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Abstract

Purpose – The purpose of this paper is to introduce an effective methodology of obtaining Perot-optimal solutions when combining system dynamics (SD) and multi-objective optimization (MOO) for supply chain problems.

Design/methodology/approach – This paper proposes a new approach that combines SD and MOO within a simulation-based optimization framework for generating the efficient frontier for supporting decision making in supply chain management (SCM). It also addresses the issue of the curse of dimensionality, commonly found in practical optimization problems, through design space reduction.

Findings – The integrated MOO and SD approach has been shown to be very useful for revealing how the decision variables in the Beer Game (BG) affect the optimality of the three common SCM objectives, namely, the minimization of inventory, backlog, and the bullwhip effect (BWE). The results from the in-depth BG study clearly show that these three optimization objectives are in conflict with each other, in the sense that a supply chain manager cannot minimize the BWE without increasing the total inventory and total backlog levels.

Practical implications – Having a methodology that enables effective generation of optimal trade-off solutions, in terms of computational cost, time as well as solution diversity and intensification, assist decision makers in not only making decision in time but also present a diverse and intense solution set to choose from.

Originality/value – This paper presents a novel supply chain MOO methodology to assist in finding Pareto-optimal solutions in a more effective manner. In order to do so the methodology tackles the so-called curse of dimensionality by reducing the design space and focussing the search of the optimization to regions of inters. Together with design space reduction, it is believed that the integrated SD and MOO approach can provide an innovative and efficient approach for the design and analysis of manufacturing supply chain systems in general.

Keywords System dynamics, Supply chain, Multi-objective optimization

Paper type Research paper

1. Introduction

Modeling is an effective way of designing, understanding or analyzing real-world processes and systems. A model helps a decision maker gain a better understanding of the complexity of a process/system and evaluate/predict its performance under various circumstances. A supply chain incorporates the integrated processes during which products are transformed from raw material, e.g., from the suppliers, to finished products delivered to end customers. Typically, these processes include different business functions in a company, e.g., procurement, production, logistics, etc., as well as the need to collaborate, coordinate and interact with each other, in order to produce the commodity of the supply chain (Kim *et al.*, 2004). Hence, supply chains can be seen as good examples of such complex systems which require the modeling of processes in the presence of multiple autonomous entities (i.e. suppliers, manufacturers, distributors, retailers, etc.), multiple performance measures and multiple objectives, both local and global, which together constitute the effects of

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very complex interaction (Keramati, 2010). Li *et al.* (2002) point out that supply chain modeling is more or less a prerequisite for supply chain integration and present four incentives for supply chain modeling: first, capturing supply chain complexities, e.g., interaction effects between supply chain members, by a better understanding and a uniform representation of the supply chain; second, designing the supply chain management (SCM) process, in order to manage supply chain interdependencies; third, establishing the visions to be shared by supply chains members and providing a basis for supply chain coordination and integration; and fourth, facilitating the reduction of supply chain dynamics at supply chain design phases.

Over the years, supply chains have been depicted by using various modeling approaches ranging from process, statistical, optimization, analytical, and simulation models. The advantage of simulation models is that they are able to model the complexities and incorporate the dynamic behavior of supply chains, as well as provide an understanding of the relationships between the input and output parameters. Despite the advantages, simulation models do not provide the capability of obtaining optimal solutions sets (Abo-Hamad and Arisha, 2011). Obtaining optimal solution sets requires evaluating a large number of system configurations, by assessing a set of output parameters from an evaluation with a specific set of input parameter settings. Optimization modeling approaches, employing, e.g., mathematical programming, require an equation-based model of the system, which is then used for optimizations using appropriate algorithms. The models also require that the developers have a comprehensive knowledge of optimization (Hong, 2005). In addition, the majority of the real-world problems are too complex to be formulated as manageable mathematical equations, so that pure optimization models, on their own, are incapable of incorporating the dynamic behavior and complexities of systems or processes such as supply chains (Better *et al.*, 2008). Hence, in a supply chain optimization problem, the supply chains need to be depicted using simulation modeling, in order to capture their dynamic behavior, and be combined with optimization methods, in order to attain optimal solution sets. This combined usage of the two approaches is called simulation-based optimization (SBO).

The modeling method for supply chains, proposed in this paper, is based on System Dynamics (SD), which is an approach based on information feedbacks and delays in the model, in order to understand the dynamical behavior of a system (Angerhofer and Angelides, 2000). A SD model facilitates the representation, both graphically and mathematically, of the interactions governing the dynamic behavior of the studied system or process, as well as the analysis of the interactions and their emergent effects. Modeling with SD enables users to take a causal view of reality and implements quantitative means to investigate the behavior of the system and its response to various policies. A SD model is derived from an internal non-linear structure of the system and is able to create new kinds of behaviors that might not have been observed in present time but may occur in the future (Bhushi and Javalagi, 2004). Sterman (2000) points out that a supply chain, being a system containing multiple autonomous entities, is characterized by a stock and flow structure for acquisition, storage, the conversion of inputs into outputs, as well as the decision rules that govern these flows. The existing flows in the supply chains, such as information, material, orders, money, etc., create important feedbacks among the members of the supply chain, thus making SD a well-suited approach for modeling and analyzing supply chains (Georgiadis *et al.*, 2005).

However, despite the increase in research within the domain of utilizing SD for SCM issues Angerhofer and Angelides (2000), Aslam *et al.* (2011) and Dudas *et al.* (2011)

show that only a few articles in the literature are related to the integration of SBO, particularly multi-objective optimization (MOO), with SD models. The area of supply chain optimization has been studied for more than two decades; however, the main focus of the research studies has traditionally been on minimizing the overall cost or maximizing the total revenue, as a single-objective optimization problem. Despite the successful implementations of several supply chain single-objective optimization studies, such as Cohen and Lee (1989), Arntzen *et al.* (1995), Voudouris (1996), Amiri (2006), Jayaraman and Pirkul (2001), Kristianto *et al.* (2012), Duan and Liao (2013), Yu *et al.* (2013), in our view, supply chain decisions are much more complex than treating them as single-objective optimization problems. For instance, while cost, revenue and flexibility, as presented in Voudouris (1996), can be the indicators that determine the performance of a supply chain, other important metrics used in supply chain analyses, such as lead time, inventory levels, service levels, work-in-process (WIP), etc., should be considered when optimizing a supply chain network. A short average lead time means that the total time a product is stored in the system is reduced, which also means that customer orders can be fulfilled more quickly, which thus leverages the overall performance of the supply chain. A low WIP means that transportation and inventory costs are reduced, which is also highly desired. Therefore, to a decision maker, an ideal configuration is the one that maximizes the level of the delivery service while it simultaneously minimizes lead time and WIP. Due to the conflicting nature of the above mentioned metrics, modeling a system using traditional optimization techniques in which a single-objective or a single weight-based objective to combine multiple objectives in an optimization would very likely lead to misleading results in a dynamic system such as a supply chain.

One of the major research areas within the supply chain domain is the bullwhip effect (BWE), which refers to a supply chain phenomenon where the demand variability of incoming orders is amplified as they move up the supply chain. Over the years, researchers have presented different proposals on how to solve the BWE issue, such as Swafford *et al.* (2008), Liang and Huang (2006), Costas *et al.* (2015). Some recent studies in which the authors have addressed the BWE through SD models are Cannella *et al.* (2015), Hwarng and Xie (2008), Udenio *et al.* (2015). In Cannella *et al.* (2015), the authors investigate the impact of inventory recording inaccuracy on the dynamic of a collaborative supply chain. Hwarng and Xie (2008), on the other hand, investigate the impact of the order of inventory variability, employing a chaos theory perspective, and its effects on a multi-level supply chain. In Udenio *et al.* (2015), the authors study and analyze a BWE phenomenon caused by the great downfall in sales, observed in the manufacturing industry at the end of 2008, following the bankruptcy of Lehman Brothers.

This paper presents an integrated SD and MOO approach to find and investigate the Pareto-optimal solutions of a pedagogical SCM model, namely, the Beer Game (BG), in which the main intention of the BG is to demonstrate the existence of the so-called BWE. In contrast to formulating inventory and backlog into a single optimization objective, in order to minimize the total cumulative cost, the current study attempts to minimize total backlog cost and minimize total inventory, within a truly MOO context. In addition to minimizing the total inventory and backlog costs, this study also considers minimizing the demand fluctuations, as the third optimization objective, for the purpose of reducing the BWE in a supply chain. However, when the number of objectives and the number of decision variables increase, it can be a big computational challenge and too time-consuming for a MOO algorithm to obtain the optimal solution set. In order to address this issue, a novel SD-MOO methodology is presented in this paper, with a twofold purpose: first, to investigate the application of MOO to supply chains analysis and second, to propose an efficient methodology which allows the MOO analysis of supply chains to be performed in a computationally cost-effective way, in terms of the efficiency, solution intensification and accuracy of the obtained Pareto-optimal front. The remainder of the paper is presented as follows: Section 2 presents the meta-heuristics approach implemented for the optimization in the paper, while Section 3 introduces the concept of applying MOO to the SCM domain. Section 4 presents the simulation-based MOO methodology. Section 5 introduces the BG, including its background and the SD model developed for the case study in this paper, and Section 6 presents the objective functions for the case study. The MOO results and analysis, particularly the use of data visualization methods like Parallel Coordinates (PC), are found in Section 7, which is followed by our conclusions.

2. Multi-objective meta-heuristics

As in the case of single-objective optimization, MOO approaches can be classified into exact algorithms and approximate algorithms, which are also known as heuristic approaches. One branch of heuristic approaches is meta-heuristics algorithms, which are general-purpose algorithms that consider high-level strategies to guide underlying heuristic algorithms in exploring the search space and solving the optimization problem (Blum and Roli, 2003). Jones *et al.* (2002) argue that the greatest advantage of meta-heuristic algorithms is their flexibility regarding their applicability to a diverse set of problem domains and optimization problems.

Over the years, researchers have also demonstrated the applicability of meta-heuristics to supply chain problems. For example, in their state-of-the-art review regarding SBO approaches in the context of SCM, Abo-Hamad and Arisha (2011) disclose that meta-heuristics has been the most popular optimization technique implemented during the last decade, within the application areas of SCM, such as inventory management, production planning and scheduling, transportation and logistics, as well as supply chain design, integration and collaboration. A compressive review regarding the implementation of meta-heuristic algorithms in the supply chain domain can be found in Abo-Hamad and Arisha (2011) and Griffis *et al.* (2012). Lourenco (2001) points out that features of the meta-heuristic algorithms are well-suited to solving SCM problems. Besides the ability to solve very complex and hard combinatorial optimization problems, their modular nature and problem independence result in shorter development and updating time of the optimization problem, which is crucial for coping with the rapid changes in a supply chain and the resulting short decision-making window for a decision maker. The features of meta-heuristics and their proven applicability in supply chain problems have motivated their use for the optimization procedure implemented in this paper. Specifically, the optimization procedure in this paper utilizes a population-based meta-heuristics so that multiple Pareto solutions can be captured in a single optimization.

Although meta-heuristic algorithms can offer many advantages, their application is, however, not completely straightforward. Talbi (2009) denotes that when meta-heuristics are applied to a multi-objective problem, the designer of the meta-heuristics algorithm has to consider the dynamic balance of intensification and diversification, where intensification refers to the exploitation of the best solutions found by the algorithm and convergence to the optimal solution sets, while diversification refers to the exploration of the search space and distribution of the obtained solutions around the optimal set. Hence, intensification ensures the generation of the approximated or near-optimal solutions and diversification ensures a wider spread of the optimal solutions covering different areas of the objective space, in order to limit the loss of valuable information regarding the trade-offs of the conflicting objectives. Another aspect to consider with meta-heuristics is that many real-world problems are NP-complete, and NP-complete problems are known to be associated with a high computational cost, since finding an optimal solution requires an extensive search (Syberfeldt, 2009). A problem can also be computationally expensive even though it is not NP-complete; real-world optimization problems generally involve an immense number of possible solutions, and hundreds or thousands of simulation evaluations are needed before an acceptable solution is found (Boesel *et al.*, 2001). This holds true especially for multi-objective problems, where a significantly larger portion of the search space needs to be explored to obtain a set of Pareto-optimal solutions (Streichert *et al.*, 2005). Even with improvements in computer processing speed, one single simulation may take a couple of minutes or even hours of computing time. This potentially requires enormous amounts of optimization time and is an issue that must be considered when applying meta-heuristics in real-world scenarios.

3. MOO for SCM

MOO is a discipline that has been studied since 1970s, and its application areas range widely from resource allocation, transportation, investment decision to mechanical engineering, chemical engineering, automation applications, to name a few. In contrast to single-objective optimization, where only one optimal solution can be expected to be found, MOO seeks to identify a set of optimal solutions which are defined as Pareto-optimal solutions. A solution is considered to belong to the Pareto set, when there is no other solution that can improve at least one of the optimization objectives without degrading any other objective. These sets of solutions are also known as the Pareto-front, when plotted on the objective space. The main concept of MOO is to evaluate two or more conflicting objectives against each other and obtain the Pareto-optimal solutions and the Pareto-front (Basseur *et al.*, 2006).

A simple method of handling a MOO problem is to form a composite objective function as the weighted sum of the conflicting objectives. Since the weight for an objective is proportional to the preference factor assigned to that specific objective, this method is also called preference-based strategy (Deb, 2001). Apparently, preference-based MOO is simple to apply, because by scalarizing an objective vector into a single composite objective function, e.g., combining all performance measures into a weighted average objective function to represent the overall system cost, a MOO problem can be converted into a single-objective optimization problem and, thus, a single trade-off optimal solution can be sought effectively. However, the major drawback is that the trade-off solution obtained by using this procedure is very sensitive to the preference vector. Therefore, the choice of the preference weights and thus the obtained trade-off solution is highly subjective to the particular decision maker. At the same time, it is also argued that using preference-based MOO to obtain a single "global" optimal solution for multi-tier systems, like supply chains, is not desirable if the "global" optimum suggests a set of decision variable values that may sacrifice the performance of the sub-system level. For example, the optimal solution found by the SBO may be optimal, when considering the overall supply chain, but totally unacceptable to the company that plays the role of the manufacturer. Therefore, for a decision maker, it would be useful if the posterior Pareto-front can be generated quickly by using a MOO algorithm, as shown in Figure 1, so that he/she can choose the most suitable configuration among the trade-off solutions generated.

Examining a supply chain clearly indicates that it is a complex system consisting of multiple entities (e.g. suppliers, manufacturers, distributors and retailers, as mentioned earlier), which individually have their own performance measures and objectives to optimize. For example, the retailer might aim to minimize the product price and lead time and the distributor might be measured on its ability to fully utilize the warehouse and its response to consolidating the customer order by shorter pick-up times or efficient pick-up routes. The manufacturer and supplier, on the other hand, have another set of key performance measures. The manufacturer aims to maximize the throughput while minimizing the WIP together with minimizing its production batch sizes and set-up times, while the supplier might seek to minimize its WIP and delivery time, as well as maximize quality and service levels. However, optimizing these individual entities is not adequate when optimizing a supply chain, since it is a dynamic network consisting of multiple transaction points with complex transportation, as well as information and financial transactions between entities. Hence, optimizing the supply chain as whole is as crucial as the optimization of the individual entities. The aim of SCM is to align and combine all these objectives, individual as well as the supply chain, so that they work toward a common goal – increasing the efficiency and profitability of the overall supply chain. SCM is thus multi-objective in nature and involves several conflicting objectives, both at the individual entity level and the supply chain level.

A comprehensive literature survey, presented in Aslam *et al.* (2011) in which the authors have investigated 42 journal papers concerning MOO for SCM problems, has shown that the majority of papers, or more exactly 53 percent, have used a mathematical approach, such as linear programming, mixed integer programming and mixed integer linear programming, etc. Further investigation showed that the most popular mathematical approach used to model supply chains is mixed integer non-linear programming, which accounts for 33 percent of the papers, followed by mixed integer linear programming, as the second most implemented mathematical approach (21 percent). The remainder of the methods are fairly equally distributed. Simulation approaches, on the other hand, like discrete event, agent-based or SD simulation,

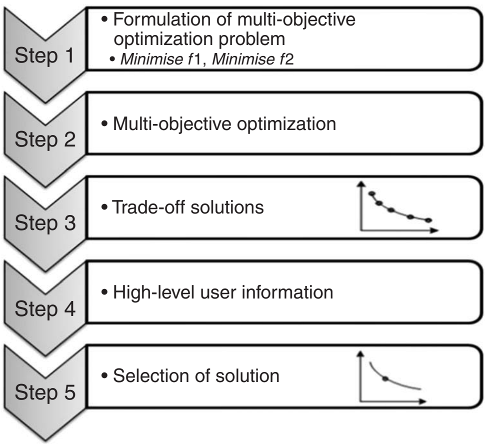

Figure 1.
General Pareto-based MOO procedure

only account for 24 percent of the implemented modeling techniques. Surprisingly, only one paper was found that implemented SD and MOO for SCM problems. As a short conclusion, it seems that the study of using SBO, especially within the context of MOO, is far from adequate. Having said that, an exception can be found in Duggan (2008) where the author proposes a similar approach as in this current paper, i.e., the use of SD and SBO for SCM. Duggan (2008) presents a MOO study of a SD BG model based on the stock management structure presented in Sterman (2000) containing only two entities, namely, the wholesaler and the retailer. The objective function for the MOO in that paper was to minimize the total cumulative cost for the two represented entities in the supply chain. In contrast to Duggan (2008), this work presents a methodology for performing supply chain MOO and investigates the MOO of the well-known BG, in which the objectives of the optimization are to find the Pareto-optimal supply chain configuration settings, by minimizing the overall supply chain inventory cost, minimizing the overall supply chain backlog cost and minimizing the BWE.

4. A methodology for MOO of supply chain models

Despite the many advantages of SBO and MOO presented in previous sections, these approaches still have some hurdles to overcome. Chen *et al.* (2002) explain that obtaining optimal solution sets for a multi-objective problem is often far more time-consuming than solving a single-objective problem where the increased computation time is not just due to the increased number of objectives, but also due to the so-called curse of dimensionality, which may increase the convergence time of the optimization algorithm. The term curse of dimensionality, also denoted as the problem of size by some (Shan and Wang, 2010), refers to the issue of rapid growth in combinatorial difficulty for problems as the number of variables (i.e. input and output parameters) or dimensions (i.e. objectives) increases (Kuo and Sloan, 2005). Also, Shan and Wang (2010) argue that the high dimensionality of input and output variables demonstrates an exponential growth in difficulty, regarding the modeling of the problem and optimization. Deb and Saxena (2005) also raise this issue and state that when the dimensionality of the objective space is increased, generally, the dimensionality of the Pareto-front is also increased, which would require an exponential number of points in the objective space to represent the Pareto-front, because adding one additional objective causes the dimension of the Pareto-front to increase by one. In connection to this, Koch *et al.* (1997) also explain that due to the combinatorial explosion of the problem, with regard to the number of variables and objectives included in the problem, both the efficiency and accuracy of the optimization are also sacrificed. Shan and Wang (2010) present several strategies for tackling the difficulties caused by the curse of dimensionality or high dimensionality. These strategies include: parallel computing, increased computer power, screening for significant variables, reduction of design space, decomposition of the problem into sub-problems, mapping, and visualization of the variable or design space.

In order to address the issue of dimensionality and combinatorial difficulty for MOO, from a supply chain problem perspective, this paper presents a methodology for executing supply chain MOO in a computationally cost-effective way, in terms of the efficiency, solution intensification, and accuracy of obtaining the Pareto-optimal front for supply chain problems. The methodology for supply chain MOO, presented in Figure 2, is based on the iteratively interactive guidance approach, which specifies that the MOO procedure utilized in this paper does not require a user-optimization interaction after each evaluation. Instead, the decision maker is presented with the

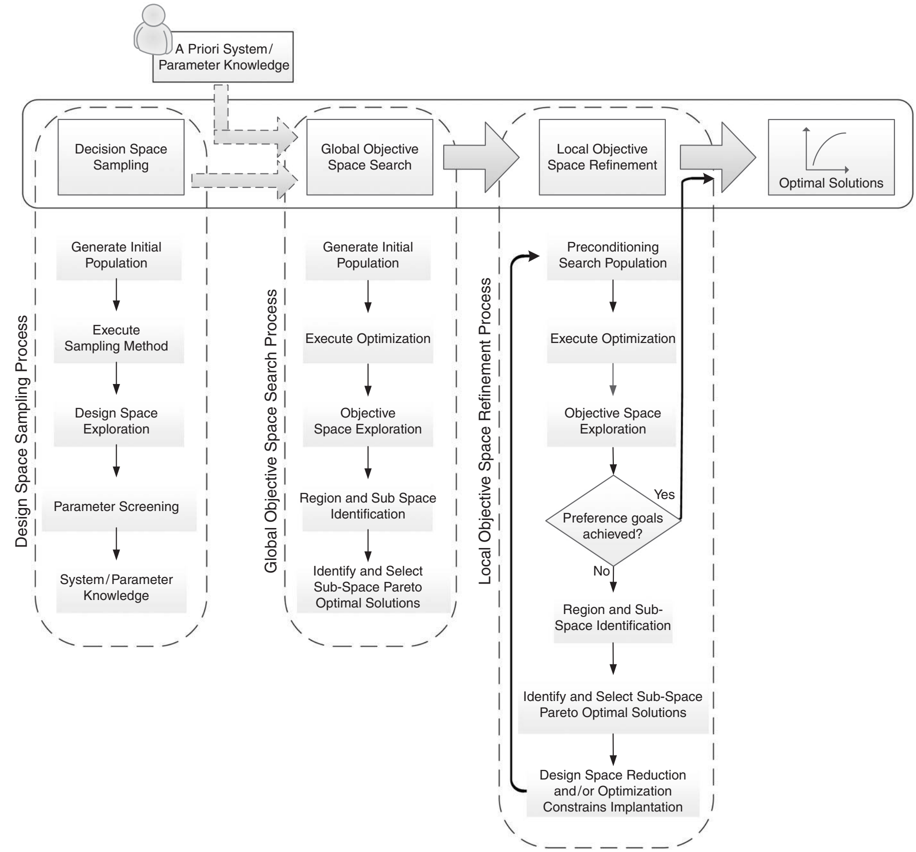

Figure 2.
Methodology for SD-MOO

search results from the optimization and subsequently evaluates whether the preference goals have been achieved or not. If the goals have not been achieved, the decision maker starts a new set of optimization runs, following the optimization methodology, in order to guide the search toward regions or sub-spaces of interest and increase the quality, accuracy, intensification, etc., of the solutions. This methodology for supply chain MOO also utilizes some of the strategies presented by Shan and Wang (2010), in order to obtain the Pareto-optimal front in a feasible time period. The methodology includes three main activities, namely, decision space sampling, global objective space search, and local objective space refinement, where each activity is established upon an internal process. Here, the aim of the decision space sampling activity is to roughly estimate the behavior of the problem, by exploring the decision space parameters and investigating how each parameter and its interaction with the other respond to the investigated problem, as well as exploring the parameter intervals, in order to set parameter interval boundaries for the optimization further on. The internal process of the decision space sampling activity starts by generating an initial population and then executing a sampling method, which can be any design of experiment approach, to fill the design space with solutions and thus initiate the design space exploration. Besides the aforementioned possibility of roughly estimating the behavior of the problem, exploring the design space also offers the opportunity to screen for significant parameters. According to Shan and Wang (2010), screening implies identifying and preserving vital input parameters and interactions, as well as removing less essential parameters or noise from the investigated problem and, thus, reducing the issue of dimensionality and combinatorial difficulty, in order to save computational cost. Hence, the decision space sampling procedure is able to provide information and understanding about the problem and the design space, in order to serve as the starting point for the subsequent global objective space search procedure. It is important to point out that the decision space sampling activity is not a prerequisite for the global objective space search, since a decision maker might already have an a priori problem, system and parameter knowledge, as well as a defined set of objectives, input parameters, and input parameter boundaries for the optimization.

In contrast to decision space sampling, which aims to provide problem and parameter-specific knowledge, the purpose of the global objective search activity is to provide a first set of Pareto-optimal solutions by executing the optimization; a prerequisite of this activity is that the user/decision maker has defined a set of objectives to optimize and a set of input parameters to manipulate, together with their upper and lower boundaries. As in the previous step, the activity is initiated by generating an initial population and then executing the optimization. The intention of this first optimization is to generate, in a feasible time period, a first set of Pareto-optimal solutions, in order to obtain an overview of the whole Pareto set. However, since this activity is a global objective space search, the solutions obtained from this global search are more likely to be spread over the objective space and over regions or sub-spaces which are not interesting for the investigated problem. Hence, in order to intensify the solutions, the search needs to be concentrated toward a region or sub-space of interest for the problem at hand. Thus, when a region or sub-space of interest has been identified, the Pareto-optimal solutions within that region or sub-space will act as a preconditioned population in the local objective space refinement activity. The final step is the local objective space refinement, which is an iterative activity that aims to focus the search and intensify the solutions in a region or sub-space of interest. The activity is initiated by implementing the Pareto-optimal solutions, identified in the previous procedure, as the population for the optimization. This approach is also known as preconditioning or preconditioned search, and, as explained, it utilizes a set of Pareto solutions as a starting point, in order to improve the search process of the optimization (Nicklow *et al.*, 2010). In terms of search efficiency and reliability, a number of studies reported by Nicklow *et al.* (2010) have shown that the preconditioned search contributes significantly to the optimization process. The authors also explain that in the aforementioned studies, the good solutions found from the search are continuously injected into the population until the search results continue to show improvements in solution quality or until a user-defined computational limit has been reached. Continuing with the internal process of the local objective space refinement activity, after executing the optimization and exploring the objective space with the new solutions, the user/decision maker needs to decide whether the goals of their preferences, e.g., in terms of quality, intensification, accuracy, etc., have been achieved. If the goals have been reached, the decision maker has obtained a set of Pareto-optimal solutions for the problem.

However, if the preference criteria have not been fully reached, one should continue and identify a region or sub-space of interest within that objective space, as well as identify a new set of Pareto-optimal solutions for the preconditioned search.

Nonetheless, before executing the preconditioned search, the user needs to reduce the design space and/or place constraints on the optimization. Design space reduction does not imply the elimination of design variables, as previously carried out during the screening process, but refers to the reduction of the design variable intervals, in order to decrease the design space, with the aim of reducing the computational effort of the optimization and focussing the optimization toward the most promising region or sub-space (Shan and Wang, 2010). While placing constraints on the optimization could limit the search space and potentially reduce the size of the complexity of the problem, in general this would require the optimization algorithm to embed an efficient constraint handling, in order to generate valid solutions (Deb, 2001). In some cases, for example, equality constraints are very difficult to handle and require special constraint handling techniques to find valid solutions. A way to handle equality constraints in SBO using linear programming and Hamilton distance can be found in Bernedixen and Ng (2014). Thus, by implementing these actions, the user/decision maker will subsequently face the same question again: have the preference goals been reached? If no, then the iteration of the local objective space refinement activity continues until the preference goals have been achieved or the optimization process has reached a user/decision maker time limit. One important aspect to mention is that the methodology presented here only concerns the optimization process under the SBO framework; the modeling or the simulation model utilized together with this optimization approach is presented in the next section.

5. The BG

The BG is a role playing simulation game which aims to replicate a multi-echelon supply chain incorporating four entities, namely, Factory (*F*), Wholesaler (*W*), Distributor (*D*) and Retailer (*R*), which together build a beer production and distribution supply chain with the overall objective to fulfill customer demand. The BG was originally developed at MIT Sloan School of Management in the 1960s (Sterman, 1989). As explained previously, the main intention of the game was to demonstrate the existence of the so-called BWE, which refers to a phenomenon in supply chains where demand variability of incoming orders is amplified as the orders move upstream in the supply chain (Lee *et al.*, 1997). It points out the role of collaboration, coordination, information management, inventory and production control, order management, purchasing, etc., in order to manage the BWE. The BG is quite straightforward and simple in its structure. Nonetheless, it incorporates a rather vast intrinsic dynamic complexity. Sterman (2000) points out that the majority of people might think of complexity in the form of number of components in a system or the amount of various combinations of inputs/information a decision maker must consider when making a decision. However, Sterman (2000) argues that in contrast to the combinatorial complexity or detail complexity of a problem or a system, the dynamic complexity can arise from very simple structures with low-combinatorial complexity, of which the BG is such a structure/model where the dynamic complexity arises from the interaction between the entities in the BG supply chain.

The original game is played on a board with physical chips/markers that move around, for instructions of the rules and regulation of this BG, the reader is referred to Sterman (1989). However, in this paper we present a replica of a SD model presented in Joshi (2012) which, in turn, is a modified version of the original SD-BG model built by Kirkwood (2012). The overall purpose of the models presented in Joshi (2012) and Kirkwood (2012), which is the same for the BG played on a board, is to show the existence of the BWE and how to manage it, by implementing different information sharing policies. However, our main intention is to implement MOO into SD, within the supply chain context, and investigate the Pareto-optimal trade-off solutions when minimizing the supply chain inventory cost, backlog cost and the BWE.

Each entity in the SD-BG model follows the generic structure presented in Figure 3; the thicker lines/arrows in the structure represent elements in the system where delay has occurred. As in the case of the original BG presented in Sterman (1989), the entities in the simulation model have no collaborative interaction between themselves. Each entity places orders with its supplier, according to the observed demand pattern from its downstream customer, two exceptions are the raw material supplier, who only delivers what is ordered by F, and the end customer, who only places orders with R. Before continuing with the model description and default settings of the BG, it is essential to describe the notions and definitions of the main variables in the generic structure, for a full and comprehensive list of the BG model, readers are referred to Joshi (2012). The main variables that are of most interest in our case study are the ordering policy, the total supply chain inventory cost, the total supply chain backlog cost and the total supply chain cost. Equations for these variables in the generic SD-BG entity model are presented below.

The inventory cost of the entire supply chain is given by:

$$INV_t^{SC} = INV_{t-1}^{SC} + \sum_i INV_t^i \tag{1}$$

where:

$$INV_t^i = INV_{t-1}^i + IU_t^i - SU_t^i \tag{2}$$

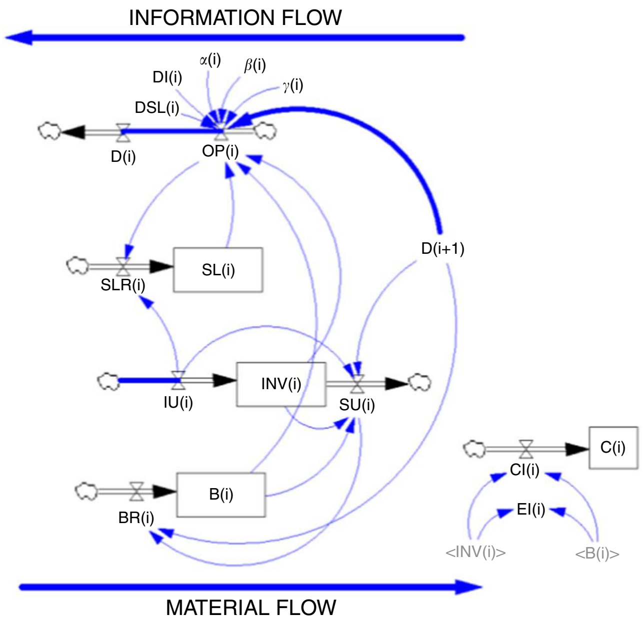

Figure 3.
A generic SD-BG entity model

and:

$$\begin{aligned} CINV_t^{SC} &= CINVC_{t-1}^{SC} + \left(INV_t^{SC} \times cf^{INV}\right) \\ cf^{INV} &= 0.5 \end{aligned} \tag{3}$$

INV_t^{SC}, inventory of the entire supply chain, in period t – indicates the aggregated inventory of the supply chain. INV_t^i, inventory of entity i, in period t – the on-hand inventory at each entity i. IU_t^i, incoming units to entity i from entity i–1 in period t – entity F, which does not have an upstream entity, receives units from a raw material supplier who just sends the number of units ordered by F; incoming units are received with a delay. SU_t^i, sold units from entity i to entity i+1, in period t – entity R, which does not have an upstream entity, sends the sold units to a sink and the units are consumed by the model. $CINV_t^{SC}$, cost of supply chain inventory, in period t – indicates the holding cost of aggregated inventory of the supply chain. cf^{INV}, cost factor for inventory – penalty factor for holding inventory.

The backlog cost of the entire supply chain is given by:

$$B_t^{SC} = B_{t-1}^{SC} + \sum_i B_t^i \tag{4}$$

where:

$$B_t^i = B_{t-1}^i + BR_t^i \tag{5}$$

where:

$$\begin{gathered} BR_t^i = D_t^{i+1} - SU_t^i \text{ for each entity} i, \\ \text{except entity } R \text{ where } D_t^{i+1} = D_t^{cust} \end{gathered} \tag{6}$$

and:

$$CB_t^{SC} = CB_{t-1}^{SC} + \left(B_t^{SC} \times cf^B\right) \tag{7}$$

B_t^{SC}, backlog of entire supply chain, in period t – indicates the aggregated backlog of the supply chain. B_t^i, backlog of entity i, in period t – indicates the aggregated backlog of entity i. BR_t^i, backlog rate of entity i, in period t – is the accumulation of backlog in entity i. D_t^i, orders placed by entity i to entity i–1, in period t – when orders are placed to entity i–1 then $D_t^{i+1} = D_t^i$; entity R, which does not have an upstream entity, receives orders placed by the end customer; orders are placed with a delay. D_t^{cust}, end customer demand. CB_t^{SC}, cost of supply chain backlog, in period t – indicates the cost of the aggregated backlog orders of the supply chain. cf^B, cost factor for backlog – penalty factor for having backlog.

The cumulative cost of the entire supply chain is given by:

$$C_t^{SC} = C_{t-1}^{SC} + CI_t^{SC} \tag{8}$$

where:

$$CI_t^{SC} = CINV_t^{SC} + CB_t^{SC} \tag{9}$$

C_t^{SC}, cost of entire supply chain, in period t – indicates the aggregated cost of the supply chain. CI_t^{SC}, rate of cost increase of the entire supply chain, in period t – is the accumulation of the cost in the supply chain.

As mentioned earlier, each entity in the SD-BG model is based on the generic structure presented in Figure 3 and includes the equations presented above. The governing variable in this structure, and thus in each entity, is the ordering policy which is based on an anchoring and adjustment heuristic, first presented in Tversky and Kahneman (1974). The anchoring and adjustment heuristic is used to estimate an unknown quantity, by first setting or defining an anchor, e.g., recalling a known reference point, and then adjusting factors, e.g., additional information or updated information, to estimate the unknown quantity (Sterman, 1989). As mentioned earlier, the entities in the simulation model have no collaborative interaction between themselves, thus the ordering policy heuristics aim to utilize is the local information available for the entities in the supply chain, such as local inventory, backlog, supply line information. The ordering policy is defined on the basis of four aspects: the order must be non-negative; order enough to cover the expected inventory losses; reduce the discrepancy between desired and actual inventory; reduce the discrepancy between desired and actual supply line.

The ordering policy at each entity i is given by:

$$OP_t^i = MAX\left(0, DOP_t^i\right) \tag{10}$$

where:

$$DOP_t^i = DF_t^i + \alpha^i\left(DI^i - \left(INV_t^i - B_t^i\right)\right) + \beta^i\left(DSL^i - SL_t^i\right) \tag{11}$$

where:

$$DF_t^i = SMOOTH\left(D_t^{i+1}, \gamma^i\right), \tag{12}$$

where:

$$D_t^{i+1} = D_t^{cust} \text{ in entity } R$$

$$\gamma^i = 1$$

and:

$$SL_t^i = SL_{t-1}^i + SLR_t^i \tag{13}$$

where:

$$SLR_t^i = OP_t^i - IU_t^i \tag{14}$$

OP_t^i, ordering policy of entity i, in period t – represents the actual order amount to be placed; this is defined once a week. DOP_t^i, desired ordering policy of entity i, in period t – represents the desired order amount, calculated with the anchoring and adjustment heuristic. DF_t^i, demand forcast by entity i, in period t demand forecast by entity i, in period t – use the Vensim® SMOOTH function to make a demand forecast; SMOOTH() function is based on exponential smoothing technique. SL_t^i, supply line of entity i, in period t – indicates the aggregated amount of units to be received for entity i. SLR_t^i, supply line rate of entity i, in period t – is the accumulation of the orders estimated by the ordering policy less those which have been delivered. DI^i, desired inventory at entity i – preferred amount of units in the inventory. DSL^i, desired supply line at entity i – preferred amount of units in the supply line. α^I, forecasting parameter at entity i – forecasting parameter for the inventory; the parameter is usually represented in the range of $\alpha^i = 0 \leqslant \alpha^i \leqslant 1$. β^i, forecasting parameter for supply line at entity i – forecasting parameter for the supply line; the parameter is usually represented in the range of $\beta^i = 0 \leqslant \beta^i \leqslant 1$. γ^i, smoothing time parameter at entity i – time input to Vensim® SMOOTH function.

The first aspect of the ordering policy, i.e., the order must be non-negative, is applied by (Equation 10) where the MAX() function in Vensim prevents OP_t^i to place order values less than zero. The other three aspects refer to the anchoring and adjustment heuristic in (Equation 11) where the depletion or surplus of inventory and supply line will require adjustment toward the desired inventory and supply line levels, which is done by $\alpha^i(DI^i-(INV_t^i-B_t^i))$ and $\beta^i(DSL^i-SL_t^i)$, respectively, in (Equation 11). Here, the α^i and β^i parameters represent the discrepancy of the amount of units needed in the inventory in the case of α^i and β^i represents the fraction of supply line taken into account when determining OP_t^i. Thus, a high α^i value would indicate that the majority of the required units for the inventory will be ordered or, e.g., that the manager at entity i will implement an aggressive policy/effort in order to adjust the inventory toward the desired inventory level. In the case of β^i, a value of, e.g., $\beta^i = 1$ would indicate that all the orders in the supply line have been taken into account, when deciding the amount of orders to place with the supplier, whereas $\beta^i = 0$ would indicate that no order in the supply line has been taken into account.

Turning to the running of the simulation model and its default settings, in the overall SD-BG supply chain, which is presented in Figure 4, one can see that the flow of information, i.e., orders, moves upstream in the supply chain and the flow of material, i.e., beer crates, moves downstream in the supply chain. The simulated BG begins at $t = 0$ and every incremental week each entity of the supply chain has to make a decision regarding how many crates need to be ordered from the supplier, which is calculated in OP_t^i for each entity, and how many crates can be shipped upstream to its customer, which is done in SU_t^i. Thus, in the default simulation settings, the models start out in equilibrium, i.e., $t = 0$, with no oscillating effect in the supply chain. The end customer demand, i.e., D_t^{cust}, starts out by ordering four crates of beer during the first four weeks, and then suddenly in week five the end customer increases its demand to eight crates a week for the remaining part of the simulation, which is run for $0 \leqslant t \leqslant 200$ weeks. It can be pointed out here that in the SD-BG model, presented in Joshi (2012), the results were presented in the interval of $0 \leqslant t \leqslant 36$ weeks. However, our output data were collected in the interval of $0 \leqslant t \leqslant 130$ weeks, in order to ensure that the output data of the BWE in the supply chain is fully captured, since tweaking the input parameters for the entities in the supply chain for the optimization might lead to the fact that some parameter settings might prolong the BWE and thus outrange the interval used in Joshi (2012).

The default initial values for variables at each entity at $t = 0$ are[1]:

$$INV_0^i, IU_0^i, D_0^i, SL_0^i, DI^i, DSL^i, \alpha^i, \beta^i, \gamma^i = 12, 4, 4, 8, 12, 14.7, 0.26, 0.088, 1$$

Figure 5 clearly shows the existence of the BWE from the output of the SD-BG model; this oscillating effect was captured using the default settings of the simulation model

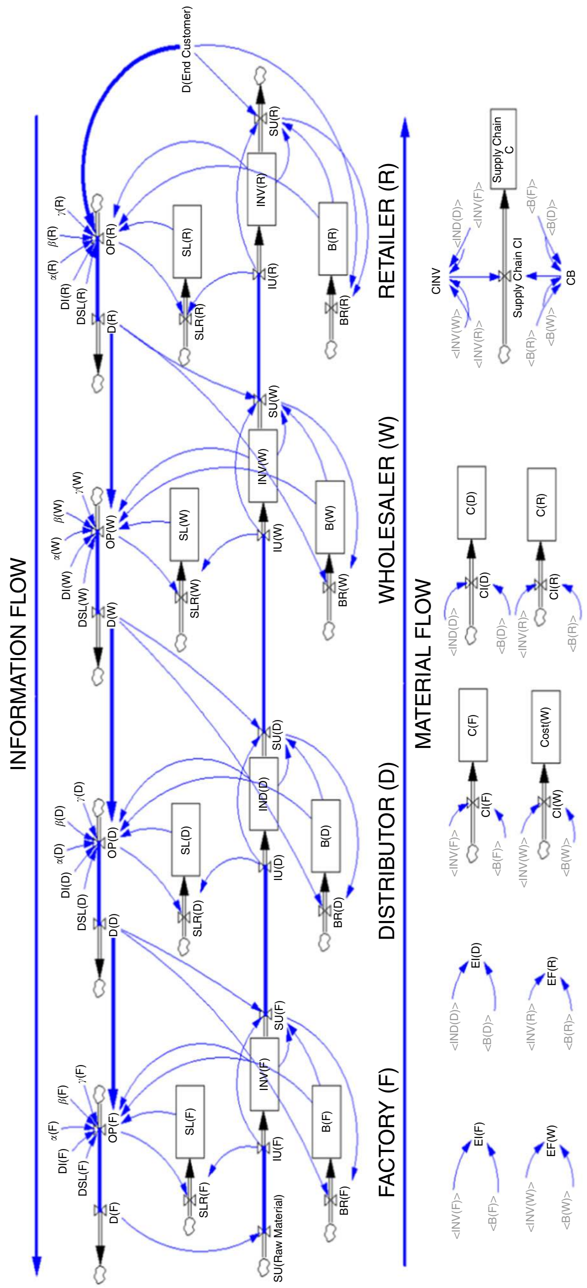

Figure 4.
The SD-BG
supply chain

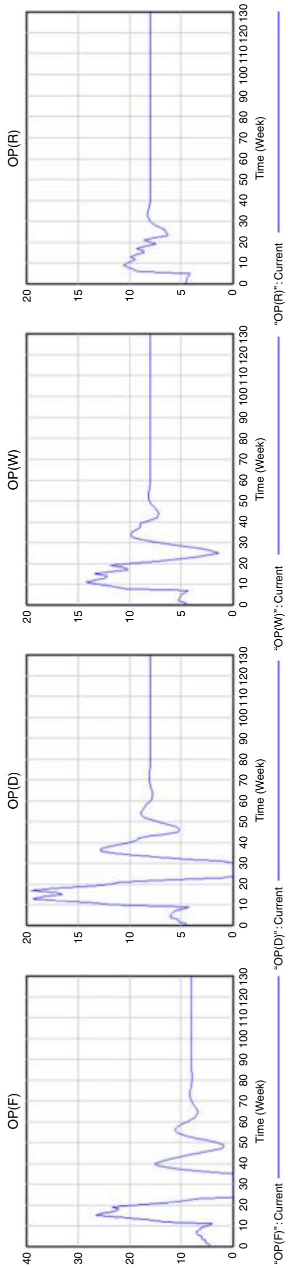

Figure 5.
The bullwhip effect

and shows how an increase in end customer demand, from four crates to eight, has led to a huge oscillating effect at the final entity F, where the demand ranges from zero to nearly 27 crates.

6. MOO of the BG

The experiment in this paper was conducted through two optimization scenarios. Both scenarios used the same function/equation/method to minimize the inventory cost and backlog cost values, however, the two scenarios differed with regard to how the BWE was minimized. In scenario 1 (S1), the BWE was minimized using an approach presented in Dudas *et al.* (2011), where the authors intended to minimize the BWE by minimizing the highest order value. On the other hand, in scenario 2 (S2) an approach presented by Chen *et al.* (2000) was implemented, in which the BWE was quantified or measured by obtaining the ratio between the variance of orders and the variance of demand. Two key factors that enable a successful MOO experiment are first, being able to formulate one's business problem into an optimization problem that can be confided in the optimization algorithm and the simulation model and second, being able to define a clear interface between the simulation model and the optimization engine. Thus, here follows a notation regarding how the business goals in this paper, i.e., minimize inventory cost, backlog cost and the BWE of the entire supply chain, formulate into an objective function that produces quantitative values for evaluation. It should be noted that the BWE in this paper is minimized by implementing the two BWE approaches at entity F, since this entity is the final one in the supply chain, as shown in Figure 5. It is this entity which experiences the highest demand fluctuations compared to other supply chain members. Hence, minimizing the BWE at entity F is crucial. Furthermore, by limiting or minimizing the demand fluctuation at entity F, it would be interesting to know whether the demand amplification from the entity R through entity D can also be reduced.

The objective functions for the optimization scenarios are denoted as:

$$O_F^{S1}\begin{cases} Min\ O_{f1}^{S1}\left(CINV^{SC}\right) = Min\ \mu_{CINV^{SC}} \\ Min\ O_{f2}^{S1}\left(CB^{SC}\right) = Min\ \mu_{CB^{SC}} \\ Min\ O_{f3}^{S1}\left(BWE_{max}^{F}\right) = Min\ max_{OP^F} \end{cases}, \tag{15}$$

$$O_F^{S2}\begin{cases} Min\ O_{f1}^{S2}\left(CINV^{SC}\right) = Min\ \mu_{CINV^{SC}} \\ Min\ O_{f2}^{S2}\left(CB^{SC}\right) = Min\ \mu_{CB^{SC}} \\ Min\ O_{f3}^{S2}\left(BWE_{var}^{F}\right) = Min\ \sigma^2_{OP^F}/\sigma^2_{D^D} \end{cases}, \tag{16}$$

where:

$$I = DI^i, DSL^i, \alpha^i, \beta^i \tag{17}$$

and:

$$O = \mu_{INV^i}, \mu_{B^i}, \mu_{SL^i}, \mu_{C^i}, \mu_{INV^{SC}}, \mu_{B^{SC}}, \mu_{C^{SC}} \tag{18}$$

where:

$$\mu_{INV^i} = \frac{\sum_{t=0}^{T} INV_t^i}{T}, \tag{19}$$

$$\mu_{B^i} = \frac{\sum_{t=0}^{T} B_t^i}{T}, \tag{20}$$

$$\mu_{SL^i} = \frac{\sum_{t=0}^{T} SL_t^i}{T}, \tag{21}$$

$$\mu_{C^i} = \frac{\sum_{t=0}^{T} C_t^i}{T}, \tag{22}$$

$$\mu_{CINV^{SC}} = \frac{\sum_{t=0}^{T} INV_t^{SC}}{T}, \tag{23}$$

$$\mu_{CB^{SC}} = \frac{\sum_{t=0}^{T} B_t^{SC}}{T}, \tag{24}$$

$$\mu_{C^{SC}} = \frac{\sum_{t=0}^{T} C_t^{SC}}{T}, \tag{25}$$

subject to:

$$CS^i = OP^i \geqslant 0,\ 0 \leqslant DI^i \geqslant 12,\ 0 \leqslant DSL^i \geqslant 12,\ 0 \leqslant \alpha^i \geqslant 1,\ 0 \leqslant \beta^i \geqslant 1 \tag{26}$$

O_F^{S1} and O_F^{S2}, all optimization objectives – states all objective functions for the optimization of respective scenario. O_{f1}^{S1} and O_{f1}^{S2}, first objective function – states the optimization function to minimize the supply chain inventory of respective scenario. O_{f2}^{S1} and O_{f2}^{S2}, second objective function – states the optimization function to minimize the supply chain backlog of respective scenario. O_{f3}^{S1} and O_{f3}^{S2}, third objective function – states the optimization function to minimize the BWE of respective scenario, where, in O_{f3}^{S1} the function/method $BWE_{max}^F$is utilized and in O_{f3}^{S2} the function/method BWE_{var}^F is utilized. BWE_{max}^F, highest order value of entity F – states the highest value of order placed (maxOPF) by entity F; for details regarding this approach readers are referred to Dudas *et al.* (2011). BWE_{var}^F, ratio of order and demand variance – states the ratio between order variance ($\sigma^2_{OP^F}$) at entity F and demand variance ($\sigma^2_{D^D}$) of entity D; for details regarding this approach readers are referred to Chen *et al.* (2000). I, input variables – indicates all the input variables utilized in the optimization of both scenarios. O, output variables – indicates all the output variables utilized in the optimization of both scenarios; each output represents a performance measure of the input variables in each optimization evaluation. CS^i, default model constraints of entity i – indicates all the constraints in the model for entity i – defined in most cases as the upper and lower bounds of decision variables, e.g I. μ_{INV^i}, mean inventory of entity i – gives the mean value of the inventory at entity i. μ_{B^i}, mean backlog of entity i – gives the mean value of the backlog at entity i. μ_{SL^i}, mean supply line of entity i – gives the mean value of the supply cline at entity i. μ_{C^i}, mean cost of entity i – gives the mean value of the overall cost at entity i. $\mu_{CINV^{SC}}$, mean inventory cost of the supply chain – gives the mean value of the inventory holding costs for the entire supply chain. $\mu_{CB^{SC}}$, mean backlog cost of the supply chain – gives the mean value of the backlog costs for the entire supply chain. $\mu_{C^{SC}}$, mean cost of the supply chain – gives the mean value of the overall cost for the entire supply chain. T, end of output data collection period – states the end time of the output data collection period; in this paper $T = 130$ weeks.

7. Results and analysis

7.1 Optimization methodology analysis

The execution of the optimization experiments is based on the aforementioned optimization methodology presented in Section 6. The experiments were not initiated through the decision space sampling activity, since the objectives, input variables, and input intervals of interest were already defined, because we had an a priori problem, system and parameter knowledge based on the models of Joshi (2012) and Kirkwood (2012). Hence, the experiments began by running the global objective space search with a total of 60,000 evaluations for each scenario, from which the optimization obtained 1,247 and 1,372 Pareto-optimal solutions for S1 and S2, respectively. The Pareto-optimal solutions obtained from the S2 scenario are presented in Figure 6. The first graph in Figure 6 clearly shows the diversity of the obtained Pareto solutions which are spread over the objective space and on regions or sub-spaces of less importance for the investigated problem.

Thus, the optimization methodology identified a region or sub-space of interest, as shown in graph 2. This region or sub-space was particularly interesting for the problem at hand, as all objectives in this case were to be minimized. In another case setting, e.g., the maximization of one of the objectives, other regions or sub-spaces would have been of interest. Thus, the Pareto-optimal solutions in the selected region or sub-space in graph 3 will act as the solution in the preconditioned search, in order to focus the

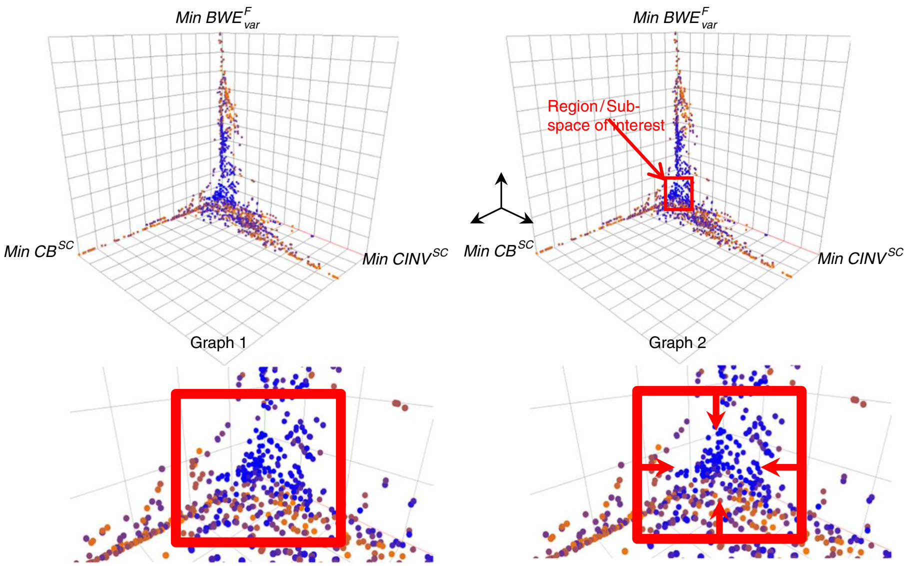

Figure 6. Pareto-optimal solutions for S2 obtained from global objective search

optimization search within this region. Graph 4 in Figure 6 intends to show that this region or sub-space is then diminished or constricted even more during the local objective space refinement activity, by reducing the design space, i.e., reducing the input parameter intervals, and implementing constraints on the optimization, which can increase the Pareto solution quality, accuracy, and intensification within the region or sub-space of interest. Figures 7 and 8 display the Pareto-optimal solutions obtained from the final local objective search iteration of the respective optimization scenario. It should also be pointed out that these Pareto solutions were obtained from the fourth local objective search iteration for each of the scenarios. Comparing Figure 7 and graph 3 in Figure 6 clearly demonstrates that by focussing the search, constricting the design space and utilizing optimization constraints, the optimization was able to increase the Pareto solution quality, accuracy and intensification, within our region or sub-space of interest.

Since it required 60,000 (60 K) evaluations in the global objective space search activity, and an additional 240,000 evaluations in the local objective space refinement activity, to reach the Pareto solutions' intensity and accuracy, as shown in Figures 7 and 8, it could be argued that by just executing a total of 300,000 (300 K) evaluations, without implementing the presented optimization methodology, one might be able to reach the intensity and accuracy of the Pareto solution shown in the aforementioned figures. In order to confirm the computational cost effectiveness, in terms of efficiency, solution intensity and accuracy of the MOO methodology presented in this application case study, a comparison was made between the Pareto-optimal solutions gained from the aforementioned global objective space search, where a total of 60 K evaluations were executed, and a global objective space search with 300 K evaluations were executed. The F-1 graph in Figure 9 presents the Pareto solutions obtained from 60 K evaluations and the F-2 graph displays the Pareto solutions obtained from 300 K evaluations, whereas the F-3 graph presents the combined Pareto solution sets of the two evaluation runs. Examining these three graphs and comparing the F-4 graph in Figure 9 to graph 3 in Figure 6, it is clear that the 300 K evaluation run has been able to obtain more Pareto solutions, approximately 600 additional Pareto solutions, than the 60 K evaluation run. However, as in the case of graph 3 in Figure 6, the F-4 graph in Figure 9 is still far from achieving an equivalent Pareto solution quality, accuracy, and intensification as presented in Figure 7. Analysis of the obtained Pareto-optimal solutions will be analyzed in the coming section.

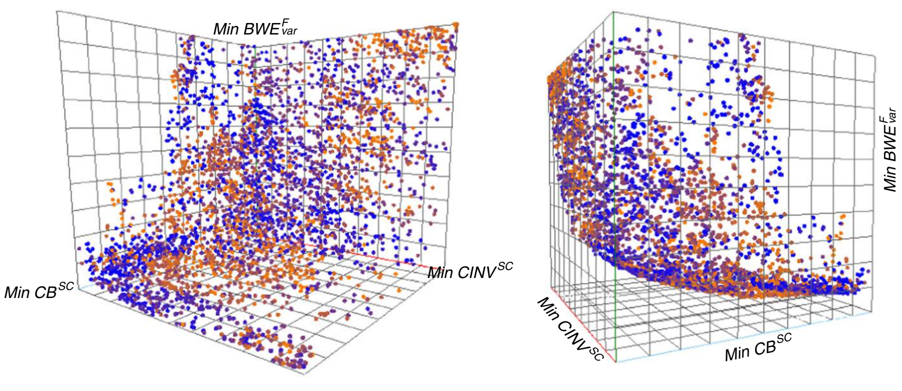

Figure 7.
Final Pareto-optimal solutions for S2 obtained from local objective search

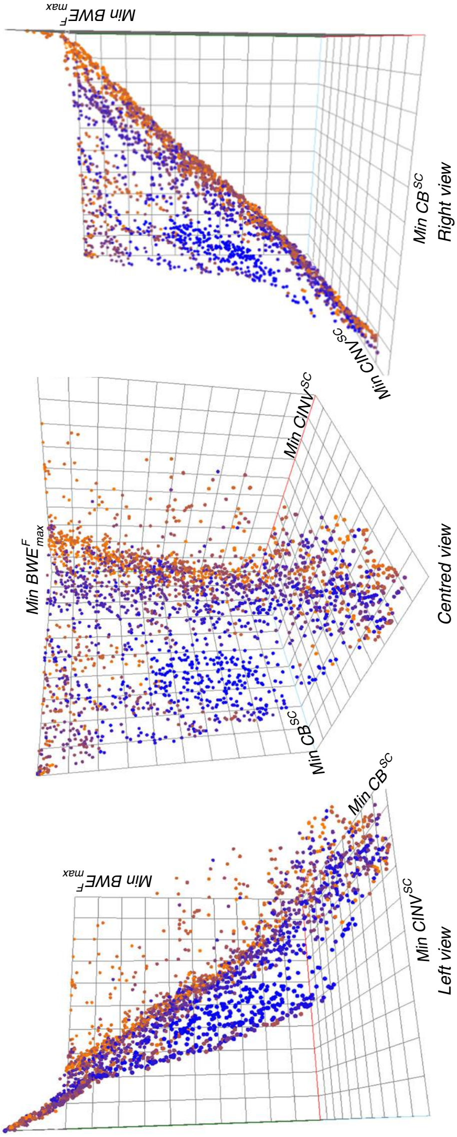

Figure 8.
Final Pareto-optimal solutions for S1 obtained from local objective search

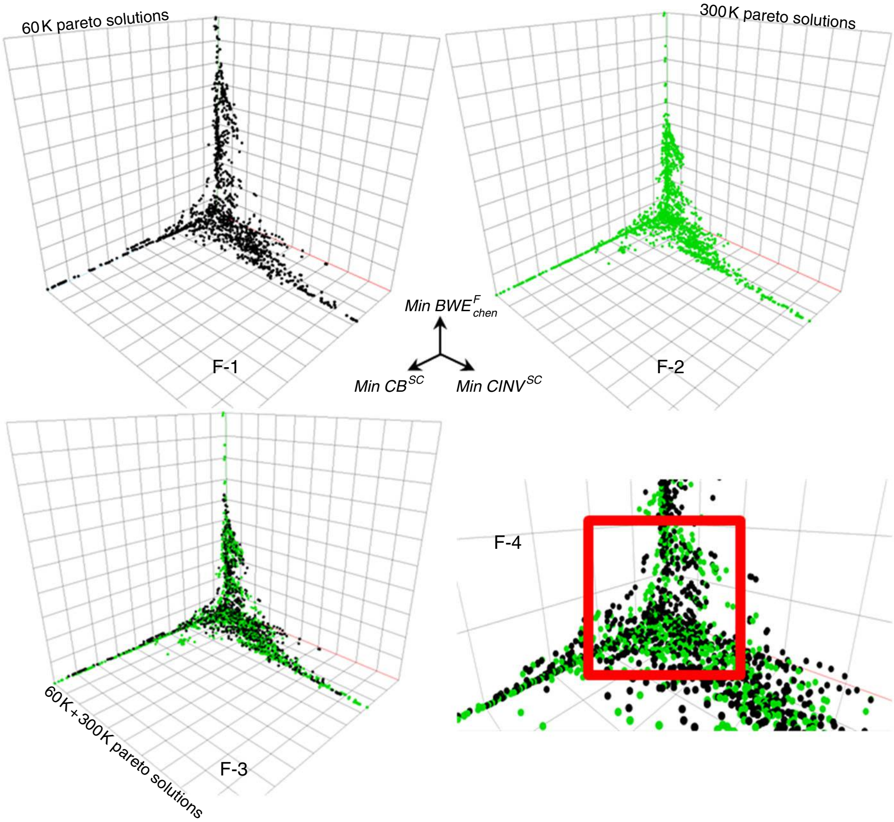

Figure 9.
Comparison of 60 K and 300 K Pareto-optimal solutions

7.2 Scenario analysis

7.2.1 Scenario 1. As mentioned earlier, the aim of S1, besides minimizing the supply chain inventory and backlog costs, was to minimize the BWE^F_{max} by utilizing the approach presented in Dudas *et al.* (2011). During the execution of the experiments, a total of 240,000 evaluations were run for S1, before the preference goals were satisfied in the local objective space iteration procedure and, from these evaluations, the optimization generated more than 2,500 Pareto-optimal solutions. Figure 8 displays these solutions as a Pareto-front on the objective space and Figure 10 displays these solutions with a PC showing the design variables and their resulting objective function values. PC-1 in Figure 10, which displays all the Pareto-optimal solutions obtained without any filter, shows that the majority of the α and β values are located in the lower regions of their parameter boundaries, except for β^R, β^D and maybe α^F with the approximate intervals of (0.014-0.59), (0-0.38) and (90.01-031) for respective parameter where the default value for β^i was 0.088.

The higher values of β^R and β^D, then β^W and β^F, indicate that for some of the Pareto-optimal solutions, the decision maker/supply chain manager in entity R or D needs to take greater consideration of its incoming supply line than the rest of the entities. This is significantly highlighted in PC-4, which shows that if the Pareto solutions are filtered

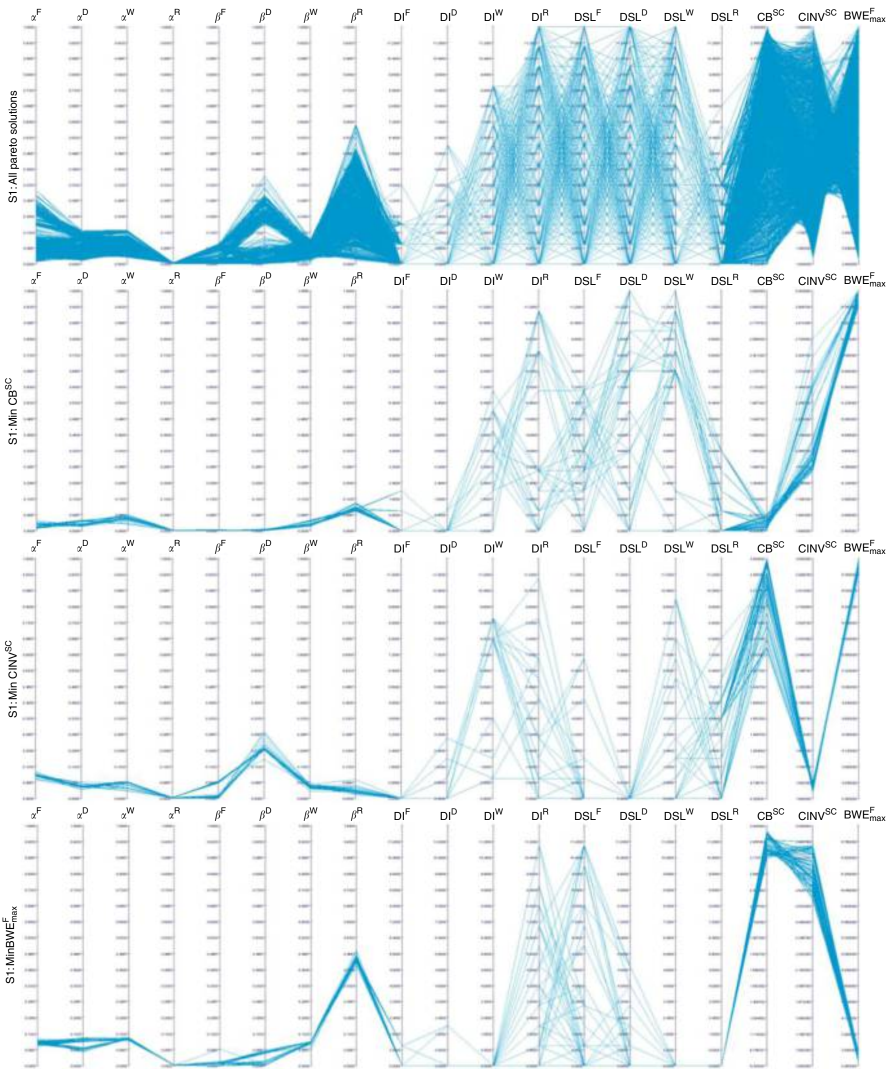

Figure 10.
Parallel Coordinate of S1 Pareto Solutions

on BWE^F_{max}, i.e., the minimization of BWE^F_{max} is prioritized, the decision maker of entity R needs to consider its supply line to a much greater degree than its supply chain partners when defining DOP^R. However, if the Pareto solutions are filtered on $CINV^{SC}$, i.e., the minimization of $CINV^{SC}$ is prioritized, then, as PC-3 depicts, the decision maker of D would have to consider its supply line to a greater degree than the rest of the supply chain members.

7.2.2 Scenario 2. In contrast to S1, scenario S2 utilizes the BWE^F_{chen} approach presented by Chen *et al.* (2000), in order to minimize the BWE; the other two objectives are the same as in S1. S2 was also run for 240,000 evaluations before the preference goals were reached. However, in comparison to S1, the optimization in S2 obtained more than 4,100 Pareto-optimal solutions, i.e., approximately 1,600 more Pareto solutions than S1. Figure 7 displays these solutions as a Pareto-front on the objective space and Figure 11 presents a PC of S2 design variables and their resulting objective function values. Examining Figure 11 and PC-5 reveals that the α and β design variables have a higher interval span where especially α^D and β^F distinguish themselves with an interval span of β^F (0.6740-1), whereas α^D which is divided into two areas, as shown in PC-5, shows that the upper region span is α^D (0.6509-0.8536). Both these parameters indicate that the manager at each of the respective entities, i.e., D and F, needs to implement an aggressive ordering policy. The α^D(0.6509-0.8536) denotes that when the manager at D defines its OP, an aggressive policy/effort will need to be implemented, in order to adjust the inventory toward the desired inventory level.

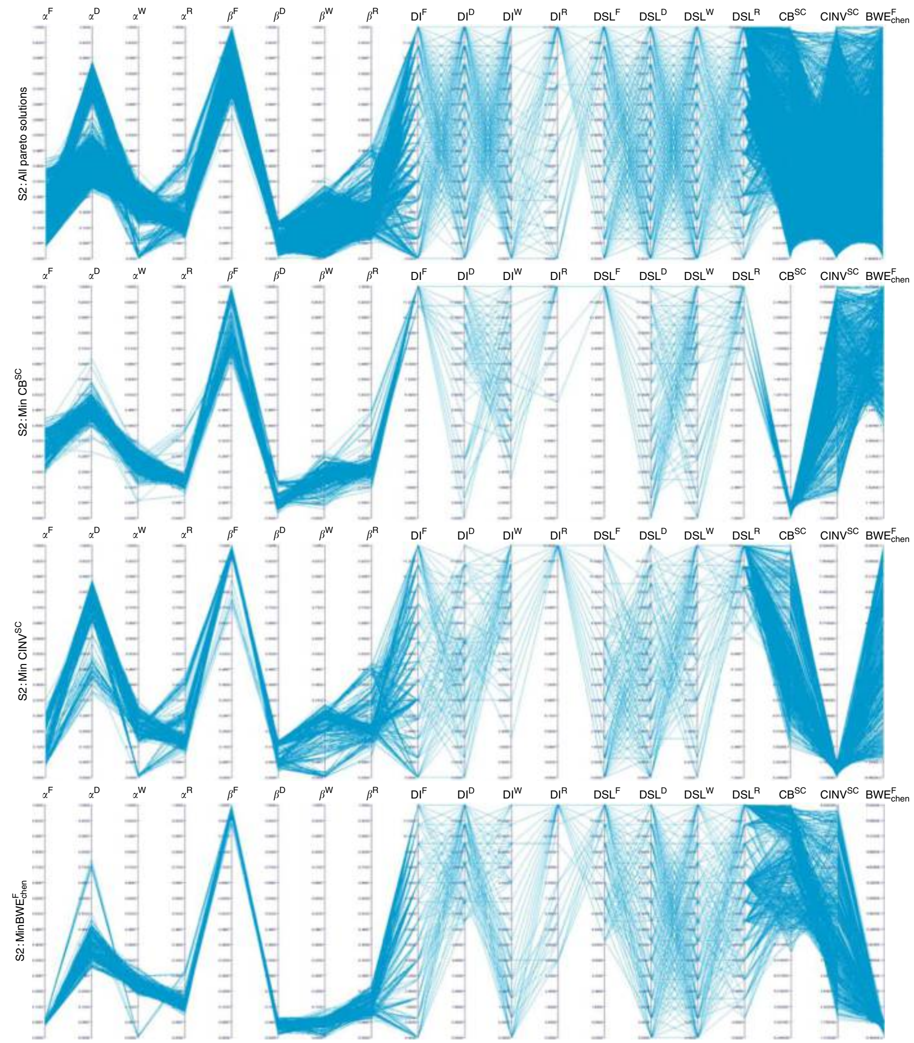

Figure 11.
Parallel Coordinate of S2 Pareto Solutions

The results in PC-5 also show that α^D is more important than β^D for the manager at entity D when defining its ordering policy according to Equation (11), since the interval span for β^D is much lower than the α^D interval presented for the obtained Pareto solutions. Hence, for the decision maker at entity D, the adjustment of the inventory toward the desired levels DI^D is more important than considering the supply line to a great extent. However, by examining the β^F (0.6740-1) and comparing it with the interval span of its α^F parameter, the opposite behavior is apparent. For the decision maker at entity F, the priority lies in considering its supply line instead of implementing an aggressive policy to adjust the inventory toward DI^F.

Filtering the Pareto solutions on CB^{SC}, i.e., the minimization of CB^{SC} is prioritized by the decision maker, reveals that these solutions presented in PC-6 are represented by the lower region of α^D(0.2847-0.5938) and that some of the DI and DSL parameters only have values within a certain interval region. For instance, PC-6 shows that DI^F is (11-12), indicating that for Pareto solutions for which the decision maker prioritizes CB^{SC}, the desired inventory for entity F should be either 11 units or 12 units. Similarly, DI^W(2-12) indicates that entity W needs to keep at least a desired inventory of two units, whereas DI^R shows that for these filtered Pareto solutions the decision maker at entity R only needs to have a desired inventory of (8), (10) and (12), all other values of DI^R are non-optimal when the obtained Pareto solutions are filtered on CB^{SC}. Observing the DSL parameter, the PC-6 diagram shows that DSL^F requires a desired supply line value of (12) at entity F for these Pareto solutions, whereas the desired supply line at R has a slightly larger interval span DSL^R(9-12) where the values indicate that for these filtered solutions entity R is required to keep a supply line of at least nine units. However, observing the aforementioned parameter in PC-7 of Figure 11, where the Pareto solutions have been sorted on $CINV^{SC}$, reveals that in $CINV^{SC}$-filtered solution α^D the upper interval span of (0.6509-0.8536) has more impact on these solutions compared to the CB^{SC}-filtered solutions presented in PC-6, where the lower interval span of α^D has a greater impact on the CB^{SC}-filtered solutions. The β^F parameter, which already has a very high interval span β^F(0.6740-1) in PC-6, has an even higher span β^F(0.9450-1) in PC-7, for the vast majority of the solutions. This illustrates that the manager at F needs to take the supply line into account to an even greater extent for the $CINV^{SC}$-filtered solutions than the CB^{SC}-filtered solutions. The DI and DSL parameter intervals in PC-7 also differ from the solutions in PC-6, where DI^F ranges from (0-12) in PC-7, instead of (11-12) in PC-6, and where DI^R requires a desired inventory of (8), (10) and (12) in PC-6, whereas in PC-7 it requires a value of 12 units at minimum. The values of the desired supply line of entity F are also spread over a larger interval in PC-7 than in PC-6 in which the CB^{SC}-filtered solutions require a minimum of 12 units for DSL^F, whereas in $CINV^{SC}$-filtered solutions the values span between DSL^F(0-12).

However, for solutions filtered on BWE^F_{chen}, one sees that in PC-8 the minimum value of DSL^F is five units, which indicates that for these solutions a DSL^F parameter value less than five units does not have any effect on the $CINV^{SC}$-filtered solutions. The PC-8 diagram also shows that the DI^R values span between two regions, that is, between (4-8) and (10-12), and that DI^D, in contrast to its interval values in PC-6 and PC-7, has an interval of (6-12), which means that the desired inventory should never be less than six units for entity D, if the manager prioritizes the BWE^F_{chen} objective over the other two objectives. The BWE^F_{chen}-filtered solutions also show that the β^F parameter requires more or less the same consideration of the supply line as the majority of the $CINV^{SC}$-

filtered solutions. However, the α^D parameter has an interval span of (0.2978-0.5388) for the vast majority of the BWE^F_{chen}-filtered solutions, which in contrast to β^F is more similar to the CB^{SC}-filtered solutions, indicating that the solutions filtered on BWE^F_{chen} and CB^{SC} require a less aggressive inventory adjustment policy/effort by the manager at entity D than for solutions filtered on $CINV^{SC}$.

7.2.3 Scenario 1 vs scenario 2. An analysis of Figures 10 and 11 clearly illustrates that the optimization objectives defined in the two scenarios are obviously in conflict. For instance, Figure 10 shows that minimizing the CB^{SC}-objective will result in a greater holding cost for the supply chain inventory and cause a significant BWE, while minimizing the $CINV^{SC}$-objective will cause an even greater demand amplification and result in a rather high backlog cost for the supply chain. However, the minimization of the bullwhip, in this case BWE^F_{max}, will generate a very high backlog cost for the supply chain, together with a quite high supply chain cost for holding inventory. This trade-off behavior between the three optimization objectives is also demonstrated in Figure 12, which depicts the average value of the 1,000 best Pareto-optimal solutions sorted on C^{SC}, i.e., total supply chain cost. An evaluation of the two averages from the respective scenario shows that S2, depicted as the black line, achieves a much lower C^{SC} than S1. The fact that S2 has a much lower total supply chain cost is because S2 also has a significantly lower backlog cost for the entire supply chain and, as we know from Equation (7), having a backlog is twice as expensive as holding inventory. This relationship can be interpreted in Figure 12, where S2 has a much higher $CINV^{SC}$, but as its CB^{SC} value is very low, having a higher inventory holding cost does not have any significant effect on the C^{SC} parameter.

The fact that the $CINV^{SC}$ value of S2 is 5.16 indicates that the supply chain must accept this average inventory holding cost, in order to achieve the level of CB^{SC} and C^{SC} for S2 depicted in Figure 12. One can also deduce from Figure 12 that, on average, the managers in S2 are required to implement a more aggressive policy/effort, in order to adjust the inventory toward the desired inventory level. In addition, they must consider the supply line, especially β^F, to a significantly greater extent, when determining the order value. The supply chain in S2 also needs to have higher desired inventory and desired supply line levels. However, all these efforts and higher values of the design parameters of S2 are rewarded by the resulting lower total supply chain and backlog costs. Besides outperforming S1 by having lower total supply chain and backlog costs, S2 also outperforms S1 in terms of minimizing the BWE^F-objective, i.e, minimizing the BWE; the $CINV^{SC}$-objective is the only S1 optimization objective that outperforms its S2 counterpart. Thus, the approach presented in Chen *et al.* (2000) outperforms the approach implemented in Dudas *et al.* (2011), in terms of total supply chain cost, with the optimization objectives to minimize the BWE, as well as the supply chain inventory and backlog costs.

8. Conclusions

The methodology presented in this paper not only defines a method for executing and combining SD and MOO for supply chain analysis, but also attempts to address the issues of the curse of dimensionality, commonly found in practical optimization problems, through design space reduction. The developed SD-MOO methodology, which is based on the SBO framework, aims to execute supply chain MOO in a computationally cost-effective way, in terms of the efficiency, solution intensification

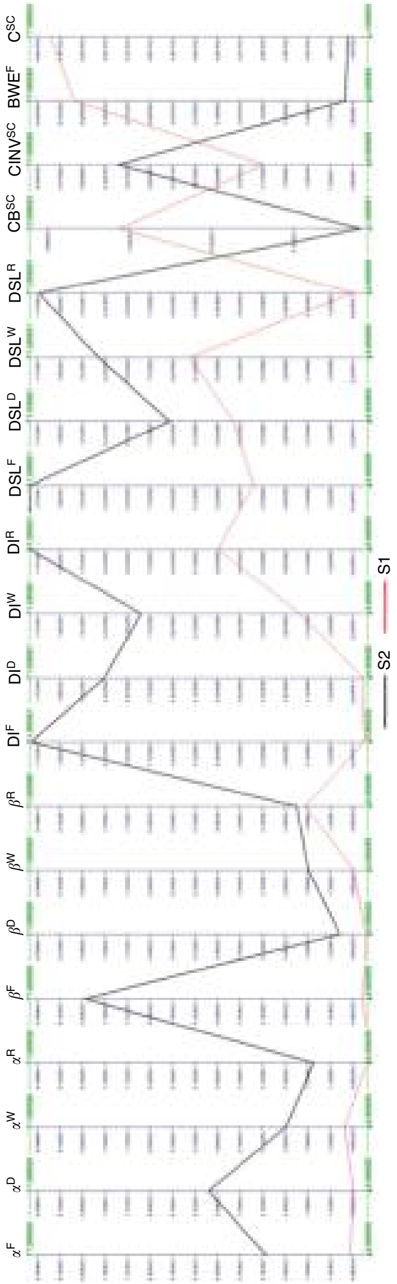

Figure 12.
S1 and S2 average values sorted on total supply chain cost

and accuracy of obtaining the Pareto-optimal front. The presented SD-MOO methodology has then been evaluated through a pedagogical SCM model, namely, the BG, in order to find and investigate the Pareto-optimal solutions in a computationally cost-effective way. The goal of achieving both solution intensification and good accuracy for a reasonable computational cost has been done through several key steps: first, performing a global search, in order to quickly generate a set of Pareto-optimal solutions, so that the behavior of the problem can be understood; second, executing an iterative refinement of the solution set, by identifying interesting regions and analyzing the properties of the solutions within the selected region; and third, subsequently focussing the search on the region of interest through limiting design variable boundaries by imposing new constraints on the optimization. The results from evaluating the methodology through the case study, in which the objectives were to simultaneously minimize the total inventory and backlog costs as well as minimize the demand fluctuations, i.e., the BWE in the supply chain, clearly show that the Pareto-optimal front has been obtained in a significantly more computationally cost-effective manner, through the use of the proposed method in the optimization process. It is believed that the SD-MOO methodology concept can further be applied to real-world supply chain problems, where the methodology would assist decision makers to effectively generate a set of Pareto-optimal alternatives. Other results gained from the integration of SD and MOO for the BG also show that the three optimization objectives, defined for the case study, are in conflict with each other, in the sense that a SC manager cannot minimize the BWE without increasing the total inventory and total backlog levels. As a conclusion, the integrated SD and MOO method is believed to provide an innovative approach for the analysis of manufacturing supply chain systems.

Note

1. Please note that only variables with an initial value > 0 are presented here.

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