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SIMULATION OPTIMIZATION FOR SUPPLY CHAIN DECISION MAKING

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ABSTRACT

Supply chain design and optimization have been a subject of interest for academia and industry alike. We focus on stochastic and hybrid models in this paper since they closely approximate reality. This paper explains the structure of supply chains, decisions required to be taken in a typical supply chain, and models developed for supply chain design and optimization. The paper further explores optimization via simulation to solve stochastic and hybrid models, its applications in the supply chain domain and future research directions arising out of recent emphasis on sustainability, robustness and resilience of supply chains and the opportunities offered by advances in Industry 4.0, Machine Learning and Big Data.

1. WHAT IS A SUPPLY CHAIN?

Chopra and Meindl (2016) define a supply chain as "all parties involved, directly or indirectly, in fulfilling a customer request. The supply chain includes not only the manufacturer and suppliers, but also transporters, warehouses, retailers, and even customers themselves."

Figure 1: Schematic diagram of physical flows in a supply chain.

Thus a supply chain consists of several suppliers supplying raw materials to a manufacturer or a network of manufacturers manufacturing components and finished products; the finished products are sent from the network of manufacturers to a network of distributor warehouses; the distributors send the finished products to a network of retailers; the customer can thereby procure the goods at the retailers. Thus the physical flows of materials are shown in Figure 1. These physical flows occur with the aid of transporters or logistics service providers.

There are, however, other flows that occur in a supply chain. The retailer places orders for goods on the distributor to replenish its inventory, the distributor places orders in turn on the manufacturer, the manufacturer informs the production manager to produce the goods and the production manager places orders on raw material suppliers and component manufacturers for supply of raw materials and components respectively. Thus there is a reverse flow of information from the retailer to the supplier. Further, there is also a reverse flow of funds occurring from the retailer to the supplier for the raw materials, components, and finished goods supplied.

The retailer maintains an inventory of finished goods at its premises to cater to uncertain demand from the customers and reduce the ordering costs associated with placing an order for replenishment from the distributor. The inventory levels must also consider the demand that may arise between the placement of an order for replenishment and its receipt from the distributor. The transporter takes a

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finite lead time to collect finished goods from the distributor warehouse and its delivery at retailer premises. However, maintaining an inventory involves a cost associated with tying up the working capital and the cost of store area dedicated to stocking the inventory. Thus, the retailer must optimize inventory levels to ensure that customer demands are met at minimum cost. The distributor and manufacturer must exercise similar judgments to ensure optimum inventory levels.

2. DECISIONS REQUIRED TO BE MADE IN SUPPLY CHAINS

Chopra and Meindl (2016) proposes three levels of decisions:

1. Completive strategic decisions: These include location and capacity of manufacturing plants and distributor warehouses; allocation of distributors to manufacturing plants and retailers to distributors; demand planning; supplier selection; and outsourcing.
2. Tactical decisions: These include production planning, distribution planning, workforce planning, and inventory control.
3. Operational decisions: These include workforce scheduling, vehicle routing, production lot sizing, and production sequencing and scheduling.

There are diverse objectives that a company wishes to achieve while making the above decisions. Min and Zhou (2002) lists the key objectives which usually guide supply chain decisions:

1. Maximization of customer satisfaction by way of product availability and response time.
2. Maximization of monetary value given by the ratio of revenue earned to cost incurred. This could involve metrics such as profit, total cost (comprising inventory carrying cost, ordering cost, and transportation cost), net asset turns (ratio of gross revenue to working capital), inventory turns (ratio of the annual cost of goods sold to average inventory investment), cube utilization (ratio of space occupied to space available) and R.O.I. (ratio of net profit to capital employed).
3. Minimization of risks associated with risk of failures associated with delivery of raw materials, machine and transportation reliability, quality of product and order picking errors. This is also associated with the concept of resilience which is the ability of the supply chain to recover post a disruption (Ponomarov and Holcomb 2009).

These objectives have to be achieved usually within boundaries set by various constraints. These constraints include customer service requirements (for example, delivery time windows and maximum holding time for backorders), maximum investment capital available, maximum production capacity, maximum inventory holding capacity, availability of workforce, and maximum working hours (including overtime hours). Further, it may be noted here that decision variables may be discrete or continuous.

3. SUPPLY CHAIN MODELS FOR DECISION MAKING

Supply chain models can be classified into four categories (Min and Zhou 2002):

1. Deterministic models which assume that all parameters are known with certainty. These could either have a single objective or multiple objectives.
2. Stochastic models which include uncertain and random parameters. Examples of uncertain and random parameters include customer demands, lead times, raw material price, transportation costs, machine availability, and quality of finished goods.
3. Hybrid models have a combination of uncertain parameters and parameters known with certainty.
4. I.T.-driven models incorporate real-time data in the models. These models include material requirements planning (M.R.P.), ERP, warehouse management system (W.M.S.), transportation management systems (T.M.S.), distribution resource planning (D.R.P.), collaborative planning, and forecasting replenishment (CPFR).

We will focus on stochastic and hybrid models in this paper since they closely approximate reality. According to literature survey done by (Mula et al. 2006; Peidro et al. 2008; Mula et al. 2010), these models have been used in the areas of aggregate planning, hierarchical production planning, materials requirement planning, capacity planning, manufacturing resource planning, inventory management, and supply chain planning. (Mula et al. 2006) has identified the analytical (including L.P., MILP, N.L.P., stochastic programming, Laplace transforms, and Markov decision processes), artificial intelligence (including expert systems, reinforcement learning, fuzzy set theory, fuzzy logic, neural networks, genetic algorithms, and multi-agent systems), and simulation (including Monte Carlo techniques, heuristic methods, network modelling, and queuing theory) approaches used for these models. Most of the models developed so far have considered one to three sources of uncertainty; the common sources being demand, supply, and process parameters (Peidro et al. 2008).

Simulation has long been strongly advocated for the analysis and design of supply chains to care of uncertain and random parameters (Ingalls 1998; Lee et al. 2002). Deterministic modelling is argued to be relevant only in the case of operational decisions wherein the time horizon is shorter (one or two weeks), and parameters can be known with certainty to a larger extent. Strategic decisions (spanning over few years) and tactical decisions (spanning over few months) cannot be taken based on deterministic models- these decisions should be taken based on models which can handle uncertain and random parameters (especially in regard to raw materials supply, finished goods demand at retailer end, finished goods quality during the production process, reliability of production process machines and lead times of transportation).

4. WHAT IS OPTIMIZATION VIA SIMULATION?

Simulation enables analysis and "what-if" evaluation of a particular scenario of supply chain systems, wherein each scenario contains different input parameter combinations (Barton 2009; Banks et al. 2014). The term "factors" is used for input parameters, and the term "responses" is used for output performance measures (Law 2015). For example, for an inventory system simulation model, the possible factors could be the reorder point and Order-up-to level. The possible responses could be the average cost per month and the average number of items in inventory. Factors are classified as controllable if the manager can change them. The manager cannot influence uncontrollable factors. However, uncontrollable factors might still be of interest to analyse system performance; for example, analysing the supply chain's performance in case of a 20 percent increase in transportation lead times.

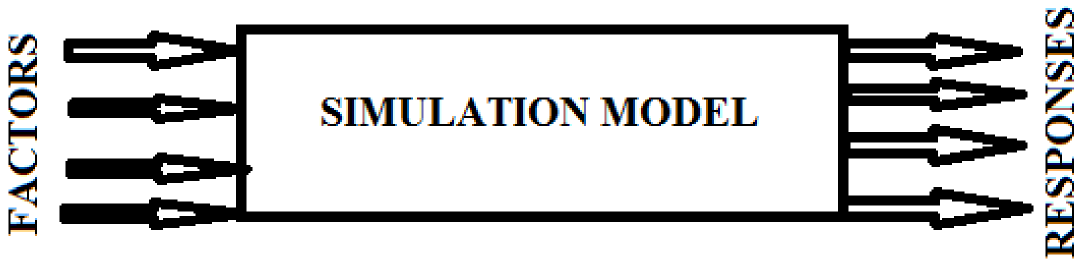

Figure 2: A typical simulation model.

Running a simulation model gives the response for a particular set of values of factors (see Figure 2). It may be noted here that running a simulation model for a particular set of values of factors consumes an enormous amount of time. Many parameters may have too many values or may have an infinite number of values (in case it is continuous). It might be impossible to evaluate all the combinations of parameter values to select the set of parameter values giving the optimal response. Further, common optimization procedures such as linear programming, non-linear programming and mixed integer programming cannot be used in such cases to determine the optimal parameter values giving the best response since there is no mathematical model.

Several methods have been developed over the years to tackle this problem of optimisation via simulation. Herein, we conceptualize a general optimization problem of the form given below (Fu et al. 2005; Figueira and Almada-Lobo 2014):

$$Min\ J(\theta), \theta \epsilon \Theta$$

$$\text{Subject to } g(\theta) \geq 0$$

Where $\theta \epsilon \Theta$ represents the vector of factor variables, Θ represents the feasible solution space, $g(\theta)$ represents the constraint function and $J(\theta)$ the response vector as a function of factor variables. $J(\theta)$ and $g(\theta)$ is not available directly but estimated through simulation runs.

The methods developed for optimization of the above problem are listed below (Meketon 1987; Fu 1994; Carson and Maria 1997; Tekin and Sabuncuoglu 2004; Barton and Meckesheimer 2006; Barton 2009; Hachicha et al. 2010; Ammeri et al. 2011; Moghaddam and Mahlooji 2016):

1. Methods developed for unimodal decision space (with single global optima) with factors which are discrete in nature: Ranking and Selection, Multiple Comparison methods for the finite or small feasible region; Ordinal Optimization, Random search, Simplex/Complex search, Nested Partition methods for large or infinite feasible region
2. Methods developed for unimodal decision space with factors that are continuous in nature: Response Surface Methodology, Regression Spline Metamodels, Spatial Correlation Metamodels, Radial Basis Function Metamodels for continuous function $J(\theta)$; Gradient Approaches (Finite Difference Estimates, Perturbation Analysis, Frequency Domain Analysis, Likelihood Ratio Estimates, Harmonic Analysis) and non-Gradient Approaches (Sample path optimization, Simplex search method, Hooke-Jeeves method) for differentiable response function $J(\theta)$
3. Methods developed for non-unimodal decision space: Evolutionary Algorithms (Genetic Algorithm and Evolutionary Programming), Tabu Search, Simulated Annealing, Bayesian/Sampling Algorithms, Gradient Surface Method.

5. APPLICATIONS OF OPTIMIZATION VIA SIMULATION FOR SUPPLY CHAIN DECISION MAKING

Though optimization via simulation methods discussed above have been in vogue for quite some time, there are relatively few papers that apply these methods in the supply chain domain. A few applications are listed here, though it cannot be claimed that it is an exhaustive list.

Abo-Hamad and Arisha (2011) is the only review paper which discusses the applications of optimization via simulation methods in the supply chain domain. They reported that papers published in the area of optimization via simulation methods in the supply chain domain for the period 2000-2009 were far less than those published in simulation–optimization in general or supply chain management in general (see Table 1). Their classification of papers published in the area of optimization via simulation methods in the supply chain domain for the period 2000-2009 is given in Table 2.

Table 1: Number of optimization via simulation papers published (Abo-Hamad and Arisha 2011).

Year	Number of papers published in area of optimization via simulation methods	Number of papers published in supply chain domain	Number of papers published in area of optimization via simulation methods in supply chain domain
2000	349	143	2
2001	315	156	3
2002	391	204	1
2003	410	273	2
2004	481	261	8
2005	561	311	6
2006	705	387	11
2007	771	442	2
2008	849	566	5
2009	1097	689	20

Table 2: Classification of applications (Abo-Hamad and Arisha 2011).

Supply Chain Application	Papers Published
Inventory management	Gradient based methods: (Gavirneni 2001; Kochel and Nielander 2005; Jung et al. 2004; Schwatrz et al. 2006; Zhao and Melmad 2007; Karaman and Altiok 2009; Caggiano etal 2009) Statistical based methods: (Ahmed and Alkhamis 2002; Pichitlamken et al. 2006) Metaheuristic algorithms: (Daniel and Rajendran 2005, 2006; Lee et al. 2008; Mahnam et al. 2009; Liao 2009) Metamodel based methods: (Wan et al. 2005; Yoo et al. 2009)
Production planning and scheduling	Two stage framework: (Marseguerra and Zio 2000; Uribe et al. 2003) Multiple regression metamodel: (Dengiz et al. 2006) Tabu Search: (Grabowski and Wodecki 2004; Geyik and Cedimoglu 2004; Cavin et al. 2004) Genetic Algorithm: (Stockton et al. 2004; Mansouri 2005; Feng and Wu 2006; Yang et al. 2007; Yin and Khoo 2007; Pan et al. 2008; Sounderpandian et al. 2008; Chung et al.2009; Zeng and Yang 2009) Simulated Annealing: (Allaoui and Artiba 2004)
Transportation and Logistics Management	Genetic Algorithm: (Ko et al. 2006; Lacomme et al. 2006; Zheng and Liu 2006) Ant Colony Optimisation: (Silva et al. 2008) Tabu Search: (Fu et al. 2004) Simulated Annealing: (Tan et al. 2001) Multiobjective Evolutionary Algorithm: (Tan et al. 2007)

Further to the review of Abo-Hamad and Arisha (2011), there have been quite a few papers published, few of which are discussed here. Merkuryeva et al. (2010) proposed integration of multiobjective genetic algorithm and response surface methodology (RSM) to optimize the cyclic planning problem of multi-echelon supply chains. Zakerifar et al. (2011) compared Kriging meta-modelling and the response surface methodology to optimize an (s, S) inventory system. They demonstrate that Kriging meta-modelling is able to identify superior solutions to those obtained by RSM approaches for multi-objective optimization. Gansterer et al. (2014) extended the method developed by (Kochel and Nielander 2005) for hierarchical production planning in a make-to-order environment.

In addition to the methodologies discussed in Section 4, there have been other attempts at optimization via simulation. Lee and Kim (2002) proposed a hybrid approach to optimize a multi-product, multi-shop and multi-period integrated production-distribution problem with stochastic machine breakdowns. They used simulation to check the capacity assumptions in case of stochastic machine breakdowns and use the updated capacity parameters for optimization. Almader et al. (2009) in a similar manner as Lee and Kim (2002), iteratively used simulation and optimization to minimize costs of a global supply chain network by simultaneously optimizing the production/transportation schedule and reducing inventory levels.

6. FUTURE RESEARCH DIRECTIONS

Supply chain design optimization promises enormous value for the industry in the renewed emphasis on sustainability, robustness, and resilience of supply chains. Let us take the case of Apple's iPad. The key components of the iPad are the display, battery, motherboard, NFC controller, Wi-Fi/Bluetooth module, flash memory, DRAM memory, CPU/GPU/NPU, power controller and touchscreen controller (Dempsey 2019). These components are supplied by 200 suppliers from 569 manufacturing facilities located in various countries such as Australia, Austria, Belgium, Brazil, Cambodia, China, Costa Rica, Czech Republic, Finland, France, Germany, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Malta, Mexico, Netherlands, Norway, Philippines, Singapore, South Korea, Taiwan, Thailand, UK, USA and Vietnam (Apple 2020). These iPad components are mostly assembled in China and finished iPads (numbering nearly 60 million) shipped to customers around the globe. These supply chains have been made possible by improved efficiency and lower costs of communication and transportations. The move towards containerization and extra-large ships have dramatically lowered the unit costs of transportation thereby promoting lengthier supply chains. For example, a single ship can today carry 18 thousand twenty-foot containers, with each container carrying ten thousand finished iPads. These lengthy supply chains have evolved from the search for best price and quality of goods of suppliers which have translated to higher profits for manufacturers.

However, such lengthy supply chains have tremendous risks associated with them. Risks are associated with a combination of the following aspects: (a) risks associated with each of the components that make up the final product (for example, in terms of their reliability, incorrect forecasting), (b) risks associated with the suppliers who are supplying the components (examples are supplier bankruptcies, piracy, regulatory risks, lack of alternate suppliers), (c) risks associated with the locations and the manufacturing facilities where these components are manufactured or assembled (for examples risk of natural disasters, political upheavals, terrorist attacks, labour unrests, breakdowns in production lines, quality issues), (d) risks associated with the flow of materials, money and information in regard to the components (for example, risks associated with breakdown of vehicles, sinking of ships or containers, congestion at loading or offloading ports, scarcity of transport crews, delays in border crossings, disruptions in internet leading to delay in information transmission, information distortions due to "Bullwhip Effect", cyber-attacks, software glitches, exchange rate fluctuations and disruptions in overseas money transfer system) and (e) risks associated with the work in progress or finished product inventory at various stages of the supply chain (for example risks of natural disasters or accidental damage of inventory) (f) risks associated with customers in terms of inability to collect receivables or cancellation of orders (Chopra and Sodhi 2004; Sheffi 2015). Recent examples of such risks materializing are the disruption in food and flower supply chain from Africa following the ash from Iceland volcanic eruption grounding air traffic across Europe in 2010; hard disk supply chain disruption following floods in Thailand in 2011; Intel's chip and Toyota's supply chain disruption following the 2012 earthquake and tsunami; shortage in chips due to factories shut down during the 2019-20 Covid pandemic affecting the production in automobiles.

It will also be evident that the effects of these risks increase manifold in case of perishable products. These risks have further been amplified with the advent of recent practices such as Just-in-time which promote the reduction of work-in-process and finished goods inventory. Further, today's products are highly complex containing a large number of components, which are in turn made from a number of components. Thus the lack of any component can result in cataclysmic effects down the supply chain (Snyder et al. 2015).

There has been a surge of research on risk management of supply chains since the disruptive events of 9/11 in 2001 and Hurricane Katrina in 2005. The research has focused on the areas of robustness, resiliency and mitigation. Robustness of a supply chain is the ability of the supply chain to withstand disruption with a loss in performance within acceptable limits (Behzadi et al. 2018). Supply chain resiliency refers to the ability of the supply chain to recover quickly from a disruption (Schmitt and Singh 2012). Resiliency of a supply chain largely depends on the safety built into the system (by inventory, supplier redundancy etc.). Time is an important factor in the determination of resiliency of supply chain. It is also possible that the performance level after recovery could be lower than that before the occurrence of the disruption. Supply chain risk mitigation requires determination of the strategies to limit the negative consequences of the risk after its materialisation (Zhengping et al. 2013; Snyder et al. 2015).

Inventories are one of the best strategies for supply chain risk mitigation. However, there are various dimensions to inventory management such as continuous vs periodic review, ordering policies, location of inventory, cost structures, variability of lead times, multi-echelon vs single-echelon etc. A second strategy for risk mitigation is through sourcing flexibility. This can be done in two ways: (a) placing orders on multiple sources simultaneously or (b) placing orders on backup suppliers if primary sources are disrupted. A third strategy for risk mitigation is through demand management. Demand management can be done in three ways: (a) firm can direct customers to another product when the supply of the main product is disrupted or (b) firm can direct customers to alternate locations in case supply to the primary location is disrupted or (c) firm can increase prices in case of fall of inventory levels due to supply disruptions. There is quite a huge body of literature which applies OR/MS models for determining when to order, from whom to order, how much to order, where to store the inventory and the manner of routing of inventory through the supply chain network for each of the strategies considered separately (Snyder et al. 2015). There is no research on efficacy of combination of two or more strategies discussed above for risk mitigation.

Since OR/MS models will be difficult to construct in cases of combination of two or more strategies, simulation optimisation methods can be applied to test the efficacy of combination of strategies towards risk mitigation. Further, these methods could also be applied for design of resilient supply chains, since simulation is better equipped to handle the issue of time of recovery rather than analytic models (Ivanov et al. 2017); it may be noted here that design of resilient supply chains is an area which has not yet fully explored (Behzadi et al. 2018). There have been however a few attempts using simulation-based optimisation and optimisation-based simulation methods to test and evaluate risk mitigation strategies, risk response scenarios, and analyse risk effects; however there is a lack of supply risk management processes that integrate the advantages of simulation optimisation and performance management system to improve the design and control of supply chains which face critical risks (Oliveira et al. 2019).

Sustainability has been defined by the World Commission on Environment and Development as "development that meets the needs of the present without compromising the ability of future generations to meet their needs." This has been interpreted to suggest that organizations engage in activities which not only result in their long term economic benefit and competitive advantage, but also positively affect the natural environment and society. In this context, corporations are realizing that supply chain risk management also entails its ability to manage the environmental, economic and social risks of its supply chain (Carter and Rogers 2008). Given the higher complexity of designing supply chains for risk management, simulation optimisation frameworks are a much better alternative to integrated mathematical modelling (Pourhejazy and Kwon 2016).

Supply chain design also needs to take into account the opportunities provided by advances in Machine learning, and Big Data (Garcia and You 2015; Hazen et al. 2015). Supply chains are now awash with Big Data- examples are sales data (with information about price, quantity, items sold, time of day, date, and customer data), consumer data (decision and purchasing behaviour, including items, browsed and bought, frequency, dollar value, and timing), inventory data (at more locations, at a more disaggregated level(e.g., style/colour/size) with monthly to hourly updates), real-time carrier capacity data and sensor data to detect item location in store, in distribution centre (picking, racks, staging, etc.), in transportation unit etc. This can lead to interesting supply chain design optimization in areas such as (i) optimizing inventory management based on sales and customer data, (ii) optimizing shelf display based on customer behaviour data, and (iii) optimization of transportation decisions using sales and inventory data (Waller and Fawcett 2013). Recently, Vieira et al. (2019) proposed a hybrid simulation model using data stored in a Big Data warehouse and statistical distributions to reproduce behaviour that has happened and not happened, respectively. Tordecilla et al. (2020) identified a few research opportunities in considering hybrid simulation-optimization methods combining metaheuristics, simulation and machine learning for designing resilient supply chains.

Machine Learning of the enormous data pool can be used to enhance the supply chain design optimization- for example, (Akbari and Do 2021; Tirkolaee et al. 2021) lists various machine learning techniques that can be deployed such as Decision Tree (D.T.), Q-learning and Support Vector Machine (SVM) algorithms for supplier selection and segmentation, SVM and D.T. algorithms for risk identification, artificial neural networks(ANN) and Bayesian networks for risk assessment modelling, data mining and fuzzy logic for demand estimation, neural networks for lead time forecasting, and adaptive neural networks for vehicle routing.

7. CONCLUSION

This paper provides an overview of the structure of supply chains, decisions required to be taken in a typical supply chain, and models developed for supply chain design and optimization. The paper further explores simulation optimization methods to solve stochastic and hybrid models, their applications in the supply chain domain and future research directions arising out of recent emphasis on sustainability, robustness and resilience of supply chains and the opportunities offered by advances in Machine

Learning and Big Data. The paper is accompanied by an extensive literature review to enable the reader to delve further into this area.

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