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Coordination of green supply chain network, considering uncertain demand and stochastic CO_2 emission level

H. Golpîra[1,*], M. Zandieh[2], E. Najafi[3], S. Sadi-Nezhade[4]

Abstract
Many supply chain problems involve optimization of various conflicting objectives. This paper formulates a green supply chain network throughout a two-stage mixed integer linear problem with uncertain demand and stochastic environmental respects level. The first objective function of the proposed model considers minimization of supply chain costs while the second objective function minimizes CO_2 emission level. The Conditional Value at Risk (CVaR) approach is used to deal with the demand uncertainty in supply chain network in addition to the scenario based approach that is employed to deal with the stochastic level of CO_2 emission. The implementation of the proposed model has been demonstrated using some randomly selected numbers and the results are analyzed accordingly.

Keywords: Green supply chain, conditional value at risk, uncertainty, stochastic programming, robust optimization.

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1. Introduction

Nowadays, Green Supply Chain (GrSC), introduces an effective approach to deal with environmental concern, as a significant global attitude (Guillén-Gosálbez and Grossmann, 2009). Therefore, Supply Chain Network Design (SCND) in compliance with green principles becomes very important area for both practitioners and researchers (Coskun et al., 2015; Sarkis, 2012). GrSC, helps reduce negative environmental impacts rather than the companies' competitiveness enhancement (Wu et al., 2015).

This paper formulates Green Supply Chain Network Design Problem (GrSCNDP) under uncertain demand with stochastic CO_2 emission level throughout a robust bi-objective programming. Wang et al. (2011) presented a multi-objective optimization for GrSCNDP. Jamshidi et al. (2012) proposed multi-objective green supply chain optimization with a new hybrid memetic algorithm using the

[*] Corresponding Author.
[1] Department of industrial engineering, Sanandaj branch, Islamic Azad University, Sanandaj, Iran.
[2] Department of Industrial Management, Shahid Beheshti University, G.C., Tehran, Iran.
[3] Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.
[4] Department of Statistics and Actuarial Science, University of Waterloo, Ontario, Canada.

Taguchi method, while, Golpîra et al. (2016) introdused a multi-objective mathematical programming to formulate multi-tiered single product GrSCNDP. However, their approaches and the contributions were quite different. Wang et al. (2011) developed a deterministic model. Jamshidi et al. (2012) pointed out the transportation modes in addition to the environmental respects and Golpîra et al. (2016) addressed the effect of CO_2 emission only in the network upstream. The proposed study of this paper has the same goal, but under uncertain and stochastic environment, which makes the proposed method more realistic through a new robust bi-objective programming formulation. Rather than the impact of CO_2 emission in the entire network, the retailers' risk averseness and demand uncertainty are successfully addressed in its' downstream. To do these, a bi-objective mathematical programming is formulated in order to design a multi-tiered single product Green Supply Chain Network (GrSCN). The initial objective function covers the environmental protection investment and fixed production, alliance, and transportation costs. The environmental aspects are formulated in the second objective function. To the best our knowledge, there is no similar research to address this collaboration incorporated with the stochastic level of CO_2 emission and risk averseness of retailers. Reformulation of the second objective function leads to a single-objective programming problem to makes it analytically solvable. The main contributions of this paper are as follows,

a) A robust optimization framework formulation for GrSCND in compliance with retailers' risk averseness and stochastic level of CO_2 emission is the main contribution of the paper. Data-driven approach in addition to DM's risk averseness makes it possible to aggregate GrSCNDP and risk management. This establishes robust linear optimization outline for GrSCND.

b) Integrating scenario based CO_2 emission level, with risk management, in a new model formulation manner, results in a new method to be employed in GrSCNDP.

c) Using the environmental protection level in the entire network, in order to formulate the GrSCNDP in a robust manner is the other novelty of the paper.

The rest of the paper is as follows: The mathematical formulation will be described in section 2 with details. Model formulation and solution approach will be pointed out in section 3. Computational results will be presented in section 4 and finally, conclusions will be presented in section 5.

2. Literature Review

GrSCN tries to find some linkage between Supply Chain Management (SCM) and environmental respects (Jamshidi et al., 2012). Bouzembrak et al. (2011) minimized the SCN total cost and CO_2 emission impacts. Sitek and Wikarek (2012) considered multimodal transportation in compliance with environmental respects. Elhedhli and Merrick (2012) formulated the problem via a single objective concave model. They employed a heuristic algorithm to solve the resulted model, which tries to find some near optimal solutions. Mirzapour et al. (2013) introduced a stochastic SCND problem under demand uncertainty. Moreover, there is a large amount of literature in the field of green and sustainable supply chain network design problem (e.g. Seuring, 2013; Elbounjimi et al., 2014; Brandenburg et al., 2014; Stefan Schaltegger et al., 2014; Gunasekaran et al., 2015; Eskandarpour et al., 2015). Feng et al. (2014) developed a closed-loop multi-tiered SCN model, considering the uncertainty of the networks' demand side. Gui-tao et al. (2014) investigated a two-type supplier by considering the manufacturers' risk awareness and customers' price rigidities.

Mallidis et al. (2014) quantified the impact of GrSCN strategic design and tactical inventory optimization problem, simultaniously in a multi-echelon SCN. Devika et al. (2014) considered the three drivers of sustainability in the SCND problem through a Mixed Integer Programming (MIP) model for a Closed-Loop Supply Chain Network (CLSCN). Talaei et al. (2015) investigated a facility location/allocation model for a multi-product CLSCN with collection/inspection, manufacturing/remanufacturing, and disposal centers. They employed robust fuzzy programming approach to formulate a MIP model, according to the uncertain costs and demand rate. Garg et al. (2015) formulated a bi-objective integer nonlinear programming problem for a CLSCN design problem, and employed interactive multi-objective programming approach algorithm to solve the model. Soleimani and Kannan (2015) considered both design and planning decision variables in a new CLSCN design problem and solved the resulted model using a hybrid meta-heuristic algorithm based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Sharifzadeh et al. (2015) designed a biofule SCN subject to seasonal and geographical uncertainties, throughout a MIP problem. Coskun et al. (2015) designed the GrSCN based on customers' green expectations through the goal programming approach. Kawasaki et al. (2015) formulated a low-carbon SCN among Malaysia, China and Japan. The model employed multi-criteria decisions for the lead times, costs and Co_2 emissions, and analyzed the effect of the lead time fluctuation. Rezaee et al. (2015) designed a GrSCN in a carbon trading environment via a two-stage stochastic programming model. Govindan et al. (2015) integrated the order allocation problem and the sustainable SCND in multi-echelone SCN under stochastic demand. They employed a novel multi-objective hybrid approach in its model formulation. Martí et al. (2015) considered operational and environmental trade-offs to obtain a comprehensive approach for GrSCNDP. Demand uncertainty and SCN responsiveness under different carbon policies are successfully addressed in their model. Kagawa et al. (2015) identified Global Supply Chain Network (GSCN) clusters with high Co_2 emissions. Their results illustrated the importance of monitoring Co_2 clusters in GSCNs. Dotoli et al. (2015) ranked the alternatives in each echelon of SCN, using the cross-efficiency Data Envelopment Analysis (DEA) and fuzzy set theory. After this ranking they employed a MIP for each level of the network in order to obtain the optimal overal SCN efficiency. Kannegiesser et al. (2015) developed a new optimal long term strategy to minimize the time to sustainability parameter. Ahn et al. (2015) proposed a deterministic mathematical programming model for microalgae biomass-to-biodiesel SCND, considering resource and demand constraints, and technology over a long-term planning horizon. Urata et al. (2015) formulated a MIP for a GSCN design problem, in order to balance the costs and the Co_2 emmision volumes. Miret et al. (2016) formulated the multi-objective optimization, considering all sustainable development dimensions to address biomass SCND problem. The competition between energy and food, and the total number of local accrued jobs are measured as the social aspects of the designed network. Chibeles-Martins et al. (2016) formulated a mixed integer linear multi-objective programming model for GrSCNDP and solved it throughout a multi-objective meta-heuristic algorithm which is based on Simulated Annealing (SA). Nakamichi et al. (2016) estimated the cost and CO_2 emissions with a sustainable cross-border supply chain in a Thailand automobile industry as a good case study. Nouira et al. (2016) investigated the impacts of a carbon emissions-sensitive demand on decisions relative to the SCND problem and examined their model in a case study from a textile industry.

The proposed method of this paper along with the work accomplished by Gui-tao et al. (2014) have the same methodology through its attention to the risk averseness parameter, however the approaches and contributions of these researches are quite different. Gui-tao et al. (2014)

considered the risk averseness of the manufacturer, whereas the proposed model is based on the risk averseness of the network demand side. Li et al. (2014) investigated a SCN designation with risk-averse retailer and risk-natural manufacturer. They considered single objective dual-channel SCND with no attention to greenness attitude. Also, the proposed model of this paper and Rezaee et al. (2015) consider the same ideas according to their attentions to the uncertain demand and environmental investment that is not addressed before but reached different results. The study of this paper not only considers the uncertain demand and stochastic level of CO_2 emission, but also considers the risk averseness of the SCN downstream, simultaneously.

3. Problem description, formulation, and solution

The proposed model consists of several enterprises to design a single product GSCN under uncertain demands and by taking DMs' risk awareness into account. The total formulated cost is defined as a summation of fixed alliances set-up costs, environmental protection investment, and transportation and manufacturing costs which should be minimized. Holding and shortage costs are not assumed in the model in order to achieve simpler model. Consumer relationship is allowed in the last tier for the SCN. That is, the demand uncertainty affects the SCN directly from this tier. The following notation for the model formulation is described:

$l \in L$	set of scenarios for the environmental respects level
$a \in A$	set of operations
$i \in I$	set of potential companies available for tier a
$j \in J$	set of potential companies available for tier $a+1$
$(i, j) \in \Gamma$	set of available alliances
$v \in V$	set of environmental protection level
N_a	number candidates in tier a
$\eta_{i,a,j,a+1}$	fixed cost of linking candidate i in tier a to candidate j in tier $a+1$
$\vartheta_{i,a,v}$	fixed environmental protection investment at candidate i in tier a according to environmental protection level v
$\tau_{i,a,j,a+1}$	transportation unit cost from candidate i in tier a to candidate j in tier $a+1$
$\xi_{i,a}$	unit processing cost at candidate i in tier a
$q_{i,a}$	the environmental protection level of candidate i in tier a
s_l^-	under-achievement of the goal according to the environmental respects level l
s_l^+	supper-achievement of the goal according to the environmental respects level l
ψ	a very large number
ϕ	unit penalty cost, assigned to control the level of CO_2 emission
α	risk averseness of the DM
ε	adequately small number as a penalty for the s^-
$\tilde{\Delta}$	uncertain amount of total CO_2 emission level in all the SCN
$\chi_{i,a,v}$	per-unit environmental influence in facility i in tier a at level v

$\pi_{i,a,j,a+1}$ amount of CO_2 emission for the arc $i, a, j, a+1$

$\tilde{d}$ uncertain demand

$x_{i,a,j,a+1}$ amount of product shipped from candidate i in tier a to candidate j in tier $a+1$

$z_{i,a}$ amount of product manufactured at candidate i in tier a

$y_{i,a,j,a+1} = \begin{cases} 1 & \text{if relation between member } i \text{ in tier } a \text{ and member } j \text{ in tier } a+1 \text{ is included} \\ 0 & \text{otherwise} \end{cases}$

$\omega_{i,a} = \begin{cases} 1 & \text{if candidate } i \text{ in tier } a \text{ is included in the chain} \\ 0 & \text{otherwise} \end{cases}$

$q_{i,a,v} = \begin{cases} 1 & \text{if the environmental protection } v \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$

The bi-objective mixed integer linear programming formulation of the model is described through equations (1) to (16).

$$\Theta = \min \sum_{a=1}^{\varphi}\sum_{j=1}^{N_{a+1}}\sum_{i=1}^{N_a}\eta_{i,a,j,a+1}y_{i,a,j,a+1} + \sum_{a=1}^{\varphi}\sum_{i=1}^{N_a}\xi_{i,a}z_{i,a} + \sum_{a=1}^{\varphi}\sum_{j=1}^{N_{a+1}}\sum_{i=1}^{N_a}\tau_{i,a,j,a+1}x_{i,a,j,a+1} + \sum_{a=1}^{\varphi-1}\sum_{i=1}^{N_a}\sum_{v=0}^{V}\vartheta_{i,a,v}q_{i,a,v} \tag{1}$$

$$\Theta' = \min \sum_{a=1}^{\varphi-1}\sum_{i=1}^{N_a} z_{i,a}\sum_{v=0}^{V}\chi_{i,a,v} + \sum_{a=1}^{\varphi-1}\sum_{i=1}^{N_a}\sum_{j=1}^{N_{a+1}}\pi_{i,a,j,a+1}x_{i,a,j,a+1} \tag{2}$$

Subject to:

$$\sum_{v=0}^{V} q_{i(a)v} - 1 \le 0, \qquad i \in I,\, a \in A, \tag{3}$$

$$\sum_{i=1}^{N_a} \omega_{i(a)} - 1 = 0, \qquad a \in A, \tag{4}$$

$$\omega_{i,a} \ge y_{i,a,j,a+1}, \qquad \forall (i,j) \in \Gamma,\; a \in A, \tag{5}$$

$$\omega_{j,a+1} \ge y_{i,a,j,a+1}, \qquad \forall (i,j) \in \Gamma,\; a \in A, \tag{6}$$

$$\omega_{i,a} + \omega_{j,a+1} \le y_{i,a,j,a+1} + 1, \qquad \forall (i,j) \in \Gamma,\; a \in A, \tag{7}$$

$$\omega_{i,a} - \sum_{v=1}^{V} q_{i,a,v} = 0 \quad , i \in I,\; a \in A, \tag{8}$$

$$\omega_{i,a} \times \psi \ge \sum_{j=1}^{N_{a+1}} x_{i,a,j,a+1}, \qquad i \in I,\; a \in A, \tag{9}$$

$$\omega_{j,a+1} \times \psi \ge \sum_{i=1}^{N_a} x_{i,a,j,a+1}, \qquad j \in J \quad a \in A, \tag{10}$$

$$\sum_{j=1}^{N_{a+1}} x_{i,a,j,a+1} = z_{i,a}, \qquad i \in I,\; a \in A, \tag{11}$$

$$\omega_{i,a} \times \tilde{d} \le z_{i,a}, \qquad i \in I,\; a \in A, \tag{12}$$

$$x_{i,a,j,a+1} \geq 0, \qquad \forall (i,j) \in \Gamma, \;\; a \in A, \tag{13}$$

$$q_{i,a,v} \in \{0,1\}, \qquad i \in I, \;\; a \in A, \;\; v \in V \tag{14}$$

$$y_{i,a,j,a+1} \in \{0,1\}, \qquad \forall (i,j) \in \Gamma, \;\; a \in A, \tag{15}$$

$$\omega_{i,a} \in \{0,1\}, \qquad i \in I, \;\; a \in A. \tag{16}$$

The total cost of the network is included in Eq. (1). Eq. (2) integrates facility-depending and linkage-depending CO_2 emission into related variables to measure the total amount of the CO_2 emission. Constraint (3) ensures that the designed SCN selects only one environmental level for any selected alternative. Constraints (4)-(7), enforce that the final network holds only one enterprise a tier, and Constraint (8) selects the environmental level only from the opening alternatives. By Constraints (9) and (10), all of products are performed only through the final designed network which is balanced by Constraints (11). Constraint (12) is to build the link between $z_{i,a}$ and $w_{i,a}$ while, the type of variables are defined by Constraints (13) to (16).

To solve the problem, the goal programming approach is adopted to the model with uncertain right hand side value that is shown in Eq. (17) and Eq. (18).

$$\Theta = \min \sum_{a=1}^{\varphi} \sum_{j=1}^{N_{a+1}} \sum_{i=1}^{N_a} \eta_{i,a,j,a+1} y_{i,a,j,a+1} + \sum_{a=1}^{\varphi} \sum_{i=1}^{N_a} \xi_{i,a} z_{i,a} + \sum_{a=1}^{\varphi} \sum_{j=1}^{N_{a+1}} \sum_{i=1}^{N_a} \tau_{i,a,j,a+1} x_{i,a,j,a+1} + \sum_{a=1}^{\varphi-1} \sum_{i=1}^{N_a} \sum_{v=0}^{V} \vartheta_{i,a,v} q_{i,a,v} \tag{17}$$

Subject to:

$$\sum_{a=1}^{\varphi-1} \sum_{i=1}^{N_a} z_{i,a} \sum_{v=0}^{V} \chi_{i,a,v} + \sum_{a=1}^{\varphi-1} \sum_{i=1}^{N_a} \sum_{j=1}^{N_{a+1}} \pi_{i,a,j,a+1} x_{i,a,j,a+1} - \tilde{\Delta} = 0 \tag{18}$$

To farther solve the model, the scenario based approach is employed. Considering scenario based approach to deal with the model, transforms Eq. (17) and Eq. (18), Eq. (19) and Eq. (20) respectively:

$$\Theta = \min \sum_{a=1}^{\varphi} \sum_{j=1}^{N_{a+1}} \sum_{i=1}^{N_a} \eta_{i,a,j,a+1} y_{i,a,j,a+1} + \sum_{a=1}^{\varphi} \sum_{i=1}^{N_a} \xi_{i,a} z_{i,a} + \sum_{a=1}^{\varphi} \sum_{j=1}^{N_{a+1}} \sum_{i=1}^{N_a} \tau_{i,a,j,a+1} x_{i,a,j,a+1} + \sum_{a=1}^{\varphi-1} \sum_{i=1}^{N_a} \sum_{v=0}^{V} \vartheta_{i,a,v} q_{i,a,v} + \sum_{l=1}^{L} \varsigma_l \left(\frac{s_l^+ + s_l^-}{r} \right) \tag{19}$$

Subject to:

$$\sum_{a=1}^{\varphi-1} \sum_{i=1}^{N_a} z_{i,a} \sum_{v=0}^{V} \chi_{i,a,v}^l + \sum_{a=1}^{\varphi-1} \sum_{i=1}^{N_a} \sum_{j=1}^{N_{a+1}} \pi_{i,a,j,a+1}^l x_{i,a,j,a+1} - \Delta_l + s_l^- - s_l^+ = 0, \quad l = 1,\ldots,L \tag{20}$$

where r is the range of the objective function that is assigned to avoid any scaling problem. The idea that is employed in this paper to deal with demand uncertainty is to remove the best realizations of the data and optimize the problem over the remaining data as a robust optimization against downside risk, introduced by Bertsimas and Brown (2009). To do this, the conditional expectation $E\left[X \mid X \leq q_\alpha(X)\right]$ is used in Eq. (21), where $q_\alpha(X)$ is the $\alpha-quantile$ of the random variable *X*.

$$q_\alpha(X) = inf\{x \mid P(X \le x) \ge \alpha\}, \ \alpha \in (0,1) \tag{21}$$

The presented problem in this paper is the minimization, so the cases with the lowest costs are removed and the tail expectation $E\left[X \mid X \ge q_\alpha(X)\right]$ is considered. A nonparametric estimator of the $E\left[X \mid X \ge q_\alpha(X)\right]$ is presented in Eq. (22):

$$\hat{R}_\alpha = \frac{1}{N_\alpha} \sum_{k=1}^{N_\alpha} X_{(k)}, \tag{22}$$

where N is the number of in-hand realizations, N_α is the number of remaining cases after trimming to the retailers' risk averseness level α $\left(N_\alpha = \lfloor N \cdot (1-\alpha) + \alpha \rfloor \approx N.(1-\alpha)\right)$ and $X_{(k)}$ is the k-th smallest component of $(X_1, \ldots X_N)$. In the presented problem, $X_{(k)}$ will be defined as the k-th greatest component.

The $E\left[X \mid X \ge q_\alpha(X)\right]$ is finally referred as the Conditional Value-at-Risk (CVaR) which is, in this paper, employed to deal with the demand uncertainty. So, the reformulation of Eq. (12) is as follows:

$$z_{i(\varphi)} \ge \beta \left(\frac{1}{s_{1-\alpha}} \sum_{s=1}^{\lfloor s_{1-\alpha} \rfloor} d_{(s)} - \left(\frac{s_{1-\alpha} - \lfloor s_{1-\alpha} \rfloor}{\lfloor s_{1-\alpha} \rfloor} \right) d_{(\lceil s_{1-\alpha} \rceil)} \right) .w_{i(\varphi)}, \qquad i = 1, 2, \ldots, N_\varphi, \tag{23}$$

4. Computational results and sensitivity analysis

4 tiered network, each contains 3 potential companies with 4 environmental investment levels is considered to numerically examine the performance of the proposed model. Each node of echelon $i\,(i = 1,2,3)$ is concerned with a node in echelon $j\,(j = i+1)$, which yields to 20736 feasible routes altogether. Table 1 involves the scenarios generated for the stochastic values of CO_2 emission level. Table 2, includes additional data for numerical example, built to study the effectiveness of the model. "Unif" in Table 2 stands for uniform distribution. It is noteworthy that this type of data generation is general in the field of robust optimization (eg. (Pan and Nagi, 2010), (Baghalian et al. 2013) and so on). The resulted problem can be solved by CPLEX 11.0 on a PC that has a 2.20GHz Intel(R) Core(TM)2 Duo CPU and 3.0G RAM. The results are shown in Table 3.

Table 1. Scenarios

Scenario probability	Value of the environmental respects
0.35	145000
0.45	150000
0.20	160000

Table 2. Data used in the problem

Data type	Range
Uncertain demand	Unif(50, 500)
Transportation unit cost	Unif(10, 15)
Fixed alliance cost	Unif(1000, 5000)
Production unit cost	Unif(20, 60)
Fixed environmental protection investment	Unif(100, 300)

Table 3. Results of computational study

1-α	α	Expected cost	Located facilities (environmental level)	Chain performance	Cost variability	Percent cost variability
0.99	0.01	16006.96	2(4)-4(1)-7(1)-12(1)	100%	-	-
0.98	0.02	15958.28	2(4)-4(1)-7(1)-12(1)	100%	48.68	0.31%
0.97	0.03	15955.95	2(4)-4(1)-7(1)-12(1)	100%	2.33	0.01%
0.96	0.04	15791.50	2(4)-4(1)-7(1)-12(1)	100%	164.45	1.03%
0.95	0.05	15723.51	2(4)-4(1)-7(1)-12(1)	100%	67.99	0.43%
0.94	0.06	15684.61	2(4)-4(1)-7(1)-12(1) 2(4)-4(1)-7(1)-10(1)	095% 005%	38.9	0.25%
0.93	0.07	15559.00	2(4)-4(1)-7(1)-12(1) 2(4)-4(1)-7(1)-10(1)	090% 010%	125.61	0.80%
0.92	0.08	15397.95	2(4)-4(1)-7(1)-12(1) 2(4)-4(1)-7(1)-10(1)	075% 025%	161.05	1.04%
0.70	0.30	13575.98	2(4)-4(1)-8(1)-11(1) 2(4)-4(1)-7(1)-12(1) 2(4)-4(1)-8(1)-12(1)	030% 055% 015%		
0.50	0.50	12625.37	2(4)-4(1)-9(1)-12(1) 2(4)-4(1)-8(1)-11(1) 2(4)-4(1)-7(1)-11(1)	005% 040% 055%	⋮	⋮
0.40	0.60	11999.64	2(4)-4(1)-8(1)-12(1) 2(4)-4(1)-8(1)-11(1) 2(4)-4(1)-7(1)-11(1)	015% 040% 045%		
0.08	0.92	9184.34	2(4)-4(1)-9(1)-12(1)	100%		
0.07	0.93	9157.37	2(4)-4(1)-9(1)-12(1)	100%	26.97	0.29%
0.06	0.94	8957.97	2(4)-4(1)-9(1)-12(1)	100%	199.4	2.18%
0.05	0.95	8953.13	2(4)-4(1)-9(1)-12(1)	100%	4.84	0.05%
0.04	0.96	8897.63	2(4)-4(1)-9(1)-12(1)	100%	55.5	0.62%
0.03	0.97	8815.91	2(4)-4(1)-9(1)-12(1)	100%	81.72	0.92%
0.02	0.98	8755.18	2(4)-4(1)-9(1)-12(1)	100%	60.73	0.69%
0.01	0.99	8750.63	2(4)-4(1)-9(1)-12(1)	100%	4.55	0.05%
			Results average		**74.48**	**0.62%**

According to the results, integrating scenario based CO_2 emission level, with risk attitude of the DM, in new formulation manner, leads to a new method in the field of GrSCNDP. As expected, the level of retailer's risk averseness has a significant impact on the designed network configuration. The analysis starts with $1-\alpha=0.99$ and then continues with decreasing the value of $1-\alpha$ according to the first column of Table 3 in which, it represents the values of properties of all the designed chains respects to the parameter α and $1-\alpha$. It is expected that by increasing the level of risk averseness, the expected cost should decrease, that is successfully illustrated in Table 3. It is obvious that here are only four deigned chain from all of the 20736 possible ones. Table 3 shows that chain 2(4)-4(1)-7(1)-12(1) is optimal for the small value of alpha and it has been substituted by the chain 2(4)-4(1)-9(1)-12(1) as the alpha value increases. Furthermore, Figure 1 clearly shows the percent cost variability of the designed networks in respect to the level of alpha. Although Natarajan et al. (2009) set the alpha level to 0.01 or 0.05, Fig. 1 in addition to Table 3 successfully demonstrates the robustness of the solution and the model in the expanded alpha range. The performance of the model for the larger range of the DM's risk-averseness is one of the superiority of the model in comparison with the others.

As per validation, the robustness of the solution and the model is clearly illustrated according to small range of the cost variation in respect to the alpha and selecting only two final networks from 20736 possible routes of the network. The expected cost variability of the network in this wide range of the α is only 74.48 that is 0.62% of the total expected cost. The Achieved very small value of this parameter represents a greater performance of the model in the case of solution robustness. On the other hands, selecting only two final paths from 20,736 eligible paths which are almost feasible for all the realizations of the scenarios makes the model to be robust rather than the solution robustness. This definition of the robustness is supported by Mulvey et al. (1995). They investigated the robustness as the integration of solution robustness and model robustness. The solution robustness was defined as the remaining of the problem solution "close" to optimal for all of the scenarios realizations. The model robustness was referred to the situation in which the model remains "almost" feasible for each realization of the scenarios. To the best our knowledge, the robustness of the solution and the model stands in the better situation in comparison with pervious researches. For instance, Pan and Nagi (2010) formulated the SCND problem in a robust manner. Their model resulted in 10 designed networks with greeter range of the cost variations for the same potential network. Also the cost variation and the number of the final designed networks of the model proposed by Baghalian et al. (2013) are far more than what is resulted in this paper.

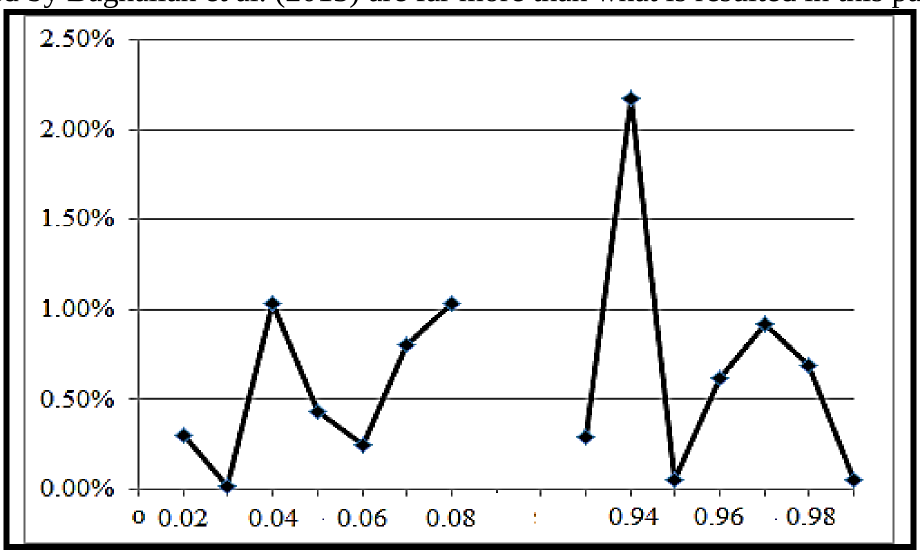

Figure 1. Percent cost variability with respect to alpha value

5. Conclusion

This paper investigates the multi echelon single product green supply chain network design problem. The bi-objective mathematical programming throughout the CVaR concept is used to address the retailers' attitude of the last tier. The model, on the other hand, reports the effect of CO_2 emission level, in the SCN as well as the demand uncertainty of the SC downstream. The preference of the model is its capability to consider demand uncertainty and stochastic CO_2 emission level in addition to the risk attitude of the networks' retailer.

The model has some superiorities in comparison with the others which are briefly discussed as follows. 1) Formulating a new robust optimization framework for GrSCNDP in compliance with retailers' risk averseness and stochastic level of CO_2 emission, which is the main contribution of the paper, 2) Integrating stochastic environmental parameters, with risk management, in a new

model formulation manner which results in a new method to be employed in GrSCNDP, 3) Obtaining model robustness and solution robustness in a larger range of the DM's risk averseness which is the other contribution and novelty of the model. 4) Using the stochastic scenario based CO_2 emission level in the entire network, in order to formulate the GrSCNDP in a robust manner is the other novelty of the paper.
In other words, we found that the level of retailers' risk averseness has a significant controllable impact on the GrSCN configuration. Moreover, using the CVaR approach to deal with uncertainty of the demand in a GrSCNDP, leads to robustness both in model and solution. Our numerical experiment simplifies the sensitivity analysis of the model to the parameter and clearly demonstrates the validity and performance of the resulted model.

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