Scenario reduction approach for a resilient supply chain network

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Abstract

Disruptions may occur in supply chains because of internal or external factors. Internal factors and especially paths disruptions between supply chain elements are considered in this paper. For employing resiliency and mitigation of disruption risks in a supply chain, three policies including backup capacity at suppliers, safety stock for each path, and using several suppliers are considered. A nonlinear two stage stochastic programming model is presented with adopting resilient strategies. Various scenarios were generated by considering disruptions in different paths. Considering all scenarios during solving the model will increase the computational time. To decrease the computational time efficiently, a sampling method can be used. In this paper different methods of sampling strategies were analyzed and compared for a three echelon supply chain problem. The best method was determined based on the ability of the method to lead us to accurate estimation with less computational time. Also the results confirm necessity of resilient stochastic consideration of the problem. Adopting resilient strategies reveal increasing profit versus non-resilient supply chain when disruptions occur. The scenario reduction schemes can improve the applicability of network designs in an uncertain environment.

Keywords
Resilient supply chain, Disruption, Mitigation risk, Sampling methods, Scenario reduction

1. Introduction

A supply chain consists of three main echelons supply, process and distribution among customers. All of these echelons may face disruption by different causes such as earthquake, fire, flood, war, labor strikes, etc. Confronting disruptions without preset strategies can reduce the profit of supply chain. Adopting resilient strategies in considered supply chain cause a quick return to normal statue. Utilizing resilient strategies is a competitive advantage between supply chain rivals, due to the fact that it causes dramatic decrease in system fluctuations. Resiliency is the advantage of system that can mitigate risks with different policies.

When disruptions are considered, several conditions that is called scenarios can occur in the supply chain. With considering scenarios, a two stage stochastic programming model is presented that determines the best decisions for obtaining optimum profit. Increasing scenarios take more computational time that it can be decreased by reducing selected scenarios. With sampling schemes, several scenarios are selected and it's crucial that samples are a good indicators form population. Due to this importance, six sampling schemes are analyzed that can be an approximate of the population. In this paper, the best scheme has been determined for each instance. It means that the proposed model chooses the sampling method which lead us to reach the near to optimum profit with less CPU time.

This paper has been organized as follows;

Section 2 reviews the related literature in resilient supply chains and scenario reduction. Section 3 explains the details of considered supply chain. Section 4 describes deterministic model of supply chain and two stage stochastic programming model with adopting resilient strategies. A model for selecting proper scenario sampling schemes is proposed in section 5. Section 6 reports computational outcomes for two stage stochastic programming model, necessity of adopting resilient strategy, validation of proposed model and comparison between profit of proper sampling scheme and improper one. Section 7 represents conclusions and future study.

2. Literature review

In the current study, it is assumed that the supply chain is considered in an uncertain environment that is defined by probability of disruptions. Disruptions are split to two main categories that the first group is uncertainty disruptions which are predicted and other one is unexpected disruptions. Resilient strategies are an economic activity for confronting with uncertainty disruptions. Huchzermeier et al. (1996) extended multi suppliers by considering several countries can lead the supply chain to manage risks and promoting resiliency of supply chains. Rezapour et al (2017) proposed a model with adopting resilient strategies under competition. This paper determined reduction of fluctuation in retailer price and market share with applying resilient strategies which products price and markets demands are determined by Nash equilibrium due to competition among rivals. Mancheri et al. (2018) analyzed different strategies for improving resiliency in tantalum supply chain by adopting various suppliers, replacing material, recycling and storage. Disruptions bring several conditions in the supply chain that are defined scenarios in the problem. Increasing in number of disruptions induces more scenarios which results in more computational effort. Kleywegt et al. (2002) introduced Sample Average Approximation (SAA) that is based on stochastic discrete optimization problems. In this method, samples calculate the expected value instead of all population. This method reaches solutions along with their optimality gap by selecting mitigated number of scenarios which resulting less computational time. Shapiro (2003) investigated Monte Carlo sampling method for stochastic programming model and presented an algorithm to improve SAA samples, he also investigated decreasing variance methods. Nickel et al. (2016) discussed about assignment and locating the number of ambulances in potential locations with stochastic demands. This paper presented some sampling approaches for reducing number of scenarios. According to our survey on previous studies, it is clear that the main problem in stochastic programming is the computational challenge for increasing of scenarios, while in real cases we may face to the large number of scenarios. So considering different sampling approaches as well as scenario reduction schemes may be valuable for research in different planning problems.

In this study, a supply chain is analyzed with the probability of disruptions in paths. In considered problem, with increasing disruption paths, the number of scenarios are growth therefore computational time is enhanced. For reducing CPU time, several sampling schemes are presented for selecting scenarios. A model is proposed for choosing the best scheme for different instances. This model considers tradeoffs between approximation of objective function value and CPU time.

3. Problem description

The investigated problem in this study is a supply chain with the predetermined flow of material throw different paths that may face to disruptions. Paths that links suppliers to markets may confront with various disruptions. This supply chain consists of three echelons that its upstream starts with suppliers and ends in downstream with markets. In assumed supply chain, several suppliers and retailers, one manufacturer are considered simultaneously. Each retailer just assigned to one market. Figure 1 presents schematic of the supply chain that is considered in this paper.

Firstly, a deterministic model (without paths disruption) is considered. The deterministic model is defined for normal statue in which all paths are available. After that a two-stage stochastic programming optimization model with assumption of disruption in paths is considered. To deal with this complexity of model and to ameliorate the supply chain performance resilient strategies are adopted. These disruptions represent model scenarios. CPU time increases when the number of scenarios is grown. Nevertheless, generating scenarios for the problem with lower computational effort and leads us to reach lower difference between objective values of sampling method and here-and-now sounds to be good. To obtaining this model *C* is proposed which seeks to choose the best sampling schemes by considering tradeoff between computational time versus closeness of objective function value to here-and-now solutions.

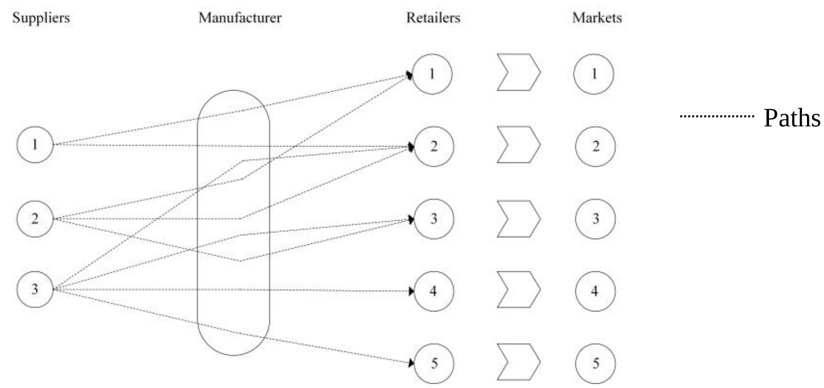

Figure 1. The schematic view of investigated supply chain

4. Mathematical model

This section is split into two sections. In the first model a supply chain network design is considered without existing of disruptions. This model is in the deterministic form. In second section a two stage stochastic programming model is analyzed with stochastic parameters. The second model considers the network structure with consideration of resilient strategy in an uncertainty environment. A two stage stochastic programming model is introduced to deal with this uncertainty. The notations of modeling are cleared as follows:

Sets

I	Set of potential suppliers
M	Set of potential markets
T	Set of available paths which can be chosen for floe of material
T^{i}	Subset of available paths which are started from supplier *i*
T^{m}	Subset of available paths which are ended at market *m*
S	Set of all scenarios

Variables

v_i	1 if supplier *i* is in the network structure of supply chain, 0 otherwise
$\overline{v}_i$	Capacity of supplier *i*
w_m	1 if market *m* is in the network structure of supply chain, 0 otherwise
x_t	The percentage of demand market *m* that is supplied by path *t* in normal condition (all paths are available)
x_t^s	The percentage of demand market *m* that is supplied by path *t* in scenario *s*
y_t^s	1 if emergency stocks are used in the retailer of path *t* in scenario *s*, 0 otherwise
Z_t	Level of emergency stocks that are kept in the retailer of path *t* when disruption occurs.

Parameters

p_m	Price of products in market *m*
q_m	Demand of market *m*
F_i	Cost of investing supplier *i*
k_i	Cost of a capacity of supplier *i*
B_m	Cost of locating a retailer for market *m*
c_t	Cost of producing and distributing for unit product through path *t*
h_m	Cost of holding unit product in the retailer of market *m*

e_t^s 1 if path t is available in scenario s, 0 otherwise

pr_s Probability of scenario s

4.1. Mathematical model without resilient strategy and SC's disruption

In this section, the deterministic model is considered in which all paths are available.

Model A:

$$\max \sum_{m=1}^{|M|}\left[\sum_{t=1}^{|T^{(m)}|}\left(p_m - c_t\right)\left(q_m\right)x_t\right] - \sum_{i}^{|I|}(k_i\overline{V_i}) - \sum_{m=1}^{|M|}(B_m W_m) - \sum_{i}^{|I|}(F_i V_i) \tag{1}$$

Subject to:

$$\sum_{t=1}^{|T^{(m)}|} x_t = W_m \qquad (\forall m \in M) \tag{2}$$

$$\sum_{t=1}^{|T^{(i)}|} x_t q_{m|m\in t} \le \overline{V_i} \qquad (\forall i \in I) \tag{3}$$

$$x_t \le V_i \qquad (\forall t \in T^{(i)}, \forall i \in I) \tag{4}$$

$$x_t \le W_m \qquad (\forall t \in T^{(m)}, \forall m \in M) \tag{5}$$

$$0 \le x_t \le 1 \qquad (\forall t \in T) \tag{6}$$

$$\overline{V_i} \ge 0 \text{ and } W_m \text{ and } V_i \in \{0,1\} \qquad (\forall m \in M, \forall i \in I) \tag{7}$$

The objective function (1) maximizes the total profit. Constraints (2) guarantee that the demands of markets should be satisfied. Constraints (3) consider suppliers' capacity. Constraints (4-5) ensure that the flow can be transferred via available paths among located supplier i and market m. Domains of decision variables are defined by constraints (6-7). The above mentioned model is based on Rezapour et al. (2017).

4.2. A stochastic model with resilient strategy and supply chain's disruption

In this section, a two stage stochastic programming is investigated. In underlying model, three different policies for mitigation risk such as several suppliers, capacity for suppliers and safety stock for retailers are considered. It is noticeable that all input parameters except the parameter which indicate the availability of paths are deterministic. The strategic decisions like supplier selection, supplier capacity, the emergency stock level at each retailer and market selection must be made before realization of uncertainty. The operational decisions are made after uncertainty is revealed.

Model B:

$$\max \sum_{s=1}^{|S|}\left\{\sum_{m=1}^{|M|}\left[\sum_{t=1}^{|T^{(m)}|}\left(p_m - c_t\right)\left(q_m\right)x_t^s - h_m\left(Z_t - q_m x_t^s y_t^s\right)\right]\right\}pr_s - \sum_{i}^{|I|}(k_i\overline{V_i}) - \sum_{m=1}^{|M|}(B_m W_m) - \sum_{i}^{|I|}(F_i V_i) \tag{8}$$

Subject to:

$$Z_t \ge q_{m|m\in T^{(m)}} x_t^s y_t^s \qquad (\forall t \in T, \forall s \in S) \tag{9}$$

$$\sum_{t=1}^{|T^{(i)}|} x_t^s (1-y_t^s) q_{m|m\in T^{(m)}} \le \overline{V_i} \qquad (\forall s \in S, \forall i \in I) \tag{10}$$

$$x_t^s \le e_t^s + y_t^s \qquad (\forall t \in T, \forall s \in S) \tag{11}$$

$$y_t^s \le 1 - e_t^s \qquad (\forall t \in T, \forall s \in S) \tag{12}$$

$$\sum_{t=1}^{|T^{(m)}|} x_t^s = W_m \qquad (\forall m \in M, \forall s \in S) \tag{13}$$

$$x_t^s \le V_i \qquad (\forall t \in T^{(i)}, \forall i \in I, \forall s \in S) \tag{14}$$

$$x_t^s \le W_m \qquad (\forall t \in T^{(m)}, \forall m \in M, \forall s \in S) \tag{15}$$

$$0 \le x_t^s \le 1 \qquad (\forall t \in T, \forall s \in S) \tag{16}$$

$$W_m \text{ and } y_t^s \text{ and } V_i \in \{0,1\} \qquad (\forall m \in M, \forall i \in I, \forall s \in S, \forall t \in T) \tag{17}$$

$$Z_t, \overline{V_i} \ge 0 \qquad (\forall t \in T, \forall i \in I) \tag{18}$$

In objective function (8), stage one decisions calculate three main cost of the supply chain, includes cost of supplying capacity, locating retailers and suppliers' investment. The rest of equation computes second stage variables value with expected value of supply chain incomes and inventory holding cost in all possible scenarios. Constraints (9) dictate that the level of emergency stock must fulfill markets demand while are used for paths. Constraints (10) state that suppliers should have enough capacity of supplying the requirements of all paths without using emergency stock. Constraint (11-12) persuade the follow of material starts from the supplier if its paths are available. It means that using emergency stock and availability don't occur simultaneously in each path. Constraints (13) supply the demands of markets. Constraints (14-15) ensure that the flow can be transferred via available paths among located supplier *i* and market *m* for each scenario. Domains of variables are determined by constraints (16-18). This model is based upon Rezapour et al. (2017).

5. Proper scenario sampling scheme

In this section, firstly, six sampling schemes are presented for reducing number of scenarios then a model is proposed for selecting the most proper scheme according to achieved results. The formulation of model is presented as follows:

sets

S' Set of problem analyzed with *s* scenarios

J Set of sampling schemes

U Set of instances

Parameters

$ct_{u,j,s'}$ CPU time of solving instance *u* with sampling scheme *j* in s' scenarios problem

$dofv_{u,j,s'}$ Difference of objective function values between sampling scheme *j* and here-and-now solution in instance *u* with s' scenarios problem

Variable

$r_{u,j,s'}$ 1 if sampling scheme *j* is selected for instance *u* in s' scenarios problem, 0 otherwise

After solving the stochastic model and investigating the CPU time, the results motivate decreasing computational time with reduced scenario sets. The first attempt to apply presented sampling scheme is sorting probability of scenarios in descending order, then the number of scenarios are reduced by applying six different sampling schemes. They are expressed in following:

Scheme 1: Fifty percent of all scenarios with highest probabilities
Scheme 2: Fifty percent of all scenarios with least probabilities
Scheme 3: Thirty-one percent of all scenarios with highest probabilities

Scheme 4: Thirty-one percent of all scenarios with least probabilities
Scheme 5: Fifteen percent of all scenarios with highest and least probabilities (thirty percent of all scenarios)
Scheme 6: Fifteen percent of all scenarios with highest and middle and least probabilities (forty-five percent of all scenarios)

Previously Nickel et al. (2016) considered abovementioned sampling mechanisms so we investigate mentioned approaches, too. After exploring sampling idea, it's crucial that choosing the best sampling approach which have the nearest objective function value to here-and-now value and simultaneously have lower computational effort among difference schemes. Model C is proposed for obtaining this goal. It is based upon an assignment problem. The model obtains the tradeoffs that are between closeness to the objective function of here-and-now and CPU time. It's proposed as follows:

Model C:

$$\min p = \sum_{u=1}^{|U|}\left[\sum_{j=1}^{|J|}\left(\sum_{s'=1}^{|S'|}\left[ct_{u,j,s'}r_{u,j,s'} + dofv_{u,j,s'}r_{u,j,s'}\right]\right)\right] \tag{19}$$

Subject to:

$$\sum_{u=1}^{|U|}\left[\sum_{j=1}^{|J|}\left(r_{u,j,s'}\right)\right] = 1 \qquad \left(\forall s' \in S'\right) \tag{20}$$

$$r_{u,j,s'} \in \{0,1\} \qquad (\forall u \in U, j \in J, s' \in S') \tag{21}$$

The objective function (19) computes the summation of CPU time and difference between here-and-now solutions and sampling approach objective function value. In constraints (20), only one sampling scheme is determined for each instance.

Constraints (21) define the domain of variables.

Figure 2 illustrates the flow of data in investigated models and achieving the most proper schemes by decision variables in model *C.*

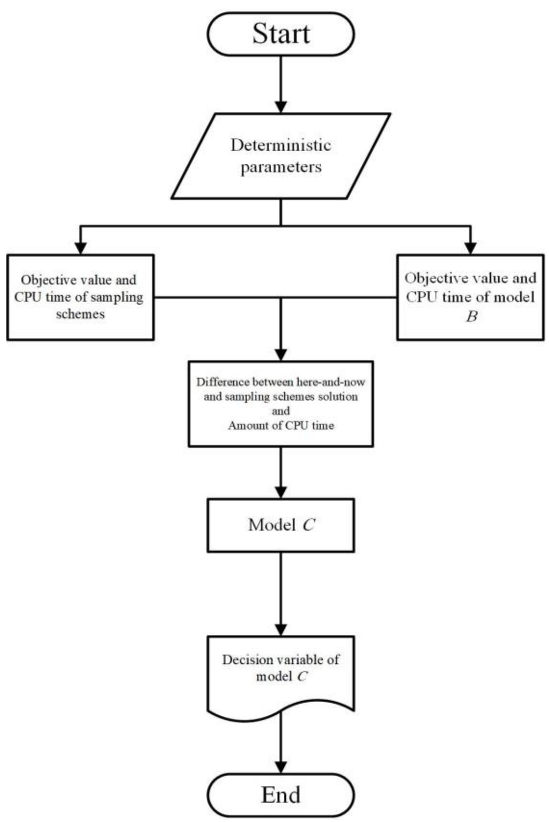

Figure 2. Flow chart of the approach for selecting the most proper scheme

6. Computational results

In computational results, three potential suppliers, one manufacturer, five potential market and nine defined paths are considered. The presented mathematical models were solved by GAMS software and run on an Intel core i7 with 2.7 GHz CPU and 16 GB RAM. Market demands, price of products, cost of the capacity of suppliers, cost of locating a retailer, cost of producing and distributing a product in the paths and the investment cost of suppliers are assumed from a uniform distribution that their ranges are reported in table 1.

Table 1. Range of parameters

	Range of uniform distribution
p_m	[5,30]
q_m	[7,35]
F_i	[30,60]
k_i	[0.4,2]
c_t	[1,4]
B_m	[20,60]
pr_t	[0,1]

6.1. Stochastic programming results

Stochastic model scenarios are defined by unavailability of paths. The probability of each scenario is acquired by multiplication of disruption probabilities. For example, figure 3 illustrates that t_{11}, t_{12}, t_{22} may be unavailable in the supply chain with determined probabilities that are specified by $p_{t_{11}}$, $p_{t_{12}}$ and $p_{t_{22}}$ respectively. The first scenario is calculated when path t_{11} is unavailable with $p_{t_{11}}\left(1-p_{t_{12}}\right)\left(1-p_{t_{22}}\right)$.

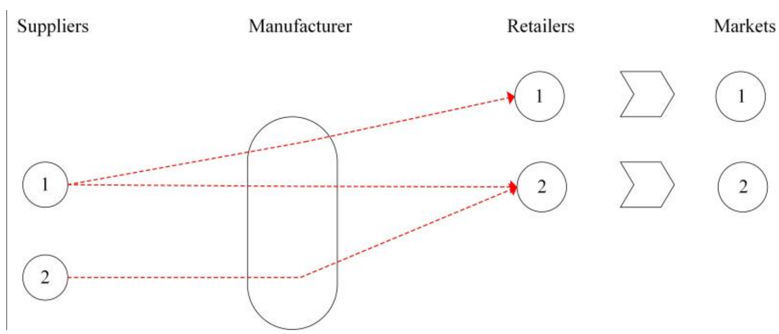

Figure 3. The schematic of supply chain whit probability of disruption in three paths

The two stage stochastic model is solved in two conditions. The first one is the supply chain with probability of disruption occurrence in six paths that the problem confronts with sixty-four scenarios. The second condition is determined with the probability of disruption occurrence in seven paths that the problem faces to one hundred twenty-eight scenarios. The computational results can be seen in table 2.

Table 2. The results of here-and-now solution for two main conditions

All Scenarios	***Objective Value***	***CPU Time***
64	1029.850	468.141
128	1029.852	1052.625

6.2. Necessity of resilient strategy

In this section, due to the presented models in section 4, the supply chain captured profit with resilient and non-resilient strategy when disruptions are occurred compared in table 3. With increasing the probability of disruptions, table 3 declares that the difference of profit with and without resilient strategies is grown. These results indicate necessity of resilient strategies.

Table 3. Comparison profit between resilient and non-resilient strategies

Coefficient of probability of disruption	***Profit with resilient strategies***	***Profit with non-resilient strategies***	***Difference of profit with and without resilient strategies***
0.1	991.435	244.1	747.335
0.2	1029.418	244.1	785.318
0.3	1029.473	244.1	785.373
0.4	1029.527	244.1	785.427
0.5	1029.581	244.1	785.481
0.6	1029.635	244.1	785.535
0.7	1029.69	244.1	785.59
0.8	1029.744	244.1	785.644
0.9	1029.798	244.1	785.698
1	1029.853	244.1	785.753

6.3. Experimental results of model *C*

In this section, some instances are simulated which they are inputs of model *C*. This model determines the best sampling scheme for each instance. The computational results declare that in ninety percent of conditions, the first scheme is the most suitable scheme for sixty-four scenarios problem and in sixty percent of instances, the model decides the third scheme is the best for one hundred twenty-eight scenarios problem. The comparison of stage one decision variables in different sampling approaches and here-and-now solutions are confirmed the results of model *C* that can be observed in table 9 to 12. In the other words, tables 9 to 12 is the validation of model *C* results.

Table 9. The comparison between here and now and sampling schemes stage one variables in 64 scenarios

	$\mathbf{V_1}$	$\mathbf{V_2}$	$\mathbf{V_3}$	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$	$\mathbf{W_4}$	$\mathbf{W_5}$	$\overline{\mathbf{V_1}}$	$\overline{\mathbf{V_2}}$	$\overline{\mathbf{V_3}}$
Here and Now	0	0	1	0	1	1	1	1	0	0	98
Scheme 1	0	0	1	0	1	1	1	1	0	0	98
Scheme 2	0	0	0	0	0	0	0	0	0	0	0
Scheme 3	0	0	1	0	1	1	1	1	0	0	98
Scheme 4	0	0	0	0	0	0	0	0	0	0	0
Scheme 5	0	0	1	0	0	1	1	0	0	0	49
Scheme 6	0	0	1	0	0	1	1	0	0	0	49

Table 10. The comparison between here and now and sampling schemes stage one resilient variables in 64 scenarios

	$\mathbf{Z_{t11}}$	$\mathbf{Z_{t12}}$	$\mathbf{Z_{t21}}$	$\mathbf{Z_{t22}}$	$\mathbf{Z_{t23}}$	$\mathbf{Z_{t32}}$	$\mathbf{Z_{t33}}$	$\mathbf{Z_{t34}}$	$\mathbf{Z_{t35}}$
Here and now	0	0	0	0	0	14	21	28	0
Scheme 1	0	0	0	0	0	14	21	28	0
Scheme 2	0	0	0	0	0	0	0	0	0
Scheme 3	0	0	0	0	0	14	21	28	0
Scheme 4	0	0	0	0	0	0	0	0	0
Scheme 5	0	0	0	0	0	0	21	28	0
Scheme 6	0	0	0	0	0	0	21	28	0

Table 11. The comparison between here and now and sampling schemes stage one variables in 128 scenarios

	V_1	V_2	V_3	W_1	W_2	W_3	W_4	W_5	$\overline{V_1}$	$\overline{V_2}$	$\overline{V_3}$
Here and Now	0	0	1	0	1	1	1	1	0	0	98
Scheme 1	0	0	1	0	1	1	1	1	0	0	98
Scheme 2	0	0	0	0	0	0	0	0	0	0	0
Scheme 3	0	0	1	0	1	1	1	1	0	0	98
Scheme 4	0	0	0	0	0	0	0	0	0	0	0
Scheme 5	1	1	1	1	1	1	1	1	28	56	126
Scheme 6	0	0	1	0	1	1	1	1	0	0	98

Table 12. The comparison between here and now and sampling schemes stage one resilient variables in 128 scenarios

	Z_{t11}	Z_{t12}	Z_{t21}	Z_{t22}	Z_{t23}	Z_{t32}	Z_{t33}	Z_{t34}	Z_{t35}
Here and Now	0	0	0	0	0	14	21	28	0
Scheme 1	0	0	0	0	0	14	21	28	0
Scheme 2	0	0	0	0	0	0	0	0	0
Scheme 3	0	0	0	0	0	14	21	28	0
Scheme 4	0	0	0	0	0	0	0	0	0
Scheme 5	14	0	14	28	0	14	42	56	0
Scheme 6	0	0	0	0	0	14	21	28	0

6.4. Importance of using best sampling scheme

Results obtained from model C determines that sampling scheme 1 is the best suitable sampling method for problem with sixty-four scenarios. Figure 4 illustrates comparison between sampling scheme 1 and 5 with increasing probability of disruptions. Growth of difference between profit that is obtained by sampling scheme 1 and 5 shows importance of applying the most proper sampling scheme.

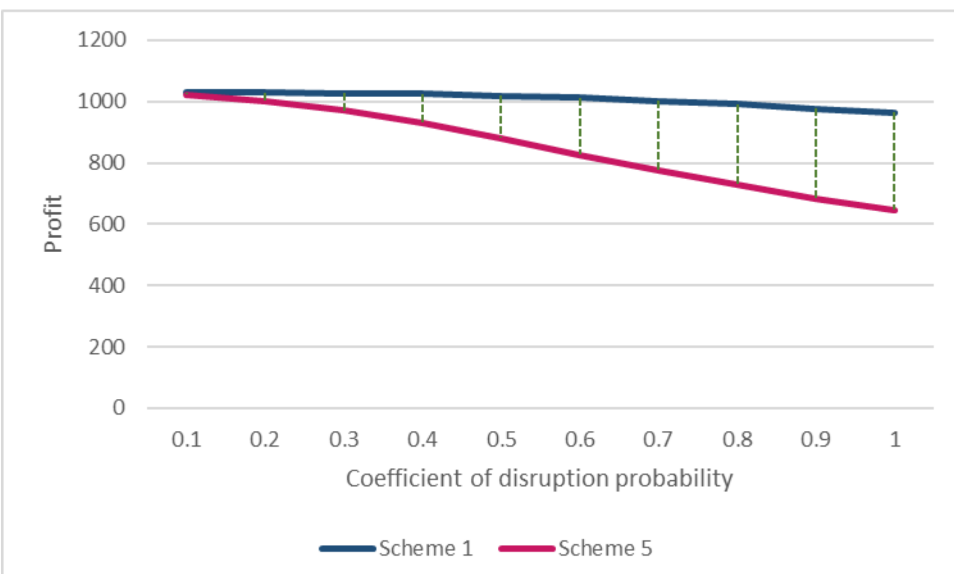

Figure 4. Growth of difference between profit of proper sampling scheme and improper one

6.5. Setup preferences in model *C*

In previous sections, equal importance is considered for difference of objective values and CPU time. For ingoing unequal preferences in model *C*, firstly, the parameters of model *C* must be standardized. After standardizing the model, the unequal preferences are entered in the form of coefficients. Results of standardized model *C* in simulated instances specify if CPU time is more important third sampling scheme most of the time is selected for sixty-four and one hundred twenty-eight scenarios that can be observed in table 13, 14.

Table 13. Selecting sampling scheme in different coefficient of CPU time for 64 scenarios problem

Coefficient of CPU time	Percentage of selecting scheme1	Percentage of selecting scheme3	Percentage of selecting scheme4
0.7	10%	90%	0%
0.75	10%	90%	0%
0.8	10%	90%	0%
0.85	0%	100%	0%
0.9	100%	0%	0%

Table 14. Selecting sampling scheme in different coefficient of CPU time for 128 scenarios problem

Coefficient of CPU time	Percentage of selecting scheme1	Percentage of selecting scheme3	Percentage of selecting scheme4
0.7	10%	90%	0%
0.75	0%	100%	0%
0.8	0%	90%	10%
0.85	0%	90%	10%
0.9	0%	80%	20%

7. Conclusion

In this paper, the considered supply chain confronts with disruptions that occurs in linking paths. For restoring to normal condition, resilient strategies are analyzed and the computational results present when disruptions occur the profit of supply chain with resilient strategies is more than non-resilient one egregiously. The differences of profit between resilient and non-resilient supply chain is growing when the probability of disruptions are increased.

Disruptions in supply chain causes different scenarios, by growth in number of scenarios the computational effort increases dramatically. To deal with this complexity that faces the problem by increasing in number of scenarios, we present sampling schemes that calculates approximation of objective function value with reduced number of scenarios. In this paper, model *C* is proposed that selects the best scheme in each simulated instance. By using model *C*, the scheme with less approximate error and CPU time is determined. The computational results indicate the importance of selecting the best schemes by illustrating profit differences between proper scheme and improper one. If preferences enter in the problem the results represent that the third scheme is the most proper when CPU time is more important.

Disruptions of supply chain facilities as well as disruptions in other echelons can be considered as a direction for future research. Adopting other resilient strategies such as storing semi-manufactured products in manufacturer can be considered as another direction for the future works.

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