Knowledge-Based Systems 95 (2016) 45–57

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Optimizing a bi-objective reliable facility location problem with adapted stochastic measures using tuned-parameter multi-objective algorithms

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ARTICLE INFO

Article history:
Received 1 June 2015
Revised 9 October 2015
Accepted 3 December 2015
Available online 12 December 2015

Keywords:
Bi-objective reliable facility location problem
Stochastic process
Non-dominated ranking genetic algorithm (NRGA)
Multi-objective biogeography-based optimization (MOBBO)
Response surface methodology (RSM)

ABSTRACT

The stochastic process is one the most important tools to overcome uncertainties of supply chain problems. Being a lack of studies on constrained reliable facility location problems (RFLP) with multiple capacity levels, this paper develops a bi-objective RFLP with multiple capacity levels in a three echelon supply chain management while there is a constraint on the coverage levels. Moreover, there is a provider-side uncertainty for distribution-centers (DCs). The aim of this paper is to find a near-optimal solution including suitable locations of DCs and plants, the fraction of satisfied customer demands, and the fraction of items sent to DCs to minimize the total cost and to maximize fill rate, simultaneously. As the proposed model belongs to NP-Hard problems, a meta-heuristic algorithm called multi-objective biogeography-based optimization (MOBBO) is employed to find a near-optimal Pareto solution. Since there is no benchmark in the literature to compare provided solutions, a non-dominated ranking genetic algorithm (NRGA) and a multi objective simulated annealing (MOSA) are used to verify the solution obtained by MOBBO while a two-stage stochastic programming (2-SSP) is employed to capture randomness of DCs. This paper uses the adapted concepts of expected value of perfect information (EVPI) and the value of stochastic solution (VSS) in order to validate 2-SSP. Moreover, the parameters of algorithms are tuned by the response surface methodology (RSM) in the design of experiments. Besides, an exact method, called branch-and-bound method via GAMS optimization software, is used to compare lower and upper bounds of Pareto fronts to optimize two single-objective problems separately.

1. Introduction

Nowadays, supply chain management (SCM) plays an important role in the organizational survival. SCM encompasses all aspects of producing, distributing and delivering products regarding minimizing total costs and maximizing service level [1]. This requires meticulous planning, often exposed to uncertain events. The unreliability of facilities, like natural disasters, sabotage, and labor actions, causes provider-side uncertainty [2]. It might be possible for facilities in an SCM like distribution centers (DCs) to be inactive once in a while; thus, it is necessary to reassign customers to other active DCs while some real models are unable to do reassigning because of constraints on capacity and budget. A well-known approach to overcome this problem is called reliable facility location problem (RFLP), managing parts of a system when there is a failure in its parts [3]. Moreover, RFLP addresses the prospect of facilities' failure and seeks to minimize the expected failure cost. In general, RFLP includes three main sub-problems which are a stochastic programming, a supply chain design, and a facility location problem.

In the stochastic programming, one of the most popular approaches used in RFLP is a two-stage stochastic programming (2-SSP), successfully employed by these studies Shen et al. [2], Gade and Pohl [4], Aydin and Murat [5], and Marufuzzaman et al. [6]. In 2-SSP approach, decision variables of a problem are categorized into the first and the second stage variables. The first and the second variables are determined before and after an uncertain event, respectively. The 2-SSP uses scenarios for characterizing uncertainties. In the terminology of RFLP, the first and second stage decisions are representatives of location and allocation dependent variables, respectively. Moreover, scenarios represent different permutations of active and inactive facilities. Thus, the first stage variables are strategic decisions that are robust and unable to be revised. The second stage variables are tactical decisions that are flexible in response to any scenario realization. Since the expected value of perfect information (EVPI) and the value of stochastic solution (VSS) estimate uncertain parameters of a problem, it is a standard practice in stochastic literature to evaluate the effectiveness of 2-SSP by EVPI and VSS [7]. EVPI estimates the uncertain parameters using the factual information while VSS

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http://dx.doi.org/10.1016/j.knosys.2015.12.001
0950-7051/

uses the expected value of uncertain parameters to estimate the uncertain parameters. In addition to stochastic programming, there are also several approaches to capture uncertainty such as hierarchical assignment of customers to the closet active DCs, continuum approximation, robust optimization, and Voronoi diagram. Billhardt et al. [8] presented a dynamic model to minimize expected arrival time to patients with respect to ambulance fleet allocation, in which a geometric optimization, called centroidal Voronoi tessellations, was used to capture uncertainty of the emergency services.

The supply chain design, the second component of RFLP, often involves conflicting objectives to fulfill both efficiency and responsiveness of the chain [9]. Thus, it is necessary to formulate problems into multi objective models to satisfy conflicting objectives, simultaneously. Altiparmak et al. [10] solved a tri-objective model in a supply chain using a genetic algorithm (GA) to minimize total cost and capacity utilization rate of facilities and to maximize service level at the same time. Moreover, Moncayo-Martínez and Zhang [11] considered a supply chain including multiple suppliers in order to minimize total cost and lead-times simultaneously using multi objective colony optimization algorithm. Besides, Latha Shankar et al. [12] provided a near-optimal Pareto solution, minimizing total cost and maximizing fill rate, using multi-objective hybrid particle swarm optimization algorithm in a single-product supply chain.

Facility location problem is the third and the main part of RFLP. Cases in which RFLP includes only location-allocation variables are unable to cover all aspects of real-world conditions such as capacity level variable [14]; thus, it seems reasonable to consider the capacity level of facilities endogenously [13]. Regarding the coverage constrain on facilities as the fundamental limitation, Li and Ouyang [14] developed a reliable fixed charge location problem with a facilities constraint to minimize expected customer transportation costs and the sum of initial facility construction costs in which there was a constraint on facilities coverage. Furthermore, Li and Ouyang [15] solved a RFLP, including traffic surveillance, using customized greedy and Lagrangian relaxation algorithms in which facilities and customers were assumed to be sensors and automobiles, respectively. In two previous studies, it is assumed that a facility serves a customer only within a given distance while the partial coverage constraint, as a new approach to overcoming uncertainties, is able to limit shipments from facilities to customers based on both their distance [16] and capacity level of facilities [17]. Thus, this paper employs this approach to near to real-world conditions.

This paper developed a bi-objective RFLP in a three-echelon SCM including plants, DCs, and customers in which DCs include probabilistic failure with a determined distribution while a set of scenarios is used to present different permutations of active and inactive DCs. Moreover, 2-SSP is adopted to capture the randomness of DCs while VSS and EVPI are used in order to validate 2-SSP. It is assumed that multi levels of capacities are available for both plants and DCs. The aim of this paper is to find a near-optimal Pareto solution including capacity level of facilities and typical location-allocation decisions to minimize total cost (expected transportation costs) and to maximize fill rate (the expected cumulative amount of satisfied customers' demand within all scenarios), simultaneously while there is a constraint on shipments from DCs to customers based on both their distance and capacity level of DCs called the partial coverage constraint. Appendix including a basic instance provides more details to improve understanding of the proposed model.

As RFLP is an NP-hard problem, proved by Peng et al. [18], it is impossible or hard to solve it with an exact method in a reasonable time. Thus, meta-heuristic optimizations, like genetic algorithm (GA) [19], are used to solve NP-hard problem such as Salimi [20] and Farahani and Elahipanah [21]. There are two approaches to solve multi objective models: classical and Pareto front [22]. The main advantage of using Pareto front is to provide a set of solutions based on objectives in which decision makers are able to present a solution with respect to the importance of objectives. Thus, the Pareto optimizations in evolutionary algorithms have been used to solve the multi objective problems such as multi-objective particle swarm optimization (MOPSO) [12], Ant-colony algorithm [11], Bees algorithm [23], and non-dominated sorting genetic algorithm-II (NSGA-II) [24].

Since the proposed model is both an NP-hard problem and a multi-objective model, this paper employs the meta-heuristic algorithms to solve it. This paper uses multi-objective biogeography-based optimization (MOBBO) to provide a near-optimal Pareto solution verified by two other algorithms namely the multi objective simulated annealing (MOSA) and the non-dominated ranking genetic algorithm (NRGA) while response surface methodology (RSM) tunes parameters of the algorithms.

The most important practical applications of Reliable Facility Location Problem (RFLP) are in inclement weather, labor actions, sabotage, change in ownership, terroristic attacks, and disaster management. This paper like other studies tries to develop RFLPs to close to real-world conditions. Therefore, in comparison to recent studies shown in Table 1, the main contribution of this paper is to develop the mathematical model based on the suggestion made by Cui et al. [25], i.e. multi-level capacities, in which the model itself optimizes and defines the capacity of facilities (endogenously in the terminology of RFLP) rather than defining it by an assumption made in the model (exogenously in the terminology of RFLP). Another expansion of this paper is to consider the partial coverage as a constraint on the model. The simple coverage constraint, studied by Li and Ouyang [14], Li and Ouyang [15] and O'Hanley and Church [26], covers customers located in defined regions while the partial coverage supports customers based on the proportion of distance to capacity level of facilities. Another contribution is to formulate two conflict objectives into a bi-objective RFLP based on suggestion made by Cardona-Valdés et al. [9] optimizing the efficiency (e.g. total cost) and responsiveness (e.g. fill rate) factors, simultaneously. Finally, this research is probably the first study employing EVPI and VSS for multi-objective models.

The rest of the paper is organized as follows. Section 2 presents mathematical model. The solution procedures and the results are shown in Sections 3 and 4, respectively. Finally, conclusion and the future research are provided in Section 5.

2. Problem formulation

This section formulates the 2-SSP and its extension for the a bi-objective concept of a partial reliable facility location problem (BPRCFLP). As a result of utilizing the 2-SSP, different decisions are made in two stages. First stage decisions determine the location and capacity level of opened DCs and plants. Second stage decisions determine the supply and distribution patterns of the chain. This involves supplying the opened and active DCs by the opened plants and then servicing. During the second stage, some of the opened DCs of the first stage may be inactive due to the realization of a specific uncertainty. Inactive DCs have zero capacity and consequently supply and distribution patterns should be made with respect to the active DCs. A scenario is an event which realizes the active and inactive DCs beyond an uncertainty. Since the outcome of an uncertainty is not clear, a set of scenarios is considered to enumerate all the events. The second stage is referred to as recourse decision. Actually, when one or more DCs is/are inactive, other active DCs should satisfy the demand. However, this may not be fully accomplished due to the capacity constraint of DCs. Since the first stage decisions are irreversible, the only legal recourse to mitigate the situation is the second stage of decision making. Here, we formulate a trade-off between costs associated with the first and second stage decisions on one hand and fill rate of customers' demand on the other hand. To customize a bi-objectives 2-SSP for BPRCFLP, notations are suggested as follows.

I, J, K Set of customers, DCs, and plants, respectively.
i, j, k Index set of customers, DCs, and plants, respectively.