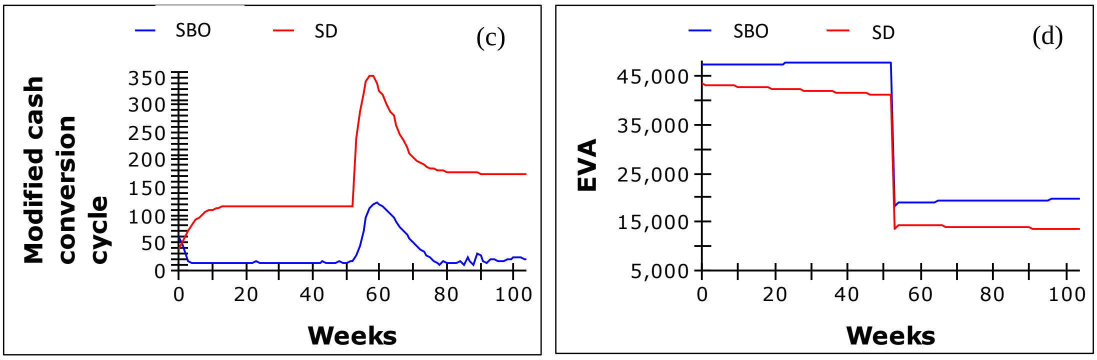


Figure 6.6. SD and SBO models performances scenario 3

Figures 6.6(a)- 6.6(d) represent the inventory, cash to cash cycle, and EVA dynamics for the SC members in scenario 3 after employing the SBO methodology. The SBO methodology significantly reduces the inventory of the distributors. After employing the SBO, the maximum inventory of the distributor is 11227 which is reached at week 53. While in the SD model, during the second year the inventory of the distributor remains at 15000. The inventory of the manufacture reduces significantly after using the SBO. The inventory of the manufacture after employing the SBO peaks at 24524 units of products at week 60. While, in the SD model it peaks at 50400 units of products at week 60. The inventory of the manufacturer between weeks 80 and 100 varies in the range of [2705, 3819] units of products. However, in the SD model it remains stable at 26600 units of products at the same period. Using the SBO reduces the cash to cash cycle significantly as the cash conversion cycle is a function of the inventories held by the supply chain members. After employing the SBO, the cash conversion cycle varies in the range of [15, 125] days. While, in the SD model it fluctuates in the range of [48, 364]. In congruence to the SD model, the EVA in the SBO model shows a significant reduction at the start of the second year caused by the plummet in customer's demand. While, in the second year the EVA values obtained from the SBO model are much higher than the ones attained from the SD model. In the second year the EVA in the SBO model varies in the range of [19125, 2086] GBP. However, in the SD model it varies in the range of [13569, 14768] GBP.

Figures 6.7- 6.9 illustrate the Pareto optimal frontier for EVA versus CCC in the scenarios 1-3. The results are determined by specifying the weighting factors for objective functions which could be selected based on the decision maker's preferences. To achieve non-dominated solutions, each single objective optimisation problem is formulated through selecting weighting factors (w_i) that are in the interval of $[0,1]$ and add up to 1. Each point in this frontier corresponds to a different combination of the decision parameters.

In order to get a more detailed insight into model's decision mechanism, two solutions in each scenario were selected and their optimal decision parameters are presented in Tables 6.4 - 6.6. Solution 1 represents the optimal decision parameters that result in minimum CCC while ignoring the added value. On the other hand, Solution 101 represents the optimal decision parameters that lead to maximum added value while ignoring cash to cash cycle.

As shown in Tables 6.4 - 6.6, solution 1 in all scenarios recommends collection of major share of the customers' order value in the form of in advance cash payment, e.g., in scenario 1, $m = 0.96$, and payment of the major share of the purchased material's value in the form of credit payment, e.g., in scenario 1, $n = 0.08$, as decreasing the level of accounts receivable and increasing the level of accounts payable yield reduction in the CCC.

Since diminishing the level of inventories, containing materials, finished and unfinished goods, is another common way to decrease the cash to cash cycle, the values for the inventory decisions parameters including safety stock coverage (SSC), material safety stock coverage $(MSSC)$, Minimum order processing time $(MOPT)$, minimum material inventory coverage $(MMIC)$, inventory adjustment time (IAT), material inventory adjustment time $(MIAT)$, WIP adjustment time $(WIPAT)$, and time to average order rate $(TAOR)$ in solution 1 are lower than the values recommended in solution 101.

On the other hand, solution 101 in all scenarios recommends a significant profit margin, e.g., in scenario 1 the sales price (SP) is 2.91 times bigger than the unit cost (UC) as it targets at maximizing the operating profit. Since decreasing the level of invested capital is another way to maximize EVA, solution 101 in all scenarios recommends allocating 100 percent of the NOPAT to working capital and dividends, i.e., $WCP = 0.5$ & $PDP = 0.5$. Both solutions in all scenarios have almost the same approach toward the new stock parameter as issuing new stocks improves neither EVA nor CCC.

Regarding the inventory decisions for the distribution centre, solution 1 in all the scenarios recommends a lower desired inventory $(DCDI)$ in order to diminish the level of inventory. In both scenarios 2 and 3, solution 1 recommends a lower level of desired supply line (DCDSL) as setting high level of desired supply line in presence of stability and shrinkage in demand is not imperative. Although, in scenario 1, solution 1 recommends a higher level for finished products within supply line in order to meet increased demand of end customer. Forecasting parameter for inventory adjustment (α) and forecasting parameter for supply line adjustment (β) represent the policy of the distribution centre in relation to bridging the gap between the desired and current levels of inventory and supply line, respectively. A high value of α indicates an aggressive policy to bridge the gap between desired and current inventory level. In the case of β, a high value implies that all the orders in the supply line have been taken into account, when deciding on the amount of orders to be placed with the upstream member. Neglecting minimization of the CCC, i.e., the weight of CCC in objective function equals to 0, there is a positive correlation between end customer demand and forecasting parameters for supply line adjustments (i.e., β). Although, the forecasting parameter for inventory adjustment (i.e., α) and the end customer demand move at the same direction.

Considering the values for the EVA, as expected, scenario 3 results in the lowest value for EVA comparing the other scenarios since there is recession in economic condition in the second year. Furthermore, the EVA in scenario 2 is lower than scenario 1 as the stagnation in the second year leads to stability in the end customer demand.

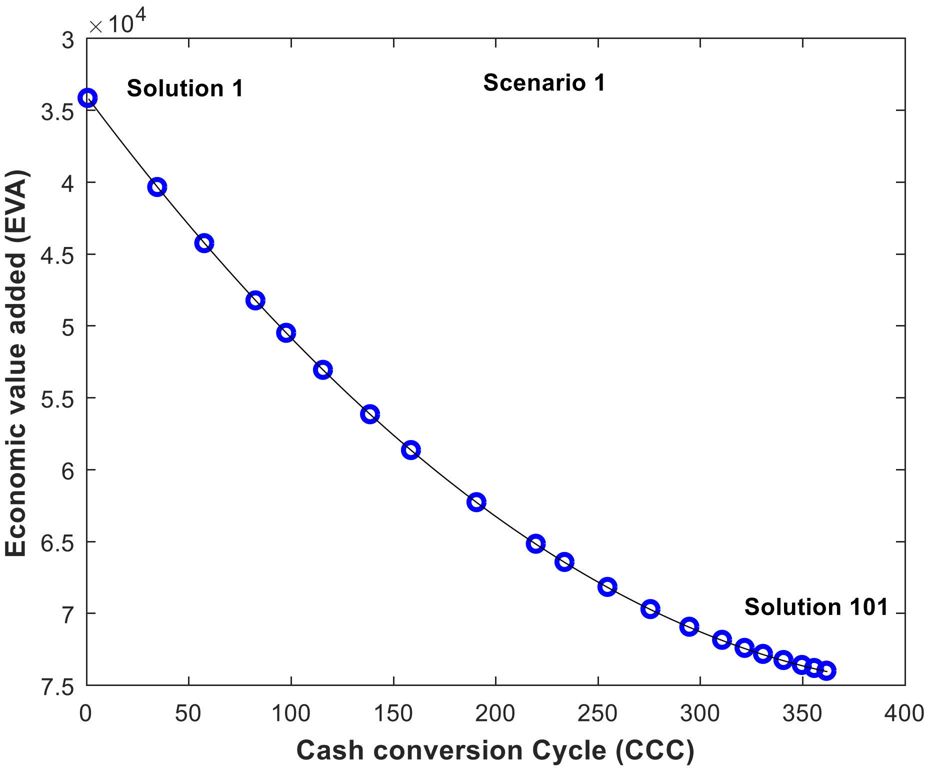


Figure 6.7. Pareto optimal frontier illustrating the trade-off between EVA and CCC in scenario 1

Table 6.4. Optimal decision parameters of two non-dominated solutions in Scenario 1

Parameter / Solution	W_{CCC}	W_{EVA}	m	IAT	DDI	β	$MIAT$	$MSSC$	$MMIC$	$MOPT$	NSP	n
Solution 1	1	0	0.96	13.37	25341	0.27	6.10	4.16	3.94	0.28	0	0.08

Solution 101	0	1	0.52	13.39	27028	0.35	8.35	5.25	9.44	9.74	0	0.23

Parameter / Solution	PDP	SSC	SP	$TAOR$	α	$DDSL$	UC	$WIPAT$	WCP	μ_{CCC}	μ_{EVA}	No simulation
Solution 1	0.50	0.32	9.29	14.42	0.47	14158	4.08	3.15	0.49	1	33471	2332
Solution 101	0.50	3.77	11.96	10.42	0.81	7179	3.06	4.42	0.50	362	74243	2411

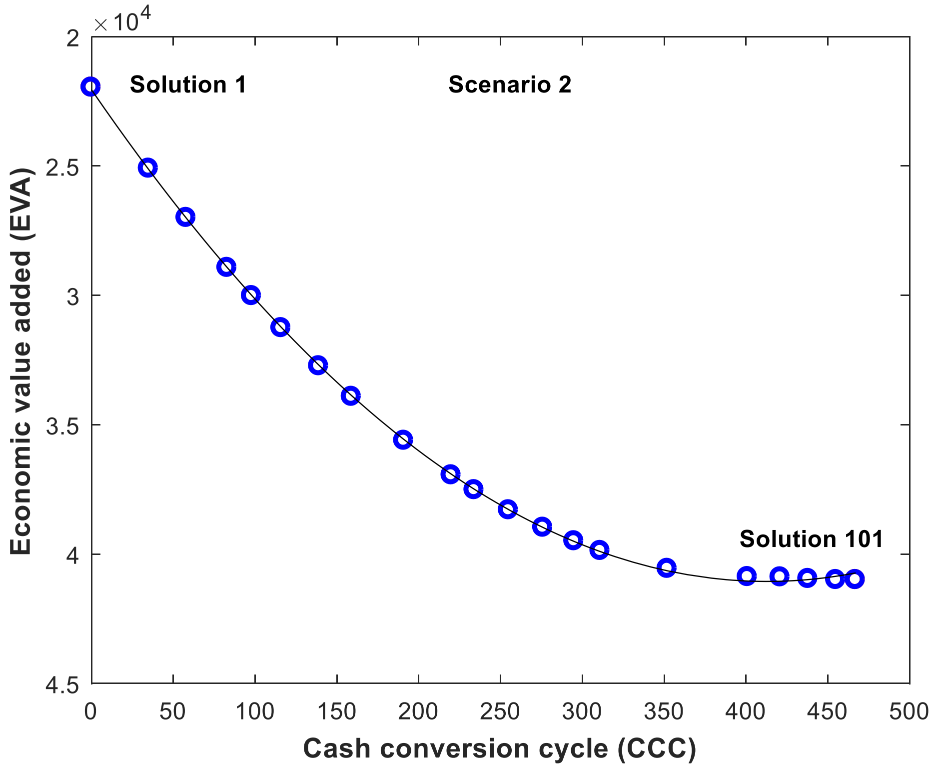


Figure 6.8. Pareto optimal frontier illustrating the trade-off between EVA and CCC in scenario 2

Table 6.5. Optimal decision parameters of two non-dominated solutions in Scenario 2

Parameter / Solution	W_{CCC}	W_{EVA}	m	IAT	DDI	β	$MIAT$	$MSSC$	$MMIC$	$MOPT$	NSP	n
Solution 1	1	0	0.91	8.66	2362	0.31	5.23	5.52	6.97	0.25	0	0.09
Solution 101	0	1	0.37	12.86	21722	0.14	13.43	6.90	8.92	9.48	0	0.42

Parameter / Solution	PDP	SSC	SP	$TAOR$	α	$DDSL$	UC	$WIPAT$	WCP	μ_{CCC}	μ_{EVA}	No simulation
Solution 1	0.50	0.25	11.31	14.11	0.45	1999	5.93	6.92	0.50	0	21218	2346

Solution 101	0.50	8.28	11.28	12.91	0.54	22342	3.01	4.98	0.50	467	41665	2402

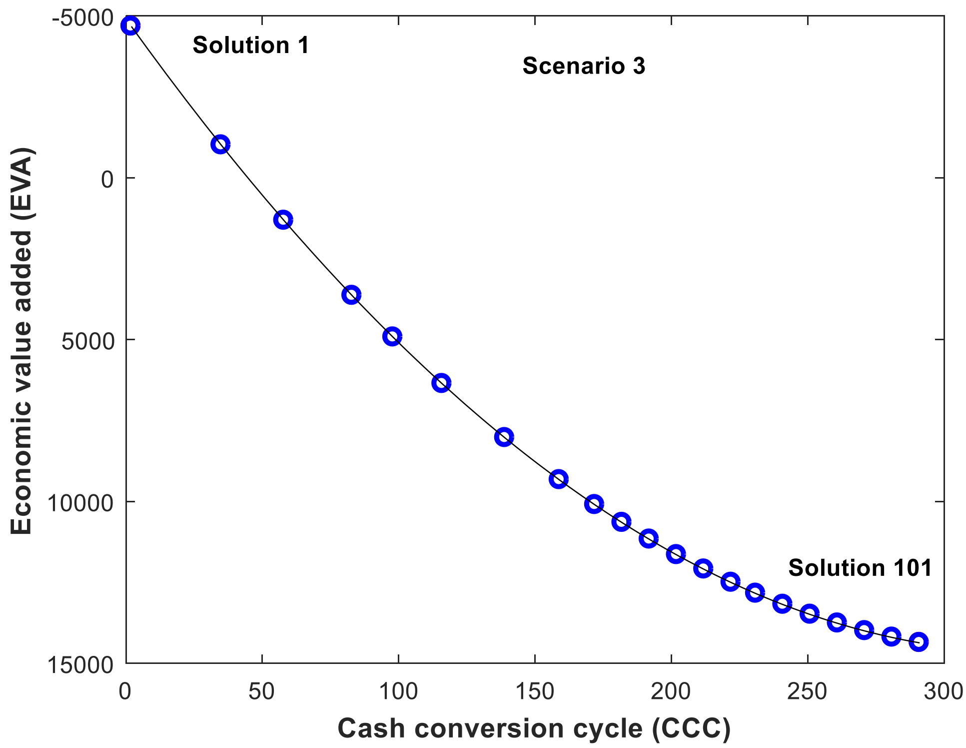


Figure 6.9. Pareto optimal frontier illustrating the trade-off between EVA and CCC in scenario 3

Table 6.6. Optimal decision parameters of two non-dominated solutions in Scenario 3

Parameter / Solution	W_{CCC}	W_{EVA}	m	IAT	DDI	β	$MIAT$	$MSSC$	$MMIC$	$MOPT$	NSP	n
Solution 1	1	0	0.91	10.06	1381	0.48	5.94	5.75	5.24	0.28	0.0005	0.39
Solution 101	0	1	0.37	12.67	11031	0.08	8.97	6.40	7.75	7.94	0	0.58

Parameter / Solution	PDP	SSC	SP	$TAOR$	α	$DDSL$	UC	$WIPAT$	WCP	μ_{CCC}	μ_{EVA}	No simulation
Solution 1	0.44	0.33	10.27	13.94	0.42	3514	5.87	2.48	0.50	2	-4675	2314
Solution 101	0.50	4.29	11.52	9.99	0.27	5085	3.54	3.23	0.50	291	14215	2486

6.5. Concluding discussion

Given the importance of incorporating financial flow modelling into supply chain planning models, this chapter presents an SBO framework that incorporates the financial flow modelling into the inventory management problem presented by Sterman (2000) under economic uncertainty. Economic uncertainty triggers uncertainty in the financial status of a company which may in turn results in sustainability risks. Financial and working capital performances are two essential pillars of financial status representing the profitability of the supply chain and the accessibility of the supply chain members to necessary funds for continuing their operation. To assess the financial and working capital performances, in this chapter, the economic value added (EVA) and cash conversion cycle (CCC) metrics are used, respectively. These two metrics are not moving towards the same direction and business managers should find a balance between them. The proposed model integrates system dynamics (SD) and a genetic algorithm (GA) to identify the optimal values to the inventory and financial decisions parameters to make the trade-off between the EVA and the CCC.

As discussed in section 2.5.3 in chapter 2 and is presented in Table 6.7, much of the literature on the application of the SD modelling for inventory management focuses on evaluating the impact of various policies on improving the system's performance in terms of efficiency and responsiveness. The effects of the improvement policies on the system's performance are measured through modifying the values to the decision parameters of the model. In other words, by applying SD modelling, the modeller is solely able to compare the effects of varied policies, i.e., different values of the controllable parameters, through performing what-if analysis which may not be an effective strategy particularly, when the decision parameters are continuous such as inventory decisions. Therefore, incorporating optimisation algorithms into the SD simulation is inevitable when the modeller aims to identify the optimal values to the continuous decision parameters. To fill the gap in inventory management using SD simulation, In this chapter, the genetic algorithm which is a metaheuristic and is an effective tool for optimisation of the continuous parameters (Mühlenbein and Schlierkamp-Voosen, 1993) is applied to identify the optimal values to the inventory decisions parameters such as inventory and supply line adjustment parameters.

Much of the literature on inventory management under trade credit applied mathematical modelling approaches, and the simulation-based modelling remains underrepresented. Moreover, cost minimization or profit maximization are the dominant objective function in the developed models in the literature, while the literature lacks the studies that manage the trade-off between profitability and liquidity through developing the multi objective models. Finally, the literature lacks the studies that consider uncertainties in economic parameters such as demand and interest rates.

Table 6.7. Literature on inventory management using SD simulation and working capital management

Current literature	**Parameters considered**	**Finding the optimal values to the continuous inventory parameters**	**Managing the trade-offs between the EVA maximization and the CCC minimization**	**Considering the economic uncertainty**	**Approaches**
(Reyes et al, 2013; Peng et al., 2014; Cannella et al., 2015; Liao, 2008; Teng, 2009; Mahata, 2012; Huang, 2007; Huang and Hsu, 2008; Teng and Chang, 2009; Ravichandran, 2007; Liao, 2008; Teng, 2009)	Inventory control parameters	×	×	×	System dynamics Mathematical modelling
This study	Inventory control parameters Price Unit cost Collection policy Payment policy	✓	✓	✓	Simulation-based optimisation (System dynamics and genetic algorithms)

To fill the gap in the inventory planning under trade credit literature, in this chapter, a simulation-based optimisation model which integrates SD simulation and a genetic algorithm is developed to manage the trade-off between financial performance and liquidity in a supply chain under economic uncertainty. To assess the financial performance and liquidity, the economic value added (EVA) and the cash conversion cycle (CCC) metrics are used, respectively. These two metrics are not moving towards the same direction and business managers should find a balance between them. This contribution extends the literature on supply chain inventory management using system dynamics simulation and supply chain working capital management (Reyes et al., 2013; Peng et al., 2014; Cannella et al., 2015; Liao, 2008; Teng, 2009; Mahata, 2012; Huang, 2007; Huang and Hsu, 2008; Teng and Chang, 2009; Ravichandran, 2007; Liao, 2008; Teng, 2009) through incorporating financial parameters including price, unit cost, collection policy, and payment policy. Moreover, it considers the EVA and the CCC in the multi-objective optimisation formulation of the inventory management model developed by Sterman (2000) under economic uncertainty. Finally, it introduces a new method for measuring the CCC in which the revceiving and payment of the advance payament are taken into account. The proposed model handles economic uncertainty through a scenario tree approach.

The developed simulation-based optimisation model is implemented using the data of a real case study introduced in Longinidis and Georgiadis (2013). Firstly, the conflicting objectives are given the same level of importance in order to compare the performance of the SBO approach, in which a genetic algorithm is incorporated into a SD simulation model, with the performance of the SD simulation model under three economic scenarios. The results show the superiority of the SBO approach over SD modelling in all three scenarios. Secondly to manage the trade-offs between the conflicting objectives, the weighted sum method is used to generate the Pareto efficient frontiers which include the non-dominated optimal solutions. These Pareto efficient frontiers provide decision makers with a portfolio of alternative optimal inventory and financial decisions that could be selected based on market condition and the power of the company within supply chain network.

In the next chapter a hybrid analytical and simulation model that integrates the presented SBO model in this chapter and mixed-integer linear programming (MILP) is developed to examine whether the hybrid model outperforms the SBO model.

Chapter 7. Hybrid analytical-SBO approach to integration of physical and financial flows in a supply chain under economic uncertainty

7.1. Introduction

Simulation and optimisation are the most utilized approaches for supply chain modelling. The advantage of simulation models lies on their ability in modelling the complexities and dynamic behaviour of the supply chains. Although, they do not provide the capability of obtaining optimal system configurations (Abo-Hamad and Arisha, 2011). On the other hand, optimisation models are not effective tools for incorporating the dynamic behaviour and complexities of the supply chains as the real world supply chain problems are too complex to be formulated in the form of manageable mathematical equations (Better et al., 2008). While, they are capable of determining the optimal values to the decision variables and decision parameters. Therefore, in a supply chain planning problem, it would be beneficial to depict the complex supply chain system using the simulation modelling and then incorporate an optimisation algorithm into the simulation model to attain the optimal decision parameter sets. This integrated usage of the two approaches is knowns as simulation-based optimisation (SBO).

Despite the capability of the SBO in identifying the optimal sets of the decision parameters, it is not capable of determining the optimal decision variables. This incapability has motivated the development of the hybrid analytical-simulation models in which the decision variables are optimised in addition to the decision parameters. Hybrid modelling is an emerging field that integrates independent optimisation and simulation models to identify the optimal solutions to the complex supply chain problems in acceptable times.

Considering the financial flow within supply chain planning models is of paramount importance as implementing the supply chain decisions relies on the availability of the financial resources. For instance, opening a new facility in the supply chain network is impossible unless the funding mechanism is explicit. Moreover, the financial and physical flows have a mutual effect on one another. For example, inventory optimisation leads to savings in the financial resources which can in turn provide the required resources for implementing other operational decisions such as production capacity expansion.

In this chapter, we propose a hybrid analytical-simulation modelling that integrates planning of cash and material flows within the supply chain networks through combining the optimisation and the simulation-based optimisation approaches. The hybrid analytical-simulation model is based on the development of independent mixed integer linear programming (MILP) and simulation-based optimisation (SBO) models which are combined to address an integrated supply chain planning and supply chain finance problem. The coupling of the MILP and SBO models is developed using an iterative process. To demonstrate the feasibility of the hybrid approach, it is applied to address an integrated strategic supply chain planning and supply chain finance problem that integrates supplier selection, network design, and asset-liability management subproblems.

The rest of the chapter is organised as follows. Firstly, the problem description and the proposed hybrid method is given in section 7.2. The framework of the hybrid analytical-SBO modelling is presented in section 7.3. Section 7.4 elaborates the developed optimisation, simulation-based optimisation, and hybrid analytical-SBO models in detail. Next, the results obtained from the various methods are presented and discussed in section 7.5. Finally, conclusions are given in section 7.6.

7.2. Problem Description

The general structure of the studied supply chain is depicted in Figure 7.1. The supply chain includes four stages: (1) suppliers, (2) production centre, (3) distribution centres, and (4) retailers. In the forward direction, suppliers are in in charge of providing the raw material to the production centre. The products are then manufactured in the production centre and shipped to the retailers via distribution centres. The retailers are responsible for meeting end customer demands which is uncertain and fluctuates in line with economic environment. In the reverse direction, the end customer pays for the products purchased from the retailers. It is assumed that the distribution centres and retailers are owned by the production centre and consequently share a common profit.

In the studied supply chain system, one product and multiple time periods are considered. The suppliers are able to fulfil the entire order of the production centre, while the capacities of other SC members are restricted. The factory is able to secure long-term and short-term loans. The receivable accounts from customers and payable accounts to the suppliers are liquidated at the end of each period.

The decisions to be determined by the proposed model are as follows:

1. The amount of raw material to be purchased from suppliers
2. The production rate at production centre
3. The number of required suppliers and distribution centres
4. The warehousing capacity at SC facilities
5. The flow of products in the network
6. The level of short-term and long-term liabilities
7. The level of equity
8. The level of fixed and current assets
9. The level of cash
10. Price of the product

Such that economic value added is maximized with respect to the physical and financial constraints. The optimal price of the product and the optimal warehousing capacity of the distribution centres are determined by the simulation-based optimisation model, as they can be formulated as controllable parameters in the SBO model. The optimal values to the remaining decisions are determined by the analytical model, as they are dynamic variables that cannot be optimised by the SBO model. The analytical model is a generalization of the SBO model that is represented by linear relationships, while the SBO model is applied to take into account interrelationships and nonlinearities rooted in supply chain networks.

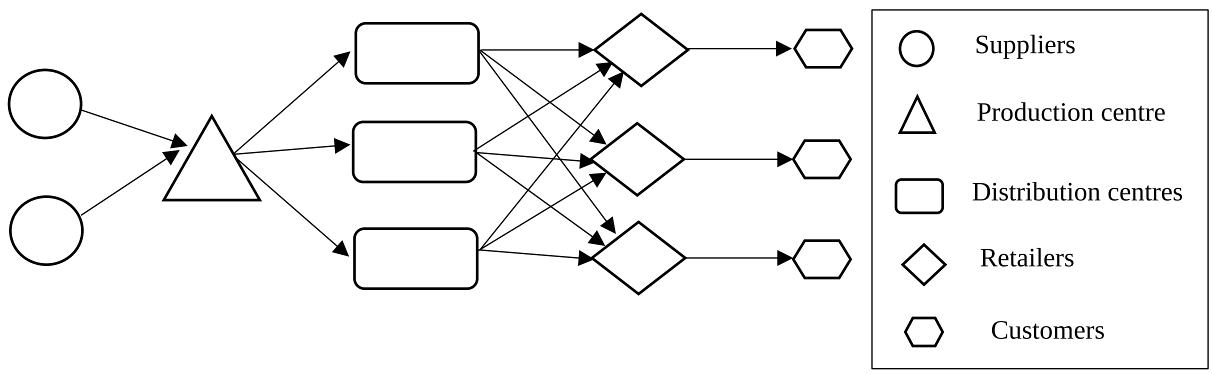


Figure 7.1. The structure of the studied supply chain

7.3. Hybrid analytical-SBO modelling approach

The objective of the current study is to apply the hybrid approach to address the supply chain planning problem. The approach consists of building independent analytical and SBO models and thereafter integrating the solution strategy. The analytical model contains a mixed integer linear programming model (MILP). The SBO model combines genetic algorithm and system dynamics simulation modelling. The connection of the two models is illustrated in Figure 7.2.

Firstly, by setting the initial price, desired cash, profit distribution policy, and stocking capacities at the production centre, distributors, and retailers, the MILP model is run to decide on the open or close decision on certain distribution centres, select suppliers and the amount of raw material which is required to be purchased from each supplier, determine the optimal production level of the production centre, and the shipment rates between the supply chain entities are identified so as to maximize the economic value added.

In step 2, the solution suggested by the analytical model is used to construct the system dynamics simulation model and genetic algorithm is applied to recommend the optimal price per tonne of the product, the optimal desired cash, the optimum profit distribution policy, and the optimum stocking capacities at production centre, distributors, and retailers. It is worth mentioning that formulating the price of the product as a variable within the analytical model converts the MILP model into a non-linear model which increases computational time dramatically. The stocking capacities of the SC facilities would be more realistic if obtained by the SBO model in which interrelationships, nonlinearities, and inventory dynamics have been considered.

In step 3, the price, the profit distribution policy, the desired cash, and the stocking capacities were obtained from the SBO model are inputted into the analytical model in which the new optimal production level of the manufacturer, the new storage locations in the network, the new suppliers, the new amount of the required raw material, and the new shipment rates between the members are determined. Taking the results of the second iteration from the analytical model, the SBO model is then run again to obtain a new solution containing the product's price, the desired cash, the profit distribution policy, and stocking capacities at the SC facilities (step 4).

At this time, the information gathered from the SBO model is used to examine whether the current solution, which is the economic value added of the network, meets the termination criteria which is set to be zero to five percent discrepancy between the current EVA and the ideal EVA given by the analytical model. If the termination criteria is satisfied, the solution suggested by the hybrid approach is accepted, otherwise, the results are used to revise the problem to be resolved by the hybrid approach in the third iteration, and so on. The revision of the problem contains the revision of the feasible intervals of the controllable parameters including price and warehousing capacities and/or modifying the initial population of the genetic algorithm. The termination criteria offers a control mechanism to ensure that the solution obtained by the SBO model honours the set of constraints described in the analytical model.

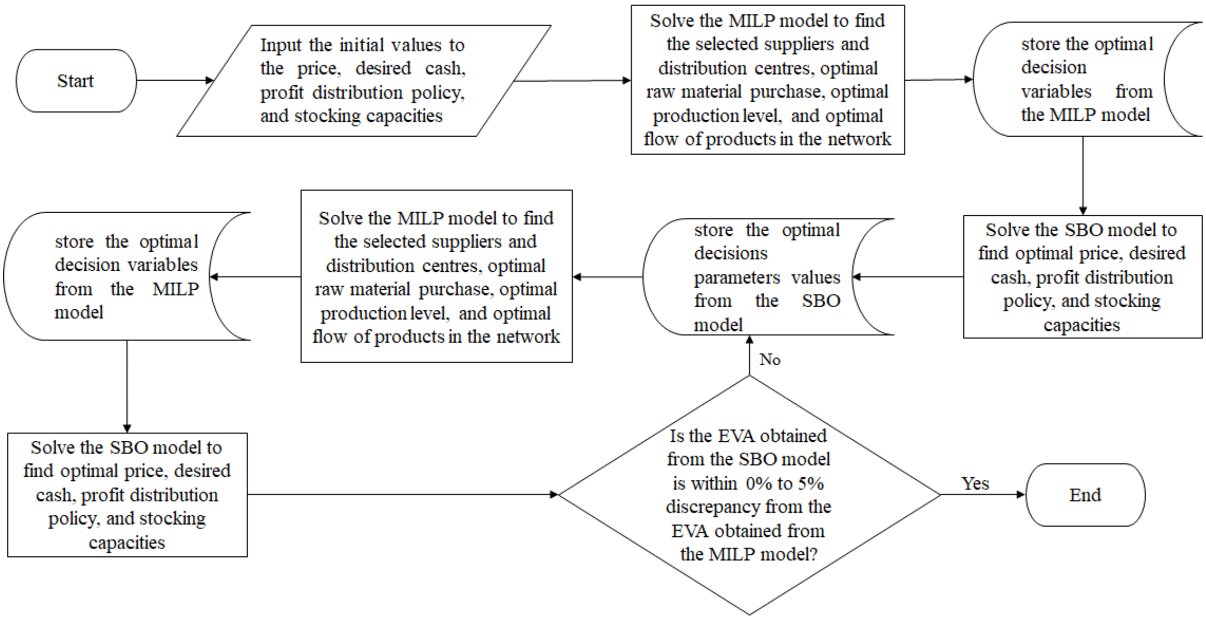


Figure 7.2. The hybrid framework

7.4. Model formulation

7.4.1. Analytical model

7.4.1.1. Objective function

To optimise the financial flow, in addition to the product flow, through the supply chain the financial performance evaluation should be incorporated into the objective function of the supply chain planning models. Economic value added (Stewart Iii, 1994) is a widely used index which integrates financial and economic performance indicators. This indicator rectifies the optimistic interpretation of how well the company performed through deducting the cost of capital employed from its net income. In this study, economic value added (EVA) is applied as the objective function. The formulation of the EVA is given in Eq. (7.1), where NOPAT is the net operating profit after tax reported in the income statement and WACC is the weighted average cost of capital, a figure representing the real costs concerned with the sources of capital employed by the company (Ogier, Rugman and Spicer, 2004).

$$EVA_t = \sum_{t=1}^{T} [NOPAT_t - (WACC_t)IC_t] \tag{7.1}$$

The WACC (7.2) is the return needed to compensate capital providers, i.e. creditors and stakeholders and is obtained via multiplying cost of debt (CD) and cost of equity (CE) by their proportional weight and take the sum of the results. The cost of debt is the weighted average of short-term and long-term liabilities. The cost of equity is measured by capital asset pricing model (CAPM) which contains three elements. The first element risk-free rate of interest (r_{f_t}) is the reward for placing capitals in a risk-free asset such as government bonds. The second element, the difference between the expected return of the market (r_{m_t}) and (r_{f_t}) is the reward for placing capitals in an investment which requires taking risks such as stock market bonds. The third element, the risk measure (β) is the amount of systematic risk present in an asset. Invested capital (IC) (7.3) accumulates the amount of financing from debt and equity.

$$WACC = \frac{E_t}{IC_t} CE_t + \frac{STL_t + LTL_t}{IC_t} CD_t \tag{7.2}$$

$$IC_t = STL_t + LTL_t + E_t \quad \forall t. \tag{7.3}$$

To calculate the NOPAT (7.4), the taxable income (TI) is multiplied by tax rate (tr). The TI (7.5) is determined by subtracting the interest paid (IP) from the earnings before interest and taxes ($EBIT$). The IP (7.6) is the interest paid for both short-term and long-term financing received from credit institutions. The IP is calculated by multiplying short term liabilities (STL) and long term liabilities (LTL) by short term interest rate (STR) and long term interest rate (LTR), respectively and take the sum of the results. The EBIT (7.7) which is the gross income of a company is calculated by subtracting the total cost (TC) from the net sales (NTS). The revenue of the chain (7.8) is obtained by multiplying the sales amounts of each customer by its price and aggregating the results.

$$NOPAT_t = TI_t(1 - tr_t) \quad \forall t. \tag{7.4}$$

$$TI_t = EBIT_t - IP_t \quad \forall t. \tag{7.5}$$

$$IP_t = STL_t STR_t + LTL_t LTR_t \quad \forall t. \tag{7.6}$$

$$EBIT_t = NTS_t - TC_t \quad \forall t. \tag{7.7}$$

$$NTS_t = \sum_{r=1}^{R} SR_{rt} pri_t \quad \forall t. \tag{7.8}$$

The total cost (7.9) of the chain contains the production cost at the production centre (PC), the transportation cost between centres (TRC), the inventory holding cost at the centres (HC), fixed costs of the centres (FC), cash holding cost (CC), and the cost of raw material purchased from the suppliers (RMC). Eq. (7.10) shows the operating cost at the production centre which is obtained via multiplying production rate (PR) and unit production cost (upc). The operating costs are the costs associated with the required activities to produce final products. The transportation cost (TRC) (7.11) includes the transportation cost from the supplier to the manufacturer (tc), the manufacturer to the distributor (tcc), and the distributor to the retailer (tcd). Eq. (7.12) represents the holding cost of products incurred by the manufacturer, distribution centres, and retailers. This cost encompasses the holding cost of the raw materials (hr) and the holding cost of the product (hp) at the production centre, in addition to the holding cost of safety stock at the distribution centres and retailers.

$TC_t = PC_t + TRC_t + HC_t + TFC_t + CHC_t + RMC_t \quad \forall t.$	(7.9)
$PC_t = upc_t PR_t \quad \forall t.$	(7.10)
$TRC_t = \sum_{s=1}^{S} tc_{st} X_{st} + \sum_{d=1}^{D} tcc_{dt} SC_{dt} + \sum_{r=1}^{R} \sum_{d=1}^{D} tcd_{drt} SDI_{drt} \quad \forall t.$	(7.11)
$HC_t = hr_t \left(\frac{FIR_t + FIR_{t-1}}{2} \right) + hp_t \left(\frac{FIP_t + FIP_{t-1}}{2} \right) + \sum_{d=1}^{D} ho_{dt} \left(\frac{FIO_{dt} + FIO_{dt-1}}{2} \right)$ $+ \sum_{r=1}^{R} hs_{rt} \left(\frac{FIS_t + FIS_{t-1}}{2} \right) \quad \forall t.$	(7.12)

The fixed cost (7.13) contains all the expenses incurred by a SC member such as employee salaries that do not depend on the number of goods and services provided by the member. This cost is obtained for the distribution centres by multiplying the fixed cost (fcd) by a binary variable that indicates the activity of the distribution centre. The fixed costs of the production canter (fcp) and retailers (fcr) are not multiplied by the binary variable as it is assumed that they are situated fixed locations. Companies hold cash in order to pay to their suppliers for their services also cover unexpected expenses which may arise. Cash holding cost (7.14) is the opportunity cost of choosing to hold cash rather than investing in more profitable options such as buying stocks. This cost in each period is calculated via multiplying unit cash cost (ucc) by the average amount of cash during the period. The raw material cost (7.15) is the cost of purchasing raw material from different suppliers which is determined through multiplying the amount purchased (X) by the price of each unit (rmc).

$TFC_t = \sum_{d=1}^{D} fcd_{dt} Y_{dt} + fcp_t + \sum_{r=1}^{R} fcr_{rt} \quad \forall t.$	(7.13)
$CHC_t = ucc_t \left(\frac{CS_t + CS_{t-1}}{2}\right) \quad \forall t.$	(7.14)
$RMC_t = \sum_{s=1}^{S} X_{st} rmc_{st} \quad \forall t.$	(7.15)

7.4.1.2. Constraints

In this section, the constraints of the model which were categorised into physical flow constraints and financial flow constrains are presented.

7.4.1.2.1. Physical flow constraints

Constraints (7.16) shows the inventory level of raw materials held in production centre at each time period is equal to the inventory left at the end of previous period plus the amount of the purchased material from the suppliers minus the amount consumed for producing the final products. The available inventory of products held in production centre at the end of period t (7.17) equals to the inventory held at the end of period $t-1$ plus production rate during the period, minus products transported from the plant to distribution centres during the same period.

$FIR_t = \sum_{s=1}^{S} X_{st} - PR_t o_t + FIR_{t-1} \quad \forall t.$	(7.16)
$FIP_t = PR_t - \sum_{d=1}^{D} SC_{dt} + FIP_{t-1} \quad \forall t.$	(7.17)

Constraints (7.18) and (7.19) state that the inventory level at each distributor and retailer member is equal to the amount of product that flows into the member inventory from the upstream echelon plus the inventory that is left over from the previous time, minus the amount of product that flows out of the member to the downstream echelon.

$FIO_{dt} = SC_{dt} - \sum_{r=1}^{R} SDI_{drt} + FIO_{dt-1} \quad \forall d, t.$	(7.18)
$FIS_{rt} = \sum_{d=1}^{D} SDI_{drt} - SR_{rt} + FIS_{rt-1} \quad \forall r, t.$	(7.19)

Constraints (7.20) enforces the amount of products shipped from each retailer to be less or equal to the end customer demand.

$$SR_{rt} \leq d_{rt} \quad \forall r, t. \tag{7.20}$$

Constraint (7.21) enforces the sum of products sold to end customers to be equal to the sum of the products sent to the retailers. Constraint (7.22) states that the sum of products shipped to the retailers should be equal to the products sent to the distribution centres.

$$SR_{rt} = \sum_{d=1}^{D} SDI_{drt} \quad \forall r, t. \tag{7.21}$$

$$\sum_{r=1}^{R} SDI_{drt} = SC_{dt} \quad \forall d, t. \tag{7.22}$$

Constraints (7.23) and (7.24) enforce that at least one of the supply and distribution centres are open at each time period.

$$\sum_{s=1}^{S} Z_{st} \geq 1 \quad \forall t. \tag{7.23}$$

$$\sum_{d=1}^{D} Y_{dt} \geq 1 \quad \forall t. \tag{7.24}$$

Constraints (7.25)-(7.28) state that the inventory level of the production centre, distribution centres and retailers at any time period must be greater than their specified safety stock levels known as the desired inventories (DI) which are determined by the simulation-based optimisation model.

$$DIRM \leq FIR_t \leq caprm_t \quad \forall t. \tag{7.25}$$

$$PDI \leq FIP_t \leq cap_t \quad \forall t. \tag{7.26}$$

$$Y_{dt}DDI_d \leq FIO_{dt} \leq Y_{dt}capd_{dt} \quad \forall t, d. \tag{7.27}$$

$$RDI_r \leq FIS_{rt} \leq capr_{rt} \quad \forall t, r. \tag{7.28}$$

Constraint (7.29) controls the production rate of the production centre not to exceed the available production capacity and not to be lower than zero.

$0 \leq PR_t \leq prcap_t \quad \forall t.$	(7.29)

7.4.1.2.2. Financial flow constraints

Constraint (7.30) formulates the basic equation of the balance sheet. This equation illustrates the equality of the assets to equity (E) and debts. The assets comprises of fixed assets (FA) and current assets (CA) while the debts includes short-term liabilities (STL) and long-term liabilities (LTL). Depreciation (DPR) is calculated in constraint (7.31) by multiplying fixed assets and depreciation rate.

$FA_t + CA_t = E_t + STL_t + LTL_t \quad \forall t.$	(7.30)
$DPR_t = dr_t FA_t \quad \forall t.$	(7.31)

The fixed assets (FA) value (7.32) at each time period is determined through aggregating the fixed assets of the SC members and then deducting the depreciation rate.

$FA_t = \sum_{d=1}^{D} D_d CD_d Y_{dt} + PCFAV_t + \sum_{r=1}^{R} RFAV_{rt} \quad \forall t.$	(7.32)

Constraint (7.33) formulates the current assets (CA) which is composed of cash (CS), receivable accounts (RA), and inventory value (INR).

$CA_t = CS_t + RA_t + INR_t + CA_{t-1} \quad \forall t.$	(7.33)

Constraint (7.34) shows the amount of cash available which is obtained by aggregating total amount of loans ($STL + LTL$), new issued stocks, and the operating profit which is accessible in the form of cash. The amount of investment in fixed assets (FA) diminishes the cash level. The portion of the operating profit that is not accessible in the form of cash is accumulated in the receivable accounts (RA) (7.35).

$CS_t = cssNOPAT_t + STL_t + LTL_t + NIS_t - FAI_t \quad \forall t.$	(7.34)

$$RA_t = (1 - css)\ NOPAT_t \quad \forall t. \tag{7.35}$$

Constraint (7.36) indicates the inventory value which is determined via multiplying sales price of each member in their corresponding inventory and then taking the sum of the results.

$$INR_t = FIR_t\ rmp + \left(FIP_t + \sum_{d=1}^{D} FIO_{dt} Y_{dt} + \sum_{r=1}^{R} FIS_{rt} \right) pri \quad \forall t. \tag{7.36}$$

The equity value (E) at any time period is calculated in constraint (7.37) through aggregating the accumulated equity from the previous period, operating profit ($NOPAT$), and the profit obtained from issuing new stocks in the market (NIS).

$$E_t = NOPAT_t + E_{t-1} + NIS_t \quad \forall t. \tag{7.37}$$

Constraint (7.38) ensures that the cash level at any time period does not exceed the desired cash level determined by the SBO model.

$$CS_t \leq DCS \quad \forall t. \tag{7.38}$$

7.4.2. Simulation-based optimisation model

In this study, the inventory management simulation and genetic algorithm optimisation constitute the simulation-based optimisation model. The inventory management model is developed based on the stock management structure (Sterman, 2000) which relates to the issue of controlling a system state or stock to meet some system objectives. For instance, all supply chain members manage their inventory to meet the demand of their customers. Stocks are solely modified through altering their inflow and outflow rates, therefore necessitates a decision maker to not only balance the inflow of the stock with its outflow, but also eliminate any discrepancy between the current and the desired state of the stock (Sterman, 2000). Furthermore, there is a delay between a decision maker control actions and its effect on the system state (stock) which is required to be formulated. For instance, a distributor seeking to increase its inventory is not able to access new units immediately but must await delivery of the orders by its supplier. The control of the stock management problem is divided into two parts, where the first part relates to constructing the stock and flow structure of the stock management system, and the second part pertains to the decision rules applied by the decision maker to control the inflow rate of the stock (Sterman, 2000).

The stock and flow structure of the inventory management model is illustrated in Figure 7.3. The raw material's inventory (7.39) is replenished by the delivery of placed orders and depleted by the material usage rate. The suppliers are able to fulfil the entire order of the production centre. Therefore, the delivery rate of the raw material (7.40) is equal to the desired delivery rate of the manufacturer. The current material inventory level either meets the demand for required raw material for production or is able to fulfil part of the demand (7.41).

$\frac{d(Material\ Inventory)}{d(t)} = Material\ delivery\ rate - Material\ usage\ rate$	(7.39)
$Material\ delivery\ rate = Desired\ material\ delivery\ rate$	(7.40)
$Material\ usage\ rate$ $= Min(Production\ start\ rate \times Material\ usage\ per\ unit, Material\ Inventory)$	(7.41)

The production start rate (7.42) is determined by the desired production rate and the feasible production from material inventory. The unfinished products are aggregated in work in process (WIP) inventory (7.43) and are converted into finished goods (FG) (7.44) after elapsing the production lead time (L_2). The inventory of the finished products (7.45) is replenished by the production rate and depleted by the shipment to the suppliers.

$Production\ start\ rate$ $= Min(Desired\ production\ start\ rate, Feasible\ production\ from\ materials)$	(7.42)
$\frac{d(WIP\ Inventory)}{d(t)} = Production\ start\ rate - Production\ rate$	(7.43)
$Production\ rate = Delay(Production\ start\ rate, L_2, initial\ value)$	(7.44)
$\frac{d(FG\ Inventory)}{d(t)} = Production\ rate - Shipment\ rate$	(7.45)

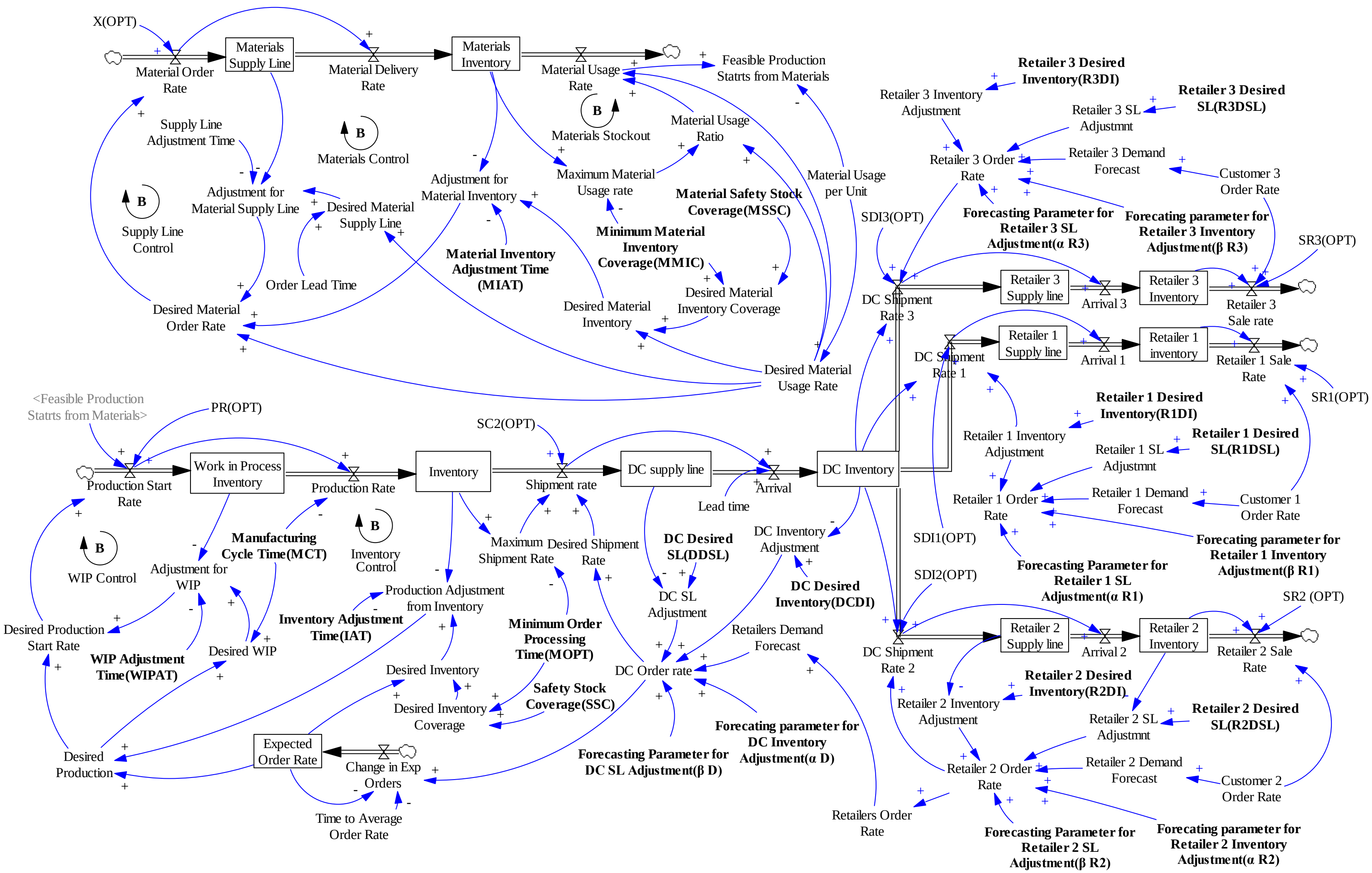


Figure 7.3. Stock and flow structure of extended inventory management model

The amount of products which are shipped to each distribution centre (MSR_d) (7.46) is a function of desired shipment rate determined by the desired shipment rate of each distributor which is equal to the distributor's order and the maximum shipment rate (7.47) that is calculated via dividing the on hand inventory of finished goods by a fixed minimum order processing time ($MMOPT$) for the manufacturer. The on hand inventory of finished goods (7.48) is calculated by subtracting the shipped products from the finished goods inventory, and its value must always be positive. It is assumed that distributor 1 precedes distributor 2 and distributor 2 precedes distributor 3 when the manufacturer allocates the inventory of finished goods to the distributors.

$MSR_d = Min(Maximum\ shipment\ rate_d, Desired\ shipment\ rate_d) \quad \forall d.$	(7.46)
$Maximum\ shipment\ rate_d = \frac{Manufacturer\ FG\ on\ hand\ Inventory}{MMOPT} \quad \forall d.$	(7.47)
$FG\ on\ hand\ Inventory = Max\left(0, Manufacturer\ FG\ Inventory - \sum_{d=1}^{d-1} MSR_d\right) \quad \forall d.$	(7.48)

The shipped products by the manufacturer to each distribution centre are accumulated in distributors supply lines (7.49) and arrive after a fixed lead time (L_d) (7.50) that represents the transportation time from manufacturer to each distribution centre. The inventory of each distributor (7.51) is replenished by arrival of the shipped products and depleted by shipment to the retailers.

$\frac{d(Distributor_d\ SL)}{d(t)} = MSR_d - Arrival_d \quad \forall d.$	(7.49)
$Arrival_d = Delay(MSR_d, L_d, initial\ value) \quad \forall d.$	(7.50)
$\frac{d(Distributor_d\ Inventory)}{d(t)} = Arrival_d - DSR_d \quad \forall d.$	(7.51)

The amount of products which are shipped from each distribution centre to each retailer (DSR_{dr}) (7.52) is a function of the distributor on-hand inventory and the retailer order. The on-hand inventory of finished goods (7.53) for each distributor is calculated by subtracting the shipped products from its inventory, and its value must always be positive. It is assumed that retailer 1 precedes retailer 2 and retailer 2 precedes retailer 3 when the manufacturer ships the inventory to the distributors.

$DSR_{dr} = Min(Retailer\ order_r, Distributor\ on\ hand\ inventory_d) \quad \forall r, d.$	(7.52)
$Distributor\ on\ hand\ Inventory_d = Max\left(0, Distributor\ Inventory_d - \sum_{r=1}^{r-1} DSR_{dr}\right) \forall d.$	(7.53)

The shipped products by the distributors to each retailer are aggregated in retailers supply lines (7.54) and arrive after a fixed lead time (L_{dr}) (7.55) which relates to the transportation time from each distributor to any retailer. The inventory of each retailer (7.56) is replenished by arrival of the shipped products and depleted by shipment to the end customers. Finally, each retailer either meets the demand of its end customer or is able to fulfil part of the demand by its current inventory level (7.57).

$\frac{d(Retailer_r\ SL)}{d(t)} = \sum_{d=1}^{D} DSR_{dr} - Arrival_r \quad \forall r.$	(7.54)
$Arrival_r = Delay(DSR_{dr}, L_{dr}, initial\ value) \quad \forall r.$	(7.55)
$\frac{d(Retailer_r\ Inventory)}{d(t)} = Arrival_r - RSR_r \quad \forall r.$	(7.56)
$RSR_r = Min(ECD_r, Retailer\ Inventory_r) \quad \forall r.$	(7.57)

The proposed inventory management model is extended through incorporating financial flow modelling in addition to the physical flow modelling. The financial stock and flow structure is depicted in Figure 7.4. The inventory of cash (7.58) is replenished by receiving cash from end customers and is depleted by cash payment to the suppliers and the third-party creditors. The initial value of the cash level is the sum of Short-term and long-term liabilities. Retailers collect part of customers' order values in cash, while the remaining part of the customer debt is

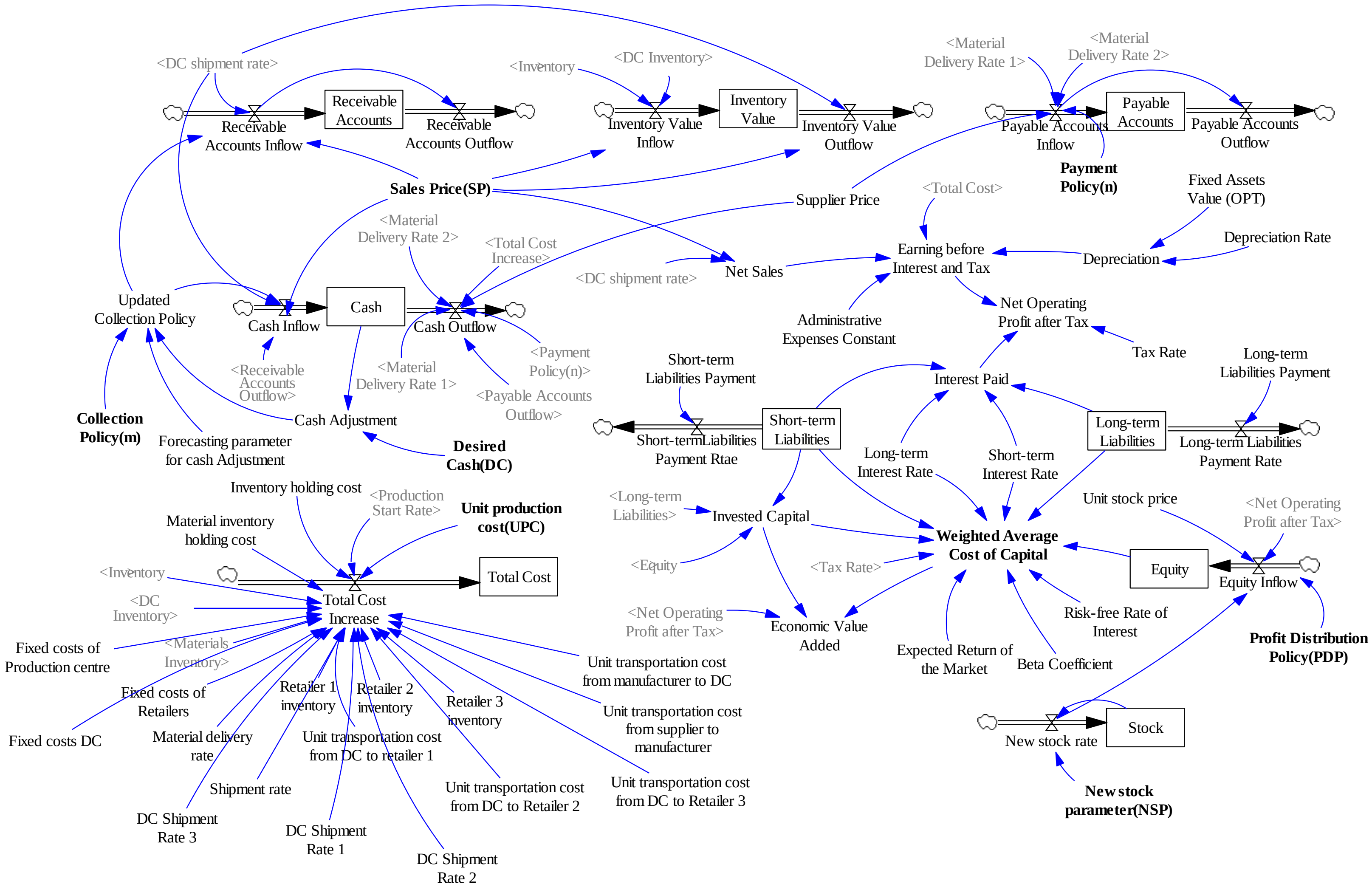


Figure 7.4. Stock and flow structure of financial flow

accumulated in receivable accounts (RA) and is paid after d_{c} weeks. The cash inflow (7.59) is calculated by aggregating the customers' cash payment and receivable accounts (7.60) from d_{c} weeks ago. The updated collection policy (um) (7.61) which is a parameter between 0 and 1 indicates the amount of customers' order value that must be collected in cash and is calculated by adding the cash adjustment to the original collection policy. The updated cash collection policy cannot exceed 1. Adjustment for cash (7.62) is calculated via multiplying cash gap percentage and the forecasting parameter for cash adjustment (γ) which represents the aggressiveness of the decision maker in bridging the gap between the desired and current cash levels. The outflow of cash (7.63) is prompted by payment to the suppliers, repayment for short-term and long-term liabilities, investment for fixed assets, and the total cost. When the manufacturer places an order to his suppliers, he pays part of the order value in cash and the outstanding debt is paid after d_1 weeks. The payment policy (n) that is a parameter between 0 and 1 shows the amount of manufacturer's order value that must be paid in cash. The remaining part of the manufacturer's debt is accumulated in payable accounts (PA) and is paid after d_1 weeks (7.64).

$\frac{d(Cash)}{d(t)} = Cash\ inflow - Cash\ outflow$	(7.58)
$Cash\ inflow = \sum_{r=1}^{R} um\ SR_r\ pri + RA\ outflow$	(7.59)
$RA\ outflow = Delay(RA\ inflow, d_{\mathrm{c}}\ , initial\ value)$	(7.60)
$um = Min(m + CS\ Adjustment, 1)$	(7.61)
$CS\ Adjustment = \gamma\left(\frac{DCS - CS}{CS}\right)$	(7.62)
$Cash\ outflow = \sum_{s=1}^{S} n\ X_s\ Spri_s - PA\ outflow - STL\ payment - LTL\ payment$ $-FA\ investment - Total\ cost\ rate$	(7.63)
$PA\ outflow = Delay(PA\ inflow, d_1, initial\ value)$	(7.64)

The total cost comprises the elements presented in Eq. (7.9), although they are not congruent in terms of formulation. The production cost (7.65) is calculated via multiplying unit production cost (upc) by production start rate which might not be equal to the production rate recommended by the optimisation model. The transportation cost (7.66) contains the shipment rates which are constrained by the maximum shipment capacity of each SC member. The inventory dynamics and cash dynamics are considered for measuring the inventory holding cost (7.67) and cash holding cost (7.68), respectively. While the optimisation model solely takes into account the inventory and cash levels at the start and the end of each time period. The fixed cost is determined by the optimisation model and inputted to the SBO model as an exogenous constant. The material order rate within the SBO model is recommended by the MILP model, therefore, the raw material costs determined by the simulation and optimisation models are identical.

$PC = Production\ start\ rate \times upc$	(7.65)
$TCR = \sum_{s=1}^{S} tc_s X_s + \sum_{d=1}^{D} tcc_d MSR_d + \sum_{r=1}^{R}\sum_{d=1}^{D} tcd_{dr} DSR_{dr}$	(7.66)
$HC = hr\ Average(FIR) + hp\ Average(FIP) + ho\ Average(FIO) + hs\ Average(FIS)$	(7.67)
$CHC = ucc\ Average(CS)$	(7.68)

The payment to the third-party creditors depletes the levels of short-term (7.69) and long-term liabilities (7.70) with a fixed rate. The initial levels of the short-term and long-term liabilities is determined by the optimisation model. In each time period the equity level rises by NOPAT rate (7.71). The WACC (7.72) is determined by including the elements of the cost of equity and cost of debt that were elaborated in Eq. (7.2).

$\frac{d(Short - term\ Liabilities)}{d(t)} = -Short\ term\ liabilities\ payment$	(7.69)
$\frac{d(Long - term\ Liabilities)}{d(t)} = -Long\ term\ liabilities\ payment$	(7.70)
$\frac{d(Equity)}{d(t)} = NOPAT$	(7.71)
$WACC_t = \left(\frac{E_t}{IC_t}\underbrace{\left(r_{f_t} + \left(r_{m_t} - r_{f_t}\right)\beta\right)}_{Cost\ of\ equity}\right) + \left(\frac{STL_t + LTL_t}{IC_t}\underbrace{\left(\frac{STL_t}{TL_t}STR_t + \frac{LTL_t}{TL_t}LTR_t\right)}_{Cost\ of\ debt}(1 - tr_t)\right)$	(7.72)

The other constituent of the SBO model is genetic algorithm that is responsible for determining the optimal values to the exogenous parameters of the simulation model known as controllable parameters. Desired inventory (DI), desired supply line (DSL), forecasting parameter for inventory adjustment (α), and forecasting parameter for supply line adjustment (β) constitute the controllable parameters of the distributors and retailers. Service level or safety stock coverage, minimum order processing time, manufacturing cycle time, WIP adjustment time, and inventory adjustment time comprise the controllable parameters of the manufacturer.

In this study, a GA is employed to specify optimal values to the simulation controllable parameters so as to maximize the economic value added (EVA). To determine the optimal values of the decision parameters, an optimisation problem which encompasses the objective function and the constraints on the controllable parameters is formulated as follows:

Objective function: $Max\ EVA = Max\ \mu_{EVA}$ Where $\mu_{EVA} = \frac{\sum_{t=0}^{T} EVA}{T}$

Decision parameters:

$\alpha_D, \alpha_{R1}, \alpha_{R2}, \alpha_{R3}, \beta_D, \beta_{R1}, \beta_{R2}, \beta_{R3}, m, n, DDI, DDSL, DIC, IAT, MIAT, MSSC, MMIC, MOPT, PDP, R1DI, R1DSL$

$R2DI, R2DSL, R3DI, R3DSL, SP, TAOR, UPC, WIPAT$

Subject to:

$0 \le \alpha_D, \alpha_{R1}, \alpha_{R2}, \alpha_{R3} \le 1;\ 0 \le \beta_D, \beta_{R1}, \beta_{R2}, \beta_{R3} \le 1;\ 0 \le m, n \le 1; 0 \le DDI \le 60;\ 0 \le R1DI, R2DI, R3DI$

$\le 30;\ 0 \le DDSL \le 60; 0 \le R1DSL, R2DSL, R3DSL \le 30; 1 \le IAT \le 5; 1 \le MIAT \le 5;$

$0 \le MSSC \le 2; 0 \le SSC \le 2;\ 0 \le MMIC \le 5; 1 \le MOPT \le 3; 0 \le PDP \le 1; 200 \le SP \le 250;$

$5 \le TAOR \le 10; 80 \le UPC \le 120;\ 1 \le WIPAT \le 5; 0 \le DC \le 2000;\ 1 \le MCT \le 3$

$\alpha_D, \alpha_{R1}, \alpha_{R2}, \alpha_{R3}$: denote the aggressiveness of the members in bridging the gap between the desired and current inventory.

$\beta_D, \beta_{R1}, \beta_{R2}, \beta_{R3}$: denote the level of consideration to the inventory on-orders at the time of order placement

$m = collection\ policy$: denotes the share of the sales is required to be collected in cash

$n = payment\ policy$: denotes the share of the raw material purchase is required to be paid in cash

$DDI, R1DI, R2DI, R3DI$: denote the desired inventory by distributor and retailers

$DDSL, R1DSL, R2DSL, R3DSL$: represent the desired inventory on order by distributor and retailers

$IAT = The\ inventory\ adjustment\ time$: represents the time period over which the manufacturer seeks to bridge the gap between the desired and current inventory of finished products

$MIAT = The\ material\ inventory\ adjustment\ time$: represents the time period over which the manufacturer seeks to bridge the gap between desired and current inventory of the raw material

$MSSC = The\ manufacturer\ safety\ stock\ coverage$: represents the time period over which the manufacturer would like to maintain a safety stock coverage to hedge against volatility in distributor's demand

$SSC = The\ safety\ stock\ coverage$: represents the time period over which the distributor would like to maintain a safety stock coverage in order to meet any variations in retailers' demands

$MMIC = The\ minimum\ material\ inventory\ coverage$: represent the minimum material inventory required by the manufacturer

$MOPT = The\ minimum\ order\ processng\ time$: denotes the minimum time required by the manufacturer to process and ship a distributor order

$PDP = The\ profit\ distribution\ policy$: denotes the dividends that is required to be paid to the shareholders

$SP = The\ sales\ price$: The price per tonne of product which is paid to the retailers by the customers

$TAOR = The\ time\ to\ average\ order\ rate$: denotes the time period over which the distributor demand forecast is adjusted to actual retailers' orders

$UPC = The\ unit\ production\ cost$: denotes the production cost per tonne of product at the manufacturer

$WIPAT = The\ WIP\ adjustment\ time$: represents the time required for the manufacturer to adjust its WIP inventory to its desired level

$DC = The\ desired\ cash$: denotes the level of cash desired to be held by the manufacturer

$MCT = The\ manufacturing\ cycle\ time$: represents the average delay time of the production process for the products from start until completion of the product

7.4.3. Hybrid analytical-SBO model

The hybrid MILP-SBO approach seeks to utilize the advantages of the both the MILP and SBO models. In the hybrid model, the decisions recommended by the MILP model and the decisions which are obtained by the balancing loops in the simulation model are integrated to determine the amount of the raw material to be purchased, the production start rate, and the shipment rates across the network. The material delivery rate (7.73) in this model is a function of the desired delivery rate from the SBO model and the material order rate from the MILP model. The production start rate (7.74) is determined by the desired production rate and the feasible production from the material determined by the inventory management model and the production rate recommended by the MILP model. The shipment rate of the manufacturer (7.75) is determined by the maximum shipment rate to each distributor, the desired shipment rate of each distributor, and the shipment rate suggested by the MILP model. The amount of products which are shipped from each distribution centre to each retailer (DSR_{dr}) (7.76) is a function of desired shipment rate of the distributor determined by the MILP model and the maximum shipment rate and the inventory of the distributor which are obtained from the SBO model. The shipment rate of each retailer (7.77) is calculated by its customer inventory, its inventory level, and the shipment rate obtained from the MILP model.

$Material\ delivery\ rate = Min\left(Desired\ material\ delivery\ rate, \sum_{s=1}^{S} X_s\right)$	(7.73)
$Production\ start\ rate$ $= Min(Desired\ production\ start\ rate, Feasible\ production\ from\ \ material, PR)$	(7.74)
$MSR_d = Min(Maximum\ shipment\ rate_d, Desired\ shipemnt\ rate_d, SC_d) \quad \forall d.$	(7.75)
$DSR_{dr} = Min(Retailer\ order_r, Distributor\ inventory_d, SDI_{dr}) \quad \forall r, d.$	(7.76)
$RSR_r = Min(ECD_r, Retailer\ Inventory_r, SR_r) \quad \forall r.$	(7.77)

7.5. Results and discussion

The advantages of the hybrid analytical-SBO modelling is investigated by comparing with individual optimisation and SBO methods through conducting the empirical tests. The data of the case study including the inventory holding, production, and transportation costs introduced in Longinidis and Georgiadis (2011) and Longinidis and Georgiadis (2013) is used to provide the data on the parameters which represent the economic uncertainty. The range of parameters values expressed in Longinidis and Georgiadis (2011) is extended to ensure that the optimal parameter values lie in the searching boundary.

The numerical experiment is scaled as follows: the number of customer zones, retailers, and distributors is three; the number of production centre is one; the number of suppliers is two, and the number of time periods is two one-year period. Tables 7.1 and 7.2 present the production, inventory holding, and cash holding costs in each time period. The transportation costs from suppliers to production centre, from production centre to distributors, and from distribution centres to the retailers are given in Tables 7.3-7.5, respectively. Table 7.6 shows the values to the four of the uncertain parameters that represent the economic uncertainty in each scenario. The fifth uncertain parameter which is demand of the customers in each scenario is represented in Table 7.7. The sales price of the product and the production capacity are presented in Table 7.8. Three models are developed based on analytical, SBO, and hybrid analytical-SBO methods. Results of each model are analysed and presented as follows.

Table 7.1. Production and cash holding cost

Production cost		Cash holding cost	
$t = 1$	$t = 2$	$t = 1$	$t = 2$
58.6	60.9	1.06	1.10

t = Time period

Table 7.2. Inventory holding cost

Production centre		Distributors		Retailers	
$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
58.6	60.9	8.2	8.9	8.2	8.9

Table 7.3. Transportation cost from suppliers to production centre

To / From	Production centre	
	$t = 1$	$t = 2$
Supplier 1	15.2	19.4
Supplier 2	18.6	20.7

Table 7.4. Transportation cost from production centre to distribution centres

To / From	Distribution centre 1		Distribution centre 2		Distribution centre 3	
	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
Production centre	20.2	23.4	25.2	61.4	65.8	72.3

Table 7.5. Transportation cost from production centre to distribution centre

To / From	Retailer 1		Retailer 2		Retailer 3	
	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
Distribution centre 1	25.7	34.3	52.6	54.5	95.4	79.8
Distribution centre 2	32.5	50.4	12.5	15.2	15.3	17.6
Distribution centre 3	89.1	68.9	69.4	63.1	29.3	33.6

Table 7.6. Uncertain parameters in each scenario

Scenario	Parameter							
	$STR_{t=0}^{[s]}$	$STR_{t=53}^{[s]}$	$LTR_{t=0}^{[s]}$	$LTR_{t=53}^{[s]}$	$r_{f_{t=0}}^{[s]}$	$r_{f_{t=53}}^{[s]}$	$r_{m_{t=0}}^{[s]}$	$r_{m_{t=53}}^{[s]}$
S_1	7.00	5.60	4.00	3.00	2.50	2.00	5.00	6.00
S_2	7.00	7.00	4.00	4.00	2.50	2.50	5.00	5.00
S_3	7.00	8.40	4.00	5.00	2.50	3.00	5.00	4.00

Table 7.7. Demand of the customer in each scenario

Scenario	Customer 1		Customer 2		Customer 3	
	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
S_1	750	1125	730	1095	570	855
S_2	750	750	730	730	570	570
S_3	750	500	730	487	570	380

Table 7.8. Sales price and production capacity

pri		prcap	
$t = 1$	$t = 2$	$t = 1$	$t = 2$
235.6	270.94	2500	2500

7.5.1. Analytical model

The analytical model solely considers the economic uncertainty through scenario analysis and ignores the lead times rooted in material delivery and cash payment. The values of the parameters in the MILP model are randomly generated in the feasible interval of the parameters' values using MATLAB software. For instance, to determine the unit production cost of the product in each time period, two random data in the interval of [58-62] were generated. To simplify the model formulation and also diminish the number of solving periods, the material delivery and cash payment lead times are assumed to be zero; otherwise, the solving period must be subdivided into shorter time periods, in this model weeks, in order to accommodate the lead times. Neglecting the material delivery and cash payment lead times and assuming zero safety stock, the model recommends keeping no inventory at all the SC members that results in a higher NOPAT comparing both SBO and hybrid MILP-SBO in which inventory, including finished goods and raw materials are held. To establish a meaningful contrast between the analytical model and the other two models, it is assumed that the SC members hold safety stock to hedge against the demand uncertainty. The safety stocks values are set to be equal to the desired inventory values obtained from the SBO model. The analytical model is then used to determine the optimal network design and the production rates at the plant. Table 7.9 shows the storage locations and the supplier determined by the analytical model for the three scenarios. Considering the possible economic conditions at the start of the second year, the analytical model suggests purchasing the raw material from the supplier no. 1 and to open the Distribution centre no. 2.

Table 7.10 illustrates the analytical model results for some physical and financial variables in each scenario. Demand variability which is caused by the economic uncertainty drives the production rate. Demand growth in scenario 1, is responded by increasing the production rate, while the demand shrinkage in scenario 3 is dealt through decreasing the production rate. In scenario 2, the model recommends diminishing the production rate at the year two, although the customer’s demand has remained unchanged. The reason is that the demand is partially met by the safety stock.

The equality of the right and left sides of the balance sheet in each time period shows the accuracy of the financial modelling. The profitability, NOPAT, and the economic performance, EVA, of the chain decrease when the economy diminishes in size as increasing cost of goods sold is not offset by neither demand growth nor reduction in financing expenses, i.e., cost of equity and cost of debt.

The structure of the current assets in each year for the three scenarios is illustrated in Figure 7.5. In all the scenarios at the end of the second year the highest and lowest shares of the current assets belong to cash and inventory value, respectively. The inventory level at the end of the second year for all scenarios is similar and is equal to the safety stock, despite the demand differences. The structure of the capital in each year for all scenarios is depicted in Figure 7.6. The analytical model in all three scenarios recommends using long-term liabilities as the source of financing rather than short-term liabilities and issuing new stocks due to its lower interest rates. The growth of the equity at the second year for all scenarios is triggered by the addition to retained earning which is set to be 45 percent of the NOPAT.

Table 7.9. Optimal storage locations and supplier selection by the analytical model under scenario 1, 2, and 3

Decision variables	Suppliers				Distribution centres					
	S1		S2		DC 1		DC 2		DC 3	
Open/Close	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
Open=1 Close=0	1	1	0	0	0	0	1	1	0	0

Table 7.10. the optimal decision variables in each scenario

Decision variables	Scenario 1		Scenario 2		Scenario 3	
	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
PR	2227.2	2500	2227.2	1890	2227.2	1207
SC	2027.2	2660	2027.2	2050	2027.2	1367
SDI	2007.2	2660	2007.2	2050	2027.2	1367
SR	2007.2	2660	2007.2	2050	2027.2	1367
$FA + CA$	720,200	768,971	720,200	743,099	720,200	720,261
$LTL + STL + E$	720,200	768,971	720,200	743,099	720,200	720,261
$NOPAT$	22222	87475	22222	58999	22222	33623
EVA	43199		8056		-23380	

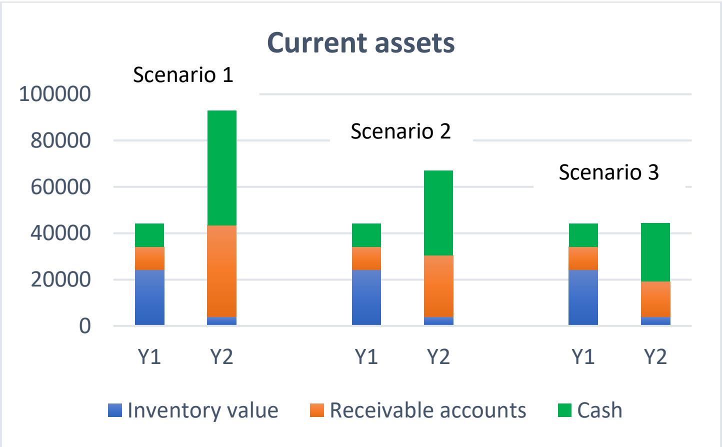


Figure 7.5. Current assets structure

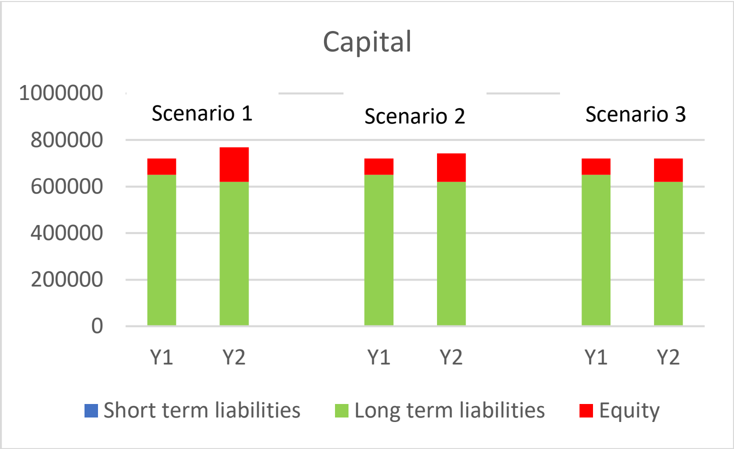


Figure 7.6. Capital structure

7.5.2. System dynamics and Simulation-based optimisation models

The system dynamics simulation model formulates the lead times rooted in distribution and payment, the collection and payment policies, feedback loops, and nonlinearities exist in the supply chain network in addition to the economic uncertainty which is taken into account through scenario analysis. The values of the model parameters such as transportation unit cost are set to be equal to the ones used in the analytical model. To test the response of the system to the changes in economic uncertainty parameters, the system is required to initialize in a balanced equilibrium. Therefore, the initial values to the inventory, and supply line for all the members and cash are set to be equal to their desired level. The expected order rate is also set to be equal to the customers' orders.

The simulation-based optimisation model is constructed through incorporating genetic algorithm into the SD simulation model. The SBO model enables the modeller to identify the optimal values to the controllable parameters such as the desired inventory levels at entities to maximize the objective function, EVA. In order to make a meaningful comparison between the SD, SBO, and MILP models, the structure of the supply chain network is set to be equal to the one recommended by the MILP model.

Figures 7.7(a) -7.7(d) represent the inventory and cash dynamics for the SC members in scenario 1 obtained from running the SD simulation model for two years, 104 weeks. As seen in Figures 7.7(a) and 7.7(b) the inventory levels for the retailers and distributor plummet at the start of the second year, week 53, as a result of the 50 percent increase in the customers' demands prompted by the boom in economy. The system is then endeavours to reach to the new equilibrium inventory levels. The inventory of manufacturer, Figure 7.7(c), rises at the first 20 weeks due to the delay time of the production process known as manufacturing cycle time. It falls at the start of the second year as a result of demand increase and stabilizes at the new equilibrium level at 230 tonnes. Figure 7.7(d) shows the inflow and outflow of cash. The cash inflow is higher than the cash outflow excepting the first 9 weeks in which the material delivery rate is high and the start of the second year for 6 weeks as a result of growing material order rate to meet the surge in customer's demands.

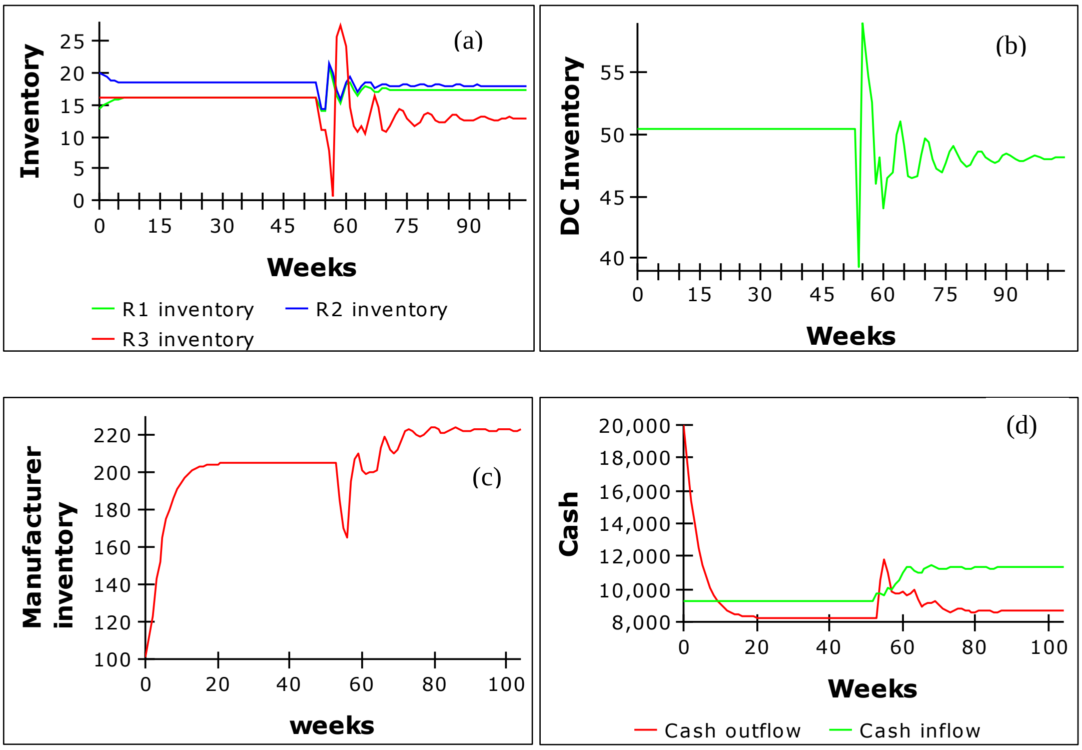


Figure 7.7. Inventory and cash dynamics for the SC members in scenario 1 obtained from the SD model

Figures 7.8(a)- 7.8(d) represent the inventory and cash dynamics for the members in scenario 1 obtained from the SBO model. The GA reduces the oscillations in the inventory levels, particularly for the distributor. The inventory peak for the manufacturer diminishes to 124 tonnes of product from 230 tonnes before applying the SBO. As the excess cash is penalized in the SBO model, the GA aims to minimize the gap between the cash inflow and outflow so as to minimize the total cost which consequently maximizes the EVA.

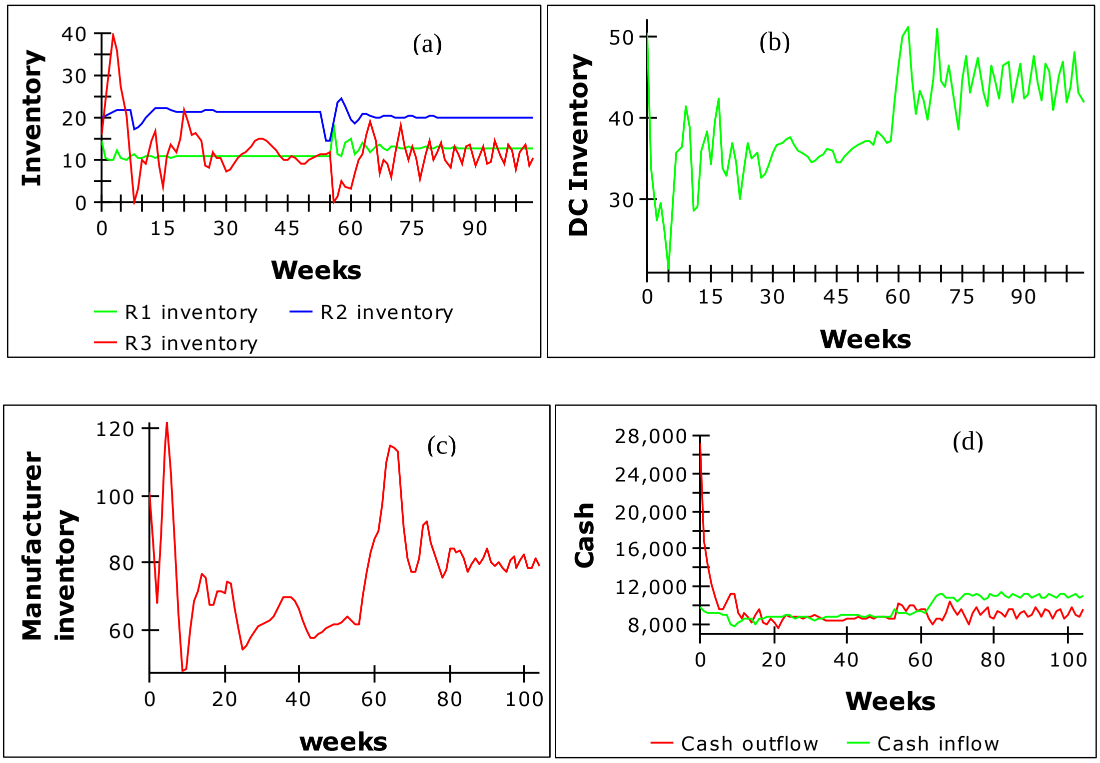
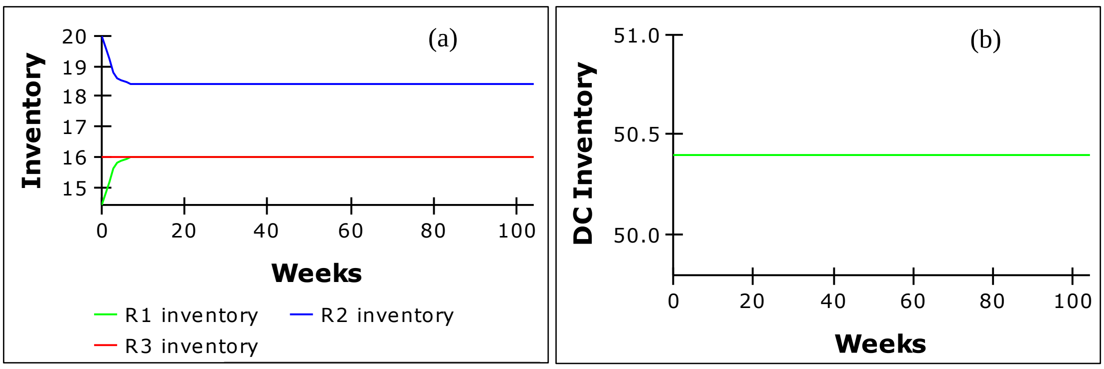


Figure 7.8. Inventory and cash dynamics for the SC members in scenario 1 obtained from the SBO model

Figures 7.9(a)-7.9(d) show the inventory and cash dynamics for the SC members in scenario 2 obtained from the SD model. There are no oscillations in the inventory levels as the customers' demands remains stable during the simulation time, therefore, the inventory levels indicate a goal seeking pattern except the inventory level of the distributor which remains unchanged during the simulation time. The cash dynamics is illustrated in Figure 7.9(d). The cash inflow exceeds the cash outflow excepting the first 9 weeks in which the material shipment rate from the supplier is high which causes higher payment.



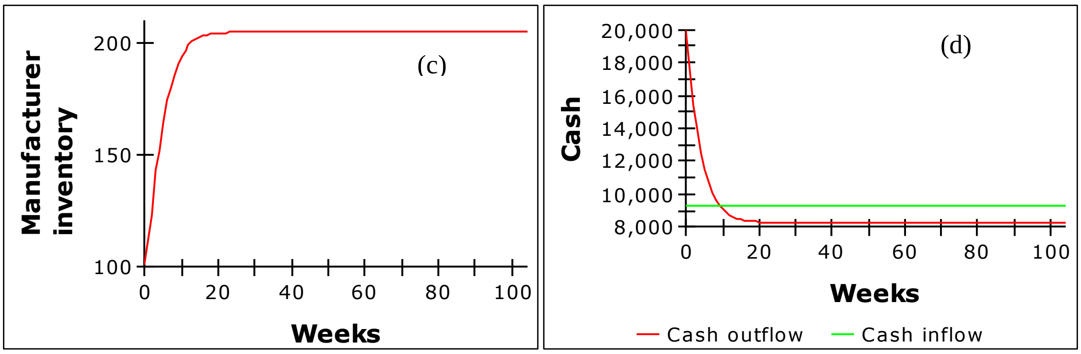


Figure 7.9. Inventory and cash dynamics for the SC members in scenario 2 obtained from the SD model

Figure 7.10(a)-7.10(d) represent the inventory and cash dynamics in scenario 2 after employing the SBO technique. The inventory levels of the retailer 1, retailer 2, and retailer 3 arrive at their customer order at weeks 15, 30, and 45, respectively as the retailer 1 precedes the retailer 2 and the retailer 2 precedes the retailer 3 in shipment of the product from the distribution centre. The inventory levels for the distribution centre reaches to the retailers' order, 39.3 tonnes of product, at week 40. The SBO model significantly reduces the inventory level held by the manufacturer. The inventory peak for the manufacturer after applying SBO is 140 tonnes of products, which lasted for a week, while before applying the SBO, the manufacturer was holding the 200 tonnes of product from week 10 onwards. As shown in Figure 7.10(d) the SBO model seeks to minimize the difference between the cash inflow and outflow in order to minimize the cash cost.

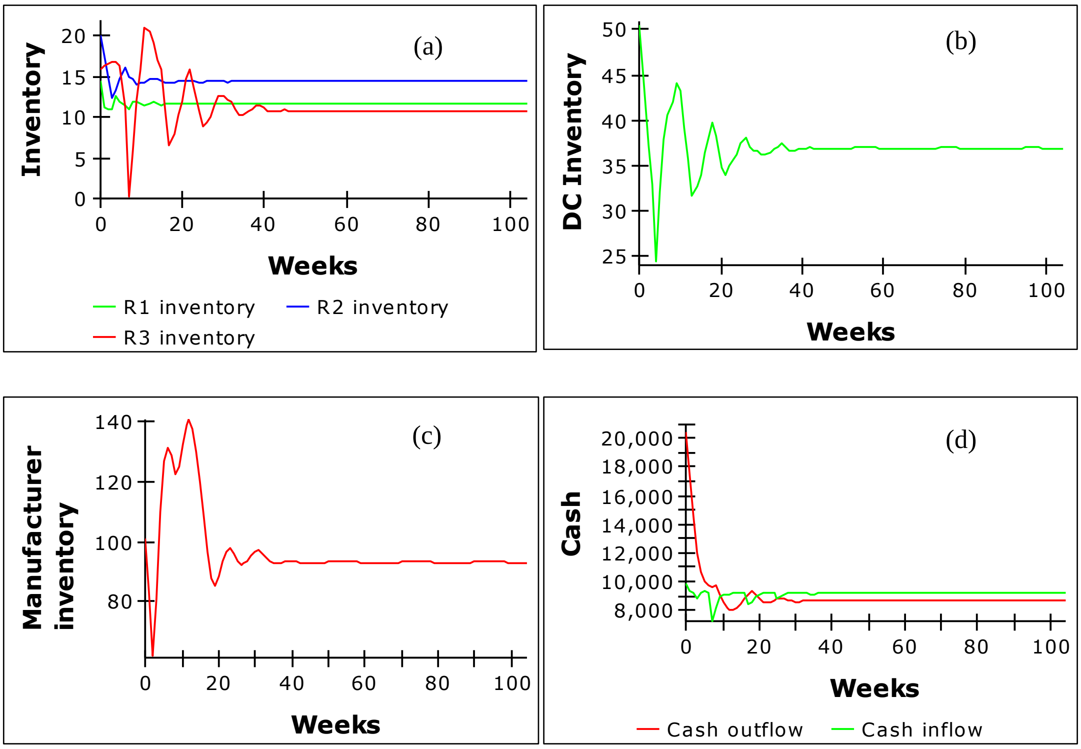


Figure 7.10. Inventory and cash dynamics for the SC members in scenario 2 obtained from the SBO model

Figures 7.11(a)-7.11(d) show the inventory and cash dynamics in scenario 3 using the SD model. The inventory level of the retailers and the distributor rise as a result of 50 percent decrease in the customers' demands. The inventory of manufacturer, Figure 7.11(c), rises at the first 20 weeks due to the delay time of the production process known as manufacturing cycle time. It rises at the start of the second year as a result of plummet in demand and stabilizes at the new equilibrium level at 175 tonnes. The inflow of cash is higher than its outflow at the first 9 weeks due to the significant delivery of the raw material from the supplier. The cash inflow supersedes the cash outflow between week 10 and week 52. From the start of the recession period, week 53, until the end of the simulation, the outflow of cash exceeds its inflow as a results of demand fall.

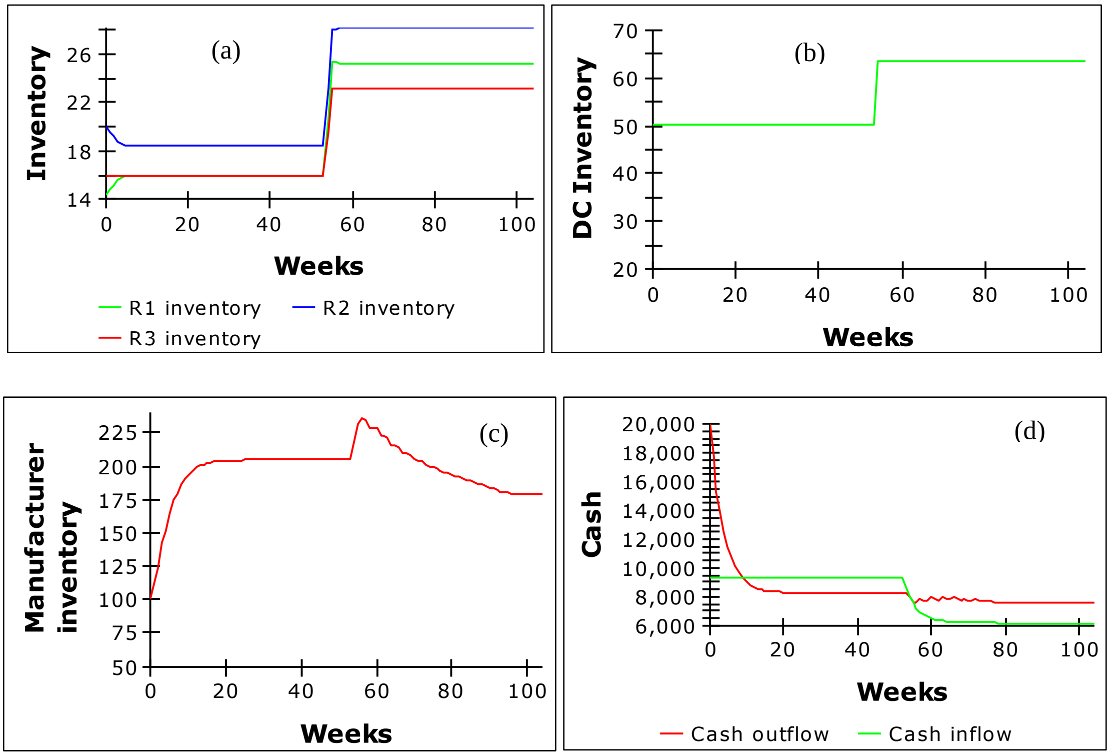


Figure 7.11. Inventory and cash dynamics for the SC members in scenario 3 obtained from the SD model

Figures 7.12(a)-7.12(d) illustrate the inventory and cash dynamics in scenario 3 after using the SBO in the case of economic recession at the start of the second year. Applying the SBO diminishes the inventory levels for the SC members. The impact of the SBO methodology on inventory reduction grows as we move toward the upstream members. The inventory of the manufacturer before using the SBO fluctuates in the range of [100, 227], while after using the SBO, the inventory level of the manufacturer varies in the range of [50, 120]. The SBO strives to mitigate the gap between the cash inflow and outflow to minimize the cash cost, although after plunge in demand the cash outflow outstrips the cash inflow which leads to a zero cost of cash.

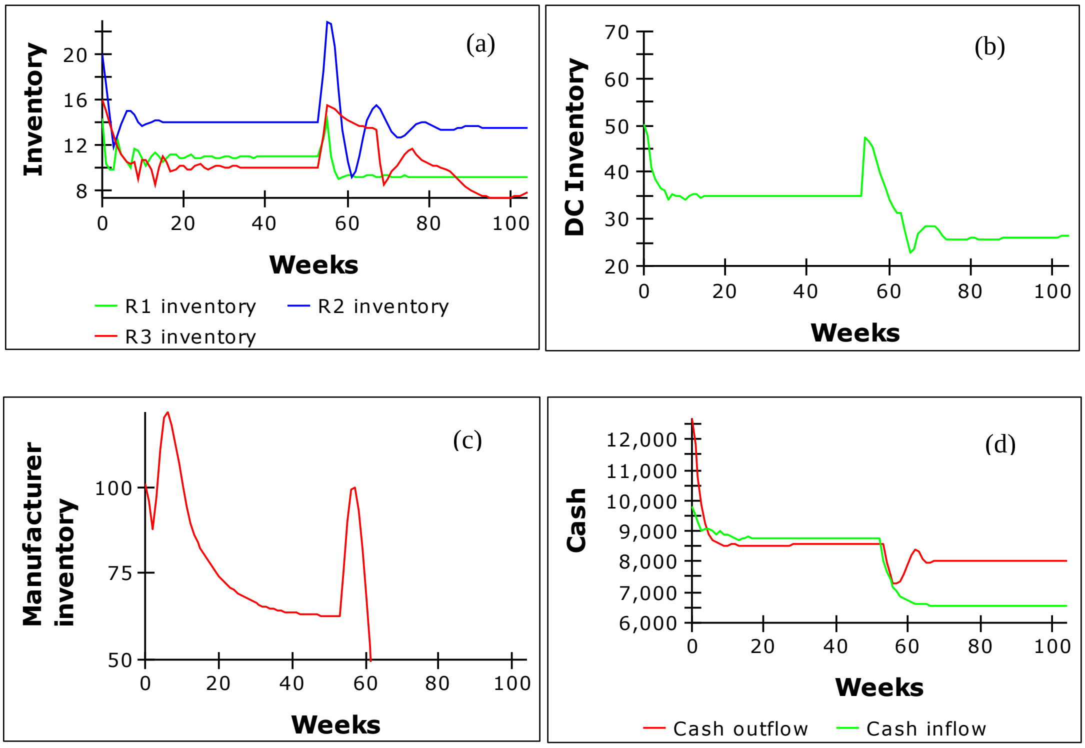


Figure 7.12. Inventory and cash dynamics for the SC members in scenario 3 obtained from the SBO model

Table 7.11 shows the values of the EVA obtained from the SD and SBO models in each scenario. The values of the EVA in all scenarios show the superiority of the SBO modelling, in which the GA is incorporated into the SD model, over the SD simulation modelling which lacks the GA. Moreover, as expected, it is observed that in all scenarios the EVA obtained from the SBO model is significantly lower than the one determined by the analytical model due to the assumption that the analytical model does not consider the distribution and payment lead times.

Table 7.11. EVA obtained from the SD and SBO models in each scenario

Scenarios	EVA (GBP)		Percentage difference between the SBO model and the SD model	Percentage difference between the SBO model and the analytical model
	SD	SBO		
Scenario 1	26452	32840	+24.15% ⬆	-23.98% ⬇
Scenario 2	4636	6008	+29.59% ⬆	-25.45% ⬇
Scenario 3	-35924	-28414	+20.91% ⬆	-21.53% ⬇

7.5.3. Hybrid Analytical-SBO

The hybrid analytical-SBO approach integrates the advantages of the both SBO and MILP models. The hybrid approach not only formulates the distribution and payment lead times, the collection and payment policies, feedback loops, and nonlinearities, but also uses the optimal decision variables determined by the MILP model to decide on the quantity of the order to be placed to the suppliers, production rate at the manufacturing site, and the shipment rates in the supply chain network. Figures 7.13(a)-7.13(d) represent the inventory and cash dynamics for the SC members in scenario 1 after using the hybrid approach. The hybrid approach is more efficient than the SBO approach in managing the inventory of the SC members. Both the inventory peaks and the oscillation in inventory ranges fall after using the hybrid approach. The inflow and outflow of cash in the hybrid model are lower than the ones from the SBO model as the optimal shipment rates between the SC members are used in the shipment rates equation. Lower inventory and cash levels in the hybrid approach yield lower inventory and cash costs comparing the SBO model.

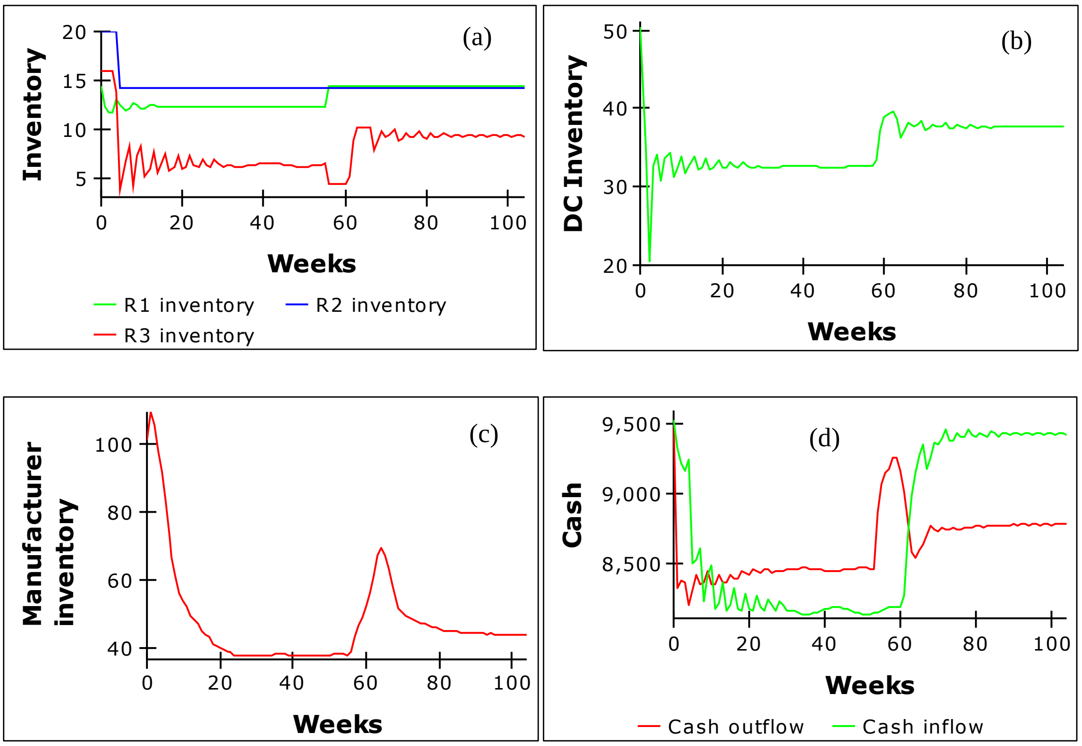


Figure 7.13. Inventory and cash dynamics for the SC members in scenario 1 obtained from the hybrid model

Figures 7.14(a)-7.14(d) illustrate the inventory and cash dynamics for the SC members in scenario 2 after using the hybrid approach. Although the performance of the hybrid approach in decreasing the inventory levels for the retailers and distributor is not noticeably better than the SBO performance, using the hybrid approach leads to a significant reduction in the inventory levels for the manufacturer. The inventory of the manufacturer in the hybrid model from week 30 until the end of the simulation fluctuates in the range of [30, 60] tonnes of product, while the inventory value at the same period in the SBO model remains stable at the level of 92 tonnes of product. Although the gap between the cash inflow and cash outflow in the SBO model is narrower than the one in the hybrid model, the number of weeks in which the cash outflow outstrips the cash inflow in the hybrid model are 40 weeks, week 20 to 60, more than the SBO model that results in the lower cash costs in the hybrid model compared to the SBO model.

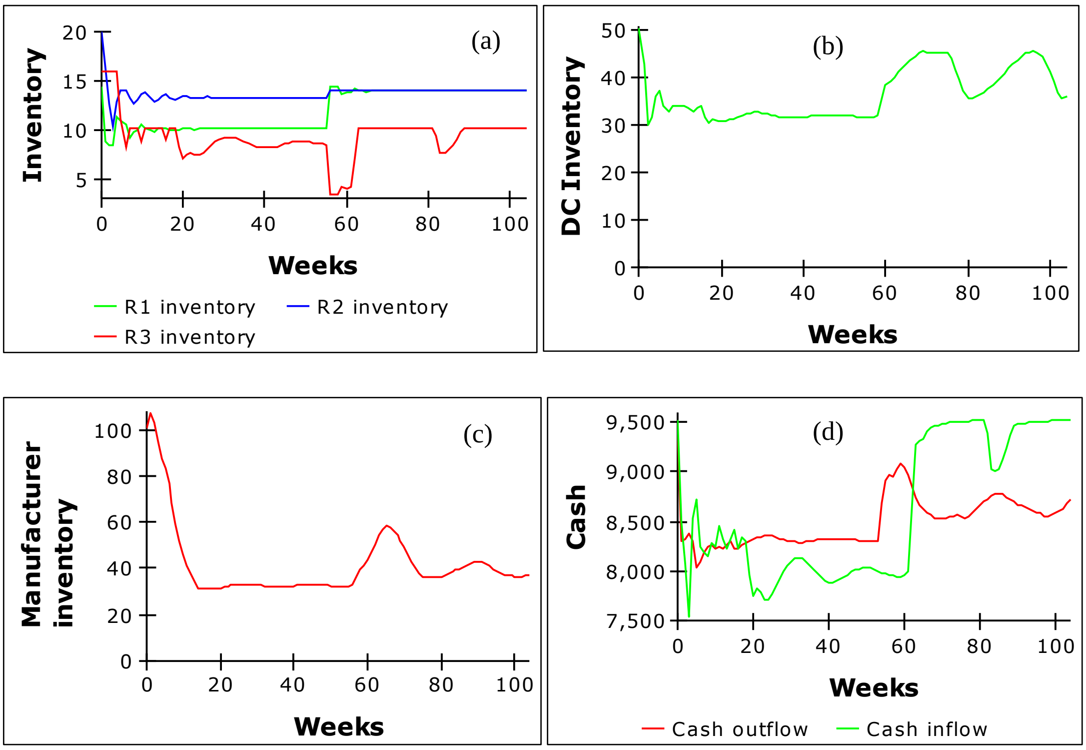


Figure 7.14. Inventory and cash dynamics for the SC members in scenario 2 obtained from the hybrid model

Figures 7.15(a)-7.15(d) illustrate the inventory and cash dynamics for the SC members in scenario 3 after using the hybrid approach. Comparing the SBO model, although applying the hybrid approach does not considerably diminish the inventory levels for the SC members, it reduces the oscillations in the inventory levels of the members. As in scenario 2, the gap between the cash inflow and cash outflow in the SBO model is narrower than the one in the hybrid model, while the number of weeks in which the cash outflow outstrips the cash inflow in the hybrid model are 30 weeks, weeks 20 to 50, more than the SBO model that results in the lower cash costs in the hybrid model compared to the SBO model.

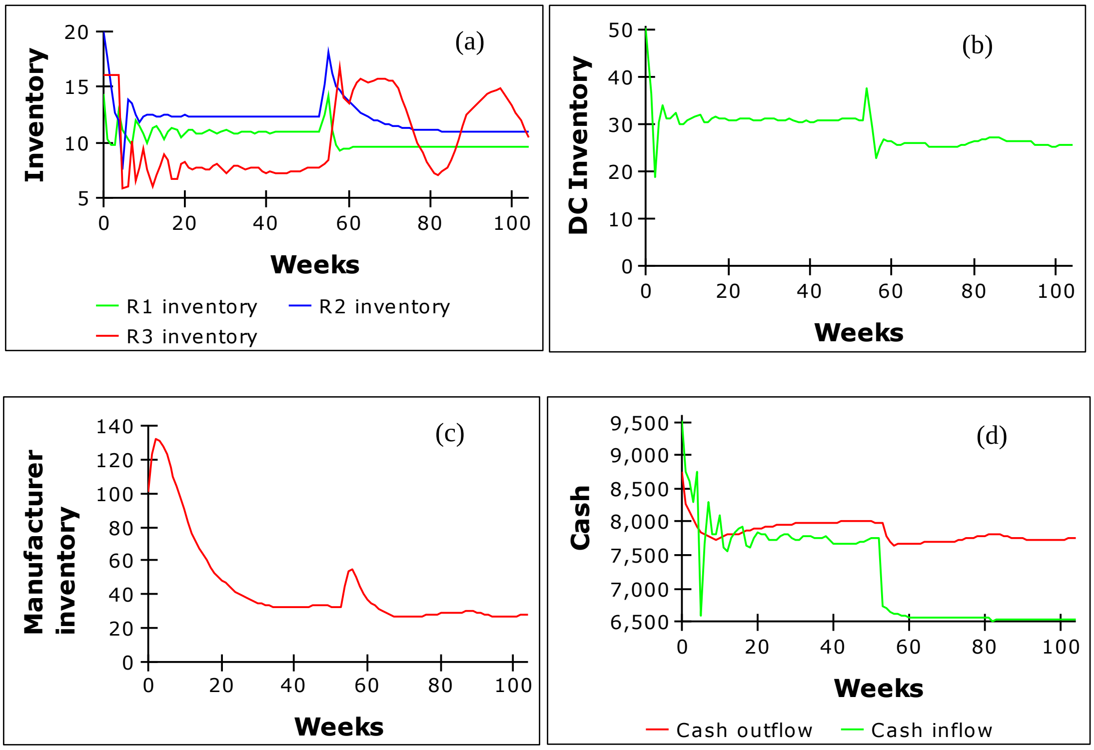


Figure 7.15. Inventory and cash dynamics for the SC members in scenario 3 obtained from the hybrid model

Table 7.12 shows the values of the EVA obtained from the hybrid model and the number of iterations performed to meet the stopping criterion, which set to be 5% difference between the EVA determined by the analytical and hybrid models, in each scenario. The results indicate the maximum stopping iterations of two in all scenarios. Although, it is not feasible to prove the fast convergence for all the test results as the GA is a stochastic search algorithm. The hybrid approach outperforms the SBO approach as it noticeably decreases the gap between the EVA obtained from the MILP and SBO models.

Table 7.12. EVA obtained from the hybrid model in each scenario

Scenarios	EVA (GBP)	Number of iterations	Percentage difference between the hybrid approach and the analytical model	Percentage difference between the hybrid approach and the SBO model
Scenario 1	38045	2	-11.93% ⬇	+15.85% ⬆
Scenario 2	6849	2	-14.98% ⬇	+14.42% ⬆
Scenario 3	-26657	2	-14.02% ⬇	+6.18% ⬆

The performance of the MILP-SBO model in maximizing the EVA is compared with the performances of the SBO model under three economic scenarios. The first scenario assumes boom at the second year of the simulation that results in increase in customer demand and expected return of the market and decrease in risk-free rate of interest, short-term interest rate and long- term interest rate. The MILP-SBO significantly reduced the inventory levels for the supply chain members and the cash held in the supply chain. Moreover, the EVA of the supply chain increased by almost 16% from £32840 to £38045. The second scenario assumes stagnation at the second year of the simulation that results in stability in customer demand, expected return of the market, risk-free rate of interest, short-term and long-term interest rates. The MILP-SBO significantly reduced the inventory levels at the manufacturer and the cash held in the supply chain. The EVA of the supply chain increased by 14% from £6008 to £6849. The third scenario assumes recession at the second year of the simulation that results in decrease in customer demand and expected return of the market and increase in risk-free rate of interest, short-term and long-term interest rate. The differences between inventory levels of the supply chain members in SBO and MILP-SBO models are negligible as 50% reduction in customers' demand at the second year makes holding high inventory levels unnecessary. Although, the MILP-SBO model reduces the oscillations in the inventory levels of the members. The EVA of the supply chain increased by 6.18% from £-28414 to £-26657.

7.6. Conclusions

strategic supply chain planning models, in which the strategic decisions such as network design and the tactical decisions such as inventory planning are integrated, show more realistic viewpoint of supply chain decisions; as different decisions in the supply chain are related to each other and deciding on them in an integrated manner results in better performance (Laínez et al., 2008; Gupta and Dutta, 2011). Moreover, incorporating flow of cash into the strategic supply chain planning models is of paramount importance as implementing the supply chain decisions relies on the availability of the financial resources.

As discussed in section 2.5.4 in chapter 2 and is presented in Table 7.13, Previous research on integrated strategic supply chain planning and supply chain finance mostly applied MILP modelling, while the hybrid analytical-simulation approach which are more efficient than the analytical approaches in capturing the nonlinearities, delays, and feedback loops exist in such problems have remained underrepresented. Previous studies take into account a limited number of uncertainties, mostly uncertainty in demand, while there is lack of studies that consider a wide range of uncertainties in the economic parameters. To fill the gap in the literature, in this chapter, a hybrid analytical-simulation model is developed to address an integrated strategic supply chain planning and supply chain finance problem under economic uncertainty. The strategic supply chain planning problem includes supplier selection, network design, inventory planning, and the supply chain finance problem includes asset-liability optimisation. The proposed hybrid model integrates a mixed integer linear programming model and an SBO model to maximize the EVA generated in a supply chain network in presence of uncertainty in economic parameters. This contribution extends the previous research on strategic supply chain planning and supply chain finance (Yousefi and Pishvaee, 2018; Melo et al., 2006; Ramezani et al., 2014; Cardoso, et al., 2016; Zhang et al., 2017; Melo et al., 2006; Naraharisetti et al., 2008; Ramezani et al., 2014; Zhang et al., 2017) by applying the hybrid modelling and considering the economic uncertainty. The developed hybrid model identifies the optimal values to the decision parameters such as inventory control parameters and optimal values to the decision variables such as the flow of products between supply chain entities.

Table 7.13. Strategic supply chain planning and supply chain finance literature

Current literature	**Parameters considered**	**Hybrid modelling**	**Considering the economic uncertainty**	**Approaches**
(Yousefi and Pishvaee, 2018; Melo et al., 2006; Ramezani et al., 2014; Cardoso, et al., 2016; Zhang et al., 2017; Melo et al., 2006; Naraharisetti et al., 2008; Ramezani et al., 2014; Zhang et al., 2017)	Inventory control parameters Fixed and current assets Short-term and long-term liabilities Equity	×	×	Analytical simulation Simulation-based optimisation

This study	Inventory control parameters Price Unit cost Collection policy Payment policy Desired Cash Fixed and current assets Short-term and long-term liabilities Equity	✓	✓	Hybrid analytical-Simulation (simulation-based optimisation and mixed-integer linear programming)

The hybrid approach is initialized by solving the MILP model to determine the optimal values to the raw materials required to be purchased from the suppliers, the production rate at the manufacturing site, and the flow of finished products between the SC members considering the existing constraints in the financial and physical flows. The solution suggested by the MILP model is then used to construct the SBO model in which the distribution and payment lead times, the feedback loops, and nonlinearities rooted in a SC networks are formulated through applying an SD simulation approach. Thereafter, the embedded GA in the SBO model is run to identify the optimal values to the price per tonne of the product, the desired cash, the profit distribution policy, and the stocking capacities at the SC members. In the next stage, the constraints of the optimisation problem are revised in accordance with the optimal parameter values recommended by the SBO model and the optimisation model is run to generate a new set of parameter values to be inputted into the SBO model. The iterative process between optimisation and SBO models continues until the stopping criterion which is 5% difference between the EVAs obtained from the models is met.

The hybrid approach enables the modeller to not only take into account the lead times, feedback loops, and nonlinearities which exist in the supply chain networks, but also dramatically bridge the gap between the desired EVA, the EVA obtained from the analytical model, and the real EVA, the EVA gained from the simulation optimisation model. To demonstrate the efficiency of the proposed model, the performance of the proposed model in solving a test problem from the recent literature is compared with the performance of the conventional simulation-based optimisation approach. The results of the comparison show that the developed hybrid analytical-simulation model outperforms the simulation-based optimisation model in all the predicted scenarios.

Chapter 8. Conclusions and future work

8.1. Introduction

This chapter presents the overall conclusions and key contributions of the thesis as well as managerial implications that this work has provided. Finally, some directions for future work are provided based on the research conducted in this thesis.

8.2. Overall conclusions

Supply chains are composed of suppliers, manufacturers, distributors, and retailers that are integrated with regard to the physical, financial, and information flows across the supply chain networks. Considering the financial flow within supply chain models is of paramount importance as implementing supply chain decisions relies on the availability of the financial resources. For instance, opening a new facility in the supply chain network is impossible unless the funding mechanism is explicit. Moreover, the financial and physical flows have a mutual effect on one another. For example, inventory optimisation leads to savings in the financial resources which can in turn provide the required resources for implementing other operational decisions such as production capacity expansion.

Research regarding the management of supply chain has been performed for a long time. However, most of the studies focus on addressing the problems such as inventory planning which are related to the planning of physical flow and overlook the planning of the financial flow. It is only in the last decade that the research community has started to incorporate financial flow planning into the supply chain models. Therefore, more research in this area is required to be performed. To contribute to the literature of the financial flow planning in supply chains, this research incorporates financial flow planning into the supply chain models to ensure that the financial resources are available to the supply chain members at the right time while the profitability of the supply chain is maximized. It also provides a more realistic view to supply chain total cost by considering the cash holding cost as a constituent of the total cost.

In general, supply chains are complex networks composed of various entities where uncertain external factors, conflicting objectives related to responsiveness and efficiency, and delays in the flows including product, information, and cash have to be taken into account. Therefore, effective tools should be applied to analyse and optimise the performance of the supply chain networks. In order to study supply chain networks, analytical approaches such as optimisation models have been frequently utilized to provide optimal values to the decision variables for supply chain members (Wu, 2006; Torabi and Hassini, 2008; Govindan et al., 2014; Hamta et al., 2015). Although pure mathematical models are useful in many cases, they may not be able to depict complex relationships, including feedback loops and delay functions, between supply chain entities existing in real-world problems (Mele et al., 2006).

On the other hand, simulation has been proved to be an efficient tool to describe and analyse inherent dynamic behaviour of complex systems such as supply chains (Dominguez, Cannella and Framinan, 2015; Macdonald et al., 2018). Although, it is not able to determine the optimal values to the decision parameters and decision variables in the supply chains. The SBO and hybrid analytical-SBO modelling that integrate simulation and optimisation are effective tools for analysing and optimizing the performance of the supply chain networks as they integrate the benefits of the simulation and optimisation modelling.

This work applies SBO and hybrid analytical-SBO frameworks to address four integrated physical and financial flows planning problems. A comprehensive literature review has shown that most of the studies that considered financial flow planning within supply chain networks presented a deterministic single objective mathematical model to represent the supply chain systems. However, the supply chains need to be depicted through multi-objective stochastic models that consider uncertainties in the exogenous parameters such as customer demand and manage the trade-offs between conflicting objectives such as bullwhip effect minimization and total cost minimization. Simulation and optimisation are effective tools for modelling the stochasticity in the supply chain networks and managing the trade-offs between conflicting supply chain objectives, respectively. Therefore, to represent the supply chain networks by multi-objective stochastic models, the simulation and optimisation modelling are required to be integrated. This integrated framework is called SBO modelling when a simulation model and an optimisation algorithm are integrated and is called hybrid analytical-SBO modelling when a simulation model and an optimisation model are paired.

The literature review on the application of the SBO for supply chain optimisation revealed that employing the system dynamics simulation within the SBO framework is far from adequate. Moreover, the literature on the hybrid analytical-simulation for supply chain optimisation showed that research on applying the hybrid analytical-SBO approach for supply chain optimisation is still in its infancy. In this study, system dynamics is used as the simulation methodology within the SBO framework and an integrated physical and financial flows planning problem is also addressed using the hybrid analytical-SBO approach.

The developed SBO framework in this study integrates the system dynamics simulation and the genetic algorithm and is implemented through two academic case studies related to the beer distribution game and one real-world application extracted from the literature. The first SBO framework for the beer game case study aims to manage the trade-offs between conflicting cash conversion cycle (CCC) minimizations for the supply chain members and minimize the collaborative CCC of the supply chain. While, the second developed SBO framework for the beer game case study aims to minimize the bullwhip effect, cash flow bullwhip, and the total cost of the supply chain. The developed SBO framework for the real-world case study aims to manage the trade-off between the economic valued added and cash conversion cycle which represent profitability and liquidity indexes, respectively.

The proposed analytical-SBO framework in this study integrates mixed integer linear programming and the SBO and is implemented through one real-world case study extracted from the literature. The developed analytical-SBO framework aims to integrate the planning of cash and material flows within supply chain networks through addressing an integrated strategic supply chain planning and supply chain finance problem that integrates supplier selection, network design, and asset-liability management subproblems. In this problem, the profitability of the supply chain network is maximized while considering the uncertain external factors and delays exist in the supply chain network.

8.3. Summary of contributions

The main contributions of this research are discussed as follows:

The first contribution of this thesis that was presented in chapter 4 is the development of an SBO model for working capital management in a supply chain. In this model financial flow modelling is incorporated into the system dynamics simulation of the beer distribution game and minimizing the cash conversion cycle for supply chain members and minimizing the collaborative CCC of the supply chain are considered as optimisation objectives. This contribution extends the previous research on working capital and supply chain management by using the SBO modelling for managing the trade-offs between conflicting CCCs minimization for supply chain members and minimizing the collaborative CCC of the supply chain (Theodore Farris and Hutchison, 2002; Ruyken et al., 2011; Lind et al., 2012; Hofmann and Kotzab, 2010; Ruyken, Wagner and Jonke, 2011). The genetic algorithm is applied to identify the optimal values to the controllable parameters including price, unit cost, forecasting parameter for the inventory, forecasting parameter for the supply line, desired inventory, and desired supply line for each supply chain member so as to make the trade-offs between conflicting CCCs for the supply chain members and minimize the collaborative CCC of the supply chain. The results showed that the CCCs of the supply chain entities and the collaborative CCC of the supply chain could be significantly decreased through identifying the optimal controllable parameters.

The second contribution of this thesis that was presented in chapter 5 is the development of an SBO model for reducing the bullwhip effect, cash flow bullwhip, and the total cost in a supply chain under deterministic demand and lead times, stochastic demand and deterministic lead times, and stochastic demand and lead times. In this model financial flow modelling is incorporated into the system dynamics simulation of the beer distribution game to identify the optimal financial decisions in addition to the optimal operational decisions. This contribution extends previous supply chain research on minimizing the bullwhip effect (Alwan et al., 2003; Zhang, 2004; Luong, 2007; Balakrishnan, et al., 2004; Hosoda and Disney, 2006; Tangsucheeva and Prabhu, 2013, 2014; Goodarzi et al., 2017; Sim and Prabhu, 2017) through diminishing the destructive effects of the bullwhip effect in supply chain financial flow in addition to the physical flow. Moreover, it incorporates the financial flow modelling into the inventory planning models and determines the optimal values to the financial decisions parameters, in addition to the inventory decisions. Finally, it incorporates CFB minimization as an objective function into an SBO model. The results show that the genetic algorithm is able to find the optimal financial and inventory decisions parameters for each member of the supply chain to reduce the total cost, bullwhip effect, and cash flow bullwhip.

The main objective of the proposed SBO model is to find the optimal values of the desired inventory, desired supply line, forecasting parameter for inventory, forecasting parameter for supply line, sales price per unit, and unit cost for supply chain entities to make trade-offs between the supply chain total cost, cash flow bullwhip, and bullwhip effect. Three experiments were developed to investigate the ability of the SBO model in identifying the optimal replenishment policy. The first experiment was the beer distribution game, which employs deterministic demand and lead times. The SBO found the optimal replenishment policy to be non-aggressive approach, i.e., forecasting parameter for inventory less than 0.5, to the inventory gap for all members, and a cautious approach to orders in the supply line, i.e., forecasting parameter for supply line less than 0.5, for the retailer and distributor. The second experiment tested random demand and deterministic lead times. The SBO found the optimal replenishment policy to be an aggressive approach to the inventory gap for the retailer and manufacturer, and a cautious approach to orders in the supply line for the retailer. The third experiment extended the second experiment through considering random lead times in addition to the random customer demand. In this experiment, an aggressive approach to the inventory gap for the distributor and wholesaler and cautious approach to orders in supply line for the distributor and wholesaler was identified to be the optimal replenishment policy. However, the recommended policy may not be optimal for every set of random customer demand and lead times. The results demonstrated the superiority of the SBO approach over system dynamics modelling with and without information sharing between supply chain members as it can manage the CFB within supply chain networks through deriving optimal values for the inventory, supply line, and financial decisions parameters in presence of conflicts between supply chain objectives. While, system dynamics is solely able to compare the effects of varied policies, different values of the controllable parameters, through performing what-if analysis which may not be an effective strategy particularly, when the decision parameters are continuous.

The third contribution of this thesis that was presented in chapter 6 is the development of an SBO model for managing the trade-offs between financial performance and liquidity in a supply chain under economic uncertainty. To assess the financial and liquidity performances, the economic value added (EVA) and the cash conversion cycle (CCC) metrics are used, respectively. These two metrics are not moving towards the same direction and business managers should find a balance between them. This contribution extends the literature on supply chain inventory management using system dynamics simulation and supply chain working capital management (Reyes et al, 2013; Peng et al., 2014; Cannella et al., 2015; Liao, 2008; Teng, 2009; Mahata, 2012; Huang, 2007; Huang and Hsu, 2008; Teng and Chang, 2009; Ravichandran, 2007; Liao, 2008; Teng, 2009) through incorporating financial parameters including price, unit cost, collection policy, and payment policy. Moreover, it considers the EVA and the CCC in the multi-objective optimisation formulation of the inventory management model developed by Sterman (2000) under economic uncertainty. Finally, it introduces a new method for measuring the CCC in which the revceiving and payment of the advance payament are taken into account. The proposed model handles economic uncertainty through a scenario tree approach. Using the data of a real case study introduced in Longinidis and Georgiadis (2013), firstly the conflicting objectives are given the same level of importance in order to compare the performance of the SBO approach, in which a genetic algorithm is incorporated into a system dynamics simulation model, with the performance of the system dynamics simulation model under three economic scenarios. The results show the superiority of the SBO approach over system dynamics modelling in all three scenarios. Secondly to manage the trade-offs between the conflicting objectives, the weighted sum method is used to generate the Pareto efficient frontiers which include the non-dominated optimal solutions. These Pareto efficient frontiers provide decision makers with a portfolio of alternative optimal inventory and financial decisions that could be selected based on market condition and the power of the company within supply chain network.

The fourth contribution of this thesis that was presented in chapter 7 is the development of a hybrid analytical-SBO model for integrating supply chain network design, supplier selection, and asset-liability management problems under economic uncertainty. The proposed hybrid model integrates a mixed integer linear programming model and an SBO model to maximize the EVA generated in a supply chain network in presence of uncertainty in economic parameters. This contribution extends the previous research on strategic supply chain planning and supply chain finance (Yousefi and Pishvaee, 2018; Melo et al., 2006; Ramezani et al., 2014; Cardoso, et al., 2016; Zhang et al., 2017; Melo et al., 2006; Naraharisetti et al., 2008; Ramezani et al., 2014; Zhang et al., 2017) by applying the hybrid modelling and considering the economic uncertainty. The developed hybrid model identifies the optimal values to the decision parameters such as inventory control parameters and optimal values to the decision variables such as the flow of products between supply chain entities.

The hybrid approach is initialized by solving the MILP model to determine the optimal values to the raw materials required to be purchased from the suppliers, the production rate at the manufacturing site, and the flow of finished products between the SC members considering the existing constraints in the financial and physical flows. The solution suggested by the MILP model is then used to construct the SBO model in which the distribution and payment lead times, the feedback loops, and nonlinearities rooted in a supply chain network are formulated through applying system dynamics simulation approach. Thereafter, the embedded GA in the SBO model is run to identify the optimal values to the price per tonne of the product, the desired cash, the profit distribution policy, and the stocking capacities at the supply chain members. In the next stage, the constraints of the optimisation problem are revised in accordance with the optimal parameter values recommended by the SBO model and the optimisation problem is run to generate a new set of parameter values to be inputted into the SBO model. The iterative process between optimisation and SBO models continues until the stopping criterion which is 5% difference between the EVAs obtained from the models is met. The hybrid approach enables the modeller to not only take into account the lead times, feedback loops, and nonlinearities which exist in the supply chain networks, but also dramatically bridge the gap between the desired EVA, the EVA obtained from the analytical model, and the real EVA, the EVA gained from the SBO model.

8.4. Managerial implications

The managerial implications of each contribution are discussed as follows:

8.4.1. Managerial implications of the contribution 1

In addition to matching the supply of products with the demand of customers within supply chain networks, the supply of cash is also required to be matched with the demand of supply chain members. Single company perspective in which each supply chain member decides independently on its cash flow decisions such as payables period results in heterogeneous distribution of cash among supply chain entities. Therefore, it is imperative for supply chain managers to ensure that the available cash in the network is fairly distributed among the supply chain members. This is achieved through collaborative working capital management in which the conflicts between cash flow optimisation objectives for supply chain members are managed. The proposed SBO model in this study assists supply chain managers to manage the conflicting objectives through identifying the optimal inventory and financial parameters for supply chain members.

8.4.2. Managerial implications of the contribution 2

Working capital optimisation in addition to the total cost optimisation plays a pivotal role in boosting the efficiency of supply chain management. Therefore, it is imperative that working capital metrics such as the cash conversion cycle (CCC) are incorporated into the supply chain models. The CCC represents the performance of a firm in managing its capital. The lower the CCC, the more successful the firm is in managing its capital. High volatility in the CCCs of the supply chain members caused by the bullwhip effect yields volatility in liquidity that may trigger inefficiencies in operational processes of the members such as purchasing, and consequently reduce SC service levels. Given the results of our study, supply chain managers should control the fluctuations in the CCCs of the supply chain members, if they want to manage the liquidity within the supply chain networks. The proposed SBO model in this research allows supply chain managers to mitigate the CFB significantly under the deterministic and stochastic demand and lead time. This is achieved through identifying the optimal values for the sales price, unit cost, and inventory decisions of the members. In the original model of the BG, the CCC for the SC members ranges from 30 to 500 days. While, after employing the SBO methodology, the CCC ranges from -15 to 32 days. In presence of demand uncertainty in the BG model, the cash to cash cycle ranges from -5 to 1500 days. Although, after employing the SBO methodology the CCC ranges from -5 to 40 days. In presence of uncertainty in demand and lead times in the beer game model, the CCC ranges from -5 to 40 days. While after applying the SBO technique, the CCC ranges from -5 to 32 days.

In addition to the CFB reduction, the proposed SBO model assists supply chain managers to reduce the supply chain total cost (SCTC) significantly. In the original model of the BG the SCTC amounted to £10816. While, after employing the SBO methodology, the SCTC decreased to £7017.94. In presence of demand uncertainty in the BG model, the SCTC amounted to £14283.42. Although, after employing the SBO methodology the SCTC reduced to £8292.74. In presence of uncertainty in demand and lead times in the BG model, the SCTC amounted to £18387.96. While after applying the SBO technique, the SCTC diminished to £8729.90. Moreover, the results of the conducted experiments show the superiority of the proposed SBO model over the information sharing strategy which is usually implemented by the supply chain managers to mitigate the SCTC. After employing the SBO technique the SCTC reduced by 29 percent comparing the SCTC of the SD model with information sharing. Similarly, the SCTC in the SBO model under demand uncertainty, and demand and lead time uncertainties, reduced by 24 percent and 18 percent, respectively comparing the SD model with information sharing. Decreasing the gap between the SD model with information sharing and the SBO model as the number of stochastic parameters increase conveys the importance of the information sharing among supply chain members in mitigating the SCTC. Therefore, SC managers who are in charge of managing SC networks which encounter various uncertainties could benefit from significant cost reduction through applying the information sharing strategy. Although, the information sharing strategy is not as efficient as the SBO technique in cost reduction.

8.4.3. Managerial implications of the contribution 3

Supply chains aim to provide a good customer service level by meeting customer demand. The higher the inventory level at supply chain members, the lower the possibility of losing customer demand. Although keeping high levels of inventory at supply chain members ensures the capability of the supply chain on meeting the customer demand, it imposes significant holding costs on supply chain members. Thus, supply chain managers should make a trade-off between minimizing the inventory levels at the supply chain members and maximizing the shipment rate to the customer. In this contribution, Minimizing the inventory levels at the supply chain members is achieved by minimizing the cash conversion cycle of the supply chain. While, maximizing the shipment rate to the customer is achieved through maximizing the economic value added of the supply chain. Furthermore, minimizing the cash conversion cycle enables the supply chain managers to decrease the cost of capital for supply chain members and accelerate cash flow within the supply chain networks by optimizing receivables level and payables level in addition to the inventory levels.

Implementing the decisions related to supply chain planning problems rely on availability of the financial resources. Therefore, the dynamics of the financial flow in a supply chain should be tracked along with the dynamics in the physical flow. Considering the dynamics of the financial flow in a supply chain necessitates incorporating the financial decision parameters such as collection policy into the supply chain planning models. The values to the financial decision parameters are decided on by the financial managers. The proposed model in this study promotes constructive cooperation between supply chain and financial mangers as it integrates inventory decisions such as inventory adjustment time made by supply chain managers and financial decisions such as collection policy made by the financial managers. Moreover, the estimation of the uncertain economic parameters such as short-term interest rates under various scenarios requires the active participation of the financial managers. Participation of the financial managers in modelling of the supply chain planning problems increases the possibility of the allocating the required financial resources for implementing the solutions recommended by the model as the allocation decisions are mainly made by the financial managers.

8.4.4. Managerial implications of the contribution 4

Businesses need to keep sufficient cash to meet their operations expenses such as buying raw material and also pay dividends to their investors. The higher the cash level held by a business, the lower the possibility of business inability in meeting operations expenses and paying dividends. Although, keeping high cash level by a business ensures its capability in meeting operations expenses and paying dividends, it imposes cash opportunity cost on the business. In other words, the business is forgoing the return that would have been derived by investing the cash in alternative options to holding it such as investing the cash in the stock market. Therefore, business managers need to make a trade-off between adequacy of cash for meeting the business expenses and minimizing the opportunity cost that the business incurs as a result of holding cash. This contribution helps the business managers in making this trade-off by considering cash holding cost as an element to the total cost of the business and ensuring the cash level by the business is minimized.

Integrating supply chain problems provide a more explicit picture of the supply chain dynamics and consequently the solutions obtained from the integrated models are more realistic compared to the solutions obtained from the segregated problems. Although, the integration may result in nonlinear models which require significant amount of time to identify the optimal solutions. Therefore, a trade-off is required to be made between the solution quality and the computational time. Hybrid analytical-SBO approach in which independent optimisation and SBO models are integrated through a feedback structure combines the advantages of the complex SBO models and abstract optimisation models. The SBO models are powerful tools in capturing uncertainties, nonlinearities, and delays exist in supply chain networks. Although, they may not result in global optimal solutions due to applying stochastic optimisation algorithms. On the other hand, optimisation models generate global optimal solutions. However, incorporating nonlinearities in these models may significantly increase the computational time. Applying the hybrid analytical-SBO approach enables the supply chain managers to access realistic high-quality solutions in a reasonable time.

Supply chains are exposed to uncertainties in macroeconomic and macroeconomic parameters that may have significant impact on their profitability. Business managers need to ensure that the impact of these uncertainties is taken into account while measuring the profitability of their supply chains. Otherwise, the profitability of the supply chain may provide a misleading view of the financial health of the supply chain. In this contribution, uncertainties in four macroeconomic parameters including short-term interest rate, long-term interest rate, expected return of the market, and risk-free rate of interest an uncertainty in one macroeconomic parameters that is demand are considered to assist the business managers to obtain a more realistic view to the profitability of their supply chains.

8.5. Limitations and future work

In this study, it is assumed that there is either full trade credit or partial trade credit among supply chain members. While in some real world supply chains the full trade credit and partial trade credit coexist. In other words, in these supply chains some members receive full trade credit from their suppliers and offer partial trade credit to their customers. The coexistence of the full trade credit and partial trade credit in a supply chain has not been considered in this study and could be addresses in future research. From cash flow perspective, existence of the either full trade credit or partial trade credit policy results in fairer distribution of the cash among supply chain members compared to coexistence of the full trade credit and partial trade credit policy. The reason for this is the accessibility of the partial trade credit merely for some members of the supply chain and not all of them.

Trade credit policy which is the basis of the financial flow modelling in this study is one of the financing solutions that are common in supply chain networks. There are many other financing solutions in supply chains such as factoring and reverse factoring that are employed in supply chains and can be used for modelling of the financial flow in supply chains. Future research might predicate financial flow modelling on financing solutions other than trade credit.

As it was explained in chapter 2 of this study some of the supply chain financing solutions such as factoring and reverse factoring require a third-party finance provider such as banks. Although these solutions expedite the access of the supply chain members to cash, they are accessible for small supply chains that do not contain companies with high business volume and annual turnover. The small supply chains will be not be able to avail of these financing solutions, unless they become part of supply chains that contain big brands and key players in their industry.

Although minimizing the cash conversion cycle for a supply chain ensures the homogenous distribution of the cash among supply chain members, it may not be appealing to the supply chain members which have a sub zero cash conversion cycle before minimizing the cash conversion cycle for the supply chain. Therefore, one of the implementation difficulties of the current study is to convince supply chain members with a sub zero cash conversion cycle to improve the cash conversion cycle of the other supply chain members in expense of increasing their own cash conversion cycle.

The opportunity cost of holding cash heavily relies on the economic condition. For instance, when the economy is growing the opportunity cost to the cash holding is high as a higher return than cash holding could be obtained by investing the cash in the stock market or other growing markets. Although, when the economy is shrinking the opportunity cost to the cash holding is negligible as the return on the alternative options to cash holding is low or there might be no return at all. Therefore, the other main difficulty to the implementation of the current study is to convince supply chain managers to minimize the cash level when there is no consensus on the future economic condition.

In addition to the assumptions and limitations of the study as a whole, the limitations of each contribution are discussed as follows.

8.5.1. Limitations and future work of the contribution 1

To recognize directions for future research, the limitations of the contribution 1 are elaborated as follows. Firstly, our simulation model was developed based on the beer distribution game structure (Sterman, 1989; Joshi, 2000). Similar simulation models can be developed to manage the conflicting CCC minimization objectives for other supply chain networks. Secondly, in this contribution, anchoring and adjustment heuristic (Tversky and Kahneman, 1974) was employed as an inventory ordering policy. There are other replenishment policies such as reorder point-order quantity (Q,r) which may be integrated into future research. Thirdly, the performance of the other optimisation algorithms in managing the conflicting working capital objectives can be compared with the GA performance in future work. Another research topic is to use collaborative cash conversion cycle (CCCC) by which the CCC of the supply chain network is measured as objective function rather than the CCC by which the CCC of each supply chain member is measured.

8.5.2. Limitations and future work of the contribution 2

To recognize directions for future research, the limitations of the contribution 2 are elaborated as follows. Firstly, our simulation model was developed based on the beer distribution game structure (Sterman, 1989; Joshi, 2000). Similar simulation models can be developed to control cash flow bullwhip (CFB) for other supply chain networks. Secondly, in this contribution, anchoring and adjustment heuristic (Tversky and Kahneman, 1974) was employed as an inventory ordering policy. There are other replenishment policies such as reorder point-order quantity (Q,r) which may be integrated into future research. Thirdly, other BWE contributors such as order batch and lead time have not been optimised in this study. Another research opportunity may arise by extending this paper through considering the aforementioned parameters. Fourthly, further work can be carried out to identify an optimisation algorithm which is more effective than the GA in CFB minimization under lead time uncertainty. Another research topic is to define other metrics rather than cash conversion cycle to measure cash flow bullwhip and controlling CFB through tuning its controllable parameters.

8.5.3. Limitations and future work of the contribution 3

The limitations of this contribution that need to be studied in the future research are as follows. Firstly, the presented simulation-based optimisation model manages the trade-off between economic profitability and working capital efficiency under economic uncertainty, although there are other trade-offs such as trade-off between working capital efficiency and credit solvency that can be considered in future research. Secondly, the uncertainty of other financial parameters such as tax rate could be considered in supply chain inventory management and working capital management problems. Thirdly, future research might extend our model by considering the fixed assets as an endogenous variable rather than a constant or incorporating leaseback of fixed assets into invested capital. Fourthly, Future research might consider a two-part trade credit policy in which some of the supply chain members receive full trade credit from their suppliers and offer partial trade credit to their customers Finally, future research can employ other optimisation algorithms to manage trade-off between economic profitability and working capital efficiency and compare the performance of these algorithms with performance of the GA that is presented in this study.

8.5.4. Limitations and future work of the contribution 4

The limitations of this work that need to be studied in the future research are as follows. Firstly, this study only examines the use of hybrid approach to address a strategic supply chain planning and finance problem. In future research other integrated supply chain planning problems such as integrated network design, distribution and transportation planning could be solved using the hybrid approach. Secondly, the simulation approach applied in this study is SD, it would be interesting to investigate the capability of optimisation-SBO models that employ simulation models rather than SD in addressing supply chain planning problems. Finally, multi-objective optimisation can also be incorporated into the developed MILP-SBO model as an extension to the present study.

Appendix

The remaining studies that applied the simulation-based optimisation modelling for addressing supply chain problems are presented as follows.

Table 2.5. Continued

Article	Research scope	Optimization algorithm	Simulation model	Optimization objective
Diaz and Bailey (2011)	SC inventory planning	Simulated Annealing	NA	Min: Total cost
Otamendi and Doncel (2012)	SC network design and inventory planning	GA	Spreadsheet simulation DES	Min: Total cost Max: Service reliability
Kabirian et al. (2013)	SC configuration design, production and inventory planning , and revenue management	GA	Spread sheet simulation DES	Max: Profit
Kulkarni and Niranjan (2013)	Inventory planning	OptQuest	DES	Min: Total cost Max: Service level
Maliki et al. (2013)	SC supplier selection, facility location, and distribution planning	NSGAII	DES	Min: Total cost Min: supply lead time
Duan and Liao (2013)	SC inventory planning	Hybrid metaheuristic algorithm (Differential Evolution, Harmony Search, Hooke and Jeeves direct search)	NA	Min: Total cost
Georgiadis and Athanasiou (2013)	SC capacity planning	Proposed MOO methodology	SD	Min:sustainability dimensions performance cost Min: remanufacturing
Li and Wang (2014)	Inventory control	PSO	NA	Min: Total cost
Chavez and Castillo-Villar (2014)	SC transportation planning	Simulated Annealing	DES	Min: Transportation time Min: Transportation cost
Fischer et al. (2014)	SC flexibility	GA PSO	DES	Min: Total cost Max: Delivery reliability
Aslam and Ng (2015)	SC production and inventory planning	NSGAII	SD	Min: Total work-in-process
Pitzer and Kronberger (2015)	SC network design and distribution planning	GA	NA	Min: Total cost
Mortazavi et al. (2015)	SC inventory planning	Reinforcement Learning Algorithm	ABS	Min: Total cost
Ye and You (2015a)	SC inventory planning	Trust-region method	ABS Monte Carlo	Min: Total cost Max: Service level
Ye and You (2015b)	SC network design and inventory planning	Trust-region method	DES Monte Carlo	Min: Total cost
Essoussi (2015)	SC inventory planning	OptQuest	DES	Min: Total cost
Chu et al. (2015)	SC inventory planning	Cutting Plane Algorithm	ABS Monte Carlo	Min: Total inventory cost Max: Demand fill rate
Hlioui et al. (2015)	SC inventory planning and quality control	Response Surface Methodology	DES Continuous Simulation	Min: Total cost
Shahi and Pulkki (2015)	SC inventory planning	OptQuest	ABS	Min: Total inventory cost

Table 2.5. Continued

Article	Research scope	Optimization algorithm	Simulation model	Optimization objective
Gülleret al. (2015)	SC inventory planning	Multi objective particle swarm optimization (MOPSO)	Object-oriented Simulation	Min: Total inventory cost Max: Service level
Zhang et al. (2015)	Remanufacturing process planning and scheduling	GA	Monte Carlo	Min: Makespan Min: Total performance score (electricity consumption or pollutant emissions)
Diaz et al. (2016)	Inventory planning	Simulated Annealing Pattern Search Ranking and Selection (SAPS&RS)	Discrete Markov-modulated Chain (DMC)	Min: Total inventory cost
Aslam and Ng (2016)	SC inventory planning and bullwhip effect	Proposed MOO methodology	SD	Min: Inventory holding cost Min: Backlog cost Min: Bullwhip effect
Davoodi et al. (2016)	SC inventory planning	Proposed algorithm by authors	Monte Carlo	Min: Inventory cost Max: Fill rate
Peirleitner et al. (2016)	SC inventory planning	NSGA-II	ABS	Min: Total cost Max: Service level
Ye and You (2016)	SC inventory planning	Trust-region method	Monte Carlo Object-oriented simulation	Min: Total daily operation cost Max: Service level
Bandaly et al. (2016)	SC inventory planning and financial hedging	GA	Monte Carlo	Min: Total opportunity cost
Yang et al. (2016)	Production planning and control	OptQuest	DES	Max: On-time delivery rate
Woerner et al. (2016)	SC inventory planning	CLM&IPA	DES	Min: Holding cost
Avci and Selim (2017)	SC inventory planning and flexibility	Decomposition-based multi-objective differential evolution algorithm (MODE/D)	NA	Min: Total holding cost Min: Premium freights ratio
Keramydas et al. (2017)	SC network design and inventory planning	OptQuest	DES	Min: Total cost Min: CO2 emissions
Chavez et al. (2017)	Integrated biomass supply analysis and logistics (IBSAL)	Simulated Annealing	DES	Min: Dry matter loss Min: Percentage of moisture content
Mokhtari et al. (2017)	SC production and inventory planning	Grid search	Monte Carlo	Max: Total profit
Shahi et al. (2017)	SC Production and inventory planning	OptQuest	ABS	Max: Net annual profit
Buisman et al. (2017)	SC inventory planning	NA	NA	Max: Profit
Sudarto, Takahashi and Morikawa (2017)	SC capacity planning	Proposed MOO methodology	SD	Min:sustainability dimensions performance cost Min: remanufacturing capacity expansion
Kara and Dogan (2018)	SC inventory planning	Q-learning algorithm Sarsa algorithm GA	Monte Carlo	Min: Total inventory cost
Afshar-Bakeshloo et al. (2018)	SC inventory planning	OptQuest	DES	Min: inventory cost Min:backlog cost Min: emission cost

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