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Amr Arisha
Dublin Institute of Technology, amr.arisha@dit.ie

Waleed Abo-Hamad
Dublin Institute of Technology

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Simulation–Optimisation Methods in Supply Chain Applications: A Review

WALEED ABO-HAMAD* AND AMR ARISHA*

ABSTRACT

The competitiveness and dynamic nature of today's marketplace is due to rapid advances in information technology, short product life cycles and the continuing trend in global outsourcing. Managing the resulting supply chain networks effectively is challenged by high levels of uncertainty in supply and demand, conflict objectives, vagueness of information, numerous decision variables and constraints. With such levels of complexity, supply chain optimisation has the potential to make a significant contribution in resolving these challenges. In this paper, a literature review – based on more than 100 peer-reviewed articles – of state-of-the-art simulation-based optimisation techniques in the context of supply chain management is presented. A classification of supply chain problems that apply simulation–optimisation techniques is proposed. The main criteria for selecting supply chain optimisers are also identified, which are then used to develop a map of optimisation techniques. Such a map provides guidance for researchers and practitioners for a proper selection of optimisation techniques.

Key Words: supply chain management; modelling and simulation; optimisation; supply chain optimisation

INTRODUCTION

Experience and intuition are often the basis of most critical decisions in enterprises. However, due to today's dynamic marketplace, these decisions are far from optimum and lead to a deterioration in performance. Supply chain (SC) managers face many decision-making challenges at different levels of a SC, including supplier selection, facility location and resource planning. These challenges emerge from the increasing complexity of SC networks which is imputable to a high level of uncertainty in supply and demand, conflicting objectives, vagueness of information, and numerous decision variables and constraints. Hundreds and thousands of individual decisions are made along a SC with different importance levels.

* College of Business, Dublin Institute of Technology

Robust tools are needed to support these decisions and to enable managers to evaluate the impact of decisions before their actual implementation. System modelling (Aguilar-Savén, 2004) is used in such cases to abstract important details of real systems. An example of an abstraction of an SC is given in Figure 1, where modelling techniques are used to capture important aspects of the underlining real-world problem, and transform these aspects into a model that describes the input–output behaviour of the system.

Despite their computational efficiency, analytical models are impractical in SC settings. This is due to the imposed simplifications on the model which hinder the modelling of important details and features of real industrial systems (Byrne and Heavey, 2006). Simulation models, on the other hand, provide the flexibility to accommodate arbitrary stochastic elements, and generally allow modelling of all the complexities and dynamics of real-world SCs without undue simplifying assumptions (Terzi and Cavalieri, 2004).

While simulation models try to explain the relationships between input and output of complex systems, they do not provide the capability of finding the optimum set of

Figure 1: Mapping of a Real System to a Model Using Modelling Techniques

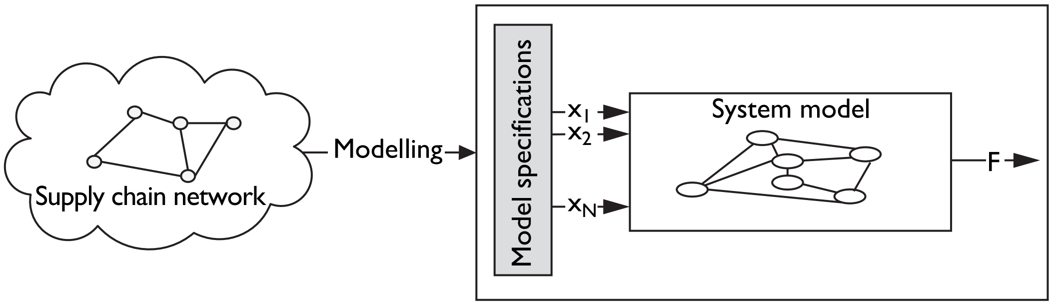
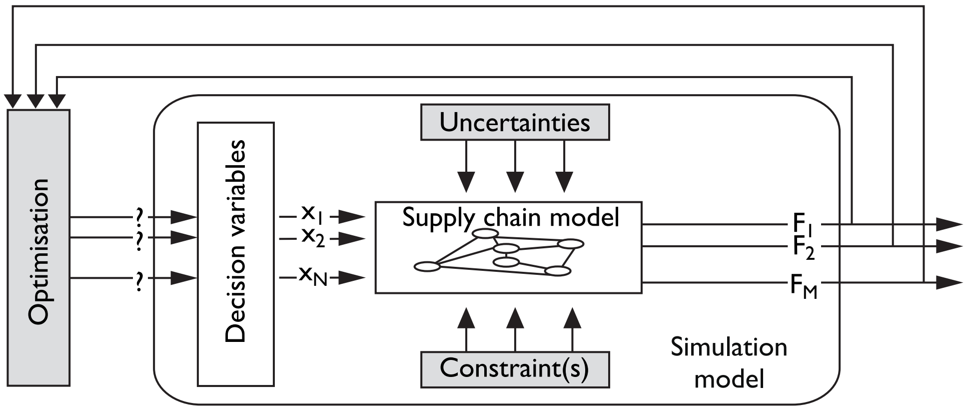


Figure 2: Interaction between Simulation Model and the Optimisation Module



decision variables in terms of predefined objective function(s). This is the purpose of optimisation models, which allow decision makers to find the best possible alternatives while their impact on the system performance is evaluated using simulation models. Figure 2 shows the interaction between the simulation model and the optimisation model. Therefore, integrating simulation and optimisation, known as 'simulation–optimisation', into an SC framework provides decision makers with a comprehensive solution toolbox.

Problem Formulation

The resemblance of SCs to dynamic engineering systems is extremely helpful when developing an integrated management framework. Most business problems can be described as:

$$\begin{array}{lll} \text{optimise} & f_i(x) & i = 1, \ldots, \mathrm{I}, \\ \text{subject to:} & g_j(x) \leq 0 & j = 1, \ldots, \mathrm{J}, \\ & h_k(x) = 0 & k = 1, \ldots, \mathrm{K} \end{array}$$

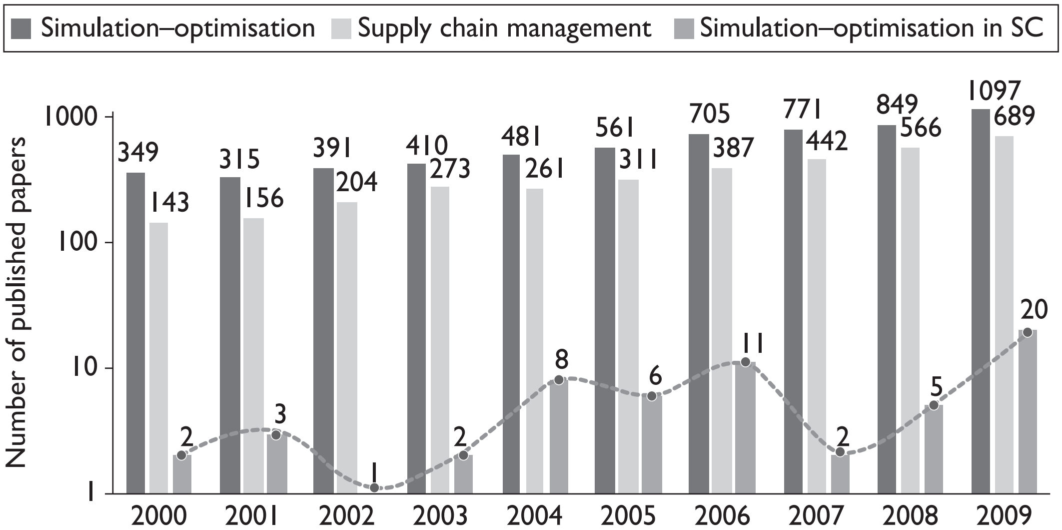
Where $f_i(x)$ is the objective function i, x represents the decision variables vector, and $g_i(x)$ and $h_k(x)$ are the set of inequality and equality constraints. Finding the set of values of decision parameters (x) that optimise (minimise/maximise) the performance criterion (f) faces many challenges:

- Firstly, obtaining a mathematical description of $f_i(x)$ is not attainable due to the unclear relationships between the system components that define its performance.
- Secondly, SCs are usually characterised by multi-objectives, which may imply conflicting objectives and ambiguous preferences between alternatives (Min and Zhou, 2002).
- Thirdly, the existence of a large number of decision variables and alternatives which are unfeasible to enumerate or simulate. In computational complexity theory, these kind of problems are known as non-deterministic polynomial-time hard (NP-hard) problems (Pardalos, 2005), and they need more sophisticated optimisation algorithms to guide the search for optimum or near-optimum solutions in a reasonable timeframe.
- Finally, optimisation methods have to consider the uncertainty embedded in SCs to provide reliable solutions (Van der Vorst and Beulens, 2002). Therefore, adjustment of traditional techniques is required to deal with different sources of uncertainty.

Research Motive

Although the potential is significant, the joint research in applying simulation–optimisation in SC applications is small. We highlighted this gap by a quick search of journal articles in the last decade having the phrase 'simulation optimisation for supply chain' either in their title, abstracts or key words by a selection of the main active publishers in business, management, decision sciences, computer science, engineering and mathematics. As shown in Figure 3, the number of papers published in applying simulation–optimisation

Figure 3: A Research Gap in Applying Simulation Modelling and Optimisation to the Supply Chain Context



for supply chain problems, from 2000 to 2009, is significantly less than those published in simulation–optimisation in general or supply chain management in general.

The purpose of this paper is to review the literature in the field of applying simulation–optimisation to supply chain applications and to provide a basis and guidelines for researchers and practitioners to link simulation–optimisation with real-world applications. Based on this premise, the scope of this review is limited to the literature that uses simulation modelling and optimisation in the context of supply chain management. In this review the following research questions are addressed:

- What are the main simulation-based optimisation techniques that are used in the context of supply chain management?
- What are the main areas of the supply chain that have applied simulation–optimisation techniques?
- What are the main criteria for choosing a supply chain optimiser?

Review Methodology

The main criterion for including an academic paper in this review is that the paper should describe an application of simulation–optimisation in one or more areas concerning supply chains in the period 2000–2009. Papers that discuss theoretical aspects of simulation–optimisation methods are also included to give a background to these techniques. Papers that discuss only simulation or optimisation methods for supply chains have been excluded.

Acknowledging that academic journals are the main resource used to acquire information and release new findings, conference papers, masters' theses, doctoral dissertations, textbooks, technical reports and unpublished working papers have been excluded.

An initial list of 250 papers was created based on reading the abstract of the papers, and a final list of 100 papers was selected based on reading the entire paper. Following the selection of papers, the following attributes were extracted from each article:

- Orientation: Does the paper discuss an application of simulation–optimisation in supply chain or a theoretical background of optimisation techniques used in a supply chain context?
- Optimisation technique: Does the paper apply a particular type of simulation–optimisation technique? If yes, what type of technique is used?
- Supply chain application: Does the article describe an application of simulation–optimisation in a particular supply chain area? If yes, what kind of supply area is described? Which kinds of decisions are considered: strategic, tactical or operational?

SIMULATION–OPTIMISATION METHODS

Generally, an objective function or performance measure cannot be described using a mathematical model because of the high level of uncertainties in SCs. Simulation models are then used to evaluate the different system configurations to be optimised (Kleijnen, 2005). This type of optimisation is known as simulation–optimisation (Tekin and Sabuncuoglu, 2004), and it is classified into four main types: gradient-based methods, meta-model-based methods, statistical-based methods and meta-heuristics methods.

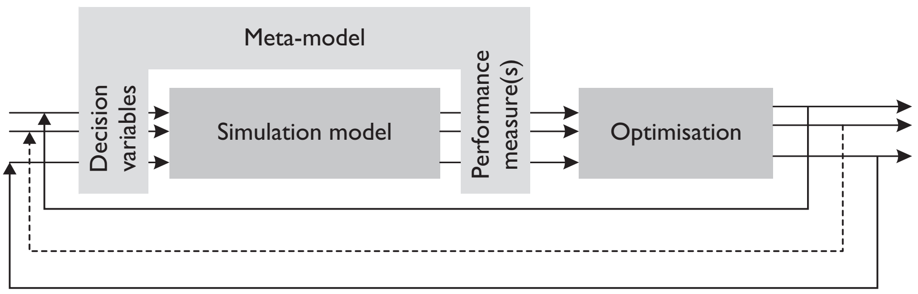
Gradient-Based Methods

Differentiation in the gradient context is usually used to simplify the objective function in order to find an optimum solution. The gradient-based approach requires a mathematical expression of the objective function. When such a mathematical expression cannot be obtained, there is a need to use an estimation technique to start the solution procedure. The estimated gradient's direction guides the search process to move from one potential solution to another in an iterative scheme in a process called stochastic approximation (Robbins and Monro, 1951). Infinitesimal Perturbation Analysis (IPA) is one of the gradient estimators that is considered unbiased (Glasserman, 1991). Its convergence rate has been studied in L'Ecuyer and Perron (1994), while variance reduction and efficient implementation of IPA was investigated in Dai (2000). Another important gradient estimator is Finite Difference Estimation (FDE), which determines partial derivatives of the system performance measures (Dong and Krylov, 2005). In order to estimate the gradient at each search point, at least ($n + 1$) evaluations of the simulation model are necessary, where n is the number of decision variables. For a more reliable estimate, multiple observations for each derivative are required. On the other hand, Likelihood Ratio Estimator (LRE) estimates the derivative of the performance measure by mathematically differentiating the underlying probability measure of the system (Glynn, 1990).

Meta-Model-Based Methods

While gradient-based estimators are used to estimate the derivatives of the objective function, meta-model-based techniques use an analytical approach to approximate the objective function. The meta-model can then replace part of the simulation model with a mathematical function that mimics the input–output behaviour of that part. Such integration of meta-models simplifies the simulation model in terms of computation time, and consequently simplifies the optimisation process (Reis dos Santos and Isabel Reis dos Santos, 2009). In Figure 4, the optimisation model interacts with the meta-model, whilst the metal-model approximates the input–output behaviour of the simulation model.

Figure 4: How the Meta-Model Interacts with the Simulation Model and the Optimisation Module



Response Surface Methodology (RSM) is based on procedures that allow regression models to be applied to simulation model responses that are evaluated at several values of decision variables using the design of experiments (DOE) methods. A comprehensive study of the use of statistical designs integrated with simulation models can be found in Kleijnen (1998), which focuses on how RSM combines regression analysis, statistical designs and the steepest descent/ascent method to optimise the objective function of the simulated system. On the other hand, Kriging (Hussain et al., 2002; Keys and Rees, 2004) is an interpolation method that predicts unknown values of a stochastic function which are more flexible than polynomial models and less sensitive to small changes in the experiment design (Meckesheimer et al., 2002). Another method is Artificial Neural Networks (ANNs), which has proven to be an effective method to approximate arbitrary smooth functions and can be fitted using stochastic response values (Fonseca et al., 2003). ANNs are developed to mimic neural processing, the inputs and outputs of which are linked according to specific topologies.

Statistical Methods

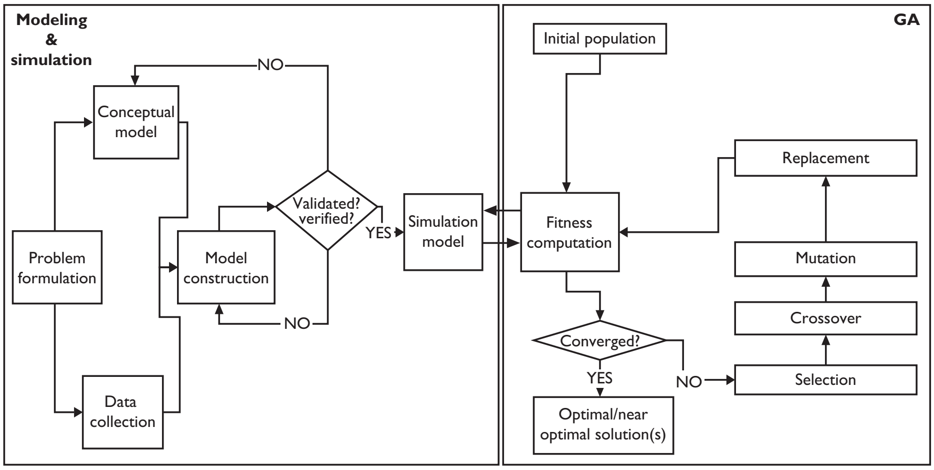
Gradient-based and meta-model-based methods are used for continuous decision parameters. In discrete decision parameters, the problem is to select one of the predetermined system configurations. The task of optimisation algorithms is then to select one of these configurations that optimise system performance based on the selected criteria. Since the system performance is not deterministic, further statistical analysis is required to compare alternatives. Different types of approaches were developed for such optimisation problems, including Ranking and Selection (R&S), Multiple Comparison Procedures (MCP) and Ordinal Optimisation (OO).

In R&S, there are two main approaches. The first is the indifference zone approach, which finds the decision variables values that make the value of performance measure different from the optimal performance by at most a small amount (i.e. the indifference zone). On the other hand, subset selection is used to reduce the feasible solution region to a small subset that at least contains the best solution. The indifference zone approach does not require extensive computation efforts and can be applied to a single replication from each solution (Kim and Nelson, 2001). The idea of MCP is to run a number of replications and then evaluate system performance by constructing confidence intervals (Swisher et al., 2003). However, it is difficult to precisely determine the best alternative from a set of predefined solutions in terms of absolute values. OO determines which solution is better, rather than focusing on the quantitative difference between the available solutions. In addition, instead of looking for the best alternative, OO selects a good enough solution (Ho et al., 2000). This crucial feature of OO makes it a robust optimisation choice when the number of alternatives is very large (He et al., 2007).

Meta-Heuristics

Statistical methods were successfully used in the case of discrete decision parameters. However, it is computationally infeasible to evaluate every possible alternative or all parameter combinations when the solution space is very large. Consequently, determining which alternative(s) to be simulated and evaluated is crucial. Besides, most of the aforementioned optimisation techniques fail to find an optimum solution when the solution space is high-dimensional and discontinuous, or when the decision variables are qualitative. Meta-heuristics are used in such cases to efficiently guide the search process towards potential solution points (Bianchi et al., 2009). They ultimately provide balance between exploration of solution space and exploitation of *good* solution(s) in an iterative process by initially starting with a solution (point-based) or set of solutions (set-based or population-based), then in each iteration the search progresses to new possibly better solution(s) in the neighbourhood of the current solution. Each meta-heuristic method has its own mechanism to define the neighbourhood structure (Andradottir, 2006). Simulated Annealing (SA) is one of the main meta-heuristics that starts with an initial solution, generally chosen randomly. A neighbour of this solution is then generated by a suitable mechanism. The performance of this solution is then calculated. If an improvement occurs, the generated neighbour replaces the current solution. If there is no improvement in the performance, the SA algorithm may accept this solution with some probability to avoid entrapment in a local optimum (Kirkpatric et al., 1983). Another famous meta-heuristic method is Genetic Algorithm (GA), which works on a population of solutions in such a way that poor solutions are excluded, whereas good solutions evolve to reach their optimum solution (Chaudhry and Luo, 2005). It generates an initial population of solutions. These solutions are then evaluated through a simulation model which is followed by a selection process in which genetic operators are applied to produce new solutions that are inserted into the population. Figure 5 demonstrates the integration process between a GA and a simulation model. This process is repeated until some stopping criterion is reached. Tabu Search (TS) is a constrained search procedure, where each step consists of solving a secondary optimisation problem (Glover et al., 2007). At each step, the search procedure removes a subset of the search space. This subset changes as the algorithm proceeds and is usually defined by previously considered solutions which are called the reigning tabu conditions (Chelouah and Siarry, 2000).

Figure 5: A Genetic Algorithm (GA) Integrated with a Simulation Model (Fitness Computation)

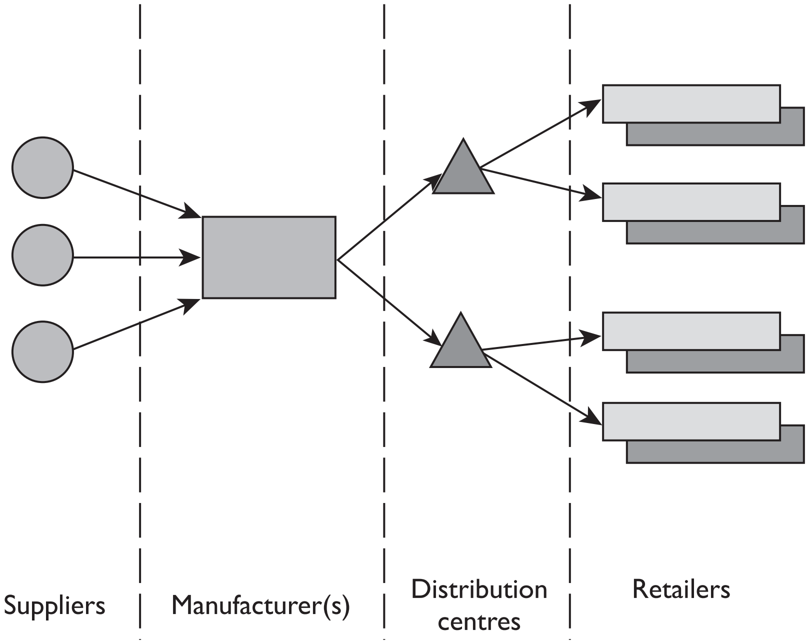


SUPPLY CHAIN APPLICATIONS

An SC can be defined as a set of entities (e.g. echelon or business tier) directly involved in the upstream (i.e. supply) and downstream (i.e. distribution) flows of products, services, finances and/or information between a source and a customer (Mentzer et al., 2001) (see Figure 6).

Managing such a chain of networks is a complex and challenging task due to current trends in globalisation, increased outsourcing, shorter product life cycles and advances in information technology. In this review, decision areas in supply chain management are classified into four main areas: inventory management, production planning and scheduling, transportation and logistics management, and supply chain collaboration, coordination and design.

Figure 6: A Simple Model of a Supply Chain



Inventory Management

The strategic impact of inventory stored at different stages of the SC is significant. Determining the minimum and maximum levels of inventory and the quantity of order to be placed are major challenges for decision makers. An (*s*, *S*) ordering policy specifies these decision variables by placing an order when the level of inventory is below *s* units, and by specifying the amount of the order by the difference between maximum inventory level (*S*) and the current inventory position. Provided that determining the optimal values of (*s*, *S*) is computationally expensive, simulation-based optimisation is a potential tool for analysing alternatives and finding these optimal values. IPA is used by Gavirneni (2001) to compute the appropriate order-up-to level in a capacitated SC. Gavirneni (2001) measured the benefit of sharing the inventory parameters of the retailer's ordering policy and demand data with the supplier, which reduced the supplier's cost by a value from 1 per cent to 35 per cent. Ranking and Selection procedures and SA are combined by Ahmed and Alkhamis (2002) to find optimal values of (*s*, *S*) inventory policy with the objective of minimising the inventory holding cost, shortage cost and ordering cost. An efficient selection-of-the-best scheme called Sequential Selection with Memory (SSM) is proposed by Pichitlamken et al. (2006) to be used during the neighbourhood search. A hybrid between simulation and GA is presented by Köchel and Nieländer (2005) to define optimal order policies in a multi-echelon inventory system. Additionally, the causal relation between the inventory decision variables and SC performance can be constructed using meta-models. Subsequently, the constructed meta-model can be used to determine the base stock levels of different SC stages in order to minimise the backlogging costs at warehouses and the holding costs at SC nodes. As an example for such integrated framework, Wan et al. (2005) optimised inventory levels for a three-stage SC where each production node has inventories for raw materials and products. In the same fashion, GA can be used to generate base stock levels while being evaluated by simulation models. This integration can be used to minimise the sum of holding and shortage costs in the entire SC (Daniel and Rajendran, 2005, 2006).

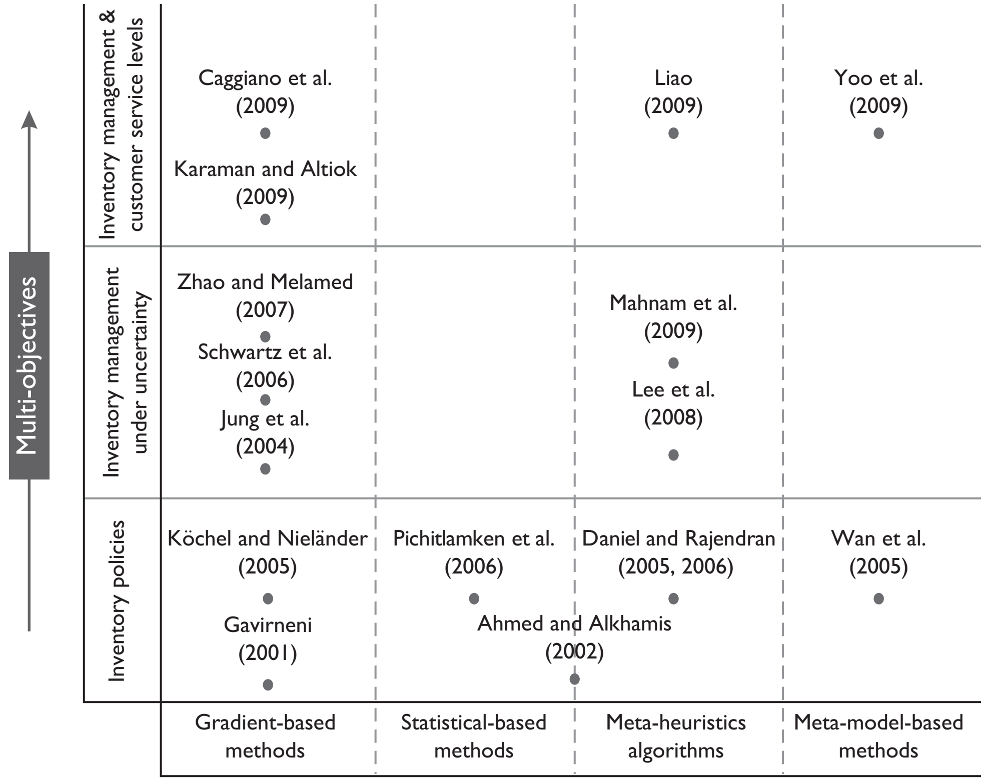
Determining optimal values of stock levels in the stochastic environment of the SC is challenged by various sources of uncertainty in the SC, resulting from the variability in customers' demand or the unreliability of external suppliers. To cope with this uncertainty in demand, Jung et al. (2004) proposed a simulation-based optimisation approach that incorporates the concept of safety stock as a time-independent lower bound on the inventory level. However, a key limitation of their approach lies in the large computing times required to address SC problems of increasing scope and scale, which consequently may result in more difficulties in determining the relationship between inventory decision variables and SC performance. Due to its gradient estimation capabilities, simultaneous perturbation stochastic approximation (SPSA) (Spall, 1998) can be used in these cases to effectively determine the optimal values of inventory stock levels (Schwartz et al., 2006). Similarly, IPA is used by Zhao and Melamed (2007) to control inventory levels in a single-stage, single-product make-to-stock production under demand uncertainty and random production capacity conditions.

Demand and production uncertainty are usually coupled with optimising more than one objective, such as total inventory cost and customer service levels. Lee et al. (2008) have presented a multi-objective simulation–optimisation framework that integrates simulation, computing budget allocation and multi-objective evolutionary algorithms to optimise inventory and replacement policies. Another multi-objective inventory model is proposed by Mahnam et al. (2009) for a multi-echelon SC that integrates multi-objective particle swarm optimisation and simulation–optimisation. Possibility theory and fuzzy numbers (Zadeh, 1999) are incorporated into their simulation model to handle the uncertainty in SCs. This incorporation has resulted in a flexible decision-making framework that allows linguistic expressions to be used for modelling the reliability of suppliers and to optimise both total inventory cost and fill rate simultaneously.

Inventory control is directly related to the quality of customer service, which is one of the key performance measures in successful SC management. Customer service levels can be computed as the percentage of times that received customer orders are fulfilled by on-hand inventory. The requirements of service levels in a multi-item, multi-echelon distribution system is studied in Caggiano et al. (2009) by developing a comprehensive simulation model to compute optimal fill rates over a wide range of base stock levels. In

Karaman and Altiok (2009), production management is linked to stock levels in a multi-echelon SC where a simulation-based optimisation framework is developed to analyse SC performance using time averages of inventory, back order levels and customer service levels as the key performance metrics of the SC. The metrics are then used by the optimisation algorithm to design the SC in order to minimise the expected total system costs. In Yoo et al. (2009), a framework is proposed to maintain customer service levels close to the target by stock levels of products at both wholesalers and manufacturers. Simulation-based experiments were performed on a three-stage SC to test the performance of the proposed framework. Such trade-offs between customer service levels and total inventory cost is further detailed in Liao (2009). A summary of the literature work in inventory management is given in Figure 7.

Figure 7: Summary of the Literature in the Area of Inventory Management



Production Planning and Scheduling

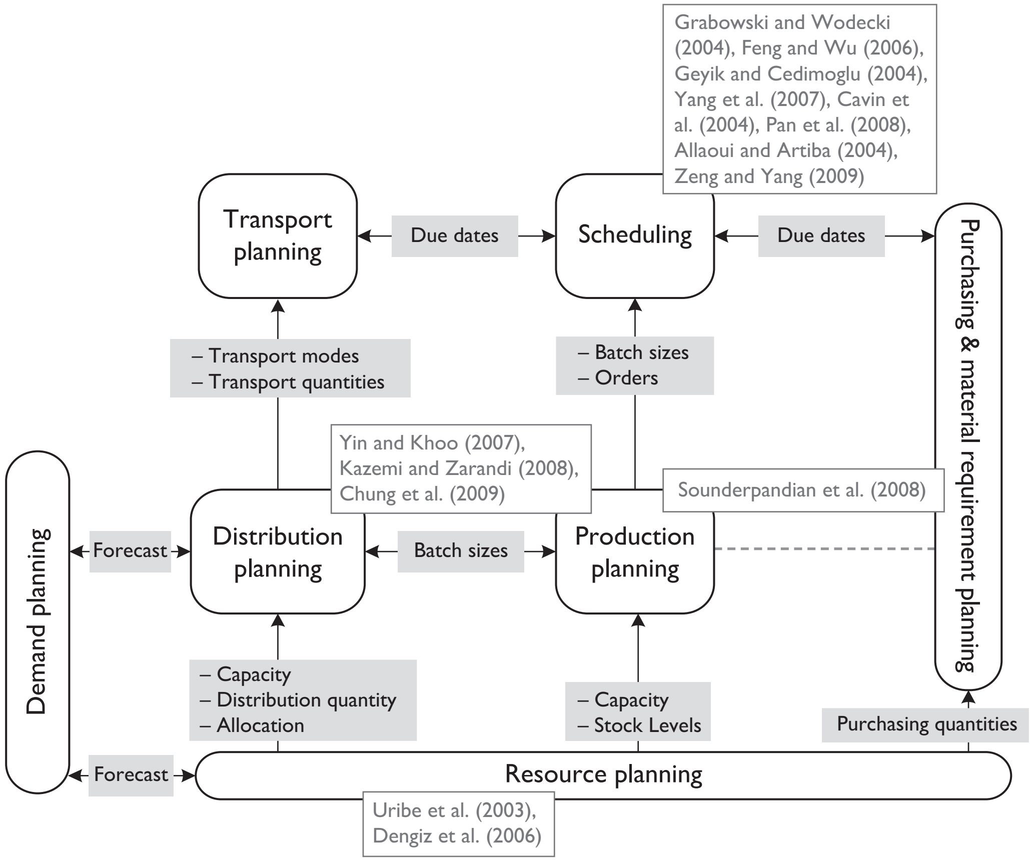
A key role in SC planning is the integration of production functions such as capacity planning, process planning, scheduling and process control. Capacity planning involves deciding how resources will be allocated to meet customer demand. However, demand uncertainty makes capacity planning a difficult task, whether the uncertainty in demand is because of the variations in forecasts of direct demand or by upstream variability in a SC. A two-stage simulation–optimisation framework for rough-cut capacity planning under demand uncertainty is presented in Uribe et al. (2003) for a semiconductor manufacturer. The first stage in their framework characterises the optimal response of the manufacturing system under demand uncertainty while these characterisations are used in the second stage to select a tool set with the addition of budget constraints. Moreover, required labour force and machines can be predicted by building a multiple regression meta-model based on simulating manufacturing systems (Dengiz et al., 2006).

Different TS strategies has been investigated in Grabowski and Wodecki (2004) and Geyik and Cedimoglu (2004) for job-shop parameters for an efficient resource allocation. TS is used by Cavin et al. (2004) to find the optimal batch design in a multi-purpose batch plant where simulation is used as a black box for the evaluation of batch processes. The intelligent search capabilities of GA are incorporated with simulation in Feng and Wu (2006) to find the optimal dispatching schedule for a batch plant. The modelling capability of discrete event simulation and GA is presented in Yang et al. (2007) for solving a multi-attribute combinatorial dispatching problem in a flow shop in a manufacturing plant. Factorial experimental design was used to collect structured data from simulation results which are then used to construct a response surface to optimise the parameters of GA. The Pareto dominance concept is applied in Pan et al. (2008) for solving no-wait flow shop scheduling problems with make-span and maximum tardiness criteria. Another integrated simulation–optimisation framework is developed in Zeng and Yang (2009) to minimise the make-span for operations scheduling; operations sequences were improved through GA while a simulation model is used to evaluate objective functions under different scheduling schemes. Meanwhile, a surrogate model based on artificial neural networks (ANN) is designed to predict objective function to decrease the times of running the simulation model.

A large production loss can occur if machines' downtime and maintenance actions are neglected during the production scheduling process. Consequently, maintenance and repair strategies for the manufacturing plant have to be considered. The flexibility of simulation models allows the inclusion of several practical aspects of these activities, such as stand-by operation modes, deteriorating repairs, aging and sequences of periodic maintenances. An optimisation method can then be utilised to optimise the components' maintenance periods and the number of repair teams (Marseguerra and Zio, 2000). A hybrid flow shop scheduling with machine unavailability intervals (due to breakdowns and preventive maintenance) is considered in Allaoui and Artiba (2004) to minimise flow time and due date. In Allaoui and Artiba's (2004) integrated framework, the simulation module evaluates the solutions generated by SA, which are combined with different dispatching rules. GA is modified in Chung et al. (2009) to deal with distributed scheduling in a multi-factory production with machine maintenance considerations.

Apparently, production facilities are more complex than other stages in SC, such as warehouses and distribution centres, in terms of resource constraints and the dynamic of production (Griffiths and Margetts, 2000). Such dynamics and variations in factory schedules might degrade the overall performance of an SC. Consequently, integrating production planning and scheduling with other SC units became evident. Figure 8 shows the application of simulation–optimisation for the planning activities in supply chain.

Figure 8: Examples of Planning Activities in Supply Chain Management



A coordination between two successive stages of an SC is discussed in Mansouri (2005) for a sequencing problem to minimise total set-ups and to minimise the maximum number of set-ups between the two stages. For solving these two NP-hard problems, a multi-objective genetic algorithm solution was proposed which had proven its capabilities of finding

Pareto-optimal solutions. An integrated framework based on GA and TS is presented in Yin and Khoo (2007) for a distributed hierarchical model for SC planning and scheduling optimisation with a consideration of SC capacity, business strategies and customer requirements. A simulation–optimisation framework is demonstrated in Sounderpandian et al. (2008) for production planning, which considered the interdependency between demand and material supplies and the uncertainties emanating upstream and downstream in the SC. Production plans were generated by GA while simulation is used for their evaluation. A joint production–distribution planning is suggested by Kazemi and Zarandi (2008) for multi-stage, multi-product SCs where the coordination level between SC components is increased by the parallel processing capabilities of their agent-based simulation framework. Stockton et al. (2004) have discussed a wide range of planning decision types, such as aggregate planning, lot sizing within material requirements planning, and production line balancing using GA.

Transportation and Logistics Management

Logistical activities may involve transporting raw materials from a number of suppliers, delivering them for manufacturing, movement of the products to various warehouses, and eventually distribution to customers. Effective management for these activities may lead to a considerable reduction in SC costs (Christopher, 1999). Due to the volatility of today's market, other crucial elements have to be considered besides logistics costs, such as customer satisfaction levels. Consequently, restructuring distribution networks to cut costs and to achieve higher customer service is another challenge that SC managers face (Jing and Jin-Fei, 2006). With such dynamics and uncertainties of SC networks, simulation modelling can be an attractive approach for analysing logistics and distribution networks (Iannoni and Morabito, 2006).

The design and deployment of a distribution logistics system using a simulation–optimisation approach has been presented by Rao et al. (2000) for a multiple-echelons SC with capacity constraints, uncertain demand and multiple products. They used an integrated model composed of network flow techniques, inventory theory and simulation-based optimisation (IPA) in order to find the optimal configuration of the distribution network of the SC that maximises the total revenues and minimises the total SC cost. Another hybrid optimisation–simulation modelling approach is presented in Ko et al. (2006) for a multi-period, two-echelon, multi-commodity, capacitated SC where GA is used to determine the dynamic distribution network structure while uncertainty in customer demands, order picking time and travel time are captured by a simulation model. However, GAs cannot cope with certain types of disturbances, such as order cancelation during the logistics scheduling process, which necessitate re-optimisation of the whole problem by GA. On the contrary, ant colony optimisation (ACO) is able to find new optimisation solutions without re-optimising the problem (Silva et al., 2008). Due to its flexibility, ACO has been used, not only for scheduling logistics that consider supplier–logistic systems, but also for a full distributed optimisation that consider all echelons of the supply chain. A generic SC model with suppliers, logistics and distributors is demonstrated in Silva et al. (2009) with the objective of minimising the tardiness (i.e. the difference between the release date and the delivery date of the order) of the total orders, minimising the number of orders that are not delivered or delayed, maximising the number of orders that delivered at the correct date, and minimising the total travelling costs of vehicles.

Optimising product delivery from suppliers to customers by vehicles is known as the vehicle routing problem (VRP). TS is investigated in Fu et al. (2004) as a way of solving a special kind of VRP called Open-VRP, where vehicles have to revisit their assigned customers in the reverse order. A truck and trailer vehicle routing problem (TT-VRP) is considered in Tan et al. (2006) with the objective of minimising the routing distance and the number of trucks required. A hybrid multi-objective evolutionary algorithm (HMOEA) is applied to find the Pareto optimal routing solutions for such TT-VRPs. Another GA is presented in Lacomme et al. (2006) based on the non-dominated sorting genetic algorithm (NSGA) for the bi-objective capacitated arc routing problem (CARP). Both the total duration of trips and the duration of the longest trip (make-span) are to be minimised. Another type of VRP is known as VRP-TW, the objective of which is to serve a number of customers within predefined time windows (TW) at a minimum travelled distance, considering the capacity and total trip time constraints for each vehicle. Such a combinatorial optimisation problem is investigated in Tan et al. (2001) by applying TS and SA. However, there is a variation in the travel time from one customer to another. Such time-varying windows are regarded by Zheng and Liu (2006) as fuzzy variables. They developed a hybrid intelligent algorithm integrating simulation and GA to minimise the total travel distance of all vehicles. Besides service time, customer demand is another parameter that may feature variability. This vehicle routing problem with stochastic demand (VRP-SD) is addressed in Tan et al. (2007) by using a hybrid between multi-objective evolutionary algorithms (MOEA) and simulation. MOEA searches and generates routes while simulation is used to evaluate the costs of routes in terms of travelling distance, driver remuneration and number of vehicles required. Fuzzy variables are used in Erbao and Mingyong (2009) to deal with these uncertainties in customer demand by integrating simulation and evolution algorithms to minimise the total travelled distance for vehicles. A summary of reviewed articles on vehicle routing problem is given in Table 1.

Table 1: Optimisation of Vehicle Routing Problems (VRPs)

Author(s)	VRP Problem	Optimisation Algorithm	Objective Functions
Fu et al. (2004)	Open-VRP	Tabu Search	- Number of vehicles - Total travelling cost
Tan et al. (2006)	TT-VRP	HMOEA	- Number of trucks - Routing distance
Lacomme et al. (2006)	CARP	NSGA	- Total trip duration - Longest trip (make-span)

(*Continued*)

Table 1: (Continued)

Author(s)	VRP Problem	Optimisation Algorithm	Objective Functions
Tan et al. (2001)	VRP-TW	Tabu Search Simulated Annealing	- Total travelled distance
Zheng and Liu (2006)	VRP-TW	Genetic Algorithm/ Fuzzy	- Total travelled distance
Tan et al. (2007)	VRP-SD	MOEA	- Total travelled distance - Number of vehicles - Driver remuneration
Erbao and Mingyong (2009)	VRP-SD	DEA/Fuzzy	- Total travelled distance

Supply Chain Collaboration, Coordination and Design

In today's volatile market environment, business organisations interact together in a collaborative manner in order to gain more benefits in different dimensions, such as a faster response to customer demands, greater flexibility for market changes, a greater reduction in inventory stocks, and higher levels of customer satisfaction (Barratt, 2004). A central coordination system is proposed by Chan et al. (2004) to model collaboration rules and to optimise demand allocations in a three-echelons SC network. The coordination system is equipped with a multi-criteria GA to optimise two types of criteria, qualitative and quantitative. Qualitative criteria include quality of supply, accuracy of due date fulfilment and accuracy of quantity fulfilment, while quantitative criteria include total cost, total lead time and equity of utilisation.

Internal coordination between SC nodes and external integration (informational consistency between the organisation and the market) are key aspects to secure price and availability of necessary supplies in the face of volatile global demand. A simulation-based optimisation study is presented by Crespo Marquez and Blanchar (2004) to define, characterise and simulate three generic types of suppliers with varying degrees of security and flexibility. Demand uncertainty is addressed by adding in-transit and warehoused inventories to asynchronous production and shipping lead times. Optimisation is then applied to measure the tradeoffs between alternative suppliers. Due to the recent increase in outsourcing, the decision-making process of supplier selection has been complicated by the fact that various criteria must be considered simultaneously. These criteria have been analysed in Ding et al. (2005) by considering purchasing costs, transportation costs, inventory costs and total backlogged demands as the target key performance indicators (KPIs). The estimated values of these KPIs – generated by a simulation model – are used to evaluate candidates' supplier portfolios. Such portfolios are created by a GA optimiser, which continuously searches different configurations of the SC, by selecting one or more suppliers plus corresponding transportation modes. This work has been extended in Ding et al. (2006) by adopting a multi-objective genetic algorithm for achieving the trade-off between conflicting objectives, e.g. costs and customer service level. Additionally, the framework addressed not only strategic decisions (e.g. network configuration), but also operational aspects of each proposed network configuration, such as inventory control parameters and transportation allocation.

The process of sequential decision making under uncertainty is investigated in Mele et al. (2006) to maximise the profit of an SC by finding decisions related to the operational/tactical levels. The presented framework relies on the use of a hybrid simulation–optimisation strategy involving two nested loops. The inner loop generates different scenarios that are then simulated using a multi-agent simulator for the SC, whereas the outer loop involves an optimisation process based on GA. Koo et al. (2008) demonstrated another application of simulation–optimisation to support optimal design and operation decisions in an integrated SC network. Decision variables (e.g. safety stock levels, investment throughput, capacity investment, production cycle time and procurement cycle time), which form a candidate solution, are passed from the optimisation module to the simulation module to be evaluated. After simulation, the performance of the candidate solution – in terms of total revenue, total procurement cost, total operating cost, total product inventory cost and customer satisfaction index – is passed back to the optimisation module, which then proposes new candidate solution(s), if necessary. In To et al. (2009), a coordination between SC nodes is addressed in terms of process design and control. Irregularity of information and data interchange among isolated functional and enterprise activity tasks are major challenges that have been addressed in their study. GA is used to find the optimum process structural model while a dependency-based process simulation is used for performance evaluation.

SELECTION CRITERIA OF SUPPLY CHAIN OPTIMISERS

Improper selection of the optimiser may result in inadequate strategic decisions made by managers. The suitability of the optimisation technique depends on many factors related to the SC application and the optimisation technique. These factors have been identified based on reviewing simulation–optimisation for a wide range of SC applications, which are discussed in the following subsections.

Decision Variables Space

In a discrete space, decision variables take a discrete set of values such as the number of machines, locations of depots, scheduling rules or policies, etc. On the other hand, in a continuous space, the feasible region consists of real valued decision variables such as order quantity and reorder quantity in inventory problems. Decision variables can be qualitative (e.g. queuing strategies) or a mixture of discrete and continuous values.

Solution Space

Solution space is the space of all possible solutions that satisfy all the constraints. Some categories of optimisation methods are preferred when the search space is finite (i.e. decision alternatives are small or the combination of variable values has a small range), whilst other categories are more effective when the solution space is very large or infinite.

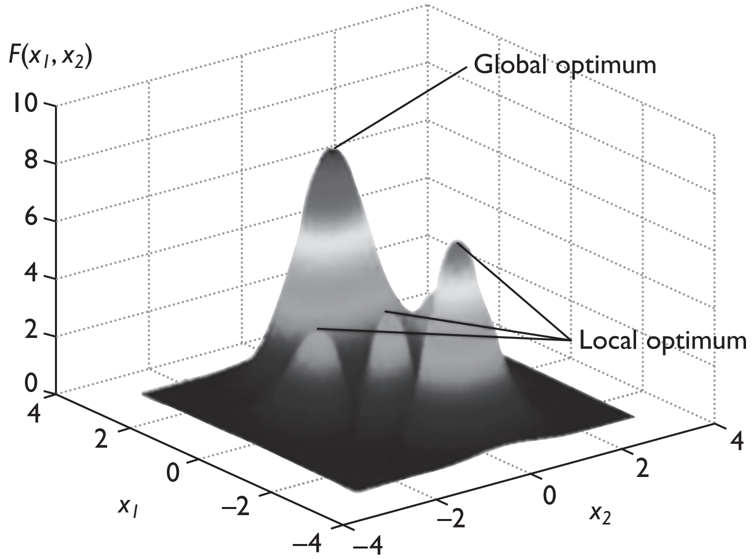
Modelling Approach

Traditionally, mathematical programming methods (Fourer et al., 1990) are used for problems that can be modelled with equations that describe the constraints and objectives of the underlined problem. Developing such analytical expressions for real-world problems is challenged by the embedded complexity and uncertainty within these systems. Instead, simulation models (Ryan and Heavey, 2006) are potent tools for analysing the dynamics of complex systems. An optimisation algorithm then interacts with the system model to provide optimal values of decision variables. Not all optimisation methods are suitable for working with both types of modelling.

Optimisation Searching Mechanism

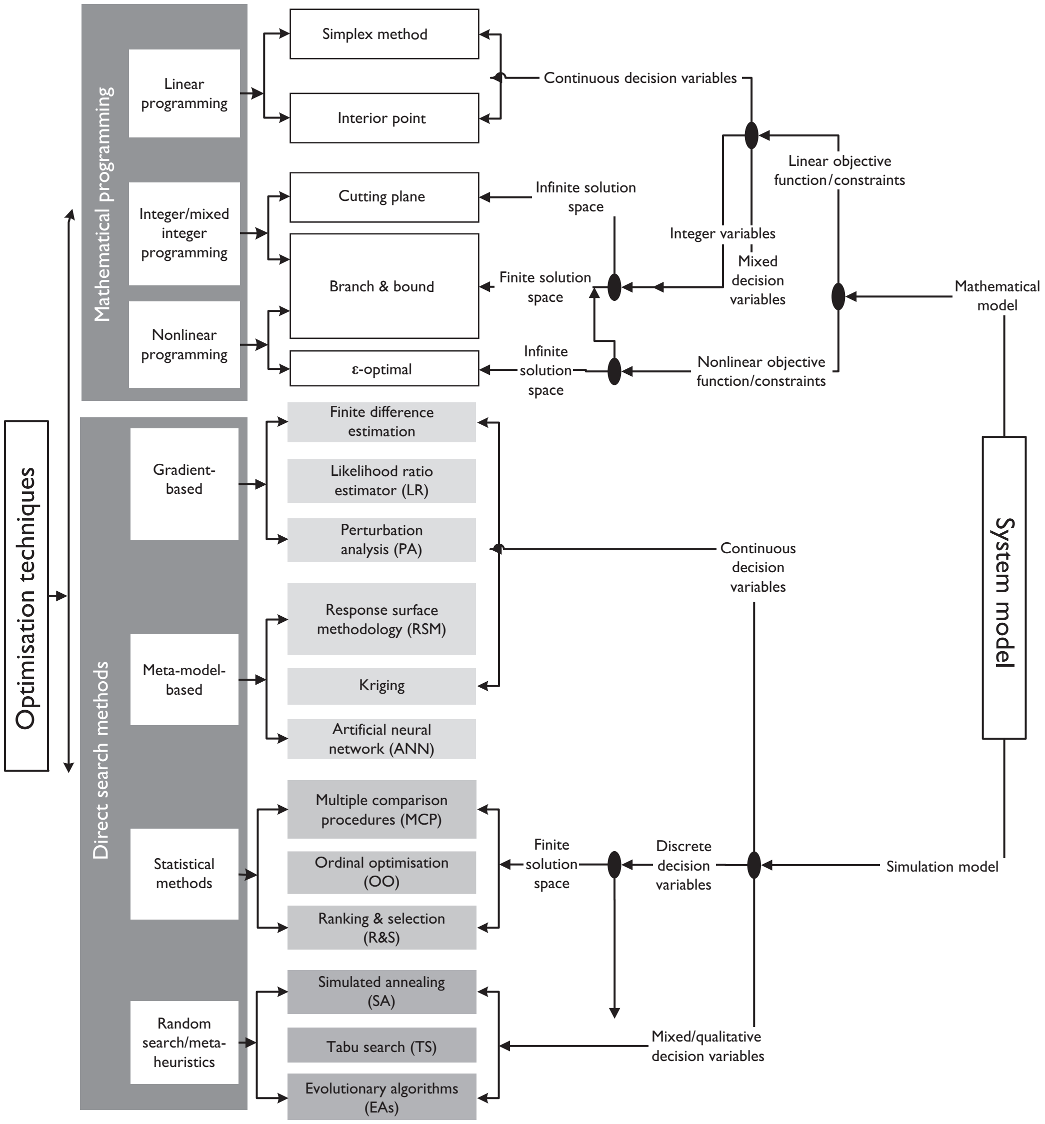
Optimisation methods use different mechanisms for searching for the optimal solution. This is highly dependent on many factors, such as the modelling approach, problem complexity and the objectives of the decision makers. The optimum solution is the vector that gives the global optimum value (maximum/minimum) of the objective function, and avoids the local optimum (see Figure 9). Based on the reviewed articles, optimisation methods can be characterised as local search methods, global search methods or guaranteed optimal methods.

Figure 9: Global Optimum vs Local Optimum



A variety of schemes have been proposed in the literature for classifying optimisation techniques. Decision variables can be used to classify optimisation methods into continuous input parameter methods and discrete input parameter methods (Swisher et al., 2000). Continuous input parameter methods include gradient and non-gradient methods; on the other hand, discrete input parameter methods include statistical methods, ordinal

Figure 10: Optimisation Techniques Map (OTM)



optimisation and meta-heuristics algorithms. The shape of the response surface (i.e. global as compared to local optimisation) can be used also to categorise optimisation techniques into local optimisation techniques and global optimisation techniques (Tekin and Sabuncuoglu, 2004). Local optimisation techniques are further divided into discrete decision space methods and continuous decision space methods; global optimisation techniques include meta-heuristics, sampling algorithms and gradient surface methods. However, simulation models are only considered in the aforementioned classifications, which neglect other modelling approaches. Different modelling methods have to be considered to provide a consistent and comprehensive classification of optimisation methods (Beyer and Sendhoff, 2007).

In this review, the factors that control the choice of optimisation technique for SC applications are considered concurrently: optimisation mechanism, decision variables, solution space and modelling approach. The classification scheme is named Optimisation Techniques Map (OTM) (see Figure 10), which can be viewed from two perspectives: from the right, the OTM starts with the modelling approach to classify the optimisation techniques into mathematical programming and direct search methods. Afterwards, decision variables and solution space are used respectively for further categorisation. On the other hand, the OTM can also be viewed from the left side of the figure as a classification of methods in terms of the optimisation mechanism: mathematical programming, gradient-based, meta-model-based and statistical methods, and meta-heuristics.

DISCUSSION

The articles discussed in this review have been published in a wide range of journals (see Figure 11), which reflects the multi-disciplinary characteristics of applying simulation modelling and optimisation in the SC context. A variety of concepts from different disciplines, such as operations research, economics and management science, engineering, artificial intelligence, expert systems and simulation modelling, come together to provide reliable and flexible tools for SC managers.

Due to the large number of daily decisions that have to be taken, inventory management and production planning and scheduling represent about 68 per cent of reviewed articles (see Figure 12). This high percentage sheds light on the powerful capabilities of simulation to incorporate more details at the operational and tactical levels.

Among other application areas of SCs, there is more emphasis on inventory management. This is because all nodes within SCs, from manufacturing plants and distribution centres to retailers, have an element of inventory management. Gradient-based optimisation methods are suitable for inventory management; for example, perturbation analysis (PA) can estimate all gradients of the performance measure by tracking the propagation of simulation results sensitivity through the system (Ho, 1985). However, to have these tracking capabilities, a deep understanding of the simulation model is required to allow system optimisers to integrate their algorithms into the model. SPSA overcomes this problem by considering the simulation model as a black box (Sadegh and Spall, 1998). However, some inventory problems have only discrete variables which prevent the use

Figure 11: The Distribution of Reviewed Articles in Academic Journals Reflects the Multi-Disciplinary Characteristic

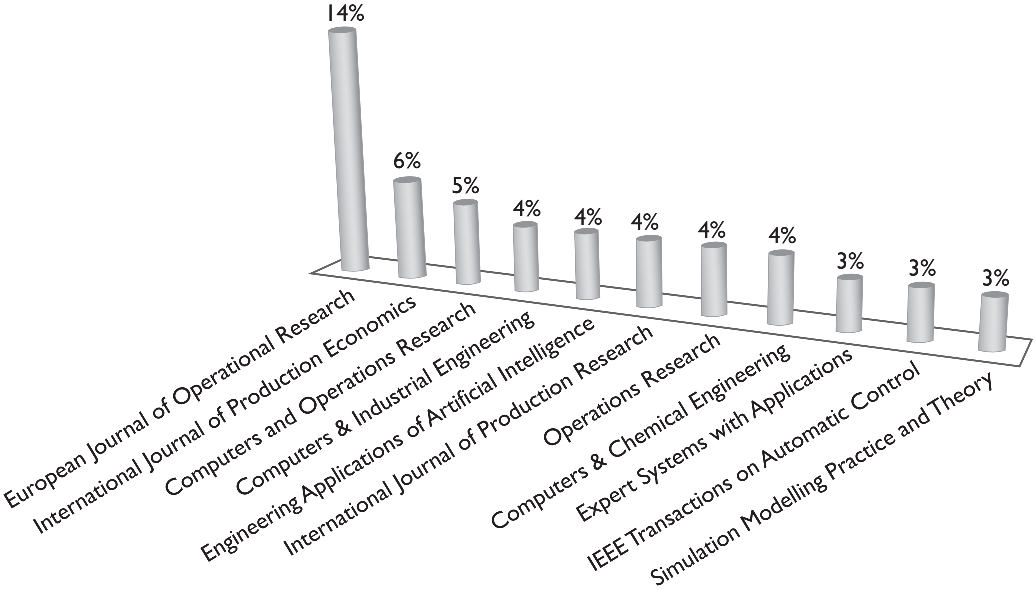
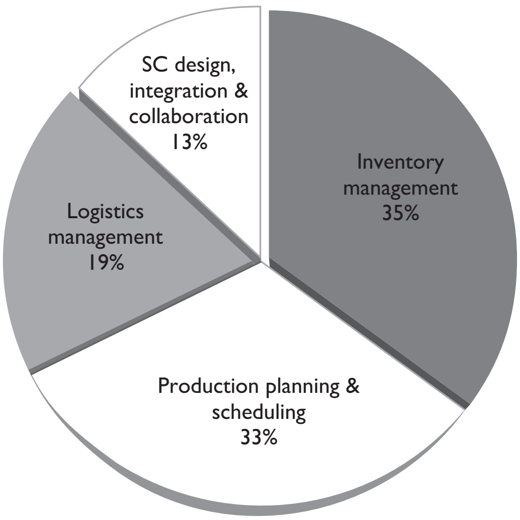


Figure 12: Percentage of Applications Area in the Literature Review

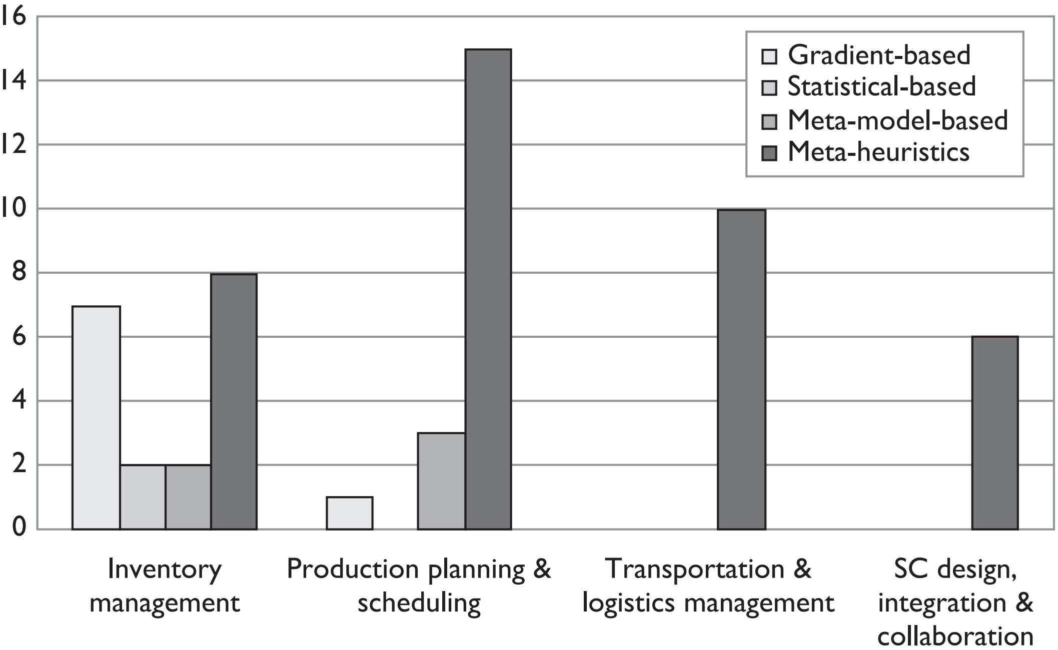


of gradient-based techniques. Statistical methods are then used for this type of problem. Subset selection approaches are most useful when the number of alternatives is quite large. Indifference zone approaches could then be used to select a single solution alternative that is within a pre-specified difference from the true optimum. The major disadvantage of ranking-and-selection procedures is the requirement of independence over competing solutions, which precludes the use of most variance reduction techniques as common random numbers. Ranking-and-selection and multiple-comparisons procedures are only powerful for optimisation when the parameter set is finite.

In the area of production planning and scheduling, these limitations of gradient-based methods and statistical techniques are avoided by more emphasis on meta-models and meta-heuristics. A key advantage of response surface methodology is its ability to optimise objective functions with unknown variance along with high levels of uncertainty (Kleijnen et al., 2004). Moreover, it can be extended to allow multiple random system responses with multi-constraints (Kleijnen, 2008). However, for some meta-model-based methods such as ANN, special attention for the training set has to be given to avoid over-fitting approximation, which directly affects the meta-model predictive accuracy (Alam et al., 2004).

As shown in Figure 13, the range of application domains solved by meta-heuristics is far greater than other methods. Problem-specific knowledge (e.g. non-standard goals,

Figure 13: Simulation-Optimisation Techniques for Each Application Area in the Supply Chain



constraints, objectives and conditions) can be more easily incorporated into the solution process, which broadens the range of problems to which multi-objective methods are applied. Besides, meta-heuristic algorithms can handle models with integer variables, discrete variables and/or qualitative variables, whereas continuous variables have to be approximated before the meta-heuristic is applied. However, more computational efforts are needed at this stage in order to increase the degree of accuracy. Moreover, meta-heuristic methods are not function optimisers. That is, their purpose is to seek and find good solutions to the problem, rather than a guaranteed optimal solution. Therefore, if the model is sufficiently simple, it is more efficient to use conventional methods to obtain an optimal solution, rather than meta-heuristics. However, most of the reviewed articles deal with complex real-world problems for which there is no conventional method that is guaranteed to find the optimal solution. A major disadvantage of meta-heuristic algorithms is the fact that there are a larger number of parameters to be set by the optimiser in meta-heuristics than in other methods. In many cases, the solution is sensitive to these parameters and hence different parameter settings are needed before a good solution is obtained. Finally, none of the multi-objective evolutionary algorithms has a proof of convergence to the true Pareto-optimal solutions (Marco et al., 2002).

CONCLUSION

Understanding and improving the performance of SCs is challenged by a high level of uncertainty, conflicting objectives, a large number of constraints and inter-connected decision variables. Making decisions that lead to the optimum performance of SCs seems to be impossible. Despite their computational efficiency, analytical models are impractical in SC settings due to their limitations in modelling important details and features of real industrial systems. On the other hand, simulation models provide the flexibility to accommodate arbitrary stochastic elements, and generally allow modelling of all the complexities and dynamics of real-world SCs. Optimisation methods are then used by decision makers to find the optimum set of decision variables and the best possible alternatives while their impact on the system performance is evaluated using simulation models. Therefore, integrating simulation and optimisation provides decision makers with a comprehensive solution toolbox. This paper presents a state-of-the-art literature review of simulation modelling and optimisation techniques in the context of SC management. Based on the literature, SC applications have been classified into four main application areas: inventory management, production planning and scheduling, transportation and logistics management, and SC collaboration, coordination and design. Moreover, a classification of optimisation techniques is provided that considers the optimisation mechanism, the type of decision variable and the search space. Meta-heuristic algorithms are presented for SC applications because of their global optimisation capabilities in stochastic environments. Statistical methods and meta-model-based methods can be incorporated with meta-heuristics to provide more reliable solutions in a reasonable timeframe. The absence of a clear guideline that considers problem factors (e.g. constraints handling, multi-objective and robust solutions) makes the decision to select an optimisation technique considerably hard. The review has identified the main criteria of selecting an SC optimiser in order to provide guidance for researchers and practitioners for a proper selection of optimisation technique.

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