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A NEW ROBUST POSSIBILISTIC PROGRAMMING MODEL FOR RELIABLE SUPPLY CHAIN NETWORK DESIGN: A CASE STUDY OF LEAD-ACID BATTERY SUPPLY CHAIN

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Abstract. Nowadays, the importance of caring about tremendous undesirable economical and technological effects of disruptions has impelled many researchers to design reliable supply chain networks. Moreover, the issue of intrinsic imprecision of input parameters should be gingerly regarded in the design of supply chain networks because it could have inverse impact on the quality of long-term planning decisions. Consequently, to handle the noted problems, in this paper, a reliable closed-loop supply chain network is formulated in which a new reliability method is introduced. The proposed formulation can effectively enable the design of a reliable network under different kinds of disruptions besides seeking for minimum overall costs of network design. On the one hand, a new effectual robust possibilistic programming (RPP) model is developed to confront with business-as-usual uncertainty in input parameters. Lastly, a real industrial case study is employed to validate the utility and practicability of the rendered model as well as presenting the efficiency and felicity of the developed RPP model.

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1. Introduction

One of the most important goals of supply chains (SCs) is to deliver needed amount of consumers' products with the lowest cost and the highest quality at the expected time. Nonetheless, due to enhanced global competition among businesses, market volatilities, reliance on global suppliers and increasing variations in product design owing to consumer's needs and short life cycle of products, companies have faced great difficulties to attain the mentioned targets [1, 2]. Therefore, design, management and implementation of integrated SCs is considered as a crucial and convoluted challenge for managers and strategists which not only helps them to overcome the mentioned struggle but also could make a long-lasting sustainable competitive advantage for business among its competitors [3–5].

Keywords. Robust possibilistic programming, reliability, supply chain network design, closed-loop supply chain.

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Besides, over the recent decades, one of the significant issues that raised the researchers and practitioners' attention, was the subject of product residuals and its relevant advantages and profits which could be gained by recovery and recycling activities [6]. It is noteworthy to mention that in the past, the main functional domain of SCs was to produce products from raw materials and delivering finished products to customers [7–9]; However, owing to exerted pressure by governments on manufacturers, growing public awareness about environmental and social issues and boost of relevant economic benefits, recycling and recovery of End-of-Life (EOL) products has become an important subject in the area of SC management. Consequently, the noted matters led to a somehow spontaneous movement among logisticians to concentrate on designing reverse and closed-loop supply chain (CLSC) networks [10–12].

Hence, with consideration of enumerated matters, SC networks are categorized in forward and reverse networks. Forward SCs consist of some consecutive echelons such as suppliers, plants, distribution centers (DCs), wholesalers and retailers which add value to the raw material and transform it into finished product to fulfill customer needs. On the other hand, reverse network contributes in collecting EOL and used products from customers and inspecting, refurbishing and recycling residues to obtain feeds for forward network as parts, products and reusable subassemblies [13, 14]. The design of both of the aforementioned networks accounts for decisions which are related to location, number, capacity levels, inventory capacity level of facilities and amount of flow between them [15–17].

Since the forward and reverse networks may relate to each other in some parts (*e.g.* recycled material may re-enter into forward chain), the performance of any of them is highly dependent to the other one. Therefore, many practitioners have come into conclusion to design integrated forward/reverse and CLSC networks (*e.g.* [8, 15, 17–22]) which optimizes both of the forward and reverse networks concurrently and avoids sub-optimalities derived from detached optimization of the networks [18, 23].

The high degree of uncertainty due to complicated essence of SCs which affects their overall performance is a remarkable point that should be considered in this context. Thus, with respect to importance of the regarded issue, it is valuable to mention that the design of SC networks includes two types of uncertainties owing to long strategic horizon of planning. The first one is called business-as-usual uncertainty which comprises environmental and system uncertainties [22, 24]. In other words, it is related to uncertainty of input parameters such as demand and capacities. A supply chain performing well under the noted kind of uncertainty is regarded as robust SC network (see [8, 25, 26]). The second one is concerned with unexpected catastrophic events (*i.e.*, disruptions) which could drastically spoil the performance of SCs. In this regard, supply chains operating effectively under disruptions occurrence are called reliable SC network [27, 28].

A great extent of the literature is involved in coping with the uncertainty of parameters. Stochastic programming (SP) is an applied method in the foregoing field (see [15, 26, 29–32]). However, unavailability of enough historical data to estimate probability distributions restricts the exploitation of the method. Possibilistic programming (PP) is the other employed method while availability of meager data and impreciseness of parameters. Several papers in the context of supply chain network design (SCND) have applied possibility theory to model the imprecise input parameters (*e.g.* [18, 19, 21, 33]). Nevertheless, the PP methods are unreliable owing to possible deviations of objective function and necessity of interactive time-consuming simulations to determine confidence level of constraints. As well, chosen confidence levels are not necessarily optimal. Notably, extension of RPP models could eradicate the aforementioned deficiencies and result in reliable outcomes.

Review of presented papers in SCND literature demonstrates that many researchers (*e.g.* [8, 10, 18, 25]) in foregoing field ignore the vulnerability of facilities against natural and manmade disruptions. However, in real situation, many risks are threatening SCs and consequently some preemptive methods are extended to cope with relevant adverse effects [34]. In reality, any kind of disruptions could damage facilities, increase transportation costs and cause loss of market share. A real example of this issue is tsunami of Japan which destroyed many industrial installations and electronic parts and conduced to tremendous losses for famous companies in the World as a result of discontinuity of Japanese suppliers. Thus, caring about disruptions in the design of networks not only makes outcome decisions trustworthy but also helps to avoid possible losses caused by possible disruptions [26, 35].

The design of reliable logistics networks which even perform well under failure of facilities caused by disruptions, have been taken into consideration by researchers. Drezner [36] considered reliability issues into two models; the first suggested model is classical p-median problem with objective of minimizing demand-weighted travel distance and the second one is (p, q) center problem in which it is assumed that at most q facilities could be completely disrupted. Minimization of maximum possible cost is provided as objective function. In each of the presented models, probability of failure is considered as a fixed parameter. Snyder and Daskin [27] proposed a reliable bi-objective model which minimizes weighted sum of nominal costs and on the other side, as a second conflicting objective, expected extra transportation costs due to failures at DCs are minimized. In the SCND model presented by Lim *et al.* [37], it is assumed that there are reliable and unreliable facilities and strike of any disruption can entirely ruin performance of uncapacitated unreliable facilities. Therefore, customers' demand assigned to disrupted facility would be served by the nearest reliable facility. A Lagrangian-relaxation method is used to solve the problem. Peng *et al.* [35] regarded a capacitated SCND problem and used P-robustness approach beside site dependent disruption probabilities to cope with the concerned problem. Azad *et al.* [34] developed the model rendered by Lim *et al.* [37] through considering partial capacity disruptions for unreliable facilities. They extended a benders decomposition algorithm to solve the established mixed integer programming model. Poudel *et al.* [38] extended a reliable model for case study of bio-fuel production. It is strived to minimize total costs of network design regarding excessive cost of transportation link failures aside with processing costs. Cui *et al.* [28] propounded a bi-echelon network including suppliers and customers that transportation modes are in danger of disruptions. Bi-level SP approach is applied to cope with adverse effects of disruptions. Rahmani and Mahmoodian [26] presented a multi-objective forward supply chain network design model that minimizes CO_2 emissions of different activities of the SC echelons aside with total costs of network design. They extended a benders decomposition approach to solve the proposed robust reliable model.

Noteworthy, few new papers are developed in the CLSC context with disruption considerations. Most of the works in this area utilized the approach introduced by Snyder and Daskin [27]. Vahdani *et al.* [19] offered a novel solution methodology by combining queuing theory, possibilistic programming and fuzzy multi-objective programming. Bi-directional uncapacitated DCs and collection centers could be disrupted in the provided formulation. In another work, Vahdani *et al.* [20] assumed that uncapacitated collection centers are subject to disruptions. Notably, queuing theory, robust optimization and fuzzy multi-objective programming are hybridized in the proposed model. Hatefi and Jolai [39] proposed a closed-loop SCND model and used p-robustness method to cope with adverse effects of disruptions. Robust programming method is applied to control risk-aversion level of output results.

Despite the notability of reliability issues in the SCND context, the related literature suffers from a number of gaps which can be announced as the following points: (1) Complete disruption of facilities is a restrictive assumption in the presented models (see [24, 27, 37]) because in real situation any disruption can even destroy a part of a facility. Furthermore, nowadays, products are constantly flowing through consecutive echelons of SCs and in fact, disruptions can destroy a percent or entire inventory of facilities instead of their capacity; this important issue is ignored in the current literature. (2) Facilities are uncapacitated in most of the proposed models (*e.g.* [8, 20, 26, 27]). However, matter of capacity of facilities is an inevitable subject, especially in partial disruption situation. (3) In all the studies conducted in the scope of the reliable SCND, researchers have strived to design single period models (*e.g.* [27, 28, 34, 35]); however, consideration for disruptions in multi-period models can lead to more effective and efficient strategic choices. (4) Lost and backlogged sales, cooperation with other members of the SC and outsourcing (*e.g.* [26, 27, 34, 38]) are some of the policies mostly used to abate execrable effects of facility failures. Nevertheless, in addition to increment of cost, these approaches intensify the dependency on suppliers. Therefore, firms could overcome the noted problems by the use of appropriate amount of safety stock (SS) in facilities exposed to disruptions. A more detailed classification of the literature is illustrated in Table 1 to clarify future research avenues that are included in this study.

Accordingly, the notable aim of this paper is to present an effective novel model for reliable multi-period integrated CLSC network design problem under uncertainty. It is noteworthy to mention that system and environmental uncertainties are considered simultaneously in the extended model. Therefore, some of the embedded

TABLE 1. Review of some existing models.

Model characteristics	[36]	[27]	[30]	[40]	[37]	[25]	[29]	[35]	[18]	[42]	[41]	[20]	[15]	[34]	[8]	[19]	[21]	[39]	[28]	[38]	[26]	This paper
Network structure																						
Closed-loop						O	O		O			O	O		O	O	O	O				O
Forward	O	O		O	O			O		O	O			O					O	O	O	
Reverse			O																			
Period type																						
Static	O	O	O	O	O		O	O	O	O	O	O	O	O	O	O		O	O	O	O	
Dynamic						O											O					O
Bill of material																						
None		O		O	O	O	O	O	O					O				O	O	O	O	
Available	O		O							O	O	O	O		O	O	O					O
Facilities capacity																						
Capacitated			O	O		O			O	O	O		O	O			O	O	O	O	O	O
Uncapacitated	O	O			O		O	O				O			O	O						
Network type																						
Reliable	O	O			O			O				O		O	O	O		O	O	O	O	O
Unreliable			O	O		O	O		O	O	O		O				O					
Disruption modeling																						
Partial														O				O				O
Complete	O	O			O			O				O			O	O			O	O	O	O
Strategy against disruption																						
Reliable facility					O																	
Penalty cost	O	O										O		O	O	O		O	O	O	O	
Outsourcing								O														O
Safety stock																						O
Uncertainty modeling																						
None	O													O								
SP		O	O		O		O	O					O					O	O	O	O	
PP				O		O			O	O		O			O	O	O					
RPP											O											O

parameters in the presented model such as transportation costs, operating costs, capacity of facilities, amount of returned products from customer zones and amount of disruptions in different periods are rendered as uncertain parameters. Moreover, for the sake of improving the practicality of the proposed model, a new reliability method is introduced through the application of multi-level SSs as a strategic choice. This method could decrease costs, reliance on competitors and outsourcing in disruption situation. On the other hand, the extended model could be used as a practical decision making tool because it covers partial and full disruption of available amount of products in facilities. A new effective RPP model is also elaborated to confront with uncertainty of parameters which enables the decision maker (DM) to adjust the degree of conservatism.

The remarkable contributions and distinctions of this paper in comparison to other related ones in the literature are as follows:

- Presenting a novel reliable multi-period CLSC network design model which can integrate the design of forward and reverse networks (horizontal integration) and tactical and strategic level decisions (vertical integration) as well as considering the issue of partial disruption.
- By the use of multi-level SSs as a strategic option in the proposed model, a new reliability approach is presented which has significant advantages and efficiently contributes in designing of a reliable network.
- Proposing a new robust possibilistic programming model which can effectively handle the uncertainty in input parameters and optimize the degree of conservatism.
- Despite the fact that the proposed model is a case based one which adduces the practicability of results in the real world, the suggested CLSC structure is general and could be applicable in many industries such as electronic part manufacturing and paper recycling industries.

The rest of this paper is organized as follows. Comprehensive problem definition and formulation based on the studied industrial case are presented in Section 2 and Section 3, respectively. The novel RPP model is elaborated in Section 4. The RPP model is implemented and evaluated by using data of the case study in Section 5. Accordingly, the results and some managerial implications are reported in the Section. Finally, conclusions and some future research guidelines are expressed in Section 6.

2. Problem definition

The presented model in this paper is based on a real industrial case study. The regarded case is an Iranian lead-acid battery manufacturer whose products are utilized in automobiles for starting, lighting and ignition (SLI). Currently, the manufacturer fulfills a portion of Iranian market demand *via* one manufacturing plant whose capacity is about one million and nine hundred thousand batteries per year. Additionally, this company owns a recycling center which supplies recycled lead to manufacturing plant as a supplier. The capacity of this recycling center is about 900 thousand batteries per year. SLI battery is composed of anode and cathode including (Pb and PbO_2), metallic grids, electrolyte, propylene and some other components (see [43]). According to Basel convention on 1992, EOL batteries are regarded as hazardous wastes due to corrosivity, reactivity and toxicity of the mentioned heavy metal and toxic materials. Consequently, they can endanger human health and cause harmful environmental damages [44, 45]. On the other hand, utilized lead in the production of SLI batteries is procured through two sources. The first source is mined lead ore and the other one is recycled lead from EOL batteries in recycling centers [46]. Recycled lead is preferable in battery industry, since recycling of EOL batteries requires less energy and cost in comparison to extracting primary lead from its ore. Moreover, recycling puts back components of batteries to the manufacturing process as a raw material. Thus, by recycling lead, environmental risks of residues would be decreased and also natural resources would be preserved for future generations [45]. In favor of previous considerations, CLSC network design for the lead-acid battery industry could be propounded as an important issue, because in addition to caring about economical dimensions of decisions, social responsibility and environmental protection are regarded as an integral part of decision making phase.

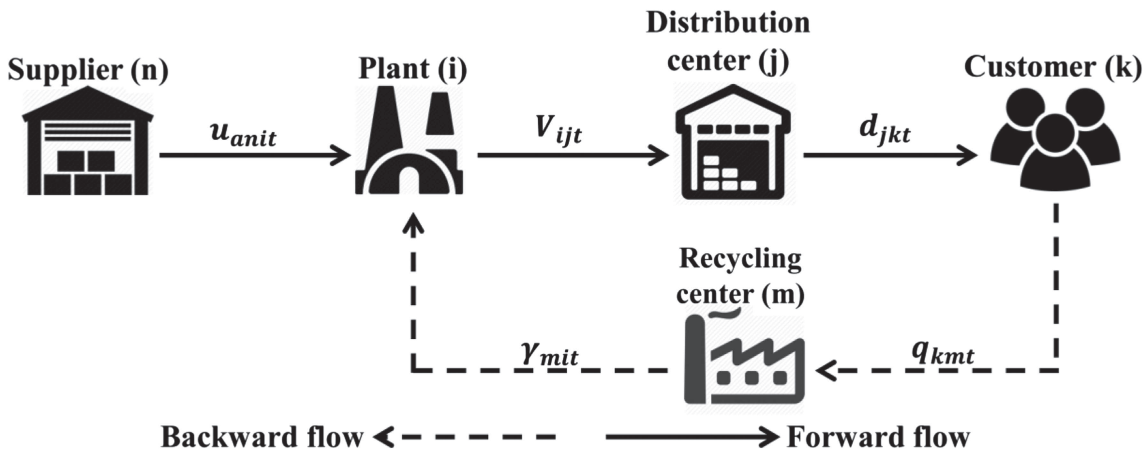

FIGURE 1. Structure of the studied CLSC network.

The multi-echelon, multi period and single product CLSC network considered in this paper is based on a real lead-acid battery SC. As it is presented in Figure 1, in the forward chain, requisite amount of raw materials to manufacture batteries are procured from suppliers. Then, produced batteries in plants are shipped to customer zones through DCs. It is noteworthy to mention that flow of batteries in the forward chain is based on the pull mechanism. In the reverse chain, EOL batteries are sent to lead recycling centers and then recycled lead is supplied to plants to fulfill a portion of needed lead in plants. Notably, only a portion of lead extracted from each battery could be recycled. Demand of each customer zone must be fully satisfied through a single DC. Moreover, at each period, a predefined percent of EOL batteries would be returned that a portion or entire could be collected and due to governmental legislations, company must pay penalty for every EOL battery that is not collected. In the presented network, location and number of suppliers and customers are fixed and predetermined.

In real situations, parts and products are continuously flowing in SCs from upstream to downstream in order to satisfy the customers' demand. Accordingly, in the concerned problem, it is assumed that DCs are prone to disruptions in which occurrence of any disruption could destroy a part or entire amount of available products and lead. In this regard, a new method is employed to alleviate the adverse effects of disruptions and respond completely to consumers demand. To this aim, instead of accepting penalty cost of buying entire disrupted amount from competitors, multi-level SS is introduced as a strategic alternative for each DC. Sufficient level of SS would be chosen based on trade-off between relevant penalty cost, fixed opening cost and incurred operating costs. Thus, if the amount of destroyed products is more than SS capacity, the amount of shortage would be procured from competitors by admission of penalty cost. This strategy could efficiently lessen the enhancement of costs incurred by disruptions. On the other side, unutilized SS capacity would be held up to next period which includes holding cost. Moreover, at the beginning of each period the amount of used SS in previous period should be procured from plants. The most important point is that SS is just held in safe rooms in DCs to cope with disruptions adverse effects and held products are not vulnerable to disruptions owing to reliability of safe rooms. Consequently, this method not only reduces cost enhancement, it even lessens dependency on competitors and outsourcing which is a great sustainable competitive advantage in long-term horizon for the concerned SC.

Owing to incompleteness and unavailability of data which is an inevitable issue in such real industrial CLSC, most of the parameters are imprecise. Application of SP and probability distribution could be considered as a relevant method to cope with these uncertainties (see [15, 26, 29, 30, 32]). Nevertheless, because of the need to rigorous data to estimate probability distribution of parameters and also, due to dynamic nature of real-life situation as well as long-term horizon of network design problem, the use of probability distribution is not possible in most of real situations [47]. Accordingly, to solve the aforementioned problem, possibility distribution is used to estimate the imprecise parameters.

The main issues to be addressed in the proposed reliable CLSC network model encompasses the determination of number and location of plants, DCs and recycling centers as well as capacity level of recycling centers and DCs and their SS level. In addition, flow quantities between sequential echelons would be determined in each period along with other mentioned decisions. Finally, to the aim of designing the aforementioned network, cost minimization is considered as an objective function.

3. Model formulation

In order to formulate the described reliable CLSC network problem, the following indices, parameters and variables are applied. Notably, the uncertain parameters are presented with a tilde on.

Indices:

n	Index of fixed location of suppliers $n = 1, \ldots, N$
i	Index of candidate locations for production plants $i = 1, \ldots, I$
j	Index of candidate locations for DCs $j = 1, \ldots, J$
m	Index of candidate locations for lead recycling centers $m = 1, \ldots, M$
k	Index of fixed location of customer zones $k = 1, \ldots, K$
o	Index of candidate capacity levels for each DC $o = 1, \ldots, O$
r	Index of candidate capacity levels for each lead recycling center $r = 1, \ldots, R$
p	Index of candidate capacity levels of SS for each DC $p = 1, \ldots, P$
a	Index of different raw materials $a = 1, \ldots, A$
t	Index of time periods $t = 1, \ldots, T$

Parameters:

$\tilde{de}_{kt}$	Demand of customer zone k at period t
$\tilde{\lambda}_{jt}$	Disrupted percentage of available products at DC j at period t
$\tilde{rd}_{kt}$	Amount of returned EOL products at customer zone k at period t
η	Fraction of recyclable lead of each battery in recycling centers
$\tilde{pl}_i$	Maximum capacity of manufacturing plant i
$\tilde{pj}_{jo}$	Maximum capacity of DC j with capacity level o
$\tilde{pm}_{mr}$	Maximum capacity of recycling center m with capacity level r
pp_{jp}	Amount of SS of DC j with capacity level p
$\tilde{fj}_{jo}$	Fixed cost of opening DC j with capacity level o
$\tilde{fm}_{mr}$	Fixed cost of opening lead recycling center m with capacity level r
$\tilde{fl}_i$	Fixed cost of opening production plant i
fp_{jp}	Fixed cost of opening level p of SS for DC j
$\tilde{cu}_{ani}$	Transportation cost per unit of raw material a from supplier n to production plant i
$\tilde{cv}_{ij}$	Transportation cost per unit of product from production plant i to DC j
$\tilde{cd}_{jk}$	Transportation cost per unit of product from DC j to customer zone k
$\tilde{cq}_{km}$	Transportation cost per unit of EOL product from customer zone k to recycling center m
$\tilde{cm}_{mi}$	Transportation cost per unit of recycled battery lead form recycling center m to plant i
$\tilde{\beta}_{an}$	Purchasing cost per unit of raw material a from supplier n
$\tilde{\theta}_i$	Processing cost per unit of product at production plant i
$\tilde{z}_m$	Recycling cost per unit of battery at lead recycling center m
$\tilde{\pi}_{jt}$	Penalty cost of procuring per unit of product from competitors at DC j at period t
$\tilde{h}_{kt}$	Penalty cost of not collecting per unit of EOL returned products in customer zone k at period t
$\tilde{\varphi}_{jt}$	Holding cost per unit of remained SS at the end of period t at DC j
$\tilde{ro}_{kt}$	Return rate of EOL products from customer zone k at period t

Variables

u_{anit} Quantity of raw material a transported from supplier n to plant i at period t

v_{ijt} Quantity of products transported from plant i to DC j at period t

q_{kmt} Quantity of collected EOL batteries transported from customer zone k to recycling center m at period t

γ_{mit} Quantity of recycled battery lead transported from lead recycling center m to plant i at period t

μ_{jt} Total quantity of products demanded of DC j through different customer zones at period t

μw_{jt} Quantity of disrupted products at DC j at period t

ε_{jt} Quantity of outsourced products due to disruptions strike at DC j at period t

$$xi_i = \begin{Bmatrix} 1 \text{ If a production plant is opened at location } i \\ 0 \text{ Otherwise} \end{Bmatrix}$$

$$xj_{jo} = \begin{Bmatrix} 1 \text{ If a DC with capacity level } o \text{ is opened at location } j \\ 0 \text{ Otherwise} \end{Bmatrix}$$

$$xp_{jp} = \begin{Bmatrix} 1 \text{ If SS level } p \text{ is opened for opened DC } j \\ 0 \text{ Otherwise} \end{Bmatrix}$$

$$xm_{mr} = \begin{Bmatrix} 1 \text{ If a recycling center is opened at location } m \text{ with capacity level } r \\ 0 \text{ Otherwise} \end{Bmatrix}$$

$$d_{jkt} = \begin{Bmatrix} 1 \text{ If demand of customer zone } k \text{ is assigned to DC } j \text{ at period } t \\ 0 \text{ Otherwise} \end{Bmatrix}$$

$$y_{jt} = \begin{Bmatrix} 1 \text{ If all disrupted products at DC } j \text{ are replaced by SS at periodt } t \\ 0 \text{ Otherwise} \end{Bmatrix}$$

With regard to the above mentioned notations, the reliable closed-loop supply chain network design (RCLSCND) model can be presented as follows:

$$\begin{aligned} \min \quad & E = \sum_i f\tilde{l}_i xi_i + \sum_j \sum_o f\tilde{j}_{jo} xj_{jo} + \sum_m \sum_r f\tilde{m}_{mr} xm_{mr} + \sum_j \sum_p fp_{jp} xp_{jp} \\ & + \sum_t \sum_a \sum_n \sum_i \left(c\tilde{u}_{ani} + \tilde{\beta}_{an}\right) u_{anit} + \sum_t \sum_i \sum_j \left(c\tilde{v}_{ij} + \tilde{\theta}_i\right) v_{ijt} + \sum_t \sum_j \sum_k c\tilde{d}_{jk} d\tilde{e}_{kt} d_{jkt} \\ & + \sum_t \sum_k \sum_m c\tilde{q}_{km} q_{kmt} + \sum_t \sum_m \sum_i \left(c\tilde{m}_{mi} + \tilde{z}_m\right) \gamma_{mit} + \sum_t \sum_j \tilde{\pi}_{jt} \varepsilon_{jt} + \sum_{t>1} \sum_j \sum_p pp_{jp} \tilde{\varphi}_{jt-1} xp_{jp} \\ & - \sum_{t>1} \sum_j \sum_i \tilde{\varphi}_{jt-1} v_{ijt} + \sum_{t>1} \sum_j \tilde{\varphi}_{jt-1} \mu_{jt} + \sum_t \sum_k \tilde{h}_{kt} r\tilde{d}_{kt} - \sum_t \sum_k \sum_m \tilde{h}_{kt} q_{kmt} \end{aligned} \tag{3.1}$$

s.t.

$$\sum_j d_{jkt} = 1 \quad \forall k, t \tag{3.2}$$

$$\sum_m q_{kmt} \le r\tilde{d}_{kt} = d\tilde{e}_{kt-1} r\tilde{o}_{kt} \quad \forall k, t \tag{3.3}$$

$$\mu w_{jt} - \sum_p pp_{jp} xp_{jp} \le \varepsilon_{jt} \quad \forall j, t \tag{3.4}$$

$$\sum_n u_{anit} = \sum_j v_{ijt} \quad \forall a > 1, i, t \tag{3.5}$$

$$\sum_n u_{anit} + \eta \sum_m \gamma_{mit} = \sum_j v_{ijt} \quad \forall a = 1, i, t \tag{3.6}$$

$$\mu_{jt} + \sum_p pp_{jp} xp_{jp} \le \sum_i v_{ijt} \quad \forall j, t = 1 \tag{3.7}$$

$$\varepsilon_{jt} \leq M\left(1 - y_{jt}\right) \quad \forall j, t \tag{3.8}$$

$$\mu_{jt} + \sum_{p} pp_{jp} xp_{jp} - M y_{jt-1} \leq \sum_{i} v_{ijt} \quad \forall j, t > 1 \tag{3.9}$$

$$\mu_{jt} + \mu w_{jt-1} - M(1 - y_{jt-1}) \leq \sum_{i} v_{ijt} \quad \forall j, t > 1 \tag{3.10}$$

$$\sum_{k} q_{kmt} = \sum_{i} \gamma_{mit} \quad \forall m, t \tag{3.11}$$

$$\sum_{j} v_{ijt} \leq \tilde{pi}_i xi_i \quad \forall i, t \tag{3.12}$$

$$\mu_{jt} + \sum_{p} pp_{jp} xp_{jp} \leq \sum_{o} \tilde{pj}_{jo} xj_{jo} \quad \forall j, t \tag{3.13}$$

$$\sum_{k} q_{kmt} \leq \sum_{r} \tilde{pm}_{mr} xm_{mr} \quad \forall m, t \tag{3.14}$$

$$\sum_{o} xj_{jo} \leq 1 \quad \forall j \tag{3.15}$$

$$\sum_{r} xm_{mr} \leq 1 \quad \forall m \tag{3.16}$$

$$\sum_{o} xj_{jo} = \sum_{p} xp_{jp} \quad \forall j \tag{3.17}$$

$$\sum_{k} \tilde{de}_{kt} d_{jkt} \leq \mu_{jt} \quad \forall j, t \tag{3.18}$$

$$\sum_{k} \tilde{de}_{kt} \tilde{\lambda}_{jt} d_{jkt} \leq \mu w_{jt} \quad \forall j, t \tag{3.19}$$

$$xi_i, xj_{jo}, xp_{jp}, xm_{mr}, y_{jt}, d_{jkt} \in \{0, 1\} \quad \forall i, j, k, m, o, p, r, t \tag{3.20}$$

$$u_{anit}, v_{ijt}, \varepsilon_{jt}, \mu_{jt}, \mu w_{jt}, q_{kmt}, \gamma_{mit} \geq 0 \quad \forall a, i, j, k, m, n, t \tag{3.21}$$

Objective function (3.1) minimizes the total fixed opening costs and variable activity costs. Variable activity costs include transportation costs, raw materials purchasing costs, processing costs, outsourcing costs, holding costs of the remained SSs at the end of periods and penalty cost of not collecting EOL returned products from customer zones. Constraint (3.2) ensures that demand of each customer zone is assigned to only one DC at each period and is entirely satisfied. Constraint (3.3) mentions that returned EOL products in each customer zone could be fully or partially collected. The amount of products which must be procured from competitors is ensured through Constraint (3.4). Presumably the first raw material in the given model is regarded as lead. Constraints (3.5) and (3.6) account for flow balance at production plants and also they imply that unless lead which is procured through suppliers and recycling centers, the other raw materials are only procured through suppliers. Constraints (3.7)–(3.10) enforce flow balance at DCs at different periods. Noteworthy, at the first period, in addition to customers' demand from each opened DC, the decided amount of SS must be procured through plants (Constraint 3.7). On the other hand, if the amount of disrupted products is more than SS capacity, the amount of shortage would be outsourced and at the next period entire capacity of SS will be replaced. However, if the amount of disrupted products is less than the pre-specified SS capacity, at the next period only the used capacity of SS will be replaced. Therefore, Constraint (3.8) determines that which one of the two previously explained situations holds at each DC. Additionally, with regard to the outcome of constraint (3.8), from the second period, flow balance at each DC is guaranteed through constraints (3.9) and (3.10). Flow balance at recycling centers is assured in Constraint (3.11). Capacity restrictions on Plants, DCs and recycling centers are imposed through constraints (3.12)–(3.14). These constraints also prohibit the assignment of flow to facilities no opened. Constraints (3.15) and (3.16) guarantee that at most one capacity level must be assigned to each DC and recycling center. Constraint (3.17) assures that if a capacity level is assigned to a DC, a SS capacity level will be assigned to that DC accordingly. Constraints (3.18) and (3.19) are auxiliary constraints which calculate total amount of received orders and disrupted products at each DC respectively. Lastly, binary and non-negativity restrictions on decision variables are regarded *via* constraints (3.20) and (3.21).

4. Proposed robust possibilistic programming model

Uncertainty can be classified into two categories; the first class is concerned with flexibility in target value of goals and constraints or in other words, indeterminacy or ambiguity of boundaries [48]. Flexible mathematical programming approach which uses preference-based fuzzy sets is employed to confront with this type of uncertainty (*e.g.* [49, 50, 52]). The second category of uncertainty is related to lack of data or knowledge about precise value of input parameters [18, 33, 51]. Consequently, the PP approaches are exploited to cope with this sort of uncertainty (*e.g.* [40, 41]). Noteworthy, imprecise parameters can be modeled by appropriate possibility distributions (*e.g.* triangular and trapezoidal possibility distributions) on the basis of inadequate existent data and knowledge of DMs and their experiences [41]. Since we are coping with ambiguous and ill-known parameters in the concerned RCLSCND problem, the regarded model pertains to the PP category.

Owing to dominant dynamic nature in industries, instability of trends and lack of knowledge about model parameters, specifying the actual value of some parameters is a very difficult and in some cases an impossible issue [8]. Accordingly, the importance of this subject has prompted many researchers to focus on developing effective PP approaches to overcome the noted problem (*e.g.* [33, 42, 47, 49, 51, 53]). Here, the PP approach extended by Pishvaee *et al.* [41] is employed while developing the proposed RPP model.

It is crucial that the results (*i.e.*, outcome decisions) of the PP models would not be always infallible because possible deviations from expected value of objective function and also, violations and thereupon infeasibility of constraints encompassing uncertain parameters, could bring great losses for different stakeholders. Furthermore, as the confidence level of constraints is determined through a subjective procedure by DM, there is no guaranty that the best possible (optimum) value is selected for this important parameter. Also, enhancement in the number of such constraints would desire to perform a large number of time-consuming interactive tests to determine the value of relevant confidence levels. Robust possibilistic programming (RPP) [41] that seeks to present risk-averse methods to deal with uncertainty in optimization problems can solve the mentioned flaws of the PP approaches by regarding for *feasibility* and*optimality robustness*. Feasibility robustness means that the solution to an optimization problem should remain feasible for almost all possible values of imprecise parameters and optimality robustness means that the value of objective function for the solution should abide close to optimal value for almost all possible values of uncertain parameters [41]. Here, a new RPP model is developed by extending the Pishvaee *et al.* [41] RRP approach based on Jimenez *et al.* [53] fuzzy ranking method.

4.1. Possibilistic programming model formulation

For ease of formulating the PP and RPP models, the compact form of the RCLSCND model can be presented as follows:

$$\begin{aligned}
\text{Min} \quad & \mathrm{E} = cx + fy \\
\text{s.t.} \quad & Ty = 1 \\
& Sx \leq rd \\
& dy \leq x \\
& \theta x + \varphi y \geq 0 \\
& \lambda x = 0 \\
& Mx - Oy \geq 0
\end{aligned}$$

$$
\begin{aligned}
& Gx \leq Ny \\
& \delta y \leq 1 \\
& \eta y = 0 \\
& y \in \{0,1\}, x \geq 0.
\end{aligned} \tag{4.1}
$$

In the compact model, vector f is related to the fixed opening cost of facilities and variable transportation cost between DCs and customer zones and vector c is related to variable processing costs, penalty costs, holding costs and variable transportation cost among different consecutive echelons of network. Constraints' coefficient matrices rd, d and N are respectively representative of amount of the returned products, customers' demand and capacity of facilities and matrices T, S, θ, ϕ, λ, M, O, G, δ and η represent other constraints' coefficient. Lastly, vectors x and y represent continuous and binary variables, respectively.

Vectors f and c are embedded uncertain parameters in the objective function and coefficient matrices d, rd and N are imprecise parameters in the second, third and seventh constraints of the compact model. Notably, in order to model the imprecise parameters, trapezoidal possibility distribution is applied.

With regard to the concerned imprecise parameters and based on the PP approaches proposed in Pishvaee *et al.* [41] and Jimenez *et al.* [53] (see the Appendix for details), the equivalent crisp model formulation which could be interchangeably entitled as basic possibilistic programming (BPP) model can be presented as follows:

$$
\begin{aligned}
\text{Min} \quad & \mathrm{E}[E] = \left(\frac{c^{(1)}+c^{(2)}+c^{(3)}+c^{(4)}}{4}\right)x + \left(\frac{f^{(1)}+f^{(2)}+f^{(3)}+f^{(4)}}{4}\right)y \\
\text{s.t.} \quad & Ty = 1Sx \leq \alpha\left(\frac{rd^{(1)}+rd^{(2)}}{2}\right) + (1-\alpha)\left(\frac{rd^{(3)}+rd^{(4)}}{2}\right) \\
& \left[\beta\left(\frac{d^{(3)}+d^{(4)}}{2}\right) + (1-\beta)\left(\frac{d^{(1)}+d^{(2)}}{2}\right)\right] y \leq x \\
& \theta x + \varphi y \geq 0 \\
& \lambda x = 0 \\
& Mx - Oy \geq 0 \\
& Gx \leq \left[\gamma\left(\frac{N^{(1)}+N^{(2)}}{2}\right) + (1-\gamma)\left(\frac{N^{(3)}+N^{(4)}}{2}\right)\right] y \\
& \delta y \leq 1 \\
& \eta y = 0 \\
& y \in \{0,1\}, x \geq 0
\end{aligned} \tag{4.2}
$$

As it is conspicuous, the average value of E, the objective function of the model (4.1), is applied to formulate the objective function of the proposed BPP model. As well, to determine the value of confidence levels of constraints (*i.e.* $0.5 < \alpha, \beta, \gamma \leq 1$), DM should determine some initial values and then in an interactive process, value of the confidence levels are revised iteratively up to reaching a congenial output from their point of view. Above all, there are four deficiencies in the explicated approach. Firstly, any increase in number of constraints embracing uncertain parameters would add legion experiments needed to be conducted by DMs and accordingly, increases the time spent on finding the desirable value of confidence levels. Nonetheless, as a second point, there is no guaranty on optimality of the final selected confidence levels. Also, the most momentous matter is that the probable deviation in constraints entailing uncertain parameters and as a result, infeasibility of constraints is a significant problem which is not regarded and could lead to great losses. Lastly, probable deviations of uncertain parameters of the objective function from their average value could decrease the reliability of the achieved solutions. To remove the aforementioned inefficiencies, in the next section, a new RPP model is developed.

4.2. Robust possibilistic programming model formulation

Pishvaee *et al.* [41] developed novel RPP models on the basis of chance constrained programming. Here, Jimenez *et al.* [53] fuzzy ranking method is applied to extend a new RPP model. Accordingly, inspired by RPP approach proposed by Pishvaee *et al.* [41], the proposed BPP model (4.2) can be converted into the RPP model as follows:

$$\begin{aligned}
\text{Min}\quad & E\left[E\right] + \phi\left(E_{max} - E\left[E\right]\right) + \omega\left[\alpha\left(\frac{rd^{(1)}+rd^{(2)}}{2}\right) + (1-\alpha)\left(\frac{rd^{(3)}+rd^{(4)}}{2}\right) - \left(\frac{rd^{(1)}+rd^{(2)}}{2}\right)\right] \\
& + \pi_1\left[\left(\frac{d^{(3)}+d^{(4)}}{2}\right) - \beta\left(\frac{d^{(3)}+d^{(4)}}{2}\right) - (1-\beta)\left(\frac{d^{(1)}+d^{(2)}}{2}\right)\right] y \\
& + \pi_2\left[\gamma\left(\frac{N^{(1)}+N^{(2)}}{2}\right) + (1-\gamma)\left(\frac{N^{(3)}+N^{(4)}}{2}\right) - \left(\frac{N^{(1)}+N^{(2)}}{2}\right)\right] y \\
\text{s.t.}\quad & Ty = 1 \\
& Sx \le \alpha\left(\frac{rd^{(1)}+rd^{(2)}}{2}\right) + (1-\alpha)\left(\frac{rd^{(3)}+rd^{(4)}}{2}\right) \\
& \left[\beta\left(\frac{d^{(3)}+d^{(4)}}{2}\right) + (1-\beta)\left(\frac{d^{(1)}+d^{(2)}}{2}\right)\right] y \le x \\
& \theta x + \varphi y \ge 0 \\
& \lambda x = 0 \\
& Mx - Oy \ge 0 \\
& Gx \le \left[\gamma\left(\frac{N^{(1)}+N^{(2)}}{2}\right) + (1-\gamma)\left(\frac{N^{(3)}+N^{(4)}}{2}\right)\right] y \\
& \delta y \le 1 \\
& \eta y = 0 \\
& y \in \{0,1\}, \qquad x \ge 0, \qquad 0.5 < \alpha, \beta, \gamma \le 1
\end{aligned} \tag{4.3}$$

Similar to the BPP model, the first term of objective function concentrates on minimizing the total average value of objective function. The second term has to do with optimality robustness which minimizes the gap between maximum possible value of E and its average value. Notably, $E_{\max}$ is regarded as follows:

$$E_{\max} = C_{\max} x + f_{\max} y$$

In other words, the noted term focuses on lessening the deviation above the mean value of objective function which its prominence to the other terms is specified through embedded coefficient parameter $\emptyset$ in the model. It is noticeable that in the concerned problem, deviations beneath the expected value of E are not regarded because they are not important for the DM. The other remaining terms are concerned with feasibility robustness. Here, total cost of constraints violation are calculated based on the amount of possible violation in constraints entailing uncertain parameters and their relevant penalty costs (*i.e.*, ω, π_1, π_2). These terms help the model to optimize the confidence levels of constraints (α, β, γ) as a variable and avoid time-consuming subjective experiments needed to determine the confidence levels in the traditional PP models. Moreover, in this method the optimality of confidence levels is assured.

Above all, the rendered RPP model is non-linear due to multiplication of variables in the third and seventh constraints and also the fourth and fifth terms of the objective function which result in increment of complexity of the model. However, by the use of some auxiliary variables and application of some extra constraints, the derived model can be made linear. In this regard, auxiliary variables υ and ψ are defined as follows:

$$\upsilon = \beta y$$

$$\psi = \gamma y$$

Accordingly, the linear version of the proposed RPP model is presented as follows:

$$\begin{aligned}
\text{Min} \quad & E[E] + \phi (E_{max} - E[E]) + \omega \left[\alpha \left(\frac{rd^{(1)} + rd^{(2)}}{2}\right) + (1-\alpha)\left(\frac{rd^{(3)} + rd^{(4)}}{2}\right) - \left(\frac{rd^{(1)} + rd^{(2)}}{2}\right)\right] \\
& + \pi_1 \left[\left(\frac{d^{(3)} + d^{(4)}}{2}\right) y - \upsilon \left(\frac{d^{(3)} + d^{(4)}}{2}\right) - (y - \upsilon)\left(\frac{d^{(1)} + d^{(2)}}{2}\right)\right] \\
& + \pi_2 \left[\psi \left(\frac{N^{(1)} + N^{(2)}}{2}\right) + (y - \psi)\left(\frac{N^{(3)} + N^{(4)}}{2}\right) - \left(\frac{N^{(1)} + N^{(2)}}{2}\right) y\right] \\
\text{s.t.} \quad & Ty = 1 \\
& Sx \leq \alpha \left(\frac{rd^{(1)} + rd^{(2)}}{2}\right) + (1-\alpha)\left(\frac{rd^{(3)} + rd^{(4)}}{2}\right) \\
& \left[\upsilon \left(\frac{d^{(3)} + d^{(4)}}{2}\right) + (y - \upsilon)\left(\frac{d^{(1)} + d^{(2)}}{2}\right)\right] \leq x \\
& \upsilon \leq My \\
& \upsilon \geq M(y-1) + \beta \\
& \upsilon \leq \beta \\
& \theta x + \varphi y \geq 0 \\
& \lambda x = 0 \\
& Mx - Oy \geq 0 \\
& Gx \leq \left[\psi \left(\frac{N^{(1)} + N^{(2)}}{2}\right) + (y - \psi)\left(\frac{N^{(3)} + N^{(4)}}{2}\right)\right] \\
& \psi \leq My \\
& \psi \geq M(y-1) + \gamma \\
& \psi \leq \gamma \\
& \delta y \leq 1 \\
& \eta y = 0 \\
& y \in \{0,1\}, \qquad x, \upsilon, \psi \geq 0, \qquad 0.5 < \alpha, \beta, \gamma \leq 1
\end{aligned} \tag{4.4}$$

In the linear model formulation, the first three added constraints guarantee that if binary variable y is equal to zero, the auxiliary variable υ will be equal to zero and otherwise, it would be equal to β. Notably, M is a sufficient large number in the presented model.

5. Implementation and evaluation

In this section, in order to demonstrate the indispensability of the developed model as well as the efficiency of the suggested RPP model, data derived from an Iranian battery manufacturing firm is applied. The firm should serve demand of nine customer zones at each period through the products manufactured in the plants. To this aim, distribution of products among customer zones should be carried out by DCs. Five candidate sites for opening DCs, two candidate capacity levels and two candidate SS levels are available for opening DCs. Moreover, to manufacture needed products, in addition to one existed plant, five candidate locations for establishing production centers are designated. On the other hand, in the reverse network, returned EOL batteries in each period are collected and recycled by recycling centers. Notably, four candidate locations and two candidate capacity levels are considered to open lead recycling centers. Also, there is one opened recycling center whose corresponding fixed opening cost is regarded as zero. The last considerable point is that entire recycled lead should be sent to plants as raw material and rest of the required raw materials would be procured through two available predetermined suppliers.

In the recent years, number of produced cars in Iran has increased considerably and accordingly the need to production and import of car batteries has augmented. Aim of the studied battery manufacturing company is responding to the current demand of customers and increasing demand of consumers in future planning periods. Also, environmental protection legislations have forced companies to collect their EOL batteries and use them as raw materials *via* recycling the batteries. The notable matter is that capacity of the established production and recycling centers is not enough for satisfying the demand of consumers in current and coming periods. In this regard, the biggest challenge of the manufacturing company is deciding about extending the manufacturing network and opening more facilities that can help to satisfy the demand of consumers and improve customer loyalty. Also, extending the reverse network could be introduced as the other important concerns of company managers that could improve social image of the company. Therefore, making strategic decisions related to establishing facilities and choosing the best processing capacity of facilities could be regarded as the most important aim of the extended SCND model. Besides the strategic network design decisions, production of batteries with the lowest cost and increasing the production and delivery speed of products are important issues that could be regarded as the second aim of the manufacturing company. To achieve to the noted aims, decisions related to determining the sources of buying raw materials, amount of battery production in each manufacturing plant and process of distributing products in different planning periods should be optimized. The aforementioned decisions are called tactical planning. Therefore, the tactical decisions should be made based on the first level strategic decisions. Concurrent optimization of strategic and tactical decisions could help to improve satisfaction level of consumers *via* maximizing delivery speed of batteries and minimizing price of products. The other important challenge of the company is strikes of disruptions that could affect effective performance of the manufacturing network. Choosing the appropriate SS level for each of the opened distribution centers could enable company to maintain its responsiveness in crisis conditions and minimize the losses caused by disruptions strikes. It should be noted that uncertainty of parameters is an undeniable part of the battery supply chain planning problem in long-term planning periods. It could adversely affect quality of output decisions *via* deviations of planning parameters. Therefore, using an appropriate method could minimize risks of losses caused by planning uncertainties in long-term planning periods.

To solve the aforementioned challenges, a group of field experts is formed and the elucidated potential structure of the battery manufacturing network is determined based on their opinion. They strived to uniformly choose the location of potential facilities in all regions of Iran. It could help to find the best locations for satisfying the demand of consumers with the lowest processing and transportation costs. Also, the designed network comprises manufacturing and recycling facilities that concurrently optimizes production and recycling processes in the battery supply chain. It could be regarded as a competitive advantage for the company because implementing recycling process results in providing raw materials with lower costs. Using safe rooms and holding SSs at distribution centers would help to control negative effects and losses caused by disruptions. It immunizes the company against disruptions strikes *via* admitting holding costs of products. The best amount of SSs levels of DCs is determined based on the opinion of the field experts that know different regions of Iran and probability of disruptions strikes. The extended strategy minimizes outsourcing costs *via* holding inventories in safe rooms that minimizes dependence of the company on its competitors. Finally, a new RPP method is extended to control uncertainty of parameters. As planning horizon is long-term, uncertainty of parameters and impossibility of estimating the exact value of parameters are undeniable issues. Therefore, possibility distributions are used to determine the changing interval of parameters in long-term planning period *via* aid of a group of company

TABLE 2. Demand of customers ($\tilde{de}_{kt}$).

Customer zone	Demand (period 1)	Demand (period 2)
(1)	(200000, 400000, 410000, 615000)	(180000, 360000, 380000, 570000)
(2)	(50000, 100000, 110000, 165000)	(60000, 120000, 130000, 195000)
(3)	(150000, 300000, 310000, 465000)	(130000, 260000, 270000, 405000)
(4)	(75000, 150000, 160000, 240000)	(80000, 160000, 170000, 255000)
(5)	(50000, 100000, 110000, 165000)	(45000, 90000, 110000, 165000)
(6)	(100000, 200000, 220000, 330000)	(110000, 220000, 230000, 345000)
(7)	(50000, 100000, 110000, 165000)	(45000, 90000, 100000, 150000)
(8)	(50000, 100000, 110000, 165000)	(55000, 110000, 130000, 195000)
(9)	(100000, 200000, 210000, 315000)	(85000, 170000, 175000, 262500)

TABLE 3. Fixed cost ($\tilde{fi}_i$) and capacity of plants ($\tilde{pi}_i$).

Location	Fixed cost	Capacity
(1)	(0,0,0,0)	(425000, 850000, 900000, 1350000)
(2)	(13900000000, 14000000000, 14300000000, 14400000000)	(315000, 630000, 650000, 975000)
(3)	(13900000000, 14000000000, 14200000000, 14500000000)	(390000, 780000, 800000, 1200000)
(4)	(15400000000, 15500000000, 15600000000, 15800000000)	(400000, 800000, 820000, 1230000)
(5)	(13400000000, 13600000000, 13700000000, 13850000000)	(340000, 680000, 700000, 1050000)
(6)	(13800000000, 13850000000, 13900000000, 14100000000)	(370000, 740000, 760000, 1140000)

TABLE 4. Capacity levels of candidate recycling centers ($\tilde{pm}_{mr}$).

Location	Capacity level 1	Capacity level 2
(1)	(235000, 470000, 490000, 735000)	(245000, 490000, 500000, 750000)
(2)	(190000, 380000, 400000, 600000)	(195000, 390000, 410000, 620000)
(3)	(215000, 430000, 450000, 675000)	(230000, 460000, 470000, 705000)
(4)	(205000, 410000, 420000, 630000)	(210000, 420000, 430000, 645000)
(5)	(220000, 440000, 450000, 675000)	(225000, 450000, 460000, 690000)

executives. The introduced method alleviates the need to historical data and minimizes the errors caused by using estimation methods in long-term planning horizons. Also, it enables company managers to control risk-aversion level of model outputs that is the greatest advantage of the extended RPP method.

The formulation of the elucidated network comprises a lot of certain and uncertain parameters and consequently, presentation of all parameters is not possible according to space limitation. Thus, only some of the momentous imprecise parameters of the model such as customers' demand, fixed cost of opening plants and their related capacities and lastly, capacity levels of each candidate site for opening recycling centers, are respectively given in Tables 2–4. Rest of the parameters which are not presented could be rendered through the interested readers' solicitation. Noteworthy, possibility distribution of uncertain parameters and their corresponding prominent points are determined on the basis of existent historical data and knowledge of an industry experts group and company executives.

It should be noted that the extended model includes strategic and tactical decisions. The strategic decisions in the SCND scope concern about location of facilities and their related capacity levels that could not be changed in long-term planning horizon. In other words, the strategic decisions affect long-term performance of the company. Also, the tactical decisions relate to flow of products between network echelons and processing of products at different facilities that could be regarded as medium-term decisions [6]. The notable matter is that concurrent optimization of the tactical and strategic decisions avoids sub-optimality of the output decisions. Reason of the

Table 5. Penaties of the RPP model.

Penalty	1	2	3	4	5	6
δ	160000	180000	200000	225000	250000	275000
π_1	13000	14500	16000	18000	20000	22000
π_2	195000	215000	240000	270000	300000	330000
π_3	195000	215000	240000	270000	300000	330000
π_4	195000	215000	240000	270000	300000	330000
π_5	160000	180000	200000	225000	250000	275000

noted matter is that tactical decisions are highly dependent on the strategic decisions and accordingly separated optimization of the noted decisions could cause unreliability of the output results. Therefore, optimizing the strategic and tactical decisions could help to choose the best processing and delivery procedure based on the opened facilities in the network [7, 8, 15]. Also, designing a supply chain network as a multi-period problem heightens precision of the estimations and accuracy of the output results. In other words, aggregation of planning periods and designing a network as a single period model increases unreliability of output decisions. Aggregated planning could adversely affect precision of the estimations and results in great losses for the company. Therefore, using different planning periods helps to minimize deviations of the estimations and maximizes reliability of the strategic output decisions [23, 25, 31]. Also, it should be noted that owing to dynamic nature of supply chain networks and changing trend of trade markets, uncertainty of parameters in long-term planning horizon is an inevitable subject. In other words, uncertainty is an inseparable part of strategic planning problems such as the SCND problem that should be controlled in the network design models. It should be noted that most of the time there is not enough historical data to estimate the probability distribution of the uncertain parameters that heightens complexity of modelling uncertain parameters. In this regard, there are two alternatives to model uncertain parameters. Stochastic scenario-based models are the first alternative that use probability distribution to model imprecise parameters (see [15,29,31,32]). However, as it was mentioned, lack of historical data restricts the usage of the scenario-based models. Also, a great number of scenarios should be defined while number of uncertain parameters increases that is a complicating and difficult issue. Also, using scenarios could not cover all real-world situations and all values of the uncertain parameters could not be modeled *via* using stochastic programming method [18, 25]. Therefore, using possibilistic programming and possibility distributions solves the aforementioned problems as the second alternative for modelling uncertain parameters. Firstly, company executives could determine changing interval of uncertain parameters based on their experience in the strategic planning horizon. It eliminates the need to historical data that is the advantage of the possibilistic programming method. Also, using possibility distributions minimizes estimation errors *via* using intervals to model uncertain parameters. Also, it should be noted that the defined possibility distributions and their corresponding intervals could cover all real world situations that is the advantage of the possibilistic programming method [42, 49, 50].

In this section, in order to prove the suitability of the presented RCLSCND model and also, to analyze performance of the proposed RPP model, the two models are firstly solved under nominal data. The BPP model is optimized with consideration for a set of distinct confidence levels (*i.e.*, 0.7, 0.8, 0.9). The objective function value of the BPP model under different confidence levels is illustrated in Figure 2. The results show that enhancement of minimum acceptable feasibility degree, has led to increment of costs due to utilization of extra resources.

In order to analyze performance of the RPP model (under unlike set of penalties presented in Tab. 5), first, eight realizations are randomly generated. To generate each realization for each uncertain parameter which has trapezoidal possibility distribution (*e.g.* $\tilde{\beta} = (\beta^{(1)}, \beta^{(2)}, \beta^{(3)}, \beta^{(4)})$), a random number should be generated uniformly between the first and the last point of the relevant possibility distribution (*i.e.*, $\beta_{\text{real}} = \left[\beta^{(1)}, \beta^{(4)}\right]$). Then, to the aim of testing the desirability of the PP and RPP outcome solutions, the generated parameters under each realization and the optimum value of variables which were determined by the RPP and BPP models under nominal data, should be embedded in following model. The variables of the following model

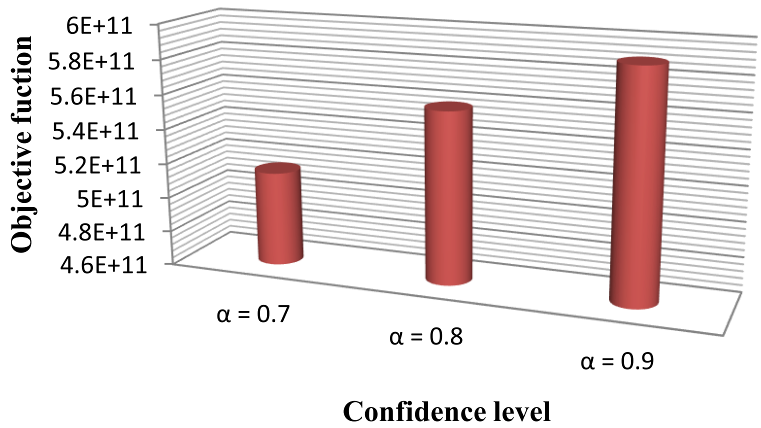

FIGURE 2. Graphical representation of objective function value of BPP model under different confidence levels.

include $rh_{kt}, rp_{kt} rj_{jt}, rdp_{jt}, rdw_{jt}, ri_{it}, rm_{mt}$ which specify violation of their corresponding constraints under each realization.

$$
\begin{aligned}
\text{Min} \quad & \mathrm{E} = \sum_i fi_i xi_i^* + \sum_j \sum_o fj_{jo} xj_{jo}^* + \sum_m \sum_r fm_{mr} xm_{mr}^* + \sum_j \sum_p fp_{jp} xp_{jp}^* \\
& + \sum_t \sum_a \sum_n \sum_i \left(cu_{ani} + \tilde{\beta}_{an}\right) u_{anit}^* + \sum_t \sum_i \sum_j \left(cv_{ij} + \tilde{\theta}_i\right) v_{ijt}^* + \sum_t \sum_j \sum_k cd_{jk} de_{kt} d_{jkt}^* \\
& + \sum_t \sum_k \sum_m cq_{km} q_{kmt}^* + \sum_t \sum_m \sum_i \left(cm_{mi} + \tilde{z}_m\right) \gamma_{mit}^* + \sum_t \sum_j \pi_{jt} \varepsilon_{jt}^* + \sum_{t>1} \sum_j \sum_p pp_{jp} \phi_{jt-1} xp_{jp}^* \\
& - \sum_{t>1} \sum_j \sum_i \varphi_{jt-1} v_{ijt}^* + \sum_{t>1} \sum_j \varphi_{jt-1} \mu_{jt}^* + \sum_t \sum_k h_{kt} rh_{kt} \\
& + \delta \sum_t \sum_k rp_{kt} + \pi_1 \sum_t \sum_j rj_{jt} + \pi_2 \sum_t \sum_j rdp_{jt} + \pi_3 \sum_t \sum_j rdw_{jt} + \pi_4 \sum_t \sum_i ri_{it} + \pi_5 \sum_t \sum_m rm_{mt} \\
\text{s.t.} \quad & \sum_j d_{jkt}^* = 1 \quad \forall k, \\
& \sum_m q_{kmt}^* \leq rd_{kt} + rp_{kt} \quad \forall k, t \\
& \mu w_{jt}^* - \sum_p pp_{jp} xp_{jp}^* \leq \varepsilon_{jt}^* \quad \forall j, t \\
& \sum_n u_{anit}^* = \sum_j v_{ijt}^* \quad \forall a > 1, i, t \\
& \sum_n u_{anit}^* + \eta \sum_m \gamma_{mit}^* = \sum_j v_{ijt}^* \quad \forall a = 1, i, t \\
& \mu_{jt}^* + \sum_p pp_{jp} xp_{jp}^* \leq \sum_i v_{ijt}^* \quad \forall j, t = 1 \\
& \varepsilon_{jt}^* \leq M(1 - y_{jt}^*) \quad \forall j, t
\end{aligned}
$$

$$\mu^*_{jt} + \sum_p pp_{jp}xp^*_{jp} - My^*_{jt-1} \leq \sum_i v^*_{ijt} \quad \forall j, t > 1$$
$$\mu^*_{jt} + \mu w^*_{jt-1} - M(1 - y^*_{jt-1}) \leq \sum_i v^*_{ijt} \quad \forall j, t > 1$$
$$\sum_k q^*_{kmt} = \sum_i \gamma^*_{mit} \quad \forall m, t$$
$$\sum_j v^*_{ijt} \leq pi_i xi^*_i + ri_{it} \quad \forall i, t$$
$$\mu^*_{jt} + \sum_p pp_{jp}xp^*_{jp} \leq \sum_o pj_{jo}xj^*_{jo} + rj_{jt} \quad \forall j, t$$
$$\sum_k q^*_{kmt} \leq \sum_r pm_{mr}xm^*_{mr} + rm_{mt} \quad \forall m, t$$
$$\sum_o xj^*_{jo} \leq 1 \quad \forall j$$
$$\sum_r xm^*_{mr} \leq 1 \quad \forall m$$
$$\sum_o xj^*_{jo} = \sum_p xp^*_{jp} \quad \forall j$$
$$\sum_k de_{kt}d^*_{jkt} \leq \mu^*_{jt} + rdp_{jt} \quad \forall j, t$$
$$\sum_k de_{kt}\lambda_{jt}d^*_{jkt} \leq \mu w^*_{jt} + rdw_{jt} \quad \forall j, t$$
$$rd_{kt} - \sum_m q^*_{kmt} = rh_{kt} - rp_{kt} \quad \forall k, t$$
$$rh_{kt}, rp_{kt}, rj_{jt}, rdp_{jt}, rdw_{jt}, ri_{it}, rm_{mt} \geq 0 \forall i, j, k, m, t \tag{5.1}$$

In the regarded model formulation, total costs of network design are calculated according to tactical and strategic costs and besides, penalty costs of violation of constraints. The other important point is that as the objective function could not distinguish the deviations over and under the determined value of EOL returned products in realizations, a new constraint with two new variables (rh_{kt},rp_{kt}) is added before the last constraint in the model formulation. The last two terms in the objective function (3.1) are also substituted with a new term in the formulation (5.1) to appropriately handle the noted obstacle. All the requisite experiments are implemented by the aid of CPLEX solver of GAMS optimization software on a Pentium quad-core 2.2 GHz computer with 4 GB RAM. Finally, after carrying out the mentioned steps and attaining optimal value of the objective function of model (5.1) under different penalty sets (see Tab. 5), average and standard deviation (SD) of the results of the BPP and RPP models under the eight realizations are computed and compared to each other. Results are depicted in Figures 3 and 4.

The obvious point represented in Figure 4 is that SD of the RPP model is always better than the BPP model under different confidence levels and also increment of penalties has led to augmentation of SDs, but dominance of the RPP model is always preserved. Hence, in this situation, the determinant factor which could prove the efficiency of the RPP model would be the average of the noted models. As it can be seen from Figure 3, average of the RPP model in the first and second sets of penalties is undesirable in comparison to the BPP model but in the third and fourth penalty series, it outperforms the BPP model under confidence levels 0.8 and 0.9. Due to lower costs of the system emanated from low conservatism of DM, performance of the RPP model is not better than the BPP model under feasibility degree 0.7. Moreover, performance of the RPP model on the basis

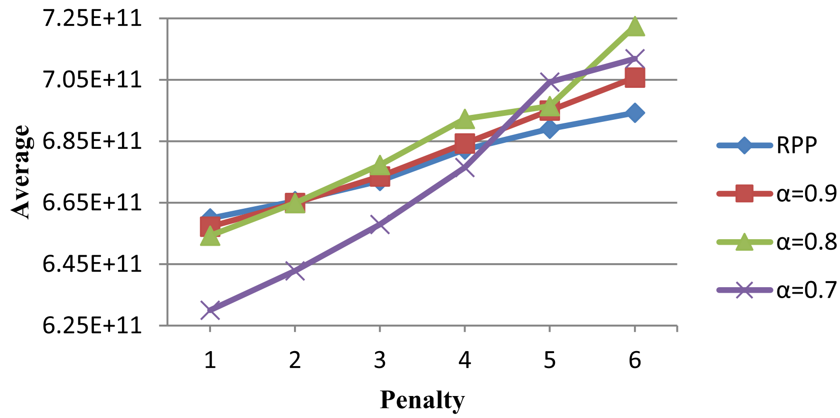

Figure 3. Graphical representation of average total costs of the RPP and BPP models under realizations.

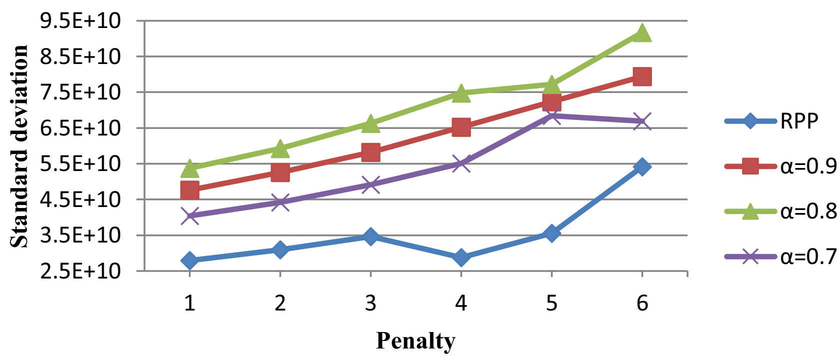

Figure 4. Graphical representation of SD of total cost of the RPP and BPP models under realizations.

of the two remained penalty sets (*i.e.*, sets 5 and 6) is significantly better than the BPP model with regard to both average and SD performance measures. Thus, it can be concluded that increase in penalty values makes the use of conservative models like the RPP model more reasonable. Due to provided conservatism level by the RPP model, the outcomes of this model face with lower risks and violations against the BPP model under high penalties.

In order to demonstrate the efficient performance of the extended reliability method, its results are compared to a model with only outsourcing option while disruptions strike. In this regard, outsourcing penalty costs are changed incrementally (each time 30%) to perform sensitivity analysis on the models outcome (*i.e.*, total costs of SCND) and appropriately compare models performance. As it can be seen in Table 6, the extended RPP and BPP models with SS alternative outperform the model with only outsourcing option. Increment of confidence levels of the BPP model has led to more outsourcing costs and accordingly better performance of the proposed model. Flow of more products and strikes of disruptions in such networks could destroy more products which is the reason of the noted matter. Also, increase of the penalty costs has intensified dominance of the proposed model which approves that the application of reliability concept in the proposed model could efficiently decrease cost augmentation. Moreover, abatement of dependency on outsourcing and competitors

Table 6. Sensitivity analysis results.

Penalties set	Strategy against disruption	BPP α=0.9	BPP α=0.8	BPP α=0.7	RPP
1	SS	597906480702	561409755917	514990276321	652035146719
	Outsourcing	619821050915	568904555637	535452742168	668316341406
2	SS	598135730702	561508180757	515261106321	653792091621
	Outsourcing	642810353415	589232735637	554131817168	691775178906
3	SS	598410830701	561872980757	515524727896	655715832856
	Outsourcing	670191588415	613492825637	576529034043	719111444531

makes a great sustainable competitive advantage in long-term horizon of planning for the concerned SC which distinguishes the propounded model from the other ones.

Notably, to find the final structure of the battery manufacturing network, the penalty costs are determined based on the opinion of company managers. They decided to set penalties to achieve to the maximum risk-aversion in output decisions. They aim to satisfy all demand of customers and maintain market share *via* on-time delivery of products to customer zones. In this regard, the model is solved based on the determined penalties by company managers and output results show that in addition to the available factory in Zanjan city, three plants should be opened in potential determined locations (*i.e.*, Tabriz, Semnan and Bam). The opened plants are uniformly distributed in different regions of the country that helps to minimize the transportation costs aside with processing costs of producing batteries. Also, three DCs should be opened in Tehran, Yazd and Borujerd cities. The opened DCs in Tehran and Yazd cities should be established with their second capacity levels and the opened DC in Borujerd city should be established with its first capacity level. The cities near to Tehran and Yazd cities are populated and accordingly higher capacity level is chosen to satisfy demand of customer zones. It shows the accurate performance of the model regarding the chosen capacity levels for the DCs. Also, the opened DCs are uniformly distributed in the country that helps to transfer products to consumer zones with the lowest cost. Also, the Safety rooms opened in Yazd and Borujerd cities are opened with their first inventory holding capacity level. Also, the safety room established in Tehran city is opened with its second capacity level. Based on the opinion of company managers, the possibility of disruptions strikes is more in the facility located in Tehran city. Therefore, holding more products as SS in the DC located in Tehran city could be regarded as a good long-term strategy. Finally, it should be noted that one recycling center should be opened in addition to the available recycling center in Zanjan city. New recycling center should be opened in Isfahan city with its second processing capacity. It should be noted that recycling centers located in Isfahan and Zanjan cities enable company to collect and recycle products with the lowest processing and transportation costs. Noted issues show that the model locates the facilities in the best potential locations to manufacture and deliver products to consumers. Also, the extended reliability strategy minimizes total costs of network in disruption situations *via* holding products as inventory in safety rooms.

Finally, with respect to the alluded points and based on the opinion of the noted firm's managers, it can be concluded that the developed RCLSCND model and the introduced RPP model can efficiently help the practitioners to design reliable networks and manage the relevant risks.

6. Conclusions

During the recent decade, supervening of abrupt disruptions and the issue of confronting their adverse effects have become a great challenge for companies' executives. Accordingly, accounting for this struggle in the design of SCs could beget long-lasting positive results due to taken decisions. In order to face with the noted problem, a new optimization model is introduced in this paper. Unlike the past researches, the proposed model optimizes both forward and reverse networks concurrently and effectively creates highly responsive and cost efficient network under probable partial and non-partial disruptions. Due to inescapable imprecise essence of the input parameters in such problem, a new RPP model is extended to counteract the stated formidable obstacle. Finally, a real case study of lead-acid battery industry is applied to indicate the effectiveness of the propounded model and the high quality performance and practicability of the proposed RPP model.

Most of the researches in the area of reliable network design have strived to minimize the overall network design costs and extra emanated costs from disruptions. However, accounting for other objectives such as responsiveness and social responsibility alongside the cost objective could lead to valuable outcomes with significant practical relevancies. Therefore, developing models with the above-mentioned ability could be considered as an attractive future research direction.

Appendix A. The Jimenez *et al.* [53] possibilistic programming method

In this section, the PP approach extended by Jimenez *et al.* [53] is introduced and explained. This method is established on the basis of "expected value" and "expected interval" of a fuzzy number. In order to elucidate the noted approach, membership function of trapezoidal fuzzy number with its four prominent values which is regarded as would be presented as follows:

$$\mu_{\tilde{r}}(x) = \begin{cases} 0, & \text{if} \quad x \leq r_1 \\ f_r(x) = \frac{x-x_1}{r_2-r_1}, & \text{if } r_1 \leq x \leq r_2 \\ 1, & \text{if } r_2 \leq x \leq r_3 \\ h_r(x) = \frac{r_4-x}{r_4-r_3}, & \text{if } r_3 \leq x \leq r_4 \\ 0, & \text{if} \quad x \leq r_4 \end{cases}$$

Upon the presented membership function, the expected value (EV) and expected interval (EI) of the corresponding fuzzy number could be defined as follows Heilpern [54]:

$$EI(\tilde{r}) = [E_1^r, E_1^r] = \left[\int_0^1 f_r^{-1}(x)\mathrm{d}x, \int_0^1 h_r^{-1}(x)\mathrm{d}x\right] = \left[\frac{1}{2}(r_1+r_2), \frac{1}{2}(r_3+r_4)\right] \tag{A.1}$$

$$EV(\tilde{r}) = \frac{E_1^r + E_2^r}{2} = \frac{r_1+r_2+r_3+r_4}{4} \tag{A.2}$$

Noteworthy equality of prominent points r_2 and r_3 would result in conversion of trapezoidal fuzzy number to triangular and accordingly, all the previously regarded terms are applicable with consideration of the aforementioned point.

Besides the alluded matters, with regard to ranking method of Jimenez [55], for each couple of fuzzy numbers $\tilde{a}$ and $\tilde{b}$, the greatness of fuzzy number a in comparison to fuzzy number $\tilde{b}$ could be given as follows:

$$\mu_M\left(\tilde{a},\tilde{b}\right) = \begin{cases} 0, & \text{if } E_2^a - E_1^b < 0 \\ \frac{E_2^a - E_1^b}{E_2^a - E_1^b - \left(E_1^a - E_2^b\right)}, & \text{if } 0 \in \left[E_1^a - E_2^b, E_2^a - E_1^b\right] \\ 1 & \text{if } E_1^a - E_2^b > 0 \end{cases} \tag{A.3}$$

Additionally, term $\tilde{a} \geq_\alpha \tilde{b}$ is equivalent to $\mu_M\left(\tilde{a},\tilde{b}\right) \geq \alpha$ which means that $\tilde{a}$ is greater than or equal to $\tilde{b}$ at least in degree of α.

Now, consider the following mathematical programming model.

$$\begin{aligned} &\min \quad z = \tilde{c}^t x \\ &\text{s.t.} \quad \tilde{a}_j x \geq \tilde{b}_j, \quad j = 1,\ldots,n \\ &x \geq 0 \end{aligned} \tag{A.4}$$

All of the parameters in the rendered fuzzy mathematical programming model are tainted with uncertainty and they are assumed as trapezoidal or triangular fuzzy numbers.

Notably, According to Jimenez *et al.* [53], feasibility degree of decision vector $x \in R^n$ in the regarded model is equal to α if $min_{j=1,\ldots,n} \left\{ \mu_M(\tilde{a}_j x, \tilde{b}_j) \right\} = \alpha$. Therefore, with regard to (A.3), the term $\tilde{a}_{jx} \geq \tilde{b}_j$ could be interchangeably written as:

$$\frac{E_2^{a_j x} - E_1^{b_j}}{E_2^{a_j x} - E_1^{a_j x} + E_2^{b_j} - E_1^{b_j}} \geq \alpha \qquad j = 1, \ldots, n \tag{A.5}$$

Moreover, the simplified form of equation (A.5) can be written as follows:

$$\text{s.t.} \left[(1-\alpha) E_2^{a_j} + \alpha E_1^{a_j} \right] x \geq \alpha E_2^{b_j} + (1-\alpha) E_1^{b_j}, \qquad j = 1, \ldots, n \tag{A.6}$$

As well, it is pointed out by Jimenez *et al.* [53] that any feasible solution such as x^o which its feasibility is proved, is an α-acceptable optimal solution of the presented model (A.4) if and only if the subsequent term (A.7) is always correct with respect to the term $\tilde{a}_j x \geq \tilde{b}_j$ which x is related to all non-negative feasible decision variable vectors.

$$\tilde{c}^t x \geq_{1/2} \tilde{c}^t x^o \tag{A.7}$$

Hence, with regard to the mentioned points, among feasible decision vectors, x^o is the best alternative if following formulation holds.

$$\frac{E_1^{\tilde{c}^t x} + E_2^{\tilde{c}^t x}}{2} \geq \frac{E_1^{\tilde{c}^t x^o} + E_2^{\tilde{c}^t x^o}}{2} \tag{A.8}$$

Lastly, model (A.4) could be converted to its equivalent crisp α-parametric form, owing to the aforementioned matters and based on the expected value and the expected interval of a fuzzy number. Consequently, the equivalent crisp model can be formulated as follows:

$$\begin{aligned} \min \quad & EV(\tilde{c})\, x \\ \text{s.t.} \quad & \left[(1-\alpha) E_2^{a_j} + \alpha E_1^{a_j} \right] x \geq \alpha E_2^{b_j} + (1-\alpha) E_1^{b_j}, \qquad j = 1, \ldots, n \\ & x \geq 0 \end{aligned} \tag{A.9}$$

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