Consumer Supply Network Planning: Literature Review And Analysis

Zeinab Hajiabolhasani [a,b]
zeinab.hajiabolhasani@mymail.unisa.edu.au

Romeo Marian [a]
romeo.marian@unisa.edu.au

John Boland [b]
john.boland@unisa.edu.au

[a] School of Engineering, University of South Australia (UniSA), Adelaide, Australia

[b] School of Information Technology & Mathematical Sciences (ITMS),
University of South Australia (UniSA), Adelaide, Australia

***Abstract*— Economic globalisation, world's population growth and significant growing of production and distribution sites across the globe have resulted in high demand for effective planning and optimisation models, algorithms and decision support systems for operational improvement along Consumer Supply Networks (CSNs). This paper reviews the various aspects of Consumer Supply Network Planning (CSNP) problems: planning scope, decision-making levels, constraints, analytical modelling approaches and the granularity level. Three groups of common modelling methods (i) analytical (ii) simulation (iii) optimisation are compared in terms of their advantages and limitations in solving the CSNP problems. After searching google scholar, a total of 45 journal papers within the context of CSNP published between 1999 and 2016 were identified that used these groups of methods. In general, the main concerns with the existing methodologies were demonstrated: (1) low complexity level, (2) independent exploitation of simulation and optimisation methods, (3) disregarding the granularity factor in the problem. It was found that methods integrate simulation and optimisation techniques are relatively superior in addressing the aforementioned concerns.**

Keywords—Supply Network; Modelling; Planning; Optimisation; Simulation; Granularity.

I. INTRODUCTION

Due to volatile global market, quick economic changes and technological turbulence, business leaders recognised that to achieve competitive advantages they need to gain more from their Supply Chains (SCs). SC, as the name suggests, is referring to a serial arrangement of companies that supply goods from raw materials to final consumers. Various businesses can be spread out in an area that can be as vast as a continent. Generally, companies provide the same functionality in a serial/parallel arrangement. Thus, due to globalisation and complexity of the economy, today's SCs are better characterised as Supply Networks (SNs).

With today's rapidly changing business circumstances, mass customization and higher levels of customer service, it is essential for firms to make effective decisions faster through leveraging a planning model that connects all components of the entire SN in a single planning run. This can be achieved by the development of advanced plans which enables companies to perform material and capacity planning simultaneously across multiple facilities over multiple horizons in a single planning run, while at the same time can provide recommendations about their future activities such as the latest demand forecast, sales orders, production and distribution status, inventory policy, etc. (Pistikopoulos, Georgiadis, & Dua, 2008).

Supply network planning (SNP) is an activity to choose, sequence and evaluate future actions for a particular decision-making unit and at various planning levels that are influenced by the design of SNs (Gunther & Meyr, 2009). SNP process is not only about decision making, but also about deciding the right level of responsiveness and efficiency to target and identify how to achieve the goal at the granularity needed (Sodhi & C.S. Tang, 2012). SNP is introduced by three principal components known as demand planning, sales and operation planning, inventory and supply planning (Feigin, 2011).

Consumer Supply Networks (CSNs) are ubiquitous in industries such as food and beverages (Bilgen & Günther, 2010; Hong, Park, Jang, & Rho, 2005), chemical pharmaceutical process (Y. Chen, Mockus, Orcun, & Reklaitis, 2012; Niziolek, Chiam, & Yih, 2012), consumer packaged products (Schmitt & Singh, 2009), retail (Abolhasani, Marian, & Loung, 2014), etc. They are complex networks comprising sets of companies working together to supply, manufacture, distribute and deliver final goods and services to end-users (Schwartz, 2008).Typical tasks that are performed in the advanced planning process of CSNs are daily demand commits, procurement, production, distribution, and sales at different granular level (Fleischmann, Meyr, & Wagner, 2015). Hence, Owing to the large body of academic literature on Consumer Supply Network Planning (CSNP), we recognise the need to summarise and categorise the research under this topic.

This paper reviews the various aspects of Consumer Supply Network Planning (CSNP) problems: planning scope, decision-making levels, constraints, analytical modelling approaches and the granularity level. Three groups of common modelling methods (i) analytical (ii) optimisation (iii) simulation are compared in terms of their advantages and limitations in solving the CSNP problems. In general, the main concerns with the existing methodologies were demonstrated: (1) low complexity level, (2) independent exploitation of simulation and optimisation methods, (3) disregarding the granularity factor in the problem. It was found that methods integrate simulation and optimisation techniques are relatively superior in addressing the aforementioned concerns.

The remainder of this paper is organised as follow: the subsequent section highlights the importance of CSNP. Section III outlines methodologies used in modelling and optimisation of CSNP problems. Those approaches are critically reviewed, and their pros and cons are investigated. Section IV presents a synopsis of research in CSNP problems. Finally, the paper is concluded in section VI.

II. Consumer Supply Network Planning

CSNs continue to be important, regarding consumption and monetary value. According to the research conducted by Food and Agriculture Organization of the United States (FAO), by the year 2050, the world's population will reach 9.1 billion, a 34% increase based on today's current headcount (Alexandratos & Bruinsma, 2012). With this growth in population, demand for food will increase by 70% that will present many complex challenges to the industry, and the associated SNs; many people are likely creating demand for a more varied high-quality food with more quantity. Hence, to remain competitive in the global market, future activities based on the evolution of demand must be planned.

Along with the dynamic structure of the market for CSNs, an unexpected crisis such as Tsunami (Japan 2011), heat wave (southern Indian- 2015) and earthquakes (Amatrice -Italy 2016) have put businesses on notice that unpredicted events can pose serious problems. Hence, companies have to pay more attention to their plans to protect their SNs and more accurately predict future activities to balance supply and demand and substantially improve the performance of their SNs. Such plans should be robust and granular to cover the nature of CSN.

A CSN model usually aims at delivering the right products at the right time to the right customer and with the right quantity. However, in practice at maximum, 50% of orders are delivered to end-users (Craig, 2016), which can substantially yield raising a high level of inefficiencies in CSNs. Hence, it is necessary for firms to take advantage of a decision-making support system that can indicate the.

A. *Planning Scope*

In CSNP problems, issues such as resources allocation, demand forecasting, inventory control, and transport routeing are investigated. A complex CSN plan is influenced by several decisions made concurrently at different subunits of the CSN. Therefore, the main objective in a CSNP problem is to define a set of decision variables, covering the entire network, to optimise the output, and to improve the overall performance of CSN. However, every single decision in CSNs is prone to uncertainty. To this end, identification of sources of uncertainty is a crucial task. Even a trivial error could result in massive damage.

B. *Uncertainty*

Uncertainty in CSNs can arise from different sources. Various categories of uncertainty have introduced in the literature which some of the most relevant ones are chronologically briefed as follows:

Subrahmanyam, Pekny, and Reklaitis (1994) classify CSN uncertainty from timeframe perspective into short-term and long-term planning. Uncertainties included in short-term, or operational planning concerns with day-to-day processing variations, cancelled/rushed orders and equipment failure, etc., whereas associated uncertainty with long-term or strategic planning refers to raw material/final product unit price fluctuations, seasonal demand variations, and production rate changes occurring over longer periods. However, the missing part of this classification is related to the well-received planning horizon by researchers known as mid-term or tactical planning activities (Eren & Turan; Shabani & Sowlati, 2013). Tactical planning involves advanced plans for maximum two years (Peidro, Mula, & Poler, 2010). They include mid-term activities and issues related to CSNP (Tako & Robinson, 2012). The main objective of mid-term planning is to find the optimal quantities of procurement, production, distribution, inventory level, sales and demand backlog associated with each facility in the CSN (Peidro, Mula, Poler, & Verdegay, 2009).

Later in 2002, Dolgui et al. propose supplying reliability, assembly and manufacturing random lead times, random level and customers demand as sources of uncertainties in Material Required Planning (MPR).

More recently, Lalmazloumian and Wong (2012) categorise uncertainties embedded in CSNs into more general classifications as supply, process/manufacturing, and demand uncertainties. Due to late or defective delivery, supplier's performance may vary that cause supply uncertainty. In addition, the unreliability of the production process is related to process uncertainty. Finally, inaccurate forecasting of demand or promptly changes demands results in demand uncertainty.

Most authors adopted the category proposed by Chiriac, Ho¨ltta, Lysy, and Suh (2011) and referred CSN uncertainty to timeframe, supply, process, and demand.

The assessment of the uncertainty is very challenging; thus, underestimating and misjudging of it and its impact on enterprises' strategies may neither safeguard a company against threats nor take advantage of opportunities that increase the levels of uncertainty (Gupta & Maranas, 2003). Thus, it is important to examine the behaviour of CSN systems under uncertainty at the individual level. Clearly, each behaviour is shown by the number of distinct aspects or features known as granularity.

C. *Granularity*

In systems engineering literature, granularity translates into the level of details one can decide to put in a model or decision-making process where same functionality is expressed with different 'sized' designs (Unhelkar, 2005).

According to Bollen, Riden, and Cox (2007) granularity of a traceability system reflect the levels and size of identifiable units that are handled by the particular system. More recently, Karlsen (2011) defines granularity as a quantity determined by size and level of the traceable units such as size and a number of batches in the manufacturing unit.

Fine granularity deals with smaller unit sizes, and coarse granularity is associated with larger unit sizes. Without a doubt, the obtained results and conclusions of the analysis are substantially influenced by the level of granularity. The finer the granularity, the deeper the level of detail. Thus, finding the optimal level of granularity to design and tune is very challenging. The finer granularity designs will take more effort to produce and need to pay extra attention to the obtained information (Grunow & Farahani, 2012). Furthermore, it allows for modelling individual component instead of group components e.g. modelling of the individual product rather than product families. Additionally, different modelling options such as back-ordering or replenishment can be considered in finer granular models. On the other hand, finer granularity will increase the complexity of the problem and will raise costs of information analysis. Consequently, it yields increment of a number of elements (subsystems, components, parts), transactions, variables, constraints, etc. (Karlsen, 2011). Thus, an appropriate decomposition of the system or definition of granularity will lead to a problem with a manageable size to solve. It is especially problematic in solving production planning and logistic problems since they are categorised as NP-hard complex systems where complexity grows exponentially very quickly (ElMaraghy, ElMaraghy, Tomiyama, & Monostori, 2012).

In this paper, the term *granularity* is used to describe the size, quantity, level and detail of the system elements. Thus, granularity in CSN problems is dependent on some measures such as the number of product families, facilities, and time periods (Arthur F. Veinott, 2005). These parameters highly influence on the running time and substantially the efficiency of the in-use algorithm. Based on this features, Mousavi, Bahreininejad, Musa, and Yusof (2014) propose a three-level problem size known as *Small*-scale, *Medium*-scale, and *Large*-scale problems which are shown in TABLE I. (e.g. a model with $P = 7, MP = 6$, $RE = 11$ and $T = 2$ is regarded as a Medium-scale problem and so forth).

TABLE I. SIZES OF THE PROPOSED INSTANCES (MOUSAVI ET AL., 2014)

Problem Size	Product Family (P)	Manufacturing Plants (MP)	Retailer (RE)	Periods (T)
Small scale	[1-5]	[1-5]	[5-10]	[1-3]
Medium scale	[6-10]	[1-10]	[11-20]	[1-5]
Large scale	[11-15]	[11-15]	[20-30]	[6-10]

However, there are other parameters associated with real CSN problem, which add more complexity to the optimisation problem e.g. geographical locations of facilities, transportation modes, etc. To this end, several OR articles (45 papers) for the last 16 years (since 1999 until present) are reviewed. The outcome of this review will contribute to the selection of a methodology, which would suit most to solve an optimisation problem concerning the size and the level of granularity.

In the remainder of the present paper, the current modelling and analysis of CSNP problems are reviewed to identify the gaps in the knowledge in the planning of the CSN problems.

D. *Modelling Methods*

According to Ahumada and Villalobos (2009), CSNP modelling methods are grouped into two broad categories: deterministic and stochastic modelling.

Deterministic modelling is composed of mathematical and optimisation modellings, and stochastic modelling consists of stochastic programming, stochastic dynamic programming, simulation modelling, and risk programming. The analytical properties of a given problem are taken into account in deterministic and heuristic approaches aim at obtaining a global or approximately global solution, but heuristic approaches are more flexible and efficient than deterministic approaches (Lin, Tsai, & Yu, 2012). However, the main downside of deterministic approaches is that they are effective to apply to large-scale optimisation problems. Hence, in order to tackle the CSNP problem, the deterministic approaches are not reliable as they involve significant overhead computational time. Therefore, heuristic approaches are used to overcome this drawback. However, obtaining a feasible or globally optimal solution is not guaranteed through utilising the heuristic methods. Therefore, integration of both approaches (deterministic and heuristics) could result in a better approach to finding the global optimal or near optimal solutions.

Compared with a single deployment of deterministic or optimisation approaches, there is a broad range of CSN models using combined methodologies (Fig. 1).

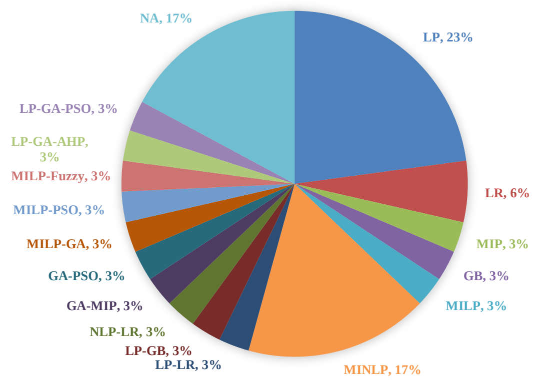


Fig. 1. Deterministic modelling approaches

In the following sections, this classification will be further refined according to the fundamental mathematical methods and the level of granularity considered to solve CSNP problems.

III. Analytical Modellings

CSNP problems are analysed utilising a variety of methodologies that belongs to three groups of classical, optimisation or simulation approaches (Fig.1) traditionally separately or recently in an integrated framework i.e. hybrid methods (Lin et al., 2012). As it was mentioned earlier, the main objectives pursued in the modelling of CSNP is to improve the overall performance according to some pre-defined KPI's (key performance indicator). Thus, the developed model can be investigated from different perspectives such as production and distribution planning, inventory control, organisational coordination, etc. (Hennies, Reggelin, Tolujew, & Piccut, 2014).

The traditional CSN optimisation problems usually involve trade-offs between several objectives such as overall cost and inventory level minimisation, and customer service and total profit maximisation, aim at finding optimal/near optimal business solution (Yimer & Demirli, 2010). The following sections A-D reviews CSNP models in which the above modelling approaches have been deployed Fig. 2). Subsequently, the pros and cons associated with each model in the developed studies will be addressed.

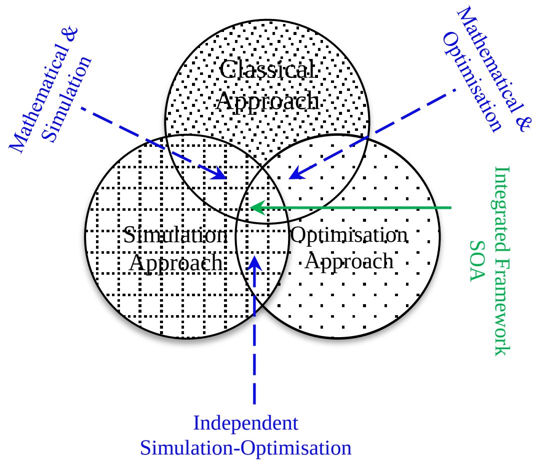


Fig. 2. Consumer supply network planning modelling methods

A. *Classical Approach*

Classical approaches compose of mathematical modelling techniques: (1) Linear Programming (*LP*), (2) Non-Linear Programming (*NLP*), (3) Mixed Integer Programming (*MIP*), (4) Non-Linear Mixed Integer Programming (*NLMIP*), (5) Lagrangian Relaxation (*LR*), and heuristic/metaheuristic approaches. A system can be analysed using these mathematical models with a set of constraints and can be optimised with specific heuristic/metaheuristic methods.

Mathematical modelling techniques are beneficial due to the lower costs involved in solving large-scale problems. In addition, since they are fully matured, obtaining best or near optimal solutions are mostly guaranteed for a specific problem.

LP approach is the simplest optimisation modelling where the objective function and conditions are linear. It has been mostly applied in location-allocation planning problems e.g. flexible cell manufacturing planning, supply network planning, and generally in economic planning phenomena. The following examples indicate the earliest time and some recent OR studies in which LP optimisation technique applied.

Richard H. Day (1963) is a pioneer in LP modelling. He deploys LP models for decision-making production problem in the agriculture sector. Using the duality theorem, he shows the entire industry including several companies, can be modelled by two single LP models where the demand and supply equations are nonlinear. This is equivalent to a direct aggregation of a solution of a set of individual firm models in which total net revenue and total cost are maximised and minimised, respectively. However, the main disadvantage of this approach is a need for very restrictive assumptions about the aggregates in the LP models of production. Moreover, any changes in decision-making policy, for instance, from management leadership may lead to a considerable degree of proportional distortion at what level aggregates should be formed.

Manne (1958) proposes a two-phase optimisation modelling for a single item inventory control problem under uncertain demand. In the first phase, decision rules developed using sequential probabilistic model and expressed by a Markov process. In the second phase; however, with LP method a solution alternative to the functional equation approach suggested minimising ordering and holding costs subject to some capacity constraints. Despite the efforts, he made to manage the complexity and size of the resulting problem; the proposed models are partially intractable.

Although formulating of LP is popular due to its nicer mathematics, richer theory, simpler calculation, and often least difficult to define, it is not appropriate for CSN applications due to increasing level of complexity. A major limitation of LP modelling is the linearity of optimisation function and constraints, which severely limits the type of problems that can be solved. Also, using LP modelling excessively complicates the model if linearization is used to approximate the function/constraints.

Consider, for example, an inventory control problem with multi items and several production facilities with different capacity limits. Controlling inventory level associated with each item, especially with time-varying demand such that inventory costs remain at a minimum while capacity utilisation reaches its maximum level are very complicated. Finding the suitable solution (e.g. cyclic schedules) can be extremely hard due to the existing wide range of dynamic behaviours in CSN. Besides, they composed of considerably a large number of unknowns or constraints with different granularity levels making them more complicated and complex problem. However, using advanced computing technology, and through sophisticated mathematical programming codes such as NLP and MILP, might make it possible to define this class of problems that can be effectively solvable.

NLP optimisation methods are mainly applicable for a category of problems that are too large and extremely complex to solve. They will be solvable if they define by particular characteristics. Similar to LP class, NLPs describe a system with some equalities and inequalities subject to a set of constraints to optimise objective functions. What differentiates NLPs from LPs is either some of the conditions are nonlinear, or the objective function is nonlinear. Hence, the focus of NLP is on the complexity of the algorithm to design and analyse (Hochbaum, 2007).

Several methodologies can be developed based on the characteristics of constraints and objective functions of the problem. For problems with nonlinear objective function, iterative search algorithms with a convergence rate proof is a leading methodology. However, it may require being restricted appropriately or replaced by a piecewise linear function that may adversely affect the complexity involved in the algorithm. To this end, it may need using some integer variables (Hochbaum, 2007). The difficulties raised in NLP will be addressed in MILP methodologies where the objective functions and sets of constraints are linear.

During investigating the literature within the context of CSN, it has been noted the advantages of mathematical techniques and heuristic and metaheuristic methods are taking into account simultaneously. Thus, in Section B articles that have used the combined techniques are reviewed.

B. *Optimisation Approach (Heuristic and Metaheuristic Techniques)*

First efforts dealing with CSN optimisation using heuristic or meta-heuristic techniques have been initiated in the late 18s in supply/demand networks (Ibrahimov, Mohais, & Michalewicz, 2009). Since many aspects of industrial and commercial processes are subject to optimisation; it has been rapidly developed and addressed in the majority of research studies covering different decision-making levels. The evolutionary techniques exploited for solving such complex problems ranges from GAs, simulated annealing (SA), Monte Carlo, to neural networks (NNs), and fuzzy logic (FL). These algorithms are population-based which can solve the multi-objectives problem (Coello, Lamont, & Veldhuizen, 2007).

As in any optimisation problems, input/output parameters, objective functions, and constraints are principle components that examine solution candidates. However, what has to be carefully considered is the size of the understudied problem. The larger is the size of the problem; a higher uncertainty level is expected; therefore, evaluation of conceptual models will be more expensive and may not guarantee to obtain a feasible or globally optimal solution (Yang, Koziel, & Leifsson, 2014). To this end, integration of deterministic and heuristic modelling may be a better applicable method (Lin et al., 2012).

1) *Linear Programming*

Vidal and Goetschalckx (2001) presented an optimisation-based LP model for global tactical CSN subject to uncertain demand. Their formulation includes distribution costs and transportation mode allocation as decision variables and a linear objective function for maximising the after-tax profits of a transfer-pricing problem shown in Fig. 3. They report the satisfactory computational results for small, medium and large-scale problems. However, regarding the granularity, the author does not consider supply and capacity constraints as well as associated costs to SN facility setup cost.

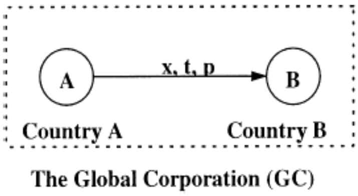


Fig. 3. The basic single-product case with two subsidiaries (Vidal & Goetschalckx, 2001)

Chan, Chung, and Wadhwa (2005) LP optimisation approach begins with utilisation of a hybrid GA for a single echelon single product CSN problem. They develop a linear programming model addressing demands allocation to manufacturers. Then total cost, fulfilment lead time, and equity of the utilisation ratios are optimised subject to linear and known constraints such as supply, demand, and capacity. One limitation of this model is that it assumes the products directly ship to the customers. Therefore, it does not reflect the complexity of the real CSN problem where some other transportation facilities are involved in the fulfilment of demands. Another shortcoming of this model is ignoring the resource constraints, although these are significant in real world SN.

2) *Mixed-Integer Linear Programming*

Amaroa and Barbosa-Póvoa (2009) introduce a MILP model for a multi-product multi-period pharmaceutical CLSC (Closed Loop Supply Chain), subject to uncertain demand and budget. They develop several scenarios and evaluate them using the branch and bound (B&B) optimisation procedure for a three months planning period. Although many efforts have been made to assess operational, economic, and market aspects by thoroughly formulating the problem, their approach is yet to be improved by considering larger planning horizon under violated price condition. This way, the B&B method may not be applicable as it does not necessarily provide information about the near-optimal solution, still very time-consuming algorithm which is limited to approximately 20 taxa (groups of taxons in an evolutionary tree i.e. a population), or less (Doyon & Chauve, 2011).

Zamarripa, Silvente, and Espuña (2012) develop a two-stage stochastic MILP model to solve a multi-echelon CSN. The model concerns multiple constraints associated with demand, resources, and capacity during decision-making procedure. The main objective of this model is to minimise the total cost of CSN covering production, inventory, distribution, and backordering costs for the period of three months. However, some characteristics of a complex CSN such as transportation of multi-products from multi-plants to multi-end-users are considered neither in their model nor the provided case study.

More recently Xiao, Cai, and Zhang (2012) study a multivariable production model of three-echelon supply driven chain under the uncertain quality environment (Fig. 4). They develop a suitable supply coordination mechanism based on a fuzzy set. Then they provide a numerical example where the stability of the analytical production control model is analysed and formulated. However, several simplifying assumptions reduce its applicability in practice. It is simulated for a three echelon CSN with three suppliers and one distribution centre for a single product over a period of 120 weeks.

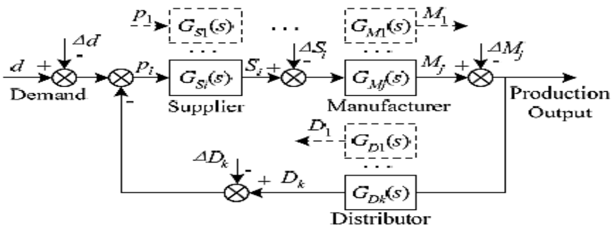


Fig. 4. An analytical production model of supply-driven chain (Xiao et al., 2012)

Waldemarsson, Lidestam, and Rudberg (2013) propose a multi-site, multi-period MILP production-distribution problem in Forestry industry (Fig. 5). Over a planning horizon of one year (time granularity of one month), the problem aims to maximise the total supply chain profit. The profit function is considered through entire SN from procurement and production to transportation of pulp products and the use of energy in pulp industry. The mathematical model was formulated using CPLEX approach via AMPL programming language. They analyse seven scenarios with five pulp mills capable of producing 15 products at each site. Even though there was a hard effort to develop such mathematical model but it was restricted only to the represented scenario not being a general model.

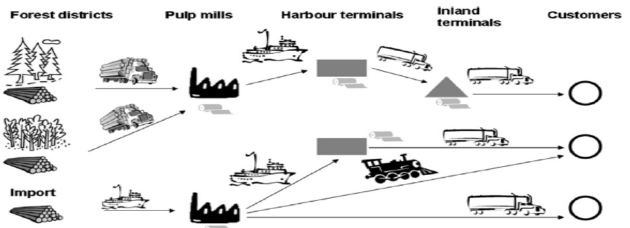


Fig. 5. Illustration of the supply chain for Sodra Cell (Waldemarsson et al., 2013)

In a more recent study on design and optimisation of CLSC, Jindal and Sangwan (2014) present a fuzzy MILP model for multi-mode production facilities considering violating demand condition (Fig. 6). Profit maximisation is the main objective function of this model. It is addressed through maximising the total number of parts supplied by the external supplier while maintaining the throughput of the network at maximum level. Their proposed model is applicable for the single period. This constitutes a shortcoming of this model since CSNP models mostly cover multi-period times in particular for controlling the inventory as the heart of CSNs.

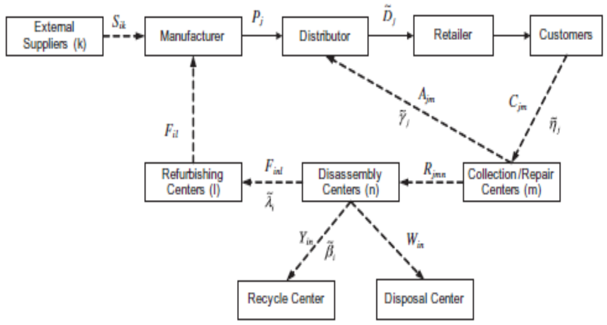


Fig. 6. CLSC framework proposed by Jindal and Sangwan (2014)

Pan and Nagi (2013) formulate a multi-echelon SN in an agile manufacturing (Fig. 7), aimed to minimise the total operational costs using Lagrangian relaxation heuristic. The main objective of their proposed model is to select companies in each layer to form the CSN. They have shown 10% improvement comparing to managerial initiative alternatives. Even though the high quantity of orders was considered in their model, but their mathematical model lacked in considering back ordering costs.

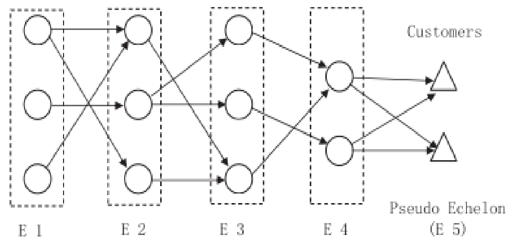


Fig. 7. Four echelon network (Pan & Nagi, 2013)

3) *Mixed-Integer Nonlinear Programming*

As the size of the problem grows, and the granularity level expands, the challenges in describing physical properties of CSNP problems and substantially the optimisation model increase. For example, consider situations in which both linear and nonlinear uncertainties are involved (see portfolio optimisation (Huanga, Chen, & Fan, 2010), production planning optimisation (Ibrahimov et al., 2009), distribution systems, CSN optimisation). Thus, the objective function of the problem is described by nonlinear functions, and some of the problem's constraints are taken integer values. This class of mathematical programming is known as MINLP via which more realistic model of a real-world CSN problem can be described.

In the MINLP model for an integrated CSN developed by Pitty, Li, Adhitya, Srinivasan, and Karimi (2008), various activities such as procurement planning, scheduling, and operation management were considered to optimise the total profit. This model mainly investigates the integrated modelling of CSN dynamics which will be referred and discussed further later in section C.

Shabani and Sowlati (Shabani & Sowlati, 2013) look into a renewable energy SN (Forest biomass). They present a dynamic multi-objective optimisation model to maximise the overall value of forest biomass (profit) and to minimise the total costs of the network. Thus, the amount of biomass to buy, store and consume in each month over a planning horizon of one year is estimated. In this model, nonlinearities deal with the monthly produced amount of electricity, and monthly average available energy in biomass storage. This model is one of a kind comprehensive and most granular CSN model that is generalizable for different planning horizon. However, Shabani and Sowlati only apply and validate their proposed model for a few number of scenarios with short-term planning horizons.

Rezaeian, Shokoufi, Haghayegh, and Mahdavi (2016) formulate a two-echelon CSN of perishable products over multi-period planning horizon with MINLP mathematical technique subject to uncertain demands, limited space in the distribution centre and the available vehicle in the logistic fleet. In their developed hybrid, methodology GA and SA meta-heuristics are utilised to minimise the entire cost of the network integrated with the inventory system. They also examine their model for small, medium and a large-scale problem where the number of product lines, factories, micro and macro periods (day/week), vehicles, and distribution centres vary between 1-10. The granularity level of this model compared to what has proposed by (Mousavi et al., 2014) is less fine. Additionally, they apply optimisation and simulation methodologies independently.

More information on application of MINLP within the context of CSN is available in (Akgul, Mac Dowell, Papageorgiou, & Shah, 2014; Amin & Zhang, 2012; K. Chen & Ji, 2004; Eren & Turan; Zamarripa et al., 2015)

4) Lagrangian Relaxation

Often the optimisation problem is an NP-hard problem in which it may need to decompose the initial problem into some subproblems and examine each of them according to their sets of easy or very hard constraints (Grunow & Stefánsdóttir, 2015; Klau, 2007). This technique is known as Lagrangian relaxation. The hard constraints are then removed by adding penalty function to the objective function i.e. the problem is relaxed.

Mutha and Pokharel (2009) present a modular multi-echelon single-product reverse logistic (RL) model with various disposal and recycling rates for each component (Fig. 8). In their research, the main focus is on deciding the number of facilities with location and allocation of used products at an optimal cost subject to capacity constraints. However, they oversimplified their model from several perspectives: (1) applying the model to scenarios including only one item, (2) considering fixed waiting time for a returned product at all of the CSN facilities, and (3) separating the warehouse (inventory) location from the distribution centre. No evidence was shown whether or not their proposed model can be generalizable to the larger problem, let's say with multi items. Overall, a medium level of granularity was considered in this study.

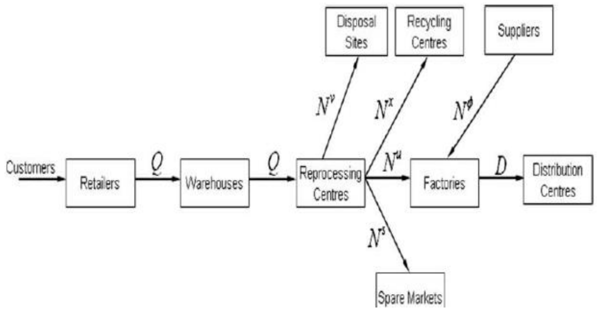


Fig. 8. Reverse Logistic Proposed by Mutha and Pokharel (2009)

Using RL method, Shi, Zhang, and Sha (2011) propose a mathematical model to examine a multi-product CLSC network subject to uncertain demand and return. The problem is to maximise the manufacturer's expected profit simultaneously through controlling the number of produced brand-new products and the quantities of remanufactured products. They evaluate the developed production plan for twenty case studies incorporating small and large-scale problems where the number of products varies between 5-50 items. However, authors of this paper did not provide any information either about the impact of increasing the number of SN facilities or the planning horizon on the computational rate of the algorithm.

Azadian, Murat, and Chinnam (2015) utilise Lagrangian Relaxation to formulate a production scheduling combined with logistic planning activities subject to predecessors and successors jobs undertaken in manufacturing scheduling. The objective function in their model is to reduce the total cost incurred in the production scheduling. However, they consider a very mild granular level of uncertainty that can be extended to a more granular model where supply and demand uncertainties are accounted.

There is a significant tendency in the deployment of the optimisation techniques combined with mathematical models to solve complex and dynamic CSN problems. Their main advantage is that validating the solution can be verified mathematically, based on a given objective function and a set of defined constraints which yields the stable optimal solution, but not the gradient of design space over time (Hennies et al., 2014). Hence, broadening the scope of the problem would significantly result in higher complexity and exponentially grown computational intensity which make them inefficient and less practical approach (Alive, Fazlohhahi, Guirimov, & Aliev, 2007). Thus, this class of methodologies alone are not efficient to provide firms with valuable insights into their assumptions and feasible solutions. Certainly, it is essential for them to utilise other methods through which the real aspect of SN related problems can be examined. In particular, when implementation of a policy is too risky, expensive, or sometimes impossible in real CSN problem.

The following section review OR papers that investigate the application of simulation modelling in conjunction with optimisation modelling in their case studies.

C. Simulation Approach

Simulation modelling approaches are unique methods that are tightly integrated with mathematical and algorithmic-based models. They can explore different *what-if* scenarios that yield in a better understanding of the system and subsequently improvement of the system's performance subject to various conditions and at any desired granular level.

Simulation modellings are highly demanded among enterprises specifically in logistic and supply chain management (LSCM). They can link the gap between brilliant ideas and business initiative. Usually, processes in association with particular business units (e.g. manufacturing plants, SNs, call centres, and inventory control systems) can be described with a simulation model; within a controlled environment (Mekenton, 1987). Truly, the simulation is a descriptive tool in modelling and analysis of complex system such as SN systems. It is capable of exploring the holistic view of mutual data communication exchanged between different echelons of SN (Mustafee, Katsaliaki, & Taylor, 2014).

The main objective of a simulation model is to mimic behaviours of a real system subject to substantial environmental changes using computer programming. Therefore, the exploration of many values per input and various combinations of these values is possible through simulation models (Dellino, Kleijnen, & Meloni, 2010). Using simulation modelling, one can reconfigure, experiment, and evaluate the resilience and robustness operation of a real system that is too dangerous, expensive, or impractical to implement. Additionally, their flexibility in developing different scenarios, reasonable high speed in examining the developed alternatives, and embedded standard reporting system make it distinctive in modelling, analysing, and validating of complex systems. Hence, the conceptual simulation model must be an accurate representation of the system under study to provide correct results (Carvalho, Barroso, machado, Azevedo, & Cruz-Machado, 2012).

The simulation model will provide the modeller with answers to questions such as *Subject to what sets of conditions, the system will perform better? Which set of configurations will optimise the performance measure? Changing of which factor will dramatically disturb the performance of the system?* etc. However, overcomplicating a simulation model could cause issues such as input/output transfer, model composition, and slow execution speed.

According to Campuzano and Mula (2011), SN simulation modelling will mainly concentrate on

- Understanding the SN processes and its key problems
- Developing a broad range of what-if scenarios and validating improvements
- Examining various decision-based alternatives without interrupting the real SN
- Quantifying benefits (e.g. demand forecasting, aggregated planning, etc.)

Different types of simulation modelling can be put into practice based on the characteristics of the problem under consideration including spreadsheet modelling, system dynamics (SD), business games, and discrete events dynamic (Almeder, Preusser, & Hartl, 2009). The Spreadsheet-based modelling as a simulation platform was introduced to company's directors back in 1997 (R). Also, using business games simulation, e.g. Beer Game (Sterman, 1989), the dynamics of SN, for instance, bullwhip effect in Beer Game can be investigated.

While the first tool is too simple to assess the real CSN problems accurately; the latter is more suitable to be used for educational purposes. However, discrete-event simulation (DES) was found to be the most appropriate simulation technique utilised in CSN.

DES is an event driven simulation tool which controls the system state changes upon an occurrence of an event. It can perfectly handle complex and dynamic problems that are significantly influenced by stochastic constraints (Schlegel et al., 2006). DES can assist system analysts to estimate the system's performance by capturing its characteristics, reproducing and examining different decision-making alternatives, and selecting the most feasible scenario (Terzi & Cavalieri, 2004). To this end, it is the most powerful tool associated with SN problems through which supply and demand risk analysis can be conducted using SC performance measures (Reiner, 2005).

There is a broad spectrum of DES software packages that are commercially available and facilitate the modeller with animations of the materials flows through the entire systems or dynamic processes. Examples include SIMPROCESS (Chatfield, Harrison, & Hayya, 2006; DeFee, 2004; Swegles, 1997) , AUTOMOD, ARENA (previously SIMAN) (Carvalho et al., 2012; Mertins, Rabe, & Jäkel, 2005; Noche & Elhasia, 2013; Persson & Araldi, 2009; Terzi & Cavalieri, 2004; Zhang, Puterman, Nelson, & Atkins, 2012), and MATLAB (for example, see (Abu-Ajamieh, Luong, & Marian, 2013; Fahimnia, Luong, & Marian, 2009; Li & Chen, 2013; MARIAN, 2003)) .

SIMPROCESS is a hierarchical modelling tool that combines process mapping, DES, and activity based costing; facilitating a user-friendly interface. AUTOMOD (Automotive Model-Based Development), and ARENA (developed by Rockwell Automation) are well-designed for DES providing the user with three main modules of Input, Output, and Process Analyser (Cimino, Longo, & Mirabelli, 2010) ("Applied AutoMod," 2010). Although these software packages are very powerful modelling tools, they consume a relatively large amount of time to generate large sample datasets. MATLAB® on the other hand, with the extended SimEvents® toolbox, and graphical modelling environment, provides the user with both optimisation and simulation Toolboxes. For example, Fig. 9 demonstrates a Kanban production system simulation model containing two types of withdrawal and work-in-progress Kanban with an assembly line developed in SimEvents and Simulink®. Two production lines manufacture two parts A and B which are assembled on an assembly line and produce the final product. In his simulation model, withdrawal Kanban is concerned with inventory management and work-in-progress Kanban is associated with production management. Therefore, to manage production activities and highlight the issues impacting on the performance of the system, DES modelling is beneficial to improve the system performance.

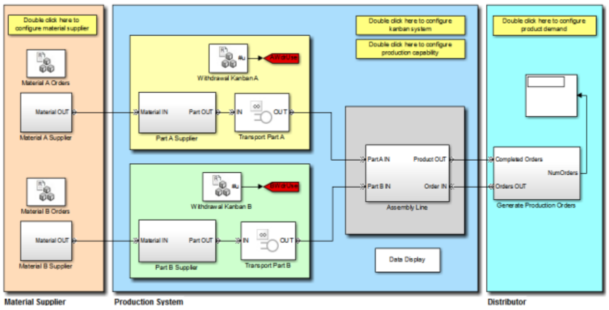


Fig. 9. Kanban production system- A discrete event simulation modelling (MATLAB(R)&SIMULINK(R), 2015)

So far, it was showed that CSNP problems are addressed either using optimisation or simulation or both modelling techniques. Utilising each single approach in a separate framework might have some benefits; however, independent deployment of them has some drawbacks too. In particular, although simulation models can evaluate different configurations of solution alternative, they cannot take into account a combination of configurations. They can only work with one set of configuration. Still, finding the optimal solution through independently using the traditional methodologies will not be an easy task since it includes heavy computing overhead. Furthermore, it was noted that those models that have utilised optimisation and simulation methods separately were less realistic models as they did not realistically represent the large-scale, stochastics and complex and dynamic CSN model. Therefore, integration of both approaches seems to be more efficient to a higher level.

The remainder of this paper reviews academic articles that deploy both simulation and optimisation methods as core components of their methodology in CSN problems.

D. Simulation Optimisation Approach

Simulation optimisation is the main component of the modern design across industries and engineering (Yang et al., 2014). Through the integrated structure approach, optimal settings for input parameters associated with a simulation model can be determined (Huerta-Barrientos, Elizondo-Cortés, & Mota, 2014). However, it embeds high computational requirements too (Jung et al. 2004; Wan et al. 2005).

Since 1972, many exciting works in simulation optimisation have been explored by researchers and practitioners, to enhance the performance measures in a controlled environment (Almeder et al., 2009; Y. Chen, Mockus, Orcun, & Reklaitis, 2010; Y. Chen et al., 2012; Dellino et al., 2010; Ding, Benyoucef, Xie, Hans, & Schumacher, 2004; Fu, 1994; Huerta-Barrientos et al., 2014; Jacoby, 1972; Jeong Hee Hong, Seo, & Kim, 2013; Jung, Blaua, Pekny, Reklaitis, & Eversdykb, 2004; Mekenton, 1987; Nelson, 2010; Schlegel et al., 2006; Wan, Pekny, & Reklaitis, 2005; Yang et al., 2014; Zhang et al., 2012). However, yet a small group of researchers has contributed to the development of its applications across the globe. Huerta-Barrientos et al. (2014) reported 355 authors across 35 countries.

CSNs are most commonly simulated by DSE and SD approaches. While strategic decision making is simulated via SD, decisions at tactical or operational levels are modelled with DES Zelenka (2010).

Michael Fu (1994), in a review on optimisation techniques via discrete-event simulation, defines DE system as "*a system of differential equations with randomness feature in the model* that *a "physical" state of the system experiences "jump" at discrete points in time upon the occurrences of events"*. Let us consider inventory control problem of the DSN, a perfect example of DE system (Fig. 10); state variables are a number of orders in the queue and the available inventory level (x_i) that vary at a particular instant of time (t_i). The values of these parameters change only when an order (entity $-e_i$) arrives or when it is received and departs. Thus, any changes in system's states can simply be implemented through computer-based modelling programs. In general, system entities, input parameters, performance measures, and mathematical equations/inequities are the fundamentals of simulation models.

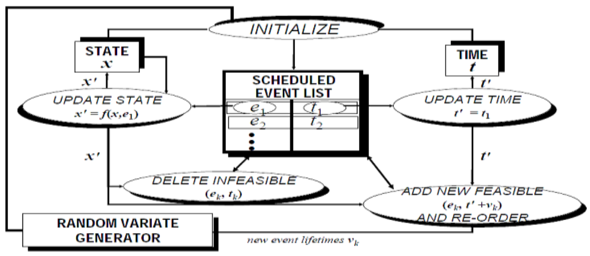


Fig. 10. Discrete Event Simulation block diagram (Cassandras)

Lee, Kim, and Moon (2002) demonstrate a hybrid of simulation and optimisation model for production-distribution network subject to capacity constraint. The objective function in their model is to minimise the overall cost of the entire network. The simulation model is the core component of this approach. It is developed to check and update the initial capacity assumptions used for a simpler linear optimisation model. Then they evaluate the developed model through a numerical example consists of two shops each with one product, two distribution centres, and three retailers over three weeks planning periods. The size of the case study is relatively small. Hence, the complexity level regarded in this paper is very low which make it unsalable/inapplicable to the real CSN.

Jung et al. (2004) propose a S-P model using SOA method shown in Fig. 11. In their developed case study two production plants (A, B) with five different process activities subject to supply and demand constraints are considered. They construct the DES model using CSIM18 & CPLEX for an operational planning level to determine the associated quantity with the manufacturing and supplying an individual product. Also, the objective function of their optimisation model incorporates production, resource supply, and shortage penalty costs which are formulated using LP model, a gradient-based search approach, aims at minimisation of the safety stock levels of each product family. However, they have ignored the integration of the entire cost; instead, have considered the separated objective function in their optimisation model. Moreover, due to the extensive computing time experienced in running experiments, they could not have implemented the developed model for similar problems with finer granularity level.

Schlegel et al. (2006) integrate optimisation into a CSN simulation model for an operational planning level of one month. They apply the proposed methodology to a CSN network with $S = 9$ and $MP = 4$, enable of producing 80 types of products to improve the service level. The uncertainty in this model originates from demand and capacity of the intermediate buffer tanks. However, they have not provided any data or reported any numerical result in order to validate their approach. Besides, they have not disclosed any information about the optimisation algorithm or the simulation model.

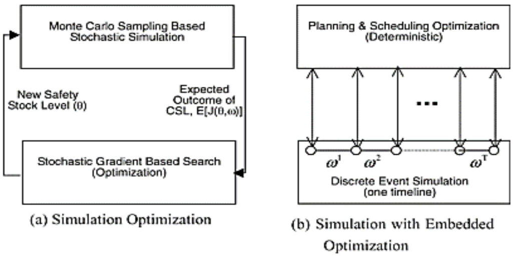


Fig. 11. Configuration of simulation and optimisation procedures (Jung et al., 2004)

Ding, Benyoucef, and Xie (2009) design a CSN considering SN configuration and operational decisions to minimise the total cost. They utilise GA for the optimisation engine and a precise formal CSN design including all possible operation decisions and decision rules for the simulation module. The uncertainties incorporate with their model are mainly related to production and handling capacities. Also, they examine the effectiveness of their model for an automobile manufacturing case study for a small-scale problem; $MP = 3, DC = 1, RE = 6$ with one transporation mode and over planning period of one week. The simulation module runs each scenario once to evaluate the best CSN configuration with minimum cost. No numerical experience is presented in this paper due to confidentiality. But the main shortcoming of this model is the coarse granularity level regarded for the sources of uncertainty, mode of transportation, and the planning horizon.

Nikolopoulou and Ierapetritou (2012) present a CSN model subject to uncertain demands and limited capacity for tactical planning horizon. They propose an SOA algorithm consists of simulation and optimisation modules, both calculating the total cost of the network individually. The SOA runs the MILP model and evaluates the fitness function (total cost) independently. In a recursive mode, then the produced solution by the optimisation module is compared with the solution obtained from the simulation module. The comparison procedure continues until the difference between two solutions exceeds a constant threshold. Finally, this paper reports some numerical data derived from applying the SOA method on a small-scale SC problem. Even though both simulation and optimisation cores included in this approach, but there is no dependency or interaction between them. As the simulation model is used to produce initial value for the mathematical model parameters. Also, no evidence is showed in regards to the possibility to generalise this model for a similar problem with larger scale. Additionally, it is not clear if solutions with better quality rather than what have achieved could have been obtained by choosing a different configuration of parameters.

Zelenka (2010) develops a simulation optimisation model for a recycling plastic job-shop manufacturing firm using a DES-based approach. By generating two scenarios, with SimEvents® and Simulink® toolboxes of MATLAB, Zelenka presents individual processing mode of two specific product families (film roll) that each produces a x number of fill roll. Then, the simulated scenarios are used to minimise the downtime (the difference between the 1st and the 2nd production time) on scroll line. However, they highlight they have disregarded some major conditions in job scheduling such as production time, downtime, resources and budget. This limits the efficiency and practical value of this model. Additionally, the small number of jobs and types of products are obvious signs of over simplification in the developed case study by Zelenka.

Zhang et al. (2012) design an integrated demographic simulation and optimisation OR decision support system reporting a Canadian heath organisation to examine long-term care capacity planning. Subject to service level criterion, two separate case studies embedding several scenarios are investigated to find the required capacity per annum. Based on this approach, they propose a look-up table containing different series of policies, with upper and lower bound of capacity level reportable to managers. Multiclass queuing system (M/M/s) with variable arrival and service time rates are considered to simulate the health system. The main objective of their model is to optimise the capacity of the required staff to reduce the admitted clients (patients) waiting time subject to satisfying some medical eligibility requirements.

Their developed approach uses two different search algorithms for the optimisation phase namely sequential and simultaneous algorithms. Even though the obtained results from the concurrent algorithm (gradient-based optimisation) shows approximately 30% improvements, computationally it is very complex and expensive. Although they provide a clear convergence criterion (average, satisfactory level), the local optimum solution (service performance with predetermined capacity) seems not too efficient for capacity planning. Because it does not propose a series of policy for capacity planning but a series of the capacity level.

A batch pharmaceutical CSN (Fig. 12) SO platform build by Y. Chen et al. (2012). They aim to minimise the clinical trial costs including production cost, holding cost, wasted product cost and penalty cost for unsatisfied demand. Through simulation model, different demand scenarios are generated and stochastically predicted to identify the number of drug packages at clinical sites. Then, they consider probabilities and resource constraints of a specific demand scenario as two main parameters required in the execution of the transportation plan. After which manufacturing operations and distribution planning of the entire SC are examined. Similar to the previous experimental design in this study, computational time exponentially increases if the total number of stock keeping units in the production plan rises.

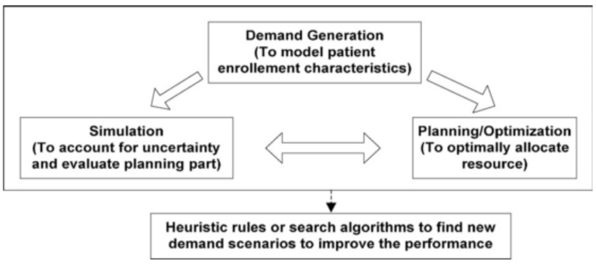


Fig. 12. Clinical trial supply chain management computational framework (Y. Chen et al., 2012)

Hubscher-Younger, Mosterman, DeLand, Orqueda, and Eastman (2012) formulate a model predictive control algorithm comprised of both discrete-event and continuous computation models for a chemical batch manufacturing process. The order systems, production system, and process analysis are the main components of SN model. They are simulated using SimEvents® Toolbox of MATLAB. Then through Global Optimisation Toolbox® the backlog of orders is minimised while considering a suitable combination of equipment to be bought at minimum cost in the plant. To overcome the computational cost issue, they deploy the Parallel Computing Toolbox™ within the same domain. It is distinguished that the integrated architecture is effectively and efficiently demonstrated in MATLAB® without switching into multiple software environments. However, the scale of the problem described in this paper was found to be small, and the objective function and constraints components are linear. It has the potential to be expanded to a real CSN problem with the higher level of complexity including all cost components and nonlinearity in the set of constraints. The most interesting part of this model is the time parameter which is entirely controllable through the simulation model. Thus, it addresses the planning period granularity comprehensively. However, other assumptions to the production model should be adjustable accordingly.

Mousavi et al. (2014) develop a modified PSO optimisation model (MPSO) for a location-allocation CSN problem. They formulate two-echelon distribution network with multi-product multi-period inventory under uncertain seasonal demands. The primary objective of this research is to determine firstly the quantity of the orders and secondly the location of the vendor. Also, Mousavi et al. use Taguchi method to tune the parameters of MPSO search mechanism. They significantly have considered all aspect of parameter tuning in their model and have conducted a sensitivity analysis for similar problems with different granularity level.

Seifbarghy, Kalani, and Hemmati (2016) in a similar study develop a discrete PSO algorithm seeking the maximum channel profit of a two-echelon single product CSN. They consider sales quantity and production rate as decision variables of their model. Through utilisation of several stochastic and metaheuristic search algorithms such as PSO, GA, and simulated annealing (SA), they conduct a rich sensitivity analysis. However, the improvement of the proposed heuristic obtained by developing another heuristic which computationally seems very expensive method.

Roba W. Salem and Mohamed Haouari (2016) model a three-echelon SN considering uncertain demand to minimise the total expected cost. Using MILP method, they formulate the model and deploy PSO algorithm to find the near optimum solution. Also, they conduct the simulation part using the Monte Carlo simulation routine. Three case studies with different supply uncertainty levels are presented to indicate the higher impact of the supply uncertainty in comparison with the demand uncertainty on the expected cost. This research is an exemplary of SOA approach; however, the developed case studies are tested against the coarse granularity level (single product-single facility) in which the information about lead time and supply costs are disregarded.

IV. A Synopsis of Research in CSNP Problems

TABLE IV. summarise the results of the investigation across the literature over a total number of 45 papers in the area of CSNP since 1999 (Fig.15). These OR articles have been reviewed according to the criteria listed in TABLE II.

TABLE II. CSNP - Classification Criteria

Planning Scope	Network Structure	Decision Variables	Sources of Uncertainty	Objective Function	Granularity Level	Modelling Approach
Operational	Single Echelon	Supplier	Supply	Total Cost (min)	Coarse	Determinist
Tactical	Multi-Echelon	Production	Demand	Total Profit max)	Medium	Stochastic
Strategic		Inventory Control	Resource	Other	Fine	SOA
		Distribution	Capacity			
		Allocation	Other			
		Other				

The majority of the models across the literature were developed considering multi-echelon as the CSN structure (Fig. 14). Also, demand, supply, resource, and capacity were taken into account almost equally as the most significant sources of uncertainty (Fig. 15-a). Besides, decisions regarding production, distribution and inventory management (PD-IC-DC) have received more attention from scientists (Fig. 15-c) mainly for the operational planning horizon (Fig. 15-b).

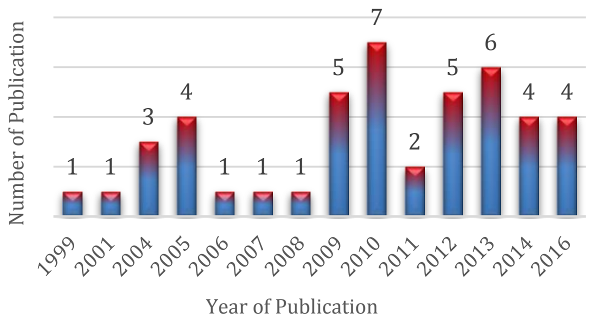


Fig. 13. The trend of CSNP problems across the literature

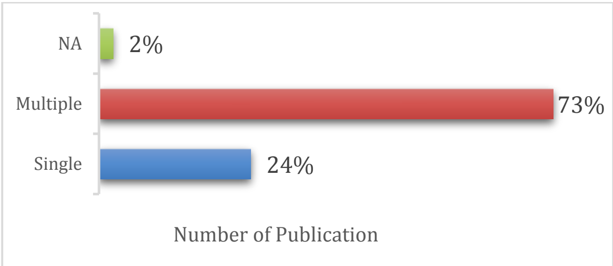
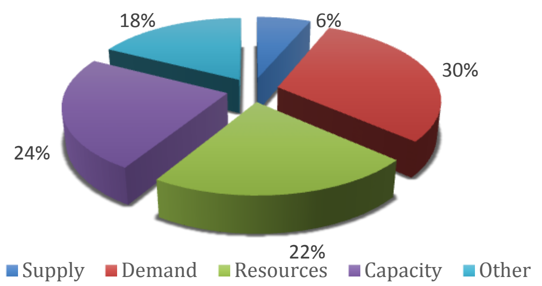
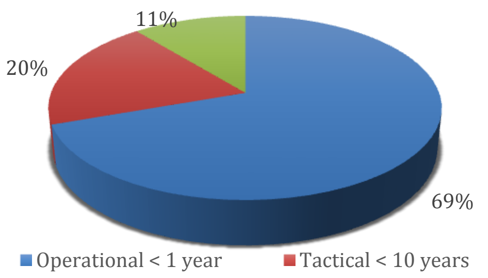


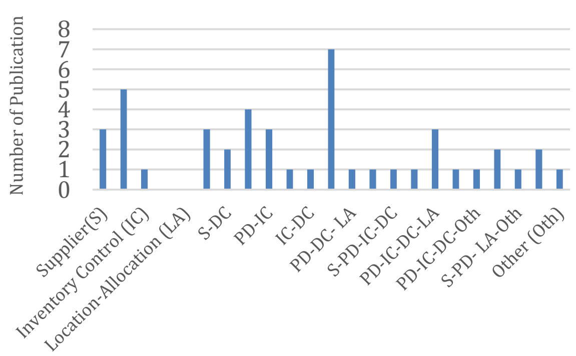
Fig. 14. The CSNP structure used in the literature



(a) Sources of constraints

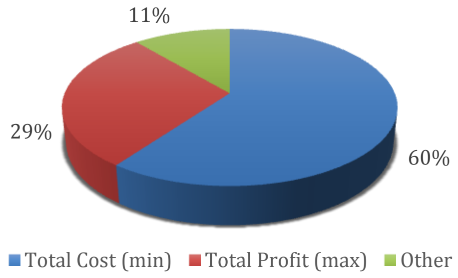


(b) Planning scope

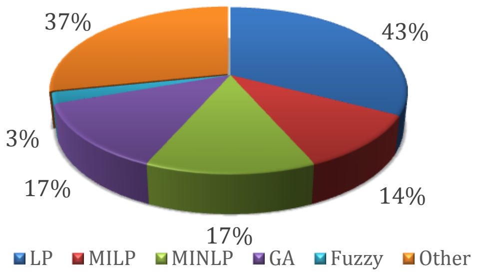


(c) Decision Variable

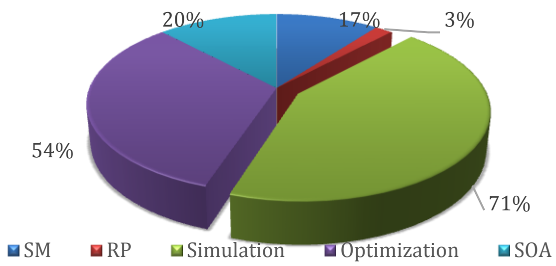
Note: PD stands for Production network, and DC refers to the Distribution network



(d) Objective function



(e) Deterministic modelling methods



(f) Stochastic modelling approach

Fig. 15. CSNP Modelling Characteristics deployed in the literature

As it is shown in Fig. 16 and Fig. 17, the majority of the models have considered a medium level of granularity (single product-multi facilities/ multi-products/single facility/multi-product-multi-facility). In addition, the coarse level (single-product single facility) stands at the second place, while the fine granularity (multi-product multi-facility multi-period) has received minimum attention (approximately 9%).

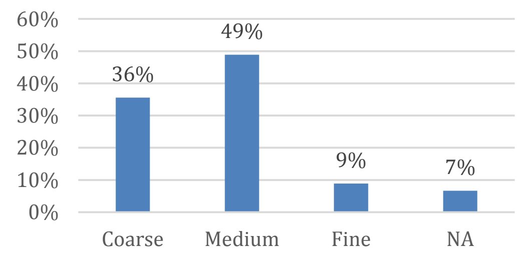


Fig. 16. The trend of CSNP granularity level across the literature

Additionally, the trend of addressing planning horizon over the past two decades (1999-2016) in the case studies was toward more works on an operational decision-making level, while the tactical and strategic planning scopes were less investigated (Fig. 17 and Fig. 18).

TABLE III. quantifies the level of granularity corresponding to each planning scope. For example, whereas around 45% of the developed case studies in operational, tactical and strategic planning horizons accommodate the medium level of granularity, 40%

take into account the course level of granularity and less than 15% consider the fine level of granularity.

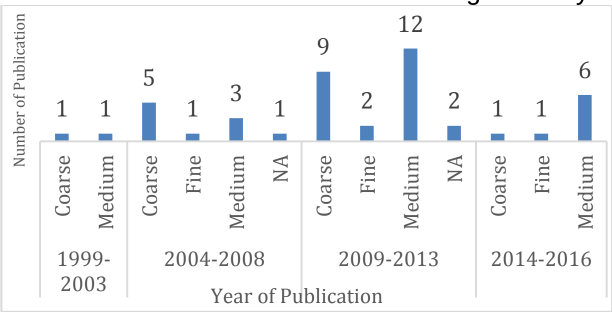


Fig. 17. CSN modelling approaches deployed in the literature

TABLE III. COUNT OF PUBLICATION ACCORDING TO GRANULARITY LEVEL AND PLANNING SCOPE

Planning Scope	Coarse	Fine	Medium	NA
Operational	34%	52%	7%	7%
Tactical	40%	40%	20%	
Strategic	50%	50%		
Operational & Tactical			100%	
Tactical & Strategic		100%		
All		50%		50%
NA	60%	40%		

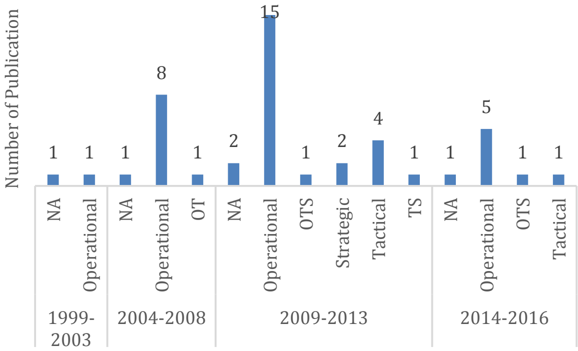


Fig. 18. The trend of Planning Scope across the literature

V. DISCUSSION ON EXISTING SIMULATION-OPTIMISATION MODELS FOR CSNP PROBLEMS

Through investigation of the present models and experimental studies in the literature, three distinct gaps of knowledge were distinguished as following:

1- Low complexity of case studies used for simulation

At this stage, all computational and mathematical approaches in the literature corresponded to relatively small-scale case studies in CSNP problems (Abu-Ajamieh et al., 2013; Carvalho et al., 2012; Chan et al., 2005; DeFee, 2004; Ibrahimov et al., 2009; Mertins et al., 2005; Noche & Elhasia, 2013; Schlegel et al., 2006; Xiao et al., 2012). In other words, the level of details considered in the developed models, except in a few (Amaroa & Barbosa-Póvoa, 2009; Fahimnia et al., 2009; Pitty et al., 2008; Seifbarghy et al., 2016), or the decision-making processes was significantly embedded the low level of complexity. Apart from the challenges involved in large-scale problems, the computational rate has been tried to be reduced by over simplifying the numerical examples like in the paper presented by Pan and Nagi (2013).

Approximately 50% of the problem were deployed considering small-scale CSN case studies to validate the efficiency of algorithms (Fig. 15-f). Often, the multi-echelon structural network was selected for the development of CSN model (~ 71% see. Fig.16-a) in which 2-4 product families, 2-4 distribution centres (including warehouses) were included and mostly for operational planning horizon (~70% see. Fig.16-b). In more than 66% of the developed CSN models, two or more than two decision variables were considered (e.g. PD (Amaroa & Barbosa-Póvoa, 2009; Pierreval, Bruniaux, & Caux, 2007; Silvente, Zamarripa, & Espuña, 2012), PD-A (Ding et al., 2004), P-IQ-DC-A (Almeder et al., 2009; Fahimnia et al., 2009; Rezaeian et al., 2016; Roba W. Salem & Mohammed Haouari, 2016), etc.). It was noticed that supply, demand, resource, and capacity sources of uncertainty were significantly addressed in the developed case studies (Fig. 15-c) to either minimising the total coat of the CSN or maximising the total profit (Fig. 15-f). However, in this research, a real and practical case scenario with more details (e.g. products families, transportation type, distribution centres, customer zones, etc.) will be utilised to overcome this shortcoming.

2- Independent problem analysis in modelling and simulation

In most of the reviewed papers, modelling, and simulation of formulated problems have been analysed independently (Fig. 19). This will decrease the validity and capability of the proposed methodologies, while an integrated modelling architecture can eliminate the complexities that are individually embedded in simulation and optimisation modules.

Separate deployment of such approaches might be appropriate for development of the small-scale experimental, but it certainly limits the development of medium and large-scale scenarios. Therefore, it is required to utilise an integrated modelling architecture which can eliminate the complexities that are individually embedded in simulation and optimisation modules.

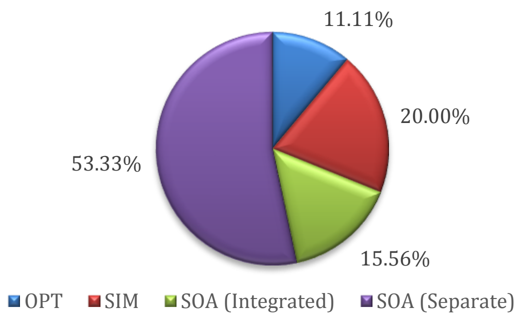


Fig. 19. Methodologies across the literature

A few number of studies were addressed the SOA in their CSN models; however, they were examined for small-scale problems (Amaroa & Barbosa-Póvoa, 2009; Schlegel et al., 2006; Wang, Guana, Shao, & Ullah, 2014).

3- Ignoring the granularity as a paramount factor in the quality of the achieved solution

Also, it was noticeably observed that granularity- the smallest level of details- greatly ignored in the modelling of the existing systems in the literature; either too narrow or too sparse level were considered.

As TABLE III. summarises, nearly 50% of the researches were conducted based on the medium granularity level (single-product single-facility or multi-products single facility), while 31% of them were examined for the short-term planning horizon. Hence, many decision variables have been entirely disregarded or underestimated in lower levels of planning. This is due to inconsistent operating of simulation and optimisation model. For instance, although the problem space has designed to function on a daily basis time bucket, optimisation model may implement for longer time bucket (weekly, or even monthly). Thus, the total cost in the specific problem will not be estimated accurately. Therefore, the obtained optimal or near optimal solution need to be reviewed. To this end, it is required to propose a new approach considering complexity and dynamism of the CSN to the finest granular extent with uncertain demands and using DES method addressing challenges involved in CSNP problems using meta-heuristics optimisation technique, Genetic Algorithm to dominate the mentioned gaps in the knowledge.

VI. Conclusion and Future Work

This study highlights the significance of CSNP problems and reviews different modelling approaches ranging from classical mathematical programming to hybrid and systematic modelling methods. Attention has been paid to classical, optimisation and simulation categories and their advantages, and limitations. In general, the main concerns with the existing modelling methods were demonstrated: (1) low level of complexity, (2) taking advantage of simulation and optimisation techniques separately, (3) disregarding the granularity factor in the problem.

Due to the increasing level of complexity in real-world CSNs and the advent of powerful computers, more sophisticated and efficient advanced planning models can be developed. Methods that integrate simulation and optimisation techniques (SOA) are relatively superior in addressing the aforementioned concerns.

Despite the suitability of SOA, only a limited number of studies applied it. Therefore, further implementations of this method in the context of CSNP can potentially increase the quality of the proposed solutions in this domain. A real-world problem built upon SOA will be presented in our subsequent study.

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TABLE IV. LITERATURE REVIEW ON METHODOLOGIES UTILISED FOR CSNP RESEARCH SINCE 1999

Studies	Year	Planning Scope			CSN Structure		Decision Variable						Constraint					Modelling Approach											Objective Function			Granularity Level		
																		Deterministic						Stochastic										
																		Mathematical Programming			Optimisation Method													
		Operational <1 year	Tactical < 10 year	Strategic >10 year	Single	Multiple	Supplier	Production	Inventory Control	Distribution	Allocation	Other	Supply	Demand	Resource	Capacity	Other	LP	MILP	MINLP	GA	Fuzzy	Other	System Dynamic	Risk Programming	Simulation	Optimisation	SOA	Total Cost (min)	Total Profit (max)	Other	Coarse SP+SF	Medium SP-MF/MP-SP/MP-MF	Fine MP-MF + Time
Petrovic et. al.	1999	X				X		X	X					X	X		X	X				X				MC[3]	X	S[5]	X			X		
Vidal & Goetschalckx	2001	NA			X			X		X	T[1]			X	X	X		X					LR			MC	X	S		X			X	
DeFee	2004	X				X		X				X			X		X									MC			X			X		
Ding et. al.	2004	X				X		X	X	X	P[2]	X		X	X	X					X		MIP			MC	X	S		X			X	
Jung et. al.	2004	X				X	X	X					X	X				X										I[6]	X				X	
Chan et. al.	2005	X			X			X		X		X		X		X		X			X		AHP				X		X		X	X		
Hong et. al.	2005	X				X	X									X		X						X			X	S		X	X		X	
Mertins et. al.	2005	NA				X	NA							X												DES			X			X		
Wan et. al.	2005	X			X		NA							X			X	X					X					I	X			X		
Schlegel et. al.	2006	X				X		X	X	X	P			X	X	X				X						DES		I				X		
Pierreval et. al.	2007	X				X		X		X				X												SD[4]								
Pity et. al.	2008	X	X			X		X	X	X	P					X		X						X		DES			X					X
Almeder et. al.	2009	X				X		X	X	X					X								MIP			DES			X				X	
Amarao & Barbosa	2009	X				X		X		X				X	X	X		X						X				I		X				X
Fahimnia et. al.	2009		X			X		X	X	X					X	X				X						MC	X	S	X					X
Ibrahimov et. al.	2009	X				X		X							X					X				X		MC	X	S		X		X		
Mutha & Pokharel	2009			X		X		X	X	X			X			X							LR			MC	X	S	X				X	
Dellino et. al.	2010	NA				X			X					X	X								X			MC	X	S	X			X		
Huang et. al.	2010	X				X		X				X		X	X		X	X									X		X				X	
Paksoy & Chang	2010	X				X			X	X				X		X			X								X	S	X				X	
Peidro et. al.	2010		X			X		X	X	X		X	X	X			X		X			X				MC	X	S	X			X		
Safaei et. al.	2010	X				X	X	X	X	X				X		X			X							MC	X	S	X				X	
Zegordi et. al.	2010	X			X		X			X						X	X		X		X						X		X			X		
Zelenka	2010	X				X						X			X		X	X								DES					X		X	
Kuo & Han	2011					X		X		X				X		X		X			X		PSO[7]			MC	X	S		X	X	X		
Shi et. al.	2011		X			X		X						X		X		NLP					LR[8]			MC	X	S		X			X	

Studies	Year	Planning Scope			CSN Structure		Decision Variable						Constraint					Modelling Approach											Objective Function			Granularity Level		
																		Deterministic						Stochastic										
																		Mathematical Programming			Optimisation Method													
		Operational <1 year	Tactical < 10 year	Strategic >10 year	Single	Multiple	Supplier	Production	Inventory Control	Distribution	Allocation	Other	Supply	Demand	Resource	Capacity	Other	LP	MILP	MINLP	GA	Fuzzy	Other	System Dynamic	Risk Programming	Simulation	Optimisation	SOA(Integrated/Separate)	Total Cost (min)	Total Cost (min)	Total Cost (min)	Coarse SP+SF	Medium SP-MF/MP-SP/MP-MF	Fine MP-MF + Time
Amin & Zhang	2012		X	X		X	X	X						X	X			X			X						X			X			X	
Carvalho et. al.	2012	X			X		X									X	X									MC					X	X		
Chen et. al.	2012	X				X		X						X	X		X	X										I	X				X	
Xiao et. al.	2012		X			X		X									X		X			X				MC	X	S	X			X		
Zamarripa et. al.	2012	X				X		X		X				X	X	X			X		X							I	X				X	
Abu-Ajamieh et. al.	2013			X			X										X									MC			X			X		
Bilgen & Celebi	2013	X				X		X	X	X				X			X		X							MC	X	S		X			X	
Noche & Elhasia	2013	X			X			X	X					X			X									MC			X			X		
Pan & Nagi	2013	X	X	X		X		X						X									LR			MC	X	S	X					
Shabani & Sowlati	2013	X				X	X	X									X			X				X		MC	X	S	X				X	
Waldemarsson et. al.	2013	X			X			X		X	P			X		X			X							MC	X	S						
Abolhasani et. al.	2014		X			X		X	X	X	T			X	X	X			X		X					MC	X	S	X				X	
Jindal & Sangwan	2014	X				X	X	X			P	X				X				X			X			MC	X	S		X			X	
Nazim et. al.	2014	X			X		X	X	X	X				X			X	X				X				MC	X	S	X			X		
Wang et. al.	2014	X			X		X			X			X					X			X		PSO					I	X				X	
Kaya & Urek	2016					X			X		F	X								X						MC	X	S		X			X	
Rezaeian et. al.	2016	X	X	X		X		X	X	X							X			X				X	X	MC	X	S		X	X		X	
Salem & Haouari	2016	X			X			X	X	X			X	X		X			X				PSO			MC	X	S	X				X	
Seifbarghy	2016	X			X			X	X								X				X		PSO			MC	X	S		X				X

[1] Transportation
[2] Production
[3] Monte Carlo simulation
[4] System Dynamic simulation
[5] Separate exploitation of the simulation and optimisation methodologies
[6] Using simulation and optimisation approaches in an integrated framework
[7] Particle Swarm Optimisation
[8] Lagrangian Relaxation