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Planning of complex supply chains: A performance comparison of three meta-heuristic algorithms

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ABSTRACT

Businesses have more complex supply chains than ever before. Many supply chain planning efforts result in sizable and often nonlinear optimization problems that are difficult to solve using standard solution methods. Meta-heuristic and heuristic solution methods have been developed and applied to tackle such modeling complexities. This paper aims to compare and analyze the performance of three meta-heuristic algorithms in solving a nonlinear green supply chain planning problem. A tactical planning model is presented that aims to balance the economic and emissions performance of the supply chain. Utilizing data from an Australian clothing manufacturer, three meta-heuristic algorithms including Genetic Algorithm, Simulated Annealing and Cross-Entropy are adopted to find solutions to this problem. Discussions on the key characteristics of these algorithms and comparative analysis of the numerical results provide some modeling insights and practical implications. In particular, we find that (1) a Cross-Entropy method outperforms the two popular meta-heuristic algorithms in both computation time and solution quality, and (2) Simulated Annealing may produce better results in a time-restricted comparison due to its rapid initial convergence speed.

1. Introduction

As the world economy is reshaped to recover and grow faster, so too global supply chains transform and become increasingly more complex and difficult to manage. Incorporating and integrating new concepts and initiatives such as agility, lean, and sustainability practices are of paramount importance for businesses to maintain competitiveness. Yet, such practices pose numerous supply chain planning and optimization challenges. Not only have analytical and decision-support tools and techniques helped businesses solve a range of supply chain planning and optimization problems, but they have also provided invaluable practical insights on tradeoffs among different factors, constraints and rules.

The two core sub-problems of supply chain planning are production planning and distribution planning which were traditionally solved sequentially in a way that the outputs of a production plan serves as inputs for distribution decision making [7]. More recent studies have demonstrated the benefits of integrated supply chain planning, yet acknowledging the increasing complexity of the resulting models [20,22]. To tackle such modeling complexities, various solution techniques such as linear solvers, meta-heuristic and heuristic algorithms, and decision support tools and approaches have been developed and rapidly evolved [21].

Among various emerging concepts contributing to supply chain complexity is green supply chain management (GSCM). Practice-oriented research has shown that executives are now more than ever concerned with greening of their supply chains [43,72]. The trend is a result of governmental pressures and incentives as well as stakeholder interests [25]. In this environment, the more competitive firms are not necessarily those that offer the best set of products and services, but those that have the most efficient, sustainable and resilient supply chains.

Much of the research in GSCM field, especially in the forward GSCM literature, has focused on general descriptive and qualitative analysis through empirical evaluations and case studies [10,27]. Mathematical modeling and quantitative analysis has not seen the same level of research and development [25]. We seek to add to this dimension of literature. Formal modeling and quantitative analysis can help convince supply chain practitioners of greening benefits by exploring opportunities for simultaneous economic and environmental growth. A common challenge in this context is that

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the incorporation of sustainability-related measures into the conventional supply chain planning practices adds to the complexity of the associated modeling efforts due to the additional variables and constraints. A range of solution methods and innovative meta-heuristic and heuristic algorithms have been designed and tested to solve the resulting optimization problems [26].

This paper seeks to contribute to both of these aforementioned knowledge areas, integrated supply chain planning and GSCM, in the following ways. A practical GSCM model is presented motivated not only by theoretical considerations but also by real word practical requirements facing an actual organization. The performance of three solution techniques for solving this nonlinear optimization model is then investigated. Genetic Algorithm and Simulated Annealing are chosen as the most popular meta-heuristic algorithms in the context of supply chain planning and optimization, and Cross-Entropy as one of the most recent and modern solution methods with demonstrated application in solving complex combinational optimization problems. Several experiments were initially conducted to establish the parameter settings of the three algorithms at which the fastest convergence rate and best solution qualities could be obtained. Our analysis in this paper focuses on comparing the numerical results obtained from solving an actual GSCM problem using these three meta-heuristic algorithms.

The remainder of this paper is organized as follows. Section 2 reviews the literature of supply chain planning followed by an overview of the related GSCM modeling efforts. The mathematical model is presented in Section 3. The meta-heuristic algorithms used to solve the proposed mathematical model are introduced in Section 4. The application of the proposed model and solution techniques is investigated in Section 5 utilizing data from an Australian garment manufacturing company. Conclusions, research limitations and directions for future work in this area are presented in concluding Section 6.

2. Literature review

2.1. Supply chain planning modeling efforts

Supply chain modeling efforts aim to provide the required analytical decision making tools to assist practitioners in efficient and effective design and planning of supply chains. In the context of supply chain planning (putting supply chain design issues outside the scope of this paper), the two core sub-problems are production planning and distribution planning. For a concerned planning horizon, production planning involves determining the quantity of products to produce in regular-time and overtime, workforce levels, outsourcing decisions, and inventory levels. Distribution planning concerns the assignment of facilities to markets and determining optimal product flow quantities. Recent investigations have shown that production and distribution decisions are mutually interrelated and a globally optimal supply chain performance can only be achieved through integrated production–distribution planning in which decisions are made simultaneously, rather than sequentially [22,54]. Cost benefits and service level improvements of integrated production–distribution planning have been widely studied in the recent past [23].

Different factors can influence the complexity level of supply chain planning problems. Some of these factors are internal to the supply chain such as those related to supply chain scale including the number of product families, suppliers, manufacturing plants, warehouses, retailers, end-users, and planning periods. External factors may include changes in governmental policies, supply disruptions, lead-time variations, demand fluctuations, and sustainability concerns [38,71]. Mixed-integer linear programming (MILP) and mixed-integer nonlinear programing (MINLP) have been the most widely used mathematical modeling approaches for addressing supply chain planning problems [23,57]. For example, Safaei et al. [64] presented a MILP formulation for an integrated multi-product, multi-period, multi-site production–distribution planning problem (a focus on internal complexities) and Esmaeilikia et al. [18] presented an MINLP model for a supply chain with multiple flexibility options (a focus on both internal and external complexities).

Various solution methods ranging from exact linear solvers to meta-heuristic and heuristic algorithms have been developed to solve supply chain optimization models. Yet, achieving quality solutions in a relatively reasonable length of time has remained a challenge for both academics and practitioners. The use of linear solvers such as CPLEX has been quite popular to tackle small and medium-size problems that can be presented in a linear form [16,23,31,35]. Meta-heuristic and heuristic algorithms have been developed to explore solutions to large and/or nonlinear optimization problems [22,26,39,50,76]. Heuristic methods are typically designed based on problem structure and mathematical particularities. Hence, they are rather problem-dependent and a heuristic method may not serve the purpose to solve a range of optimization problems. Meta-heuristics, on the other hand, are general-purpose algorithms that can be applied to solve a range of optimization problems.

Simulate Annealing (SA) and Genetic Algorithms (GA) have been undoubtedly amongst the most popular meta-heuristics for solving large-scale and/or nonlinear optimization problems [17,4]. The literature has evidenced the increasing popularity of GA and SA in the context of supply chain management, and more specifically in the area of supply chain planning and optimization [19,23,3,33,5]. GA has been successfully employed in different supply chain problems, such as production and transportation planning [50,79], vendor-managed inventory problem [17,49], lot-sizing and delivery scheduling [69] and supply chain design and planning [22,3]. The application of SA has also been investigated in a broad range of production and operations management problems such as production sequencing [45], facility location [4], location and routing [48] and distribution planning [39].

Cross-Entropy (CE) is one of the more recent meta-heuristic solution method with demonstrated application in solving complex optimization problems such as buffer allocation [1], capacitated lot-sizing [13], vehicle routing [73], project scheduling [8], network design [2] and more recently supply chain planning [18,26,29]. The performance of the CE method, in terms of runtime and solution quality, against some of the well-known algorithms has been investigated in some of past studies [1,12,2,40], but not in the context of supply chain planning and optimization and against the more popular meta-heuristics methods.

Within the supply chain planning domain, the performance of meta-heuristic algorithms has been benchmarked in various studies. Sadegheih ($year$) [63] showed the superiority of GA over SA in computation time for solving a production scheduling problem. Ramezanian et al. ($year$) [58] compare the performance of Tabu Search (TS) and GA in solving an aggregate production planning problem. They find that GA returns better solutions (lower total cost) than TS for both small and large size problems, but the GA's computational times are higher for large size problems. Comparing SA, GA, TS and Ant Colony (ACO) for a transport network design problem, [42] find that GA, ACO and TS outperform TS in solution quality but SA beats GA and ACO in runtime. Arostegui et al. ($year$) [4] compare performance of GA, SA and TS for a facility location problem and conclude that SA is superior for solving a multi-period facility location problem, whilst GA outperforms SA in solving a multi-commodity facility location problem. We aim to add to this literature set by comparing the performance of the CE