Green and Reverse Logistics Management Under Fuzziness

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Abstract Green supply chain management (GrSCM) has its roots in supply chain management (SCM) and environmental management. In fact, adding "green" concept into traditional SCM leads to studying environmental impact of SCM-related processes. Logistics activities which form the main part of SCM-related processes belong to the most influential sources of environmental pollution and greenhouse emissions which may cause harmful impacts both on human health and ecosystem quality. In order to reduce hazardous environmental impacts of logistics activities, the concept of green logistics (GrLog) and reverse logistics (RL) was introduced. Similar to traditional supply chain, uncertainty plays an important role in GrSCM; however, considering the environmental factors beside the quantity and quality of end-of-life products elevates the degree of uncertainty in GrLog and RL problems. In this chapter, designing and planning problems in GrLog and RL are investigated in a fuzzy environment via a systematic review and analysis of recent literature. Three selected fuzzy mathematical models from the recent literature are elaborated. A real industrial green logistics case study is described and investigated and a number of avenues for further research are finally suggested.

Keywords Green logistics · Green supply chain management · Reverse logistics · Fuzzy mathematical programming

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1 Introduction to Green and Reverse Logistics Management

The design and operation of supply chains has traditionally been upon economical and technological objectives such as maximizing revenue/minimizing cost, maximizing responsiveness, increasing flexibility, etc. For example, companies take into account various factors such as price, quality and flexibility when selecting their suppliers or just consider economical aspects when choosing their production technologies or selecting their transportation modes.

Since 1990s, green issues are increasingly considered by governments, people, industries and scientists in design and planning problems in both micro and macro levels. For example, governments force manufacturers to include green aspects into their products and production processes and taking into account green considerations in their logistics-related processes such as supplier selection and material movements. People prefer to buy products from those companies with higher reputation in environmental protection. As a result, including green aspects in products gradually becomes as a competitive advantage for manufacturers. Establishing international standards (such as ISO 14000 series) and international conventions (such as Kyoto Protocol in 1997) could also be considered as important drivers for environmental protection.

Among the logistics activities, manufacturing and transportation activities are the main sources of waste generation, ecosystem disruption, and depletion of natural resources (Fiksel 1996). As such, governments force the firms to decrease the environmental impact of their activities and all of these urge the manufacturers to consider environmental issues through their supply chains (Büyüközkan 2012). Paying more attention to GrLog not only can decrease the ecological impact of industrial activities but also can maintain or even increase quality, reliability, performance, energy efficiency or decrease cost (Srivastava 2007).

1.1 Importance and Drivers

The growing importance of GrSCM/GrLog is driven mainly by the escalating deterioration of the environment. Nevertheless, it is not only environmental issues that matters; it is good business sense and higher profits too (Srivastava 2007). In fact, the perspective of "greening as a burden" gradually changes toward "greening as a potential source of competitive advantage" (Van Hoek 1999).

According to the study of De Brito and Dekker (2004), companies involve in green practices either because they can profit from it (competitive advantages); or/and because they have to doing so due to environmental legislations; or/and because they "feel" socially motivated to do it (social responsibility).

By reviewing a great number of papers in the relevant literature, the following drivers of GrSCM/GrLog could be realized:

- Deterioration of the environment involving:
  - limited natural resources;
  - diminishing raw material resources;
  - increase in solid and hazardous wastes (Fiksel 1996);
  - increasing level of pollution (water and air);
- economic advantages and savings (Porter and Van der Linde 1995a, b) by saving resources, eliminating wastes and productivity improvement;
- environmental legislations and regulatory requirement like:
  - Montreal Protocol in 1987 that limit the production of substances harmful to the stratospheric ozone layer, such as CFCs;
  - the Kyoto Protocol in 1997 that limits the emissions of greenhouse gases from industrialized countries;
- environmental management standards and guidelines (e.g., ISO 14000 series);
- consumer pressures (Lamming and Hampson 2005; Elkington 1994).

In addition to abovementioned drivers, benefits acquired by managing used product for further utility, adding customer's value, etc., are some other drivers enforcing manufacturers to address RL in their production activities (Wang and Sun 2005).

1.2 Definition and Scope

Zhu and Sarkis (2004) mentioned that the scope of GrSCM can range from a simple act of green purchasing to implementing an integrated green supply chain flowing from suppliers to customers, and even reverse flows of logistics. On the other hand, Srivastava (2007) defined the range of GrSCM as "the flow of material from the final customers back to retailers, collection points, manufacturers, and/or disposal sites". According to this definition, the scope of GrSCM includes reactive monitoring of the general environmental management programs and/or proactive practices implemented through reduce, re-use, rework, refurbish, reclaim, recycle, remanufacture, or as a whole, reverse logistics activities. Particularly, in the area of reverse logistics, researchers have explored various topics and issues, including reusing, recycling, remanufacturing, etc. (see Kroon and Vrijens 1995; Barros et al. 1998; Jayaraman et al. 1999).

RL was defined by Council of Logistics Management as "The role of logistics in recycling, waste disposal, and management of hazardous materials; a broader perspective included all relating to logistics activities carried out in source reduction, recycling, substitution, reuse of materials and disposal".

Also, Rogers et al. (1999) have defined RL as "the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal".

Srivastava (2007) defined GrSCM as “integrating environmental thinking into supply chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers as well as end-of-life management of the product after its useful life”.

Sarkis et al. (2011) reviewed different concepts and definitions related to GrSCM including “sustainable supply network management (Young and Kielkiewicz-Young 2001; Cruz and Matsypura 2009), Supply and demand sustainability in corporate socially responsible networks (Kovacs 2004; Cruz and Matsypura 2009), supply chain environmental management (Sharfman et al. 2009), green purchasing (Min and Galle 1997) and procurement (Günther and Scheibe 2006), environmental purchasing (Carter et al. 2000; Zsidisin and Siferd 2001), green logistics (Murphy and Poist 2000) and environmental logistics (Gonzalez-Benito and Gonzalez-Benito 2006) and sustainable supply chains (Linton et al. 2007; Bai and Sarkis 2010)”.

According to the above-mentioned descriptions, here we define GrSCM as “integrating environmental and economical aspects into all decisions of supply chain management through all stages of product life cycle (cradle-to-grave) in order to create (more) sustainable value for broad range of stakeholders”.

1.3 Classification of Planning Problems in Green and Reverse Logistics Management

Different classifications on green supply chain have ever been proposed in the literature. Among them, Srivastava (2007) introduced a classification based on problem context in which GrSCM is classified into (1) green design and (2) green operations. In this classification, subjects such as life cycle assessment (LCA) and ergonomic comfort design (ECD) are related to green design while green manufacturing and remanufacturing, reverse logistics, network design and waste management are subfields of green operations.

Recently, Ilgin and Gupta (2010) classified environmentally conscious manufacturing and product recovery into four main categories including (1) product design, (2) reverse and closed-loop supply chain, (3) remanufacturing and (4) disassembly.

Similar to the traditional SCM, GrSCM can also be classified according to the length of decision horizon, i.e., strategic (STRG), tactical (TCTL) and operational (OPRL) decisions. Issues such as green supply chain network design and integrated forward-reverse logistics network design are considered as strategic decisions; problems concerning with the amount of material flows between each pair of network’s facilities at each medium-term time period (e.g., monthly) with respect to their environmental concerns as well as cost objectives are known as tactical decisions and finally decisions such as green daily production scheduling and material transportations are operational level ones.

In the literature, there are several multi-attribute decision making (MADM) techniques used to evaluate the performance of whole GrSCM/GrLog/RL, suppliers and third-party logistics providers (see Shen et al. 2013; Ravi 2012; Lin 2013; Kannan et al. 2009; Kannan et al. 2013; Govindan et al. 2013; Dhouib 2013; Akman and Pışkın 2013); however, in this chapter we have focused on GrLog and RL designing and planning problems.

From the operations research (OR) perspective, different modeling approaches including mixed-integer linear programming (MILP), multi-objective integer linear programming (MOILP), mixed-integer goal programming (MIGP), multi-objective mixed integer programming (MOMIP), fuzzy goal programming (FGP), credibility-based fuzzy mathematical programming (CFMP), multi-objective possibilistic mixed integer linear programming (MOPMILP) have been used to formulate planning problems in the context of GrSCM/GrLog. In addition, in order to solve the developed mathematical models, different approaches are often applied in the literature which include: commercial optimization solvers (like CPLEX) to find optimal solutions in small to medium-scaled problems, decomposition-based exact/approximation methods (like Benders decomposition/Lagrangean relaxation) and heuristic or metaheuristic methods to yield near-optimal or optimal solutions in large-scaled instances.

As discussed before, uncertainty plays an important role in GrSCM/GrLog and RL contexts. Three main approaches including: (1) fuzzy programming, (2) stochastic programming and (3) robust programming are used to cope with uncertainty. Uncertainty is usually considered in the model parameters involving: Demands (D), Transportation Costs (TC), Handling Costs (HC), Quantity of Returns (QnR), Quality of Returns (QlR), Fixed Opening Costs (FOC), Manufacturing Costs (MC), Processing Costs (PC), Operations Costs (OC), Remanufacturing Costs (RC), Capacity levels (Cap), Recovery Percentages (RPer), Landfill Percentages (LPer), Number of Created Jobs (NCJ), Emission Factors (EF), Production Rates (PR), Collection Costs (CC), Distribution Costs (DC) and Recovery Fractions (RF) or is incorporated into the objective function(s) such as Flexibility of Goals (FG) and Preference of DM's over objective function (POF) in multi-objective models.

A detailed review of selected papers from the literature related to GrSCM/GrLog, RL and closed-loop supply chain (CLSC) based on abovementioned classifications is provided in Table 1.

For more comprehensive and detailed review of GrSCM/GrLog and RL, interested readers can consult with (Srivastava 2007; Sbihi and Eglese 2007; Ilgin and Gupta 2010; Sarkis et al. 2011), and (Fleischmann et al. 1997; Beamon 1999; De Brito and Dekker 2004; Wang and Sun 2005; Pishvaee et al. 2010a; Souza 2013), respectively.

The rest of the chapter is organized as follows. In Sect. 2, the concept of GrLog and RL management under uncertainty is discussed. A classification for different types of uncertainty, main programming approaches to cope with uncertainties, advantages of fuzzy mathematical programming approach over other competing approaches and a classification for fuzzy mathematical models are also given in this section. Afterwards, in Sect. 3, three selected fuzzy mathematical models

Table 1 Classification of some selected papers

Author	Scope	Modeling approach	Solution approach	Type of uncertainty	Uncertain parameters
Pati et al. (2008)	STRG, TCTL	MIGP	Solver	–	–
Mele et al. (2009)	STRG	MOILP	Solver	–	–
Pishvaee et al. (2009)	STRG	MILP	Solver	Stochastic	D, TC, QnR, QIR
Tsai and Hung (2009)	TCTL, OPRL	FGP		Fuzzy	FG, POF
Kannan et al. (2010)	TCTL, OPRL	MILP	Metaheuristic	–	–
Pishvaee and Torabi (2010)	STRG, TCTL	MOPMIL	Solver	Fuzzy Possibilistic	D, TC, QnR, FOC, MC, PC, RC, Cap
Pishvaee et al. (2010a)	STRG	MOMIP	Metaheuristic	–	–
Pishvaee et al. (2010b)	STRG	MILP	Metaheuristic	–	–
Qin and Ji (2010)	STRG	MILP	Hybrid fuzzy and GA	Fuzzy	QnR, FOC, HC
Wang and Hsu (2010)	TCTL	MILP		Fuzzy	D, RPer, LPer
Abdallah et al. (2011)	STRG, TCTL	MILP	Solver	–	–
Pinto-Varela et al. 2011	STRG, TCTL	MILP	Solver	Fuzzy	FG
Pishvaee et al. (2011)	STRG	MILP	Solver	Robust	D, QnR, TC
Pishvaee and Razmi (2012)	STRG	MOPMIL	Solver	Fuzzy	D, QnR, FOC, TC, PC, Cap
Ubeda et al. (2011)	OPRL	MILP	Heuristic	–	–
Wang et al. (2011)	STRG, TCTL	MOMILP	Solver	–	–
Zhang et al. (2011)	TCTL	MILP	Piecewise Interval Programming	–	–
Cardoso et al. (2013)	TCTL	MILP	Solver	Stochastic	D
Chaabane et al. (2012)	STRG, TCTL	MOMILP	Solver	–	–
Jamshidi et al. (2012)	STRG	MOMILP	Hybrid Memetic and Taguchi	–	–

(continued)

Table 1 (continued)

Author	Scope	Modeling approach	Solution approach	Type of uncertainty	Uncertain parameters
Pishvaee et al. (2012a)	STRG	MOMILP	Solver	Robust Possibilistic	D, FOC, NCJ, Cap
Pishvaee et al. (2012b)	STRG, TCTL	MILP	Interactive fuzzy	Credibility-based fuzzy	D, Cap, FOP, TC, PC, EF
Vahdani et al. (2013a)	STRG	MOMILP	Solver	Fuzzy Possibilistic Queuing	FOP, TC, CC, DC, MC, RC, D, PR, QnR, RF
Vahdani et al. (2012)	STRG	MOMILP	Solver	Fuzzy Robust Queuing	FOP, TC, PR, OC, Cap

addressing GrLog and RL planning problems are presented and discussed. In Sect. 4, an industrial case study is provided and finally, some possible future directions for further research are presented in Sect. 5.

2 Green and Reverse Logistics Management Under Uncertainty

The complex nature and structure of commercial supply chains and working in a dynamic and chaotic business environment, imposes a high degree of uncertainty in supply chain planning decisions and significantly affects their overall performance (Klibi et al. 2010). The degree of complexity in green and reverse logistics is even greater than traditional supply chains, since highly imprecise parameters such as quantity and quality of returned products and environmental factors should also be taken into account (Erol et al. 2011; Pishvaee et al. 2012b).

As it could be seen in Table 1, most of the published papers are related to strategic level decisions rather than tactical or/and operational decisions. Decisions regarding locations and number of required manufacturing, remanufacturing, and collection centers as well as aggregated material flows between these centers and consumers in forward and reverse directions are some of main decisions made in the strategic level. It is quite clear that the degree of uncertainty in strategic decisions is significantly higher than mid-term and short-term decisions. The reason goes back to difficulty of forecasting and providing confident values for input parameters in a longer time horizon.

In the light of above-mentioned points, accounting for uncertainty in GrLog and RL is inevitable. Therefore, different approaches to cope with uncertainty are used in the literature including stochastic programming (e.g., Pishvaee et al. 2009; Cardoso et al. 2013), fuzzy programming (e.g., Tsai and Hung 2009; Qin and Ji 2010; Wang and Hsu 2010; Pishvaee and Torabi 2010; Pishvaee and Razmi 2012; Pishvaee et al. 2012a; Pishvaee et al. 2012b; Pinto-Varela et al. 2011; Vahdani et al. 2013a; Vahdani et al. 2012) and robust programming (e.g., Pishvaee et al. 2011; Pishvaee et al. 2012a; Vahdani et al. 2012) approaches. Among these approaches, fuzzy programming methods are mostly utilized in recent years due to their capability in handling both epistemic and vague uncertainties.

In this section, a useful taxonomy is provided to classify different kinds of uncertainty in green and reverse logistics planning problems. Then, various types of fuzzy programming methods which have already been applied in the context of GrLog and RL along with their characteristics are studied and analyzed.

2.1 Classification of Uncertainties

Different general and SCM-related classifications for uncertainty have ever been proposed in the literature from different points of view. Among them, according to

Tang (2006) and Klibi et al. (2010), uncertainty in supply chains can be classified into two groups: (1) business-as-usual (or operational) uncertainty, such as usual fluctuations in demand and supply data which mostly includes events with low to medium impact, medium to high likelihood; (2) disaster uncertainty, that covers rare events with high business impacts but low likelihood such as uncertainty in supply disruptions due to occurrence of a natural disaster (e.g., flood or earthquake) in supplier location. Terms such as "hazard" and "disruption" can also be used instead of the term "disaster" here. This type of uncertainty can be originated generally from natural sources i.e., earthquake, flood, Tsunami or man-made sources such as war, terrorist attacks, labor strikes, sanctions, etc.

From a general view, Dubois et al. (2003) classified uncertainty as: (1) uncertainty in input data, and (2) flexibility in constraints and goals. The first type is the most common uncertainty faced in supply chains which is usually referred to epistemic uncertainty and possibilistic programming methods are used to handle such kind of uncertainty. The second type of uncertainty deals with flexibility in target value of fuzzy goals and/or right hand side (RHS) of soft constraints for which flexible mathematical programming models are utilized to cope with such flexible values (Bellman and Zadeh 1970; Mula et al. 2006).

Uncertainty in data can be classified into two categories (Mula et al. 2006; Mula et al. 2007): (1) randomness, that stem from the random nature of parameters and stochastic programming methods are the most applied approaches to cope with this sort of uncertainty; (2) Epistemic uncertainty, that deals with ill-known and imprecise parameters arising from lack of knowledge regarding the exact value of these parameters for which possibilistic programming approaches are usually applied (Pishvaee and Torabi 2010; Mula et al. 2006).

From a different point of view, Davis (1993) classified the potential sources of uncertainty in supply chains in three main categories, i.e., (1) supply uncertainty, (2) process uncertainty and (3) demand uncertainty. In general, changes in supplier's performance such as lateness in delivery of raw materials or delivery of defective materials by suppliers leads to supply uncertainty. On the other hand, faults occurring in production and/or distribution processes are the main sources of process uncertainty. Finally, imprecise estimation of future demands for special products, changes in market, changes in customers attitude, changes in fashion, etc. are the main sources of demand uncertainty which is the most frequent uncertainty in real-life situations.

Another classification of uncertainty in the context of production systems is provided by Ho (1989) as: (1) environmental uncertainty and (2) system uncertainty. Similar to afore-mentioned classifications in the context of supply chain, environmental uncertainty is related to demand side uncertainties derived from customer behavior and market trends as well as supply side uncertainties stemmed from the performance of suppliers. Furthermore, system uncertainty refers to those uncertainties within the production, distribution, collection and recovery processes for example uncertainties pertaining to production costs/times and actual capacity of different processes.

It should be mentioned that all of the reviewed classifications are meaningful in the context of GrSCM/GrLog, RL and CLSC but the main point is that how should we cope with these uncertainties in mathematical models?

2.2 Overview of Different Approaches to Cope with Uncertainty

As the body of literature shows, three main approaches are mostly employed to deal with uncertainty in the context of mathematical programming, i.e., (1) stochastic programming, (2) fuzzy programming and (3) robust optimization. Based on the structure and context of the concerned problem, type of uncertainty and the level of incompleteness in the model's parameters, one or a combination of these approaches can be applied. Nevertheless, each method has its unique characteristics which differentiate it from the others. Hence, one should delicately study and analyze the type(s) of uncertainty involved in the concerned problem and then choose the most appropriate method(s) to cope with recognized uncertainty or uncertainties.

2.2.1 Stochastic Programming

Stochastic programming methods can be used whenever randomness is the main source of uncertainty in input data for which random variables with known probability distributions are often utilized.

Sahinidis (2004) classified stochastic programming into two main categories: programming with recourse (i.e., two-stage stochastic programming) and probabilistic (chance constrained) programming. In the former, the decision variables are partitioned into two sets. The first stage decisions are those that have to be made before the actual realization of the uncertain parameters and the second stage decisions are those that must be made after realization of uncertain parameters. This method is mostly suggested when infeasibility is allowed with charging penalty costs. Traditionally, the second-stage variables are interpreted as corrective measures or recourse against any infeasibilities arising due to a particular realization of uncertainty. From a different point of view, one can refer to first-stage decisions as strategic decisions and the second-stage decisions as tactical or operational decisions following the first-stage plan that has been made in an uncertain environment. The objective is usually to determine the first-stage decisions in such a way that minimizes total first-stage costs and the expected value of second-stage costs. On the other hand, the former focus on the reliability of the system, i.e., the ability of system to meet feasibility in an uncertain environment. This reliability could be translated as a minimum requirement on the probability of satisfying constraints (i.e., the confidence level of satisfaction).

For detailed classification on stochastic programming approaches and their mathematical challenges, the reader may consult with Sahinidis (2004) and Birge and Louveaux (1997).

2.2.2 Robust Optimization

Robust programming/optimization provides risk-averse methods to cope with uncertainty in optimization problems. According to Pishvaee et al. (2012a), "a solution to an optimization problem is said to be robust if it has both feasibility and optimality robustness. Feasibility robustness means that the solution should remain feasible for (almost) all possible values of uncertain parameters and optimality robustness means that the value of objective function should remain close to optimal value or have minimum (undesirable) deviation from the optimal value for (almost) all possible values of uncertain parameters".

Robust programming approaches can be classified into three groups (Pishvaee et al. 2012a): (1) hard worst case robust programming (Soyster 1973; Ben-Tal and Nemirovski 1998; Ben-Tal et al. 2009), (2) soft worst case robust programming (Inuiguchi and Sakawa 1998; Bertsimas and Sim 2004) and (3) realistic robust programming (Mulvey et al. 1995).

The hard worst case approach is the most pessimistic approach since in this approach it is assumed that all parameters could get their worst case value simultaneously. Although this approach gives maximum safety against uncertainty by giving feasible solution for all realization of uncertain parameters, the matter of highly conservatism made by this approach found itself confronted by intense criticisms (Bertsimas and Sim 2004). That is, they believe that it is highly unrealistic or over pessimistic approach. However, Ben-Tal et al. (2009) supports this approach because it does not need any information about the possibility or probability distribution of uncertain parameters. Also, Pishvaee et al. (2012a) expressed that hard worst case is appropriate for risk averse DMs and it is especially applicable in the cases that a small perturbation from the expected performance of the system causes catastrophic outcomes (e.g., in military and emergency cases).

The second approach is more flexible than hard worst case approach. By this approach, like the hard worst case, one tries to minimize the worst case value of objective function but the difference is that it does not satisfy (all) the constraints in their extreme worst case.

Finally, the realistic robust programming approach aims to seek trade-off between the robustness of achieved solution and the cost of robustness (a cost–benefit logic). This approach is appropriate for profit-seeking and flexible DMs and could be applicable in most of business cases (Pishvaee et al. 2012a).

For more information about the RP theory, the interested readers are referred to Beyer and Sendhoff (2007), Ben-Tal et al. (2009) and Pishvaee et al. (2012a).

2.2.3 Fuzzy Programming

Fuzzy programming can handle both epistemic uncertainty in data as well as flexibility in goals and/or elasticity in constraints. Using this approach, imprecise parameters are modeled by appropriate possibilistic distributions in the form of fuzzy numbers. Moreover, flexible target values and vague (soft) inequalities/equalities are formulated through fully subjective preference-based fuzzy membership functions.

Accordingly, fuzzy mathematical programming can be classified into two main classes (Inuiguchi and Ramík 2000; Mula et al. 2006; Torabi and Hassini 2008): (1) possibilistic programming and (2) flexible programming. Possibilistic programming is used when there is lack of knowledge (epistemic uncertainty) about exact values of input data (parameters) due to unavailability or insufficiency of required data. Accordingly, suitable possibilistic distributions based upon both available objective data and subjective opinions of DMs are introduced for modeling imprecise data in the form of fuzzy numbers. On the other hand, flexible programming is used to cope with flexibility in target value of goals and/or elasticity in soft constraints. The latter refers to those constraints tainted with soft inequalities/equalities in the form of $\tilde{\leq}$, $\tilde{\geq}$ and $\cong$ in which tilde sign shows the softness of respective constraints. For example, $x_1 \tilde{\leq} 20$ means that x_1 should be less than or equal to 20 but small deviations could be accepted subject to less constraint's satisfaction degrees. In flexible programming, a subjective, i.e., preference-based fuzzy membership function is usually adopted for each vague target value or soft constraint. It is quite clear that both possibilistic and flexible programming approaches could be simultaneously applied in a mathematical model when there is a mixture of aforementioned types of uncertainties.

2.3 *Advantages of Fuzzy Approaches*

In many cases, due to lack of historical data, it is hard or even impossible to fit a probability distribution for some objective-natured parameters such as products' demands or unit processing times of manufacturing operations. Furthermore, some other input data have a fully subjective nature like those of judgmental data quoted by expert(s) in most of decision making situations. In the former case, it is a reasonable option to fit a suitable possibilistic distribution for each parameter based upon the available (but often insufficient) objective data as well as subjective opinions of DMs, but in the latter, a fully subjective (preference-based) fuzzy set is adopted for each judgmental data based upon expert's subjective knowledge, experience and feelings. However, in both cases, fuzzy numbers can be used to formulate the incomplete, vague and ambiguous data and fuzzy programming approaches are the most suitable tools for coping with such uncertainties (Qin and Ji 2010; Wang and Hsu 2010).

In the context of GrLog and RL, there is not only greater lack of historical data but also existence of more complex relationships between some data, makes the estimation of related parameters even more impossible. To overcome this deficiency, the fuzzy mathematical programming approaches are being more employed in the context of GrLog, RL and CLSC (Pishvaee and Torabi 2010; Qin and Ji 2010).

In brief, the major advantages of fuzzy programming can be summarized as follows (Mula et al. 2006; Pishvaee and Torabi 2010): (1) it can appropriately handle both the imprecise and vague data; (2) it can integrate subjective and objective data (i.e., using of both available historical data and human subjective knowledge) to formulate business decision problems in practical situations; (3) it can resolve the issue of infeasibility in some decision making situations such as applications of hierarchical planning (Torabi et al. 2010); (4) problems formulated as fuzzy programming models can be easily reformulated to their equivalent crisp counterparts for which commercial optimization solvers could be used to obtain optimal solutions; (5) fuzzy programming can offer enough flexibility for obtaining various solutions by taking into account the tolerances provided by fuzzy data which can then be evaluated by DM to find a most preferred final solution based on her/his preferences; (6) compared to the stochastic programming approach that its deterministic counterpart increases numerical complexity of the problem in a great degree, by using a fuzzy programming approach, a final solution could be obtained with much fewer computation. In the next subsection, a comprehensive review of fuzzy programming approaches is provided in the context of green and reverse logistics.

2.4 Review of Relevant Papers

As mentioned in Sect. 2.2, the fuzzy programming approaches can be classified into two groups: flexible programming and possibilistic programming.

Literature review demonstrates that the most of published works in the context of reverse and green logistics addressing the fuzziness, use either one of the possibilistic programming approaches (see for example: Pishvaee and Torabi 2010; Qin and Ji 2010; Pishvaee and Razmi 2012; Pishvaee et al. 2012a; Pishvaee et al. 2012b; Vahdani et al. 2013b) or a mixture of possibilistic and flexible programming approaches (see for example: Tsai and Hung 2009; Wang and Hsu 2010; Özceylan and Paksoy 2013) when different type of fuzziness (i.e., imprecise coefficients in objective functions and/or constraints as well as flexible target values for objectives and/or soft inequalities) are introduced in the formulated problem. In this subsection, the related papers are reviewed in more details.

2.4.1 Possibilistic Programming

Pishvaee and Torabi (2010) propose a possibilistic programming approach for a closed-loop supply chain network design problem in which some parameters are imprecise. A bi-objective possibilistic mixed-integer programming model is proposed which integrates the strategic network design for both forward and reverse flows with material flows tactical decisions. An efficient interactive fuzzy solution approach is developed by combining Jimenez et al. (2007), Parra et al. (2005), TH (see Torabi and Hassini 2008) and SO (see Selim and Ozkarahan 2008) methods, that is capable of generating both balanced and unbalanced efficient solutions based on decision maker's preferences.

Qin and Ji (2010) propose three credibility measure based fuzzy programming approaches, i.e., expected value (see Liu and Liu 2002), chance constrained programming (see Liu and Iwamura 1998) and dependent-chance constrained programming (see Liu 1999) to design a product recovery network. In order to solve the proposed MILP models, a hybrid intelligent algorithm is used that integrates fuzzy simulation and genetic algorithm.

Pishvaee and Razmi (2012) propose a multi-objective fuzzy mathematical programming model for designing an environmental supply chain. In the proposed model, a life-cycle assessment (LCA) based method is applied in order to quantify the environmental impact of different options. The main decisions of the proposed model are the location of production and collection centers as well as flow quantities between different facilities under two different objectives, i.e., minimization of total costs and total environmental impacts. In order to solve the proposed model, an interactive fuzzy solution approach based on the ε-constraint method is developed and finally a real industrial case study is provided to show the usefulness of the proposed model as well as the solution approach.

Pishvaee et al. (2012a) propose a novel robust possibilistic programming (RPP) approach and use it for design of a socially responsible supply chain network. This approach involves six variants of RPP which are elaborated in the next section. The model aims to select a set of locations for plants and distribution centers among candidate locations, an appropriate production technology for each opened plant and estimate material flows between different facilities while 1) minimizing the total costs including fixed opening costs, variable production costs and transportation costs, and 2) maximizing the social responsibility of the concerned network including: maximization of job opportunities, minimization of total produced wastes, lost days caused from work's damages and the number of potentially hazardous products. Finally, a real industrial case is provided to illustrate the efficiency and applicability of this novel approach.

Pishvaee et al. (2012b) propose a bi-objective credibility-based fuzzy mathematical programming model for designing supply chain network design in which green issues are also taken into account. The model aims to make a trade-off between two conflicting objectives, i.e., minimization of total costs and minimization of the environmental impacts by defining CO_2 equivalent index in order to quantify the environmental burden of logistics activities. Also, an interactive fuzzy solution approach by mixing two credibility measure based approaches (i.e., expected value and chance constrained programming) is developed to solve the original bi-objective fuzzy model. A real industrial case study is also provided that supports the applicability of the proposed model.

Finally, Vahdani et al. (2013a) propose a possibilistic-queuing model for designing a reliable closed-loop supply chain network. The model aims to minimize the total costs and the expected transportation costs after failure of bi-directional facilities of the concerned network. A new probabilistic queuing constraint is introduced in order to overcome capacity limitations and an efficient hybrid solution method by combining the queuing theory, possibilistic programming and fuzzy multi objective programming approaches is developed to solve the model.

2.4.2 Flexible Programming

Among the relevant papers, Tsai and Hung (2009) introduce a fuzzy goal programming approach for green supply chain optimization. In the proposed approach, the well-known activity-based costing (ABC) and performance evaluation in value-chain structure are integrated aiming to find the optimal supplier selection and flow allocation. Also, analytical hierarchy process (AHP) is utilized to determine the final objective structure and as an illustrative case example, the green supply chain of mobile phone is studied.

Also, Wadhwa et al. (2009) propose a flexible multi criteria decision-making (MCDM) model based on fuzzy-set theory for reverse logistics systems. Their model collect required information from DMs in order to select the most suitable alternative(s) for product reprocessing concerning five different criteria, i.e., cost/time, environmental impacts, market factors, quality factors and legislative factors. To assess the rating of the criteria, they use verbal values collected from product return experts instead of crisp values due to this fact that the crisp evaluation of the criteria is quite impossible.

2.4.3 Mixed Possibilistic and Flexible Programming

Wang and Hsu (2010) study a closed-loop supply chain network design in which some imprecise parameters and soft constraints are introduced. The decisions to be made involve: the location of production, distribution and dismantler centers and amount of material flows between these centers. An interval programming method is applied in order to reformulate the crisp counterpart of the original fuzzy model.

Özceylan and Paksoy (2013) propose a multi-objective mixed-integer fuzzy mathematical model for optimizing an integrated forward and reverse closed-loop supply chin network with multiple period and multiple items. The concerned decisions consist of: opening of potential plants and retailers alongside with amount of shipment between different set of facilities while minimization of total transportation, purchasing, refurbishing and fixed costs simultaneously. In the proposed model, capacity and reverse rates as model parameters and also objective and demand constraints are considered as fuzzy data. In order to build the crisp counterpart, the linear membership functions are defined for all fuzzy objective functions and α-value and weighted average methods are used to convert the fuzzy inequality constraints into crisp ones.

3 Selected Fuzzy Mathematical Models

In this section, three different fuzzy mathematical models are elaborated in the context of green and reverse logistics in which different fuzzy programming approaches are employed to capture inherent fuzziness in the data. For the sake of simplicity, the notations used in this section are the same as those represented in the original papers.

3.1 A GrLog Model with Mixed Expected Value and Chance Constrained Programming Approach

In this subsection, a brief discussion of fuzzy mathematical model introduced by Pishvaee et al. (2012b) along with the respective defuzzification process to formulate the crisp counterpart are provided as a sample in the current GrLog literature under fuzziness. The problem is a single product, three-echelon supply chain which includes multiple production and distribution centers and customer zones. Products are produced in production centers and are then transported to the distribution centers through which are finally delivered to the customer zones. The locations of the customers are fixed and each customer has its own demand which must be completely fulfilled. There are a number of potential sites for establishing production and distribution centers at different capacity levels. Furthermore, multiple options of production technologies are available for each established production center and different transportation modes can be used for transporting products between each pair of nodes in the network. The model aims to determine the number, location and required capacity of production and distribution centers alongside the preferred production technology at each production center as well as transportation mode between each pair of nodes. The model has two different objectives i.e., minimization of overall opening, production and transportation cost and minimization of overall environmental effects. In order to assess and quantify burden of logistics activities including production and transportation activities on environment, the CO2 equivalent index based on the Eco-indicator 99 database (Goedkoop and Spriensma 2000) is used. The structure of the problem is depicted in Fig. 1 and notations are described thereafter.

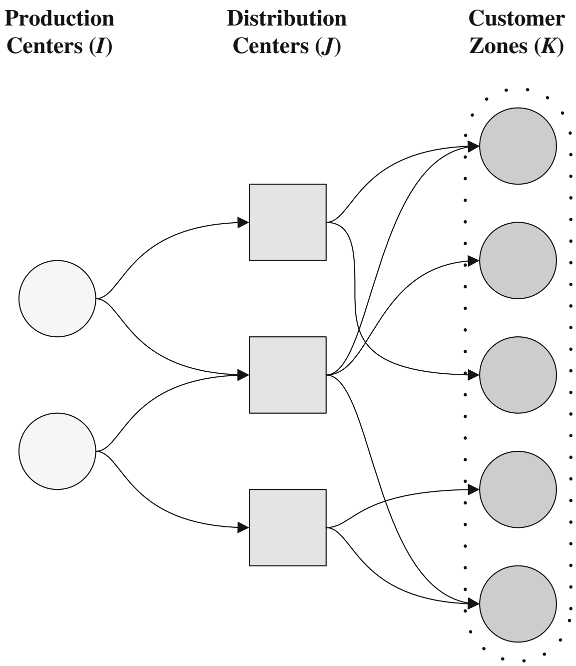

Fig. 1 Structure of the discussed green logistics network (adopted from Pishvaee et al. 2012b)

Indices

i index of candidate production centers $i \in \{1, 2, \ldots, I\}$
j index of candidate distribution centers $j \in \{1, 2, \ldots, J\}$
k index of fixed customer zones $k \in \{1, 2, \ldots, K\}$
m index of capacity levels available for production centers $m \in \{1, 2, \ldots, M\}$
n index of capacity levels available for distribution centers $n \in \{1, 2, \ldots, N\}$
l index of potential production technologies $l \in \{1, 2, \ldots, L\}$
p index of potential transportation modes $p \in \{1, 2, \ldots, P\}$.

Parameters

d_k demand of customer zone k
f_i^{ml} fixed cost of opening production center i with capacity level m and production technology l
g_j^n fixed cost of opening distribution center j with capacity level n
c_{ij}^p unit transportation cost from production center i to distribution center j via transportation mode p
a_{jk}^p unit transportation cost from distribution center j to customer zone k via transportation mode p
ρ_i^l unit manufacturing cost at production center i with production technology l
τ_i^m capacity of production center i with capacity level m
φ_j^n capacity of distribution center j with capacity level n

l CO_2 equivalent emission per unit product produced using technology l

t_{ij}^{p} CO_2 equivalent emission per unit product shipped from production center i to distribution center j using transportation mode p.

s_{jk}^{p} CO_2 equivalent emission per unit product shipped from distribution center j to customer zone k using transportation mode p.

Variables

u_{ij}^{lp} quantity of product manufactured at production center i using technology l and shipped to distribution center j using transportation model p

q_{jk}^{p} quantity of products shipped from distribution j to customer zone k using transportation mode p

x_{i}^{ml} 1, if potential production center i with capacity level m and technology l is opened; 0, otherwise

y_{j}^{n} 1, if potential distribution center j with capacity level n is opened; 0, otherwise

Using abovementioned notation, the proposed mathematical model is as follows:

$$\min w_1 = \sum\nolimits_{i,m,l} f_i^{ml} x_i^{ml} + \sum\nolimits_{j,n} g_j^n y_j^n + \sum\nolimits_{i,j,l,p} \left(\rho_i^l + c_{ij}^p\right) u_{ij}^{lp} + \sum\nolimits_{j,k,p} a_{jk}^p q_{jk}^p \quad (1)$$

$$\min w_2 = \sum\nolimits_{i,j,l,p} \left(l + t_{ij}^p\right) u_{ij}^{lp} + \sum\nolimits_{j,k,p} s_{jk}^p q_{jk}^p \quad (2)$$

$$s.t: \sum\nolimits_{j,p} q_{jk}^p \geq d_k \quad \forall k \quad (3)$$

$$\sum\nolimits_{i,l,p} u_{ij}^{lp} = \sum\nolimits_{k,p} q_{jk}^p \quad \forall j \quad (4)$$

$$\sum\nolimits_{j,p} u_{ij}^{lp} \leq \sum\nolimits_{m} x_i^{ml} \tau_i^m \quad \forall i, l \quad (5)$$

$$\sum\nolimits_{k,p} q_{jk}^p \leq \sum\nolimits_{n} y_j^n \varphi_j^n \quad \forall j \quad (6)$$

$$\sum\nolimits_{m,l} x_i^{ml} \leq 1 \quad \forall i \quad (7)$$

$$\sum\nolimits_{n} y_j^n \leq 1 \quad \forall j \quad (8)$$

$$x_i^{ml}, y_j^n \in \{0,1\} \quad \forall i, j, l, m, n \quad (9)$$

$$u_{ij}^{lp}, q_{jk}^p \geq 0 \quad \forall i, j, k, p \quad (10)$$

Objective function (1) minimizes the total fixed opening costs, production costs and transportation costs while objective function (2) minimizes the total CO_2 equivalent emission. Demand fulfillment of each customer zone is guaranteed by constraints (3). Constraints (4) ensure that all of the manufactured products must be transported to distribution centers. Equations (5) and (6) are the capacity constraint for production and distribution centers, respectively. Equation (7) ensure that at most one capacity level and one technology can be assigned to each production center at each candidate location. Similarly, assigning at most one capacity level to each distribution center at each candidate location is guaranteed via (8). Finally, the binary and non-negativity restrictions on the corresponding decision variables are indicated in (9) and (10).

As mentioned earlier, most of the parameters in logistics network design are tainted with epistemic uncertainty. To cope with this uncertainty, a new credibility-based chance constrained programming model is proposed in this paper. Modeling all of the imprecise parameters in the model as trapezoidal possibility distributions, and substituting Eqs. (1)–(3), (5) and (6) with Eqs. (11)–(15), the possibilistic programming counterpart of the discussed problem could be formulated as below:

$$\begin{aligned}\min E[w_1] = {} & \sum\nolimits_{i,m,l} E\left[\tilde{f}_i^{ml}\right] x_i^{ml} + \sum\nolimits_{j,n} E\left[\tilde{g}_j^n\right] y_j^n \\ & + \sum\nolimits_{i,j,l,p} \left(E\left[\tilde{\rho}_i^l\right] + E\left[\tilde{c}_{ij}^p\right]\right) u_{ij}^{lp} + \sum\nolimits_{j,k,p} E\left[\tilde{a}_{jk}^p\right] q_{jk}^p\end{aligned} \tag{11}$$

$$\min E[w_2] = \sum\nolimits_{i,j,l,p} \left(E[l] + E\left[\tilde{t}_{ij}^p\right]\right) u_{ij}^{lp} + \sum\nolimits_{j,k,p} E\left[\tilde{s}_{jk}^p\right] q_{jk}^p \tag{12}$$

$$Cr\left\{\sum\nolimits_{j,p} q_{jk}^p \geq d_k\right\} \geq \beta_k \quad \forall k \tag{13}$$

$$Cr\left\{\sum\nolimits_{j,p} u_{ij}^{lp} \leq \sum\nolimits_{m} x_i^{ml} \tau_i^m\right\} \geq \lambda_i \quad \forall i, l \tag{14}$$

$$Cr\left\{\sum\nolimits_{k,p} q_{jk}^p \leq \sum\nolimits_{n} y_j^n \varphi_j^n\right\} \geq \theta_j \quad \forall j \tag{15}$$

In this model, the expected value method is used to convert the possibilistic objective functions into their crisp ones. To do so, according to Liu and Liu (2002), the expected value of a trapezoidal fuzzy number $\tilde{\Psi}$ with four prominent points $\tilde{\Psi} = \left(\Psi_{(1)}, \Psi_{(2)}, \Psi_{(3)}, \Psi_{(4)}\right)$ will be equal to $\left(\Psi_{(1)} + \Psi_{(2)} + \Psi_{(3)} + \Psi_{(4)}/4\right)$. Meanwhile, by adopting a chance-constrained programming approach, a minimum confidence level is set to ensure satisfaction of each possibilistic constraint pertaining to most critical constraints (i.e., demand and capacity restrictions) at some acceptable level. A, based on (Zhu and Zhang 2009), for α-critical values greater than 0.5, the following substitutions could be used:

$$Cr\{\Psi \leq r\} \geq \alpha \leftrightarrow r \geq (2 - 2\alpha)\Psi_{(3)} + (2\alpha - 1)\Psi_{(4)} \tag{16}$$

$$Cr\{\Psi \geq r\} \geq \alpha \leftrightarrow r \leq (2\alpha - 1)\Psi_{(1)} - (2 - 2\alpha)\Psi_{(2)} \tag{17}$$

Consequently, after converting abovementioned possibilistic terms into their crisp equivalents, the crisp counterpart of (11)–(15) is reformulated as below:

$$\begin{aligned}\min E[w_1] = & \sum\nolimits_{i,m,l}\left(\frac{f^{ml}_{i(1)}+f^{ml}_{i(2)}+f^{ml}_{i(3)}+f^{ml}_{i(4)}}{4}\right)x^{ml}_i + \sum\nolimits_{j,n}\left(\frac{g^{n}_{j(1)}+f^{n}_{j(2)}+f^{n}_{j(3)}+f^{n}_{j(4)}}{4}\right)y^n_j \\ & + \sum\nolimits_{i,j,l,p}\left(\frac{\rho^l_{i(1)}+\rho^l_{i(2)}+\rho^l_{i(3)}+\rho^l_{i(4)}+c^p_{ij(1)}+c^p_{ij(2)}+c^p_{ij(3)}+c^p_{ij(4)}}{4}\right)u^{lp}_{ij} \\ & + \sum\nolimits_{j,k,p}\left(\frac{a^p_{jk(1)}+a^p_{jk(2)}+a^p_{jk(3)}+a^p_{jk(4)}}{4}\right)q^p_{jk}\end{aligned} \tag{18}$$

$$\begin{aligned}\min E[w_2] = & \sum\nolimits_{i,j,l,p}\left(\frac{{}^{l}_{(1)}+{}^{l}_{(2)}+{}^{l}_{(3)}+{}^{l}_{(4)}+t^p_{ij(1)}+t^p_{ij(2)}+t^p_{ij(3)}+t^p_{ij(4)}}{4}\right)u^{lp}_{ij} \\ & + \sum\nolimits_{j,k,p}\left(\frac{s^p_{jk(1)}+s^p_{jk(2)}+s^p_{jk(3)}+s^p_{jk(4)}}{4}\right)q^p_{jk}\end{aligned} \tag{19}$$

$$\sum\nolimits_{j,p} q^p_{jk} \geq (2-2\beta_k)d_{k(3)} + (2\beta_k - 1)d_{k(4)} \quad \forall k \tag{20}$$

$$\sum\nolimits_{j,p} u^{lp}_{ij} \leq \sum\nolimits_m x^{ml}_i\left[(2\lambda_i - 1)\tau^m_{i(1)} + (2-2\lambda_i)\tau^m_{i(2)}\right] \quad \forall i,l \tag{21}$$

$$\sum\nolimits_{k,p} q^p_{jk} \leq \sum\nolimits_n y^n_j\left[\left(2\theta_j - 1\right)\varphi^n_{j(1)} + \left(2-2\theta_j\right)\varphi^n_{j(2)}\right] \quad \forall j \tag{22}$$

3.2 RL Using Dependent-Chance Constrained Programming

In this part, the model proposed by Qin and Ji (2010) is presented as a sample model for reverse logistic in which three different credibility measure based possibilistic programming methods, i.e., expected value, chance constrained programming and dependent-chance constrained programming are implemented independently on the original model.

The problem is of reverse logistics network design type that includes multiple consumers, collection centers and manufacturing centers. Suppose that there is a set of potential sites for collection centers and the DM must make decision about the number and location of collection centers as well as the quantity of returned products from each customer zones to each collection center. In the proposed model, minimization of total setup costs, penalty costs, handling and transportation costs are considered as the objective function. The following notations are used for model formulation.

Indices

i index of consumer zones $i \in \{1, 2, ..., I\}$
j index of candidate collection centers $j \in \{1, 2, ..., J\}$.

Parameters

ξ_i quantity of returned product from consumer zone i
η_j cost of opening collection center j
ζ_j unit handling cost in collection center j
c_i penalty cost per unit of uncollected returned product from consumer i
p_{ij} unit transportation cost from consumer zone i to collection center j
q_j unit transportation cost from collection center j to manufacturing center
V_j maximum capacity of collection center j
M maximum number of opened collection centers
γ minimum service level.

Variables

x_{ij} quantity of returned products from consumer zone i to collection center j
y_j equal 1, if collection center j is opened and 0 otherwise.

Using the abovementioned notations, the proposed mathematical model is as follows:

$$\text{Min}C(x,y) = \sum\nolimits_j \eta_j y_j + \sum\nolimits_{i,j} p_{ij} x_{ij} + \sum\nolimits_i c_i \left(\xi_i - \sum\nolimits_j x_{ij}\right) + \sum\nolimits_{i,j} (\zeta_j + q_j) x_{ij} \tag{23}$$

$$s.t: \gamma \xi_i \leq \sum\nolimits_j x_{ij} \quad \forall i \tag{24}$$

$$\sum\nolimits_i x_{ij} \leq y_j V_j \quad \forall j \tag{25}$$

$$1 \leq \sum\nolimits_j y_j \leq M \tag{26}$$

$$x_{ij} \geq 0 \quad \forall i, j \tag{27}$$

$$y_j \in \{0, 1\} \quad \forall j \tag{28}$$

The objective function (23) is to minimize total opening costs, transportation costs, handling costs and penalty costs of not collected returned products from consumer zones. Constraints (24) ensure that minimum service level must be fulfilled for each consumer zone. Capacity constraint for each collection center is proposed via (25). Constraint (26) ensures that at most M collection centers from all candidate sites could be opened and finally decision variables types are assured via (27) and (28).

Since it is difficult or even impossible to predict the quantity of returned products as well as opening and transportation costs exactly, these parameters, i.e., $\xi_i, \eta_j$and ζ_j are then considered as independent possibilistic variables modeled by fuzzy numbers and three different possibilistic programming approaches, i.e., expected value, chance constrained programming and dependent-chance constrained programming are applied independently on the original mathematical model. Also, the imprecise parameters might have triangular, trapezoidal or normal membership functions. Since the first two approaches are employed in the previous model, in this subsection, we only elaborate the dependent-chance constrained programming for the concerned model.

Dependent-chance constrained programming was first introduced by Liu (1999) and then became one the most commonly used possibilistic programming approaches. In this approach, the decision maker tries to maximize the credibility degree of a possibilistic term not exceeding from a given value (here the total costs not exceeding from the capital limit (C_0)) subject to some credible constraints (here the demand fulfillment constraints). Accordingly, for the discussed model, we would have:

$$\max \quad Cr\{C(x,y) \le C_0\} \tag{29}$$

$$s.t: Cr\left\{\gamma\xi_i \le \sum\nolimits_j x_{ij}\right\} \ge \beta_i \quad \forall i \tag{30}$$

$$(25)\text{-}(28)$$

Now, suppose that $\xi_i, \eta_j$and ζ_j are independent fuzzy numbers with normal membership functions $\nu\left(e_i^1, \sigma_i^1\right), \nu\left(e_i^2, \sigma_i^2\right)$and $\nu\left(e_i^3, \sigma_i^3\right)$, respectively. Hence, the linear crisp counterpart of the above dependent-chance programming model is as follows:

$$\max \quad \left(1 + exp\left(\frac{\pi(e^* - C_0)}{\sqrt{6}\sigma^*}\right)\right)^{-1} \tag{31}$$

$$s.t: \sum\nolimits_j x_{ij} \ge \gamma e_i^1 + \frac{\sqrt{6}\gamma\sigma_i^1}{\pi} ln\left(\frac{1-\beta_i}{\beta_i}\right) \forall i \tag{32}$$

$$(25)\text{-}(28)$$

in which e* and σ* are as follows:

$$e^* = \sum\nolimits_i c_i e_i^1 + \sum\nolimits_j \left[y_j e_j^2 + \left(e_j^3 + q_j\right) \sum\nolimits_i x_{ij}\right] + \sum\nolimits_{i,j} p_{ij} x_{ij} \tag{33}$$

$$\sigma^* = \sum\nolimits_i c_i \sigma_i^1 + \sum\nolimits_j \left(y_j \sigma_j^2 + \sigma_j^3 \sum\nolimits_j x_{ij}\right) \tag{34}$$

The interested reader may refer to Qin and Ji (2010) for more details.

3.3 RL Using a Robust Possibilistic Programming Approach

To benefit from the advantages and capabilities of both robust programming and possibilistic programming, a novel approach entitled "robust possibilistic programming" was introduced by Pishvaee et al. (2012a) for the first time in the literature.

In that chapter, five different robust possibilistic programming (RPP) approaches covering hard worst case, soft worst case and realistic robust programming approaches are proposed and efficiency of each one is tested by using an industrial case study. The results show that each of the proposed approaches has its strengths, weaknesses and are useful to be applied in some specific situations. For example, the hard worst case is useful for risk-averse decision makers (DM) while soft worst case is suitable for risk-neutral or benefit seeking DMs. In the studied case study, it is proved that among the developed RPPs, the RPP-II model is more effective than other introduced approaches. This model is useful when DM is only sensitive about over deviation from expected optimal value like situations where achieving lower total cost is more desirable. Also, one of the main advantages of this method is that the model optimizes the minimum confidence level since it is defined as decision variable in the model.

Since the structure of the problem discussed in Qin and Ji (2010) is similar to that of presented by Pishvaee et al. (2012a), here we modify the model developed by Qin and Ji (2010) as an application for RPP-II model.

In this new version of model developed by Qin and Ji (2010), the capacity of collection centers (V_j) in addition to previously mentioned parameters are considered as imprecise ones whose their possibilistic distributions are of trapezoidal type, i.e., $\tilde{\eta}_j = \left(\eta_{j(1)}, \eta_{j(2)}, \eta_{j(3)}, \eta_{j(4)}\right)$, $\tilde{\xi}_i = \left(\xi_{i(1)}, \xi_{i(2)}, \xi_{i(3)}, \xi_{i(4)}\right)$, $\tilde{\zeta}_j = \left(\zeta_{j(1)}, \zeta_{j(2)}, \zeta_{j(3)}, \zeta_{j(4)}\right)$ and $\tilde{V}_j = \left(V_{j(1)}, V_{j(2)}, V_{j(3)}, V_{j(4)}\right)$. Accordingly, the RPP-II version of this model is as follows:

$$\text{Min } E[C(x,y)] + \tau\left(C(x,y)_{max} - C(x,y)_{min}\right) + \sum_i \delta\left[\xi_{i(4)} - (1-\beta_i)\xi_{i(3)} - \beta_i \xi_{i(4)}\right] + \sum_j \pi\left[\alpha_j V_{(1)j} + \left(1-\alpha_j\right)V_{(2)j} - V_{(1)j}\right]y_j \tag{35}$$

$$s.t: \gamma\left[(1-\beta_i)\xi_{i(3)} + \beta_i \xi_{i(4)}\right] \le \sum_j x_{ij} \quad \forall i \tag{36}$$

$$\sum_i x_{ij} \le \left[\alpha_j V_{1(j)} + \left(1-\alpha_j\right)V_{(2)j}\right]y_j \quad \forall j \tag{37}$$

$$0.5 \le \alpha_j, \beta_i \le 1 \quad \forall i,j \tag{38}$$

(26)-(28)

where parameters $\delta$and π are the penalty rate of violating the demand and capacity constraints. In practice, these parameters could be considered as penalty cost of not collecting each unit of returned products and cost of each unit of extra capacity needed in collection centers to handle all collected returned products. Also, in abovementioned model we have:

$$E[C(x,y)] = \sum_j E(\eta_j) y_j \sum_{i,j} p_{ij} x_{ij} + \sum_i c_i \Big(E(\xi_i) - \sum_j x_{ij} \Big) + \sum_{i,j} \big(E(\zeta_j) + q_j \big) x_{ij} \tag{39}$$

$$C(x,y)_{max} = \sum_j \eta_{(4)j} y_j + \sum_{i,j} p_{ij} x_{ij} + \sum_i c_i \Big(\xi_{(4)i} - \sum_j x_{ij} \Big) + \sum_{i,j} \big(\zeta_{(4)j} + q_j \big) x_{ij} \tag{40}$$

$$C(x,y)_{min} = \sum_j \eta_{(1)j} y_j + \sum_{i,j} p_{ij} x_{ij} + \sum_i c_i \Big(\xi_{(1)i} - \sum_j x_{ij} \Big) + \sum_{i,j} \big(\zeta_{(1)j} + q_j \big) x_{ij} \tag{41}$$

In fact, the first term of objective function is the expected value function while the second and third terms refer to optimality and feasibility robustness, respectively. Also, equations (36) and (37) are crisp counterpart of possibilistic form.

As could be seen, the last term of objective function is non-linear. Therefore, by introducing new variables $\mu_j = \alpha_j . y_j$, the linear counterpart of the model can be written as below.

$$\text{Min } E[C(x,y)] + \tau \big(C(x,y)_{max} - C(x,y) \big) + \sum_i \delta \big[\xi_{i(4)} - (1-\beta) \xi_{i(3)} - \beta \xi_{i(4)} \big] + \sum_j \pi \big[\mu_j V_{(1)j} + \big(y_j - \mu \big) V_{(2)j} - y_j \cdot V_{(1)j} \big] \tag{42}$$

$$\sum_i x_{ij} \leq \big[\mu_j V_{1(j)} + \big(y_j - \mu_j \big) V_{(2)j} \big] \quad \forall j \tag{43}$$

$$\mu_j \leq L \times y_j \quad \forall j \tag{44}$$

$$\mu_j \geq L \times \big(y_j - 1 \big) + \alpha_j \quad \forall j \tag{45}$$

$$\mu_j \leq \alpha \quad \forall j \tag{46}$$

$$(26), (28), (36), (38) \tag{47}$$

It should be noted that the parameter L in the model is a large number.

4 Case Study

In this section a real green supply chain case study, presented in Pishvaee and Razmi (2012) is reviewed. The case study is related to an Iranian single-use medical needle and syringe manufacturer that has one production plant with capacity of producing about 600 million products per year. The firm feeds both domestic and overseas customers. Reviewing the World Health Organization (WHO) report (2005) demonstrates that around 16 billion injections are carried out per year while reusing unsterilized needles and syringes leads to 8-16 million hepatitis B, 2.3-4.7 million hepatitis C and 80000-160000 human immunodeficiency virus (HIV) infections around the globe. These data shows that the end-of-life (EOL) management of this medical product is very critical from the environmental viewpoint. In order to decrease infection risks, needles and syringes are put into safety boxes and one of available EOL options such as following ones are used:

- Incineration methods like cement incinerator and rotary kiln incinerator which can be used conveniently with low cost, and are capable of energy recovery but at the same time are considered as a major source of emissions with considerable amount of negative impact on environment;
- non-incineration methods, such as steam autoclave with sanitary landfill and microwave disinfection;
- recycling that can be used by considering solutions for disinfecting the used products.

The respective supply chain structure is depicted in Fig. 2 in which new products that are produced in manufacturing centers are transported to the customer zones in forward network and after being used, the EOL products are transported to the collection centers by reverse flows. After that, the EOL products can be delivered to incineration and/or recycling centers. It is assumed that all the customer demands must be fulfilled and also all of the returned products (a predefined percent of customer's demand) must be collected.

The manufacturer serves 13 domestic and two foreign customer zones from two neighbor countries but the firm is just in charge of collecting the EOL products from domestic customer zones. The firm has already opened one plant with about 600 million production capacity per year but seven other potential locations are available for increasing the production capacity of needles and syringes. At the reverse side, there are 11 candidate locations which can be selected for establishing collection centers. Furthermore, four steel and plastic recycling centers and three incineration centers are also available for handling used products. The aim of model is to find the number and location of opened production/collection centers as well as quantity of the material flows between different facilities with respect to two conflicting objective functions, i.e., minimization of total cost and minimization of total environmental impact in which Eco-indicator 99 (see Goedkoop and Spriensma 2000) is used to quantify the second objective.

Due to lack of sufficient historical data and also dynamic nature of the problem which does not guarantee that behavior of uncertain parameters comply with historical data, the uncertain parameters are presented by fuzzy numbers and possibilistic programming approach is used to handle these uncertain parameters in the model. In order to solve the problem, an interactive fuzzy solution method based on ε-constraint method is used in which for each value of minimum

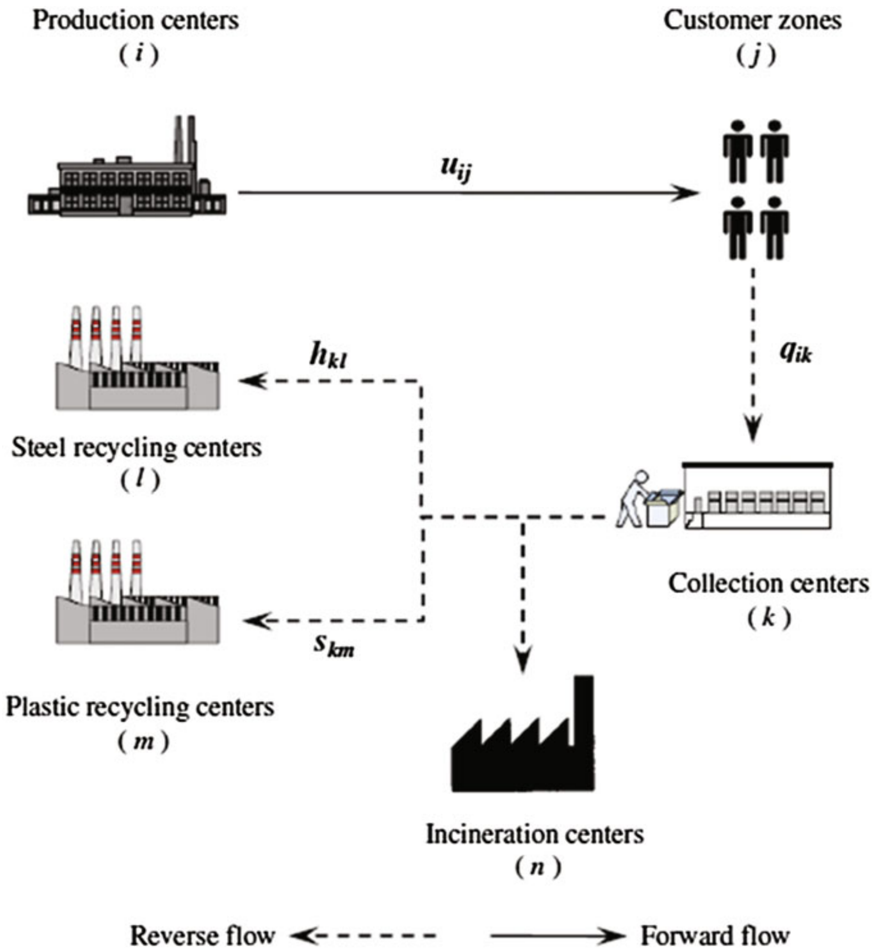

Fig. 2 The structure of the concerned supply chain (adopted from Pishvaee and Razmi 2012)

acceptable feasibility degree (α) ranged from 0.6 to 1, six Pareto-optimal solutions are generated. It should be mentioned that in the proposed method, the satisfaction degree of environmental objective (μ_1) is kept as the objective function of the ε-constraint method and satisfaction degree of cost objective (μ_2) is used as a side constraint.

Solving the discussed model using abovementioned method, one can see that when α-level value increases (in response to uncertainty with higher confidence level), it will lead to increase in values of both objective functions because more resources (raw material, products, transportations, etc.) must be used to fulfill the demand and collection of returned products.

In addition, as it was expected, the two objective functions are in conflict. In fact, the cost-based objective function has a tendency towards designing a centralized network with less total cost while the environmental-based objective function offers a more decentralized network since this structure decreases transportation distances between centers that has less negative environmental impacts. Finally, based on the firm's preference, the decision maker sets minimum acceptable feasible degree (α) equal to 0.9 by which the satisfaction degree for both objectives were selected as $\mu_1 = 0.85$ and $\mu_2 = 0.694$. In this preferred solution, two production centers and five collection centers should be opened.

5 Future Research Directions

Given the current state-of-the-art literature in GrLog and RL areas, there are various avenues for further research among them we refer to the following ones:

- Considering social aspects when designing commercial supply chains is so limited in the current literature. Therefore, to move towards more sustainable supply chain networks, it is necessary to include the social aspects beside the environmental and economical dimensions,
- Integrating tactical and operational planning issues into the current strategic models to broaden the scope of developed models could be another interesting research direction with significant practical relevance,
- It can be realized that some lessons from best practices in commercial supply chains (such as applying Milk-run systems when collecting used products) could be learnt and might be beneficial for reverse logistics,
- Accounting for flexibility in objectives' target values and/or elasticity in soft constraints along with imprecise input data and accordingly developing new mixed flexible-possibilistic approaches to cope with this kind of mixed uncertainty can fill a major methodological gap in this research stream,
- Since most of real life problems are large, and the exact methods can solve only small to moderate sized problem instances, devising tailored solution approaches including heuristics, meta-heuristics or Mat-heuristics (the interoperation of meta-heuristics and mathematical programming techniques) would be of particular interest.

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