Improving the Decision-making of Reverse Logistics Network Design Part II: An Improved Multi-criteria Scenario-based Risk-averse Solution Method and Numerical Experimentation

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Abstract. The study of the network design problems related to reverse supply chain and reverse logistics is of great interest for both academicians and practitioners due to its important role for a sustainable society. However, reverse logistics network design is a complex decision-making problem that involves several interactive factors and faces many uncertainties. Thus, in order to improve the reverse logistics network design, this paper proposes a new optimization model under stochastic environment and an improved solution method for network design of a multi-stage multi-product reveres supply chain. The study is presented in a series of two parts. Part I presents the relevant literature and formulates a stochastic mixed integer linear programming (MILP) for improving the decision-making of the reverse logistics network design. Part II improves the solution methods for the proposed stochastic programming and illustrates the application through a numerical experimentation.

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1.1 Introduction

Decision-making of a real world problem is hardly done with all relevant information available, but, in most cases, the decision has to be made even if some parameters cannot be accurately predicted or estimated at the time of decision-making (King and Wallace, 2012). For example, when a manufacturing facility is planned, the size of the facility is usually determined by the predication of future demand, however, the prediction of the future is always wrong as discussed in many research works (Chopra and Meindl, 2007). Thus, we have to make a proper decision with "the wrong predication of the future", and this will have a significant influence on the performance of the facility, say, an overoptimistic predication may lead to a waste of capacity or a high level of inventory, while a pessimistic estimation probably results in the incapability to fulfill the customer demands. With a deterministic model, this problem is usually tackled with a sensitivity analysis in order to determine the sensitivity of the optimal result to some key parameters. Nevertheless, the main shortcoming of this method is that sensitivity analysis can tell you to which degree the key parameters will affect the optimal result of the studied problem, but it cannot give you any suggestions on how to react to those changes (King and Wallace, 2012). Therefore, in reverse logistics network design, it is a much better way to treat the uncertainties in the modeling process with different techniques, i.e., fuzzy programming (Chu et al., 2010, Govindan et al., 2016), stochastic programming (El-Sayed et al., 2010, Ramezani et al., 2013, Pishvaee et al., 2009), robust optimization (Talaei et al., 2016), etc.

In order to provide a better tool for reverse logistics network design under uncertainty, this research uses stochastic optimization in the modeling of the problem, and it also improves the solution method and presents some managerial implications. The first part of this research presents a MILP under stochastic environment for reverse logistics network design, and this paper focuses on the development of an improved multi-criteria scenario-based risk-averse solution method and the numerical experimentation.

1.2 An Improved Multi-criteria Scenario-based Risk-averse Solution Method to the Stochastic Problem

The advantage of stochastic optimization is that it presents a proper model for the complex decision-making problem without the exact information of what is going to happen in the future (King and Wallace, 2012). Due to this reason, several possibilities and scenarios have to be accounted in a stochastic model in comparison with its deterministic form, which makes the model becoming more complex to solve. Many research works published in operational research and mathematical programming focus on the solution methods of stochastic optimization problems

(Wallace and Ziemba, 2005, Kall et al., 1994, Higle and Wallace, 2003, Birge and Louveaux, 2011). In this paper, based upon a recently published paper by Soleimani et al. (2016), we develop an improved multi-criteria scenario-based risk-averse solution method for the reverse logistics network design under stochastic environment.

Fig. 1.1 presents the procedures of the solution method. As illustrated in the figure, the initial stage is to calculate the indicators for performance evaluation. There are three steps have to be conducted in this stage. First, the scenarios of the stochastic optimization problem are generated with respect to the change of uncertain parameters. Second, for each scenario generated, the problem becomes a MILP and can be resolved independently. The optimal reverse logistics network configurations calculated in each scenario are considered the candidates to the stochastic optimization problem. Third, all scenarios are tested for each candidate and indicators for evaluation including mean, standard deviation (SD) and coefficient of variation (CV) are calculated.
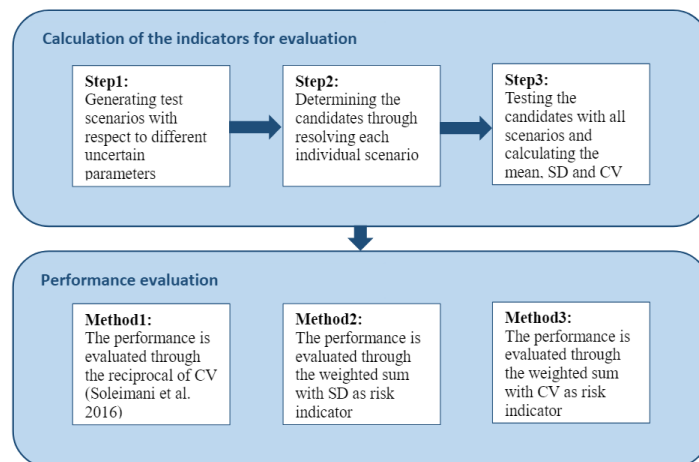
Calculation of the indicators for evaluation

Step1:
Generating test scenarios with respect to different uncertain parameters

Step2:
Determining the candidates through resolving each individual scenario

Step3:
Testing the candidates with all scenarios and calculating the mean, SD and CV

Performance evaluation

Method1:
The performance is evaluated through the reciprocal of CV (Soleimani et al. 2016)

Method2:
The performance is evaluated through the weighted sum with SD as risk indicator

Method3:
The performance is evaluated through the weighted sum with CV as risk indicator

Fig. 1.1 The procedures of the multi-criteria scenario-based risk-averse solution method with different performance evaluation.

The performance of different candidates is compared with the reciprocal of CV in accordance with Soleimani et al. (2016)'s method. The method aims to maximize the profit generated by the reverse logistics system while simultaneously minimize the risk of decision-making through the minimization of SD. SD is a very important measures of data dispersion in statistics and econometrics (Washington et al., 2010), say, how far in average the data dispersed from the mean. In reverse logistics network design, SD is used as the indictor for risk assessment, and a large SD implies a high risk on the realization of the expected profit. It is noteworthy that the risk or stability is not always considered an indicator for performance evaluation of the

solutions to a stochastic problem, and the use of it heavily depends on the circumstance or problems modelled. For example, a venture capital may pursue a high return of investment (ROI), and the preference in this case is to have a high expectation of ROI and SD even if it leads to a high risk as well. However, the objective of reverse logistics network design is to have a stable profit generation with low risk, which gives long-term benefits to the players within the reverse supply chain. Thus, the evaluation with the reciprocal of CV is to maximize profit expectation while minimize the potential risk.

The evaluation method proposed by Soleimani et al. (2016) has a significant shortcoming which may result in a sub-optimal solution dramatically affected by the risk or SD. For example, comparing with two candidates A (mean=5000, SD=1000) and B (mean=1000, SD=100), the reciprocal of CV of the two candidates are 5 and 10, respectively. Thus, the optimal solution is candidate B according to the performance evaluation method. However, it is obvious that candidate A has a much higher profit expectation than candidate B even if the worst-case scenario happens. Candidate B is with very low potential risk, but the performance in profit generation is weak as well, so it is not a wise choice for the decision-maker. The reason is that when the mean and SD are composited, the relative importance of them is not accounted in the reciprocal of CV, so when there is a big difference in the mean, the optimal result calculated may be the one with both low risk and weak profitability. Besides, the evaluation method cannot be applied when the objective becomes a minimum function, e.g., min-cost, due to the simultaneous minimization of the mean and SD. In addition, there are also some challenges in the interpretation of the managerial implication as CV is used mainly for comparing the relative dispersion of data but not for decision-making of a stochastic problem (Yu and Solvang, 2016a).

$$Method_1 = \partial \frac{(M_{max} - M_c)}{(M_{max} - M_{min})} + (1 - \partial) \frac{(SD_c - SD_{min})}{(SD_{max} - SD_{min})} \qquad (1)$$

$$Method_2 = \partial \frac{(M_{max} - M_c)}{(M_{max} - M_{min})} + (1 - \partial) \frac{(CV_c - CV_{min})}{(CV_{max} - CV_{min})} \qquad (2)$$

In order to resolve the problems mentioned above, this paper further develop the multi-criteria scenario-based risk-averse solution method with the help of a weight sum function as illustrated in Eqs. (1) and (2). As shown in the equations, the mean and SD are first normalized before they can be combine in the weighted sum. It is noteworthy that the potential risk is measured by both absolute indicator (SD) and relative indicator (CV), and the result will be compared in the numerical experimentation. Furthermore, the weighted sum formula can be easily modified in order to determine the optimal solution of a minimum objective function.

1.3 Numerical Experimentations

In this section, the proposed stochastic MILP model and improved multi-criteria scenario-based risk-averse solution method are tested with a numerical experimentation. The problem includes 2 products, 15 customers, 8 candidates for collection & disassembly centers, 5 candidates for reuse/repair centers and 5 candidates for recycling centers. First, the parameters are given based upon uniform distribution. Then, three benchmark scenarios are defined as best-case (max-profit and max-product), deterministic (mean-profit and mean-product) and worst-case (min-profit and min-product), respectively. With the combination of the stochastic parameters, another 8 scenarios are generated in a logically reasonable way as illustrated in Table 1.1, meanwhile, the computational effectiveness is also considered in this process. For detailed introduction of scenario generation for a stochastic problem, refer to the research works given by King and Wallace (2012) and Kaut and Wallace (2003).

Table 1.1 Generated scenarios for the numerical experimentation

Stochastic parameter	Scenario										
	best	basic	worst	1	2	3	4	5	6	7	8
Amount of used products	Max	Mean	Min	L	L	L	L	H	H	H	H
Price/subsidy for reuse	Max	Mean	Min	L	L	H	H	L	L	H	H
Price/subsidy for recycling	Max	Mean	Min	L	H	L	H	L	H	L	H

Note: H=high, L=low

The model is coded with Lingo programming and the optimal solution of each scenario is first calculated as a MILP problem. Fig. 1.2 shows the profit generated from the reverse logistics system in each candidate solution and the mean value. It is clearly that there are a fair allocation of the tested scenarios around the mean, this represents a large variety of potential scenarios may happen in future under market fluctuation with both optimistic and pessimistic expectation. Even if more scenarios can be generated, but as many argues (Pishvaee et al., 2009, El-Sayed et al., 2010), this dramatically increases the complexity of problem, but the benefit yielded is extremely limited. Thus, the scenarios generated in this numerical experiment is in a rational and efficient way.
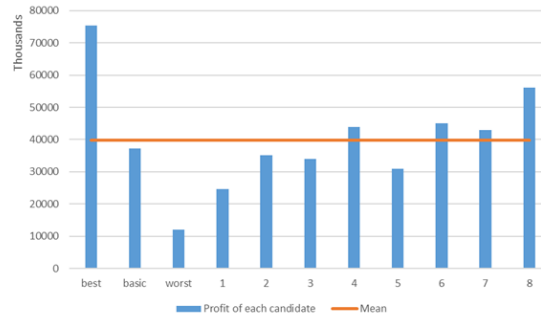
Fig. 1.2 The profit of each candidate and the mean.

In a stochastic optimization problem, the objective is to determine the optimal solution through all the scenarios. As discussed by King and Wallace (2012), there are two characteristics of the optimal solution of a stochastic problem, namely, robustness and flexibility. In some situations, the optimal solutions should be robust to withstand all the possible situations in future without many changes, e.g., a bus schedule, while in many other circumstances, the focus of a stochastic programming is to be flexible and easy to adapt to the changes and fluctuations, e.g., a schedule or plan of a fast delivery company. In the reverse logistics network design, both robustness and flexibility are focused in the decision-making, say, the long-time strategic decisions (locations of different facilities) should be robust and remain unchanged for a long period, while the short-term tactical decisions (distribution of used products and transportation strategies) should be flexible and updated periodically in order to maximize the profit generated under market fluctuation. Therefore, the stochastic MILP model formulated in this paper is two-stage in nature. The first stage variable is facility location decisions, and the second stage variable is the decisions related to the distribution and transportation of used products.

In the second step of the solution method, the candidates are tested through all scenarios. The first stage decisions will not change, while the second stage decisions are flexible with the changing price and generated amount of used products in order to maximize the economic performance of the reverse logistics system. The comparison of the profit expectation (mean) and level of risk (SD) is given in Fig.1.3. As shown in the figure, the expected profit is higher with the candidate solutions calculated under high amount of used products generated, while the level of risk is better maintained with the candidates calculated under low generation of used products.
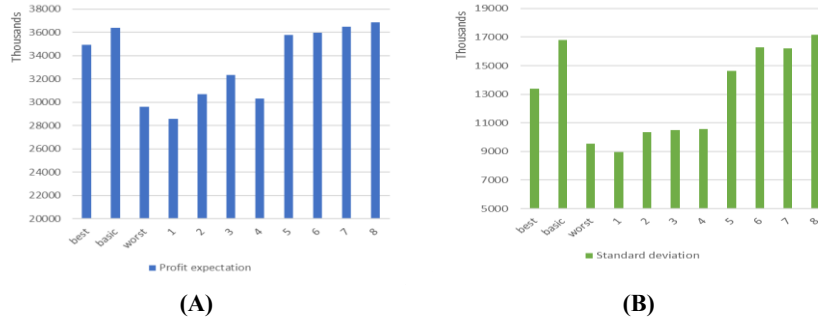
Fig. 1.3 The performance of candidates through all scenarios: (A) Profit expectation; (B) Standard deviation.

In the testing phase, we observed infeasibilities when some candidate reverse logistics network configurations are implemented in the scenarios with high generation of used products. The reason for the infeasibility is the conflict between service constraint and capacity constraint, say, the facility capacity is not large enough to handle all the used products generated. In order to solve this problem, the model needs to be relaxed and a compromise has to be made based on the decision-maker's objective, either to provide a reduced service or to have more investment for increasing the capacity of reverse logistics system. In this paper, the relaxation of the capacity constraint is made in some scenarios in order to generate feasible solutions, and the relaxation is made in such a way that the change to the original network configuration is kept at the minimum level.

Table 1.2 Generated scenarios for the numerical experimentation

Scenarios	Evaluation method		
	Method1	Method2	Method3
best	2.6099	0.3257	0.3016
basic	2.1698	0.3253	0.3304
worst	3.1043	0.6347	0.6309
1	3.1933	0.7000	0.7000
2	2.9605	0.5746	0.5715
3	3.0837	0.4397	0.4057
4	2.8748	0.6109	0.6208
5	2.4456	0.3002	0.2815
6	2.2069	0.3465	0.3543
7	2.2494	0.2988	0.2923
8	2.1489	0.3000	0.3000

The performance of the candidates are measured with three different methods, and the result is given in Table 1.2. For implementing the weighted sum methods, several combinations of weights are tried and $\partial = 0.7$ is selected for methods 2 and

3. As illustrated in the table, the optimal results from different evaluation methods vary significantly. The optimal solutions evaluated by methods 1, 2 and 3 are candidates 1, 7 and 5, respectively.
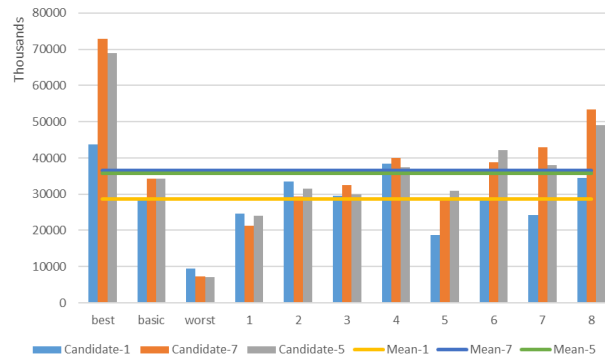

Fig. 1.3 Comparison of the mean and profit expectation in test scenarios of the optimal solutions calculated with the three different method.

Fig. 1.3 presents the comparison of the mean and profit expectation in each scenario of the three candidates. As shown in the figure, the overall profit expectation of candidate 1 is much lower than that of candidates 7 and 5, and the overall profit expectation of candidate 7 is slightly higher than that of candidate 5. When the amount of used products generated is low, candidate 1 has a slightly better performance than the others, but when the generation of used products is high, the economic performance of candidates 7 and 5 are much better. Thus, it is obvious that the optimal solution calculated by the reciprocal of CV is with lower level of risk and lower economic performance. Compared with candidate 1, even if the level of risk is higher, both candidates 7 and 5 have much better economic performance particularly when the generation of used products is high. To distinguish with the two candidates, candidate 7 has a slightly higher profit expectation of the reverse logistics system, while candidate 5 has a slightly better level of risk (slightly better performance in low generation scenarios).

From the discussion above, it is clearly that the optimal solution calculated by the original method is a weak performance one even if the level of risk is low. Both of the other methods with weighted sum can generate better solutions compared with the original method, and the optimal solution may be selected based upon the decision-maker's preference.

1.4 Conclusion

In this paper, we developed a new MILP model under stochastic environmental for designing a multi-product multi-level reverse logistics network, and an improved multi-criteria scenario-based risk-averse solution method was also proposed for resolving the stochastic optimization problem. The objective of the proposed model is to maximize the overall profit generated in the reverse logistics system under market fluctuation, and the solution method in a recently published research work is improved so that both profit expectation and potential risk are taken into consideration in the decision-making. A numerical experimentation is conducted, and the application of the model and the effectiveness of the improved solution method are explicitly presented.

For future improvement of the research, the consideration of environmental and social sustainability should be taken into account in the reverse logistics network design (Yu and Solvang, 2016b, Govindan et al., 2016). The simultaneous consideration of several conflict objectives under uncertain environment may significantly increase the computational complexity, so the development of advanced solution algorithms is also suggested as a promising direction for the future research.

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