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Multi-Objective Supply Chain Network Design Under Demand Uncertainity Using Robust Goal Programming Approach

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Abstract

Supply Chain Network design involves strategic decisions on the location of production, distribution facilities, capacities and transportation quantities. Supply chains are subjected to different types of Disruptions. In this paper, the disruptions in the demand side are considered. A robust optimization approach is developed for the supply chain network design under demand uncertainty. The supply chain problem considered is a multi-product multi-period multi-echelon. The problem is formulated as a multi-objective model and solved using Goal programming. The objectives are to maximize contribution, minimize the investment and disruptions costs. Installment of production modules incrementally based on the demand at each planning period has significant effect on reducing the total investment of the supply chain and the savings depends on the value of applied interest rate. The results showed that the design vary significantly with demand range of variability. The profit, contribution and total cost are highly sensitive to the ratio between disruption losses and selling price.

Keywords
Supply Chain, Disruption Management, Multi-objective, Demand uncertainty

1. Introduction

Supply chain disruptions are unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain and, as a consequence, expose firms within the supply chain to operational and financial risks (Craighead et al. 2007). The disruptions can be classified into supply side disruptions, process disruptions, and demand side disruptions. Demand uncertainty is considered a source of disruption and can be used as measure for disruption quantification. Different techniques are used to model demand uncertainty. Among of these techniques is the Stochastic Programming and fuzzy approaches. In stochastic approach, uncertain parameters are assumed to follow a particular probability distribution. However, in many cases, full distributional information is unknown or very hard to determine. (see El-Sayed et al. 2010). Robust Optimization modeling considers uncertainty in parameters as deterministic uncertainty sets in which all possible values of these parameters reside. "Robust optimization attempts to compute feasible solutions for a whole range of scenarios of the uncertain parameters, while optimizing an objective function in a controlled and balanced way with respect to the uncertainty in the parameters" (Akbari and Karimi 2015).

Different types of uncertainty may be due to uncertainty in demand, cost parameters, capacity requirements etc. Akbari and Karimi (2015) addressed process uncertainty by proposing a robust optimization approach for the design and planning of a multi-echelon, multi-product, multi-period supply chain network. The objective was to minimize the sum of location, allocation, transportation, and inventory carrying costs. It was formulated as a mixed integer linear programming problem. Two uncertainty sets were assumed for production capacity requirement of each product. A simulation-based procedure was developed to determine appropriate uncertainty budgets which lead to the robust solution of acceptable feasibility and good performance.

Jin et al. (2014) considered supply chain network design, under uncertain market demand and cost. They proposed robust optimization which was divided into two parts. The first part was facility location decision using a tabu search algorithm. The second part was flow decision which was addressed using the all-or-nothing method to design the capacity of the plant. The robust optimization model was not only capable of reducing the risk of market, but it also was able to avoid the error from the shortage cost. Zokaee et al. (2014) addressed uncertainty in demand, supply capacity and cost parameters (transportation and shortage cost). A base model that aimed to determine the strategic location and tactical allocation decisions for a deterministic four-echelon supply chain was proposed. The model was then extended to incorporate uncertainty in key input parameters using a robust optimization approach that could overcome the limitations of scenario-based solution methods in a tractable way. The application of the approach was investigated in an actual case study where real data was utilized to design a bread supply chain network. Tian and Yue (2014) considered uncertain demand and cost scenarios in the p-robust supply chain network design and suggested a framework to obtain the relative regret limit.

Hosseini et al. (2014) addressed uncertain customer demands and transportation costs for the design of a distribution network problem in a three-echelon supply chain. A mixed integer linear programming model was extended in a robust optimization framework and three heuristic approaches based on genetic and memetic algorithms and a mathematical programming approach were developed to solve this problem. Bai and Liu (2014) considered uncertain demands and transportation costs. The modeling approach selected was a fuzzy value-at-risk (VaR) optimization model, in which the uncertain demands and transportation costs were characterized by variable possibility distributions. The experimental results showed that the proposed parametric optimization method could provide an effective and flexible way for decision makers to design a supply chain network. Rezapour et al. (2013) proposed a method that included stochastic and robust models for designing the network structure of a three echelon supply chain under random demands of markets and by considering disruption probabilities in the procurement facilities and connecting links of the chain.

Ashayeri et al. (2014) formulated a mixed integer programming (MIP) model with specific downsizing features. It maximized the utilization of investment resources through a combined operation of demand selection and production assets reallocation. The corresponding robust counterparts of the MIP model were further developed based on robust optimization techniques for dealing with uncertainties of demands and exchange rates.

Moreover, Pishvaee et al. (2011) tackled uncertainty of input data in a closed-loop supply chain network design problem. First, a deterministic mixed-integer linear programming model was developed for designing a closed-loop supply chain network. Then, the robust counterpart of the proposed mixed-integer linear programming model was presented by using the recent extensions in robust optimization theory. The uncertain data were the quantity of returned products from the first market customers, the demands of second market customers and the transportation costs between facilities and they were assumed to be varied in an uncertain closed box set. The robustness of the solutions obtained by the robust optimization model was compared to that generated by the deterministic mixed-integer linear programming model in a number of realizations under different test problems. Computational results showed the superiority of the proposed robust model in both handling the uncertain data and the robustness of respective solutions against to the solutions obtained by the deterministic model. Hasani et al. (2012) considered strategic closed-loop supply chain network design for perishable goods. The supply chain was multi-period, multi-product, and multi-echelon. The uncertainty was considered in the demand and purchasing cost. The proposed model was handled via an interval robust optimization technique. The computational results of solving the proposed model via LINGO 8 had demonstrated efficiency of the proposed model in dealing with uncertainty in an agile manufacturing context.

Hatefi and Jolai (2014) considered uncertain parameters and facility disruptions . A robust model for an integrated forward-reverse logistics network design was proposed. The model was formulated based on a robust optimization approach to protect the network against uncertainty. Furthermore, a mixed integer linear programming model with augmented p-robust constraints was proposed to control the reliability of the network among disruption scenarios. The objective function of the proposed model was minimizing the nominal cost, while reducing disruption risk using the p-robustness criterion. Baghalian et al. (2013) considered demand-side and supply-side uncertainties simultaneously. A stochastic mathematical formulation was developed for designing a network of multi-product supply chains comprising several capacitated production facilities, distribution centers and retailers in markets under uncertainty. A transformation based on the piecewise linearization method was developed to solve the model. Taha et al. (2014) studied the plant disruption and their effect on the network reliability considering regret cost and recovery cost. Genetic algorithm was used to solve the problem and the results showed that, disruption cos affect the supply chain design for optimizing the total cost including disruption cost.

Most of the reviewed literature did not consider the uncertainty or variation in demand as a source of disruption. The objective of this work is to study the effect of uncertainty of demand on the design of the supply chain network. A multi-objective multi-period multi-echelon model is proposed to design supply chain using robust optimization for uncertain demand. The model allows for the assignment of modulated facilities of different capacities every period. Hence, investment cost considers time value of money. The performance of the solution is measured in terms of total disruption cost. The mathematical model is made to optimize separately the investment cost and contribution.

2. Problem description.

The design of a multi-echelon multi-product multi-period supply chain network is considered. This supply chain consists of suppliers, plants, distribution centers, and customers (retailers). The plants considered are modulated where each can accommodates for more than one production module of specific capacity and investment cost. The decision of assigning a module to any plant is made every period depending on the demand level and which minimizes the investment cost and disruptions. The investment cost is measured by its present worth based on the applied interest rate. The supply chain allows for building up of inventory at the distribution centers for optimization purposes. The supply chain can accommodate for the production of more than one product with different production rate. The average demand of each product during any planning period can be forecast. The demand at any period is assumed to suffer from random variations in between lower and upper limits. The demand variability range is determined from historical data. The structure of the proposed supply chain network is shown in figure 1.

The proposed model is capable of finding:

1. The optimal locations of the suppliers, plants, and distributors centers,
2. The number of modules installed in each manufacturing plant at each planning period,
3. The quantities transferred between the members of each echelon in the supply chain,
4. The amount of inventory held at each period for each distribution center,
5. The product mix that yields maximum profit contribution

The assumptions associated with the proposed model are:

1. The network consists of four echelons; suppliers, plants, distribution centers, and customers.
2. The potential plants and distribution centers have predetermined maximum capacities.
3. The production modules have predetermined capacities for certain investment cost.
4. Any production module can produce all types of products.
5. The supplier capacity is indefinitely large.
6. Customer demand is uncertain with upper and lower limits.
7. Inventory is allowed at the distribution centers.
8. Links between the different echelons are available.
9. Products flow through the network in batches of a pre-determined size.
10. Additional production modules can be installed to facilities in any period as required.

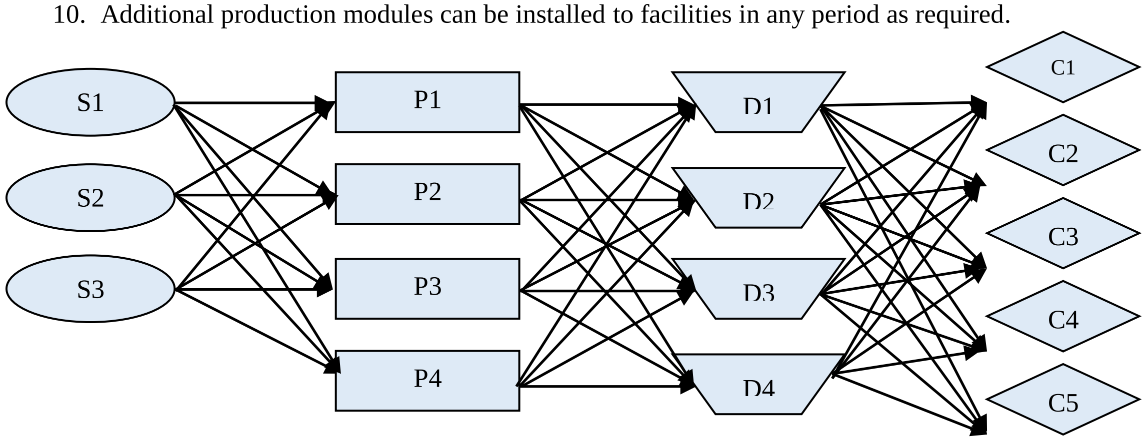

Figure 1: **Proposed supply chain network configuration**

Notations

C : Total number of customers c = [1, 2, 3…C]

D : Total number of operating distribution centres d = [1, 2, 3…D]

M	:	Total number of production modules m = [1, 2, 3…M]
P	:	Total number of operating plants p = [1, 2, 3…P]
Q	:	Total number of products q = [1, 2, 3…Q]
S	:	Total number of suppliers s = [1, 2, 3…S]
T	:	Total number of planning periods t = [1, 2, 3…T]
U	:	Under capacity cost per unit for un-used capacity in plants
h	:	Holding cost per unit
r	:	Interest rate
SC	:	Losses per unit for shortage in customers' demand
OC	:	Losses per unit for over production than the customers' demand
δ	:	The range of variability
$AvgDem_{cqt}$	:	Average quantities of demand at customer (*c*) for product (*q*) at period (*t*)
$Dcap_{\mathrm{d}}$	:	Maximum capacity of distribution centre (*d*)
Dem_{cqt}	:	Uncertain demand at customer (*c*) for product (*q*) at period (*t*)
FCd_d	:	Fixed cost of operating distribution centre (*d*) per period
FCm_m	:	Fixed cost of operating production modules (*m*) per period
FCp_p	:	Fixed cost of operating plant (*p*) per period
$Mcap_{\mathrm{mq}}$	:	Capacity of production modules (*m*) to produce product (q)
PC_q	:	Production cost per unit of product (q)
$Pcap_{\mathrm{p}}$	:	Maximum capacity of plant (p)
SP_q	:	Selling price per unit of product (*q*)
Tdc_{dc}	:	Transportation cost of the link between distribution centre (d) and customer (c) per unit product
Tpd_{pd}	:	Transportation cost of the link between plant (p) and distribution centre (d) per unit product
Tsp_{sp}	:	Transportation cost of the link between supplier (s) and plant (p) per unit product

Decision Variables

Qsp_{tqsp}	:	Quantities of raw material for product (*q*) transported from supplier (*s*) to plant (*p*) at time period (*t*)
Qpd_{tqpd}	:	Quantities of product (*q*) transported from plant (*p*) to distribution centre (*d*) at time period (*t*)
Qdc_{tqdc}	:	Quantities of product (*q*) transported from distribution centre (*d*) to customer (c) at time period (*t*)
$Qprod_{tqp}$	:	Quantities of products (*q*) produced at plant (*p*) at time period (*t*)
$Qinv_{tqd}$	:	Quantities of products (*q*) stored at distribution centre (*d*) at time period (*t*)
Xp_{pt}	:	Binary variable for plant (p) at period (t) $\begin{cases}1 & open\\ 0 & closed\end{cases}$
Xd_{dt}	:	Binary variable for distribution centre (*d*) at period (t)) $\begin{cases}1 & open\\ 0 & closed\end{cases}$
Ym_{mpt}	:	Number of production modules of type (m) installed in plant (p) at period (t)

3. Model objectives and constraints

The proposed model considers three objectives. (1) minimizing the investment cost, (2) maximizing the contribution, and (3) minimizing the disruption cost.

The investment cost is the sum of fixed costs from opening the plants and its modules, and distribution centers. Since it is allowed to increase the production modules of plants in the future, the investment cost accounts considering time value of money and interest rate. The first objective given in equation (1) .

$$\text{Investment cost} = \sum_{t=1}^{T}\sum_{p=1}^{P}\frac{\mathrm{FCp_p}\cdot\mathrm{Xp_{pt}}}{(1+\mathrm{r})^{\mathrm{t}}} + \sum_{t=1}^{T}\sum_{d=1}^{D}\frac{\mathrm{FCd_d}\cdot\mathrm{Xd_{dt}}}{(1+\mathrm{r})^{\mathrm{t}}} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{m=1}^{M}\frac{\mathrm{FCm_m}\cdot\mathrm{Ym_{mpt}}}{(1+\mathrm{r})^{\mathrm{t}}} \tag{1}$$

The contribution is the difference between the revenue and the variable cost. The revenue is shown in equation (2). The variable cost is the sum of production costs, transportation costs and holding-up costs which is detailed in equations (3) to (5). The second objective shown in equation (6) is maximizing the contribution.

$$Revenue = \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{d=1}^{D}\sum_{c=1}^{C} SP_q \cdot Qcd_{tqcd} \tag{2}$$

$$\text{Production cost} = \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{p=1}^{P} \mathrm{PC_q} \cdot \mathrm{Qprod_{tqp}} \tag{3}$$

$$\mathrm{TC} = \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{s=1}^{S}\sum_{p=1}^{P} \mathrm{Tsp_{sp}} \cdot \mathrm{Qsp_{tqsp}} + \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{p=1}^{P}\sum_{d=1}^{D} \mathrm{Tpd_{pd}} \cdot \mathrm{Qpd_{tqpd}} + \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{d=1}^{D}\sum_{c=1}^{C} \mathrm{Tcd_{cd}} \cdot \mathrm{Qcd_{tqcd}} \tag{4}$$

$$\text{Holding cost} = \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{d=1}^{D} \mathrm{h} \cdot \mathrm{Qinv_{tqd}} \tag{5}$$

$$\begin{aligned} Contribution = & \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{d=1}^{D}\sum_{c=1}^{C} SP_q \cdot Qcd_{tqcd} \\ & - \Bigg[\sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{p=1}^{P} \mathrm{PC_q} \cdot \mathrm{Qprod_{tqp}} + \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{s=1}^{S}\sum_{p=1}^{P} \mathrm{Tsp_{sp}} \cdot \mathrm{Qsp_{tqsp}} \\ & + \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{p=1}^{P}\sum_{d=1}^{D} \mathrm{Tpd_{pd}} \cdot \mathrm{Qpd_{tqpd}} + \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{d=1}^{D}\sum_{c=1}^{C} \mathrm{Tcd_{cd}} \cdot \mathrm{Qcd_{tqcd}} \\ & + \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{d=1}^{D} \mathrm{h} \cdot \mathrm{Qinv_{tqd}}]\Bigg] \end{aligned} \tag{6}$$

The disruption cost is the sum of the over production and shortage cost. The third objective is given in equation (7). The value of w is shown in equation (8,9)

$$\text{Disruption cost} = \sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{c=1}^{C} \left| \mathrm{Dem_{cqt}} - \sum_{d=1}^{D} \mathrm{Qdc_{tqdc}} \right| \cdot \mathrm{W} \tag{7}$$

$$\text{where } W = SC \text{ if } \quad \mathrm{Dem_{cqt}} > \sum_{d=1}^{D} \mathrm{Qdc_{tqdc}} \tag{8}$$

$$W = OC \text{ if } \quad \mathrm{Dem_{cqt}} < \sum_{d=1}^{D} \mathrm{Qdc_{tqdc}} \tag{9}$$

Model constraints:

1- Capacity constraints for the production modules, plants and distribution centers are given in the following equations (10-12)

   a. Modules capacity

$$\sum_{q=1}^{Q} \frac{\mathrm{Mcap_{m1}}}{\mathrm{Mcap_{mq}}} \cdot \mathrm{Qprod_{tqp}} \le \mathrm{Mcap_{m1}} \cdot \mathrm{Ym_{mpt}} \;\; \forall \;\; \mathrm{m, p, t} \tag{10}$$

   b. Plants capacity

$$\sum_{m=1}^{M} \mathrm{Mcap}_{mq} \cdot \mathrm{Ym}_{mpt} \leq \mathrm{Pcap}_{p} \cdot Xp_{pt} \quad \forall \mathrm{p, q, t} \tag{11}$$

c. Distribution centers capacity

$$\sum_{p=1}^{P} \mathrm{Qpd}_{tqpd} + \mathrm{Qinv}_{tqd} \leq \mathrm{Dcap}_{d} \cdot Xd_{dt} \quad \forall \mathrm{d, q, t} \tag{12}$$

2- Balance constraints at the plants and the distribution centers are given in the following equations (13-14)
   a. Balance at plants

$$\mathrm{Qprod}_{tqp} = \sum_{d=1}^{D} \mathrm{Qpd}_{tqpd} \quad \forall \mathrm{p, q, t} \tag{13}$$

   b. Balance at distribution centers

$$\mathrm{Qinv}_{(t-1)qd} + \sum_{p=1}^{P} \mathrm{Qpd}_{tqpd} = \mathrm{Qinv}_{tqd} + \sum_{c=1}^{C} \mathrm{Qdc}_{tqdc} \quad \forall p, q, t \tag{14}$$

3- Number of modules constraints ensures that the number of installed modules in next period (t+1) must be greater than or equal to the number of modules in the current period (t)

$$\mathrm{Ym}_{mpt} \leq \mathrm{Ym}_{mpt+1} \quad \forall \mathrm{t, p} \tag{15}$$

4- Demand constraints; upper and lower demand limits under uncertainty

$$Dem_{cqt} < (1 + \delta) \cdot AvgDem_{cqt} \tag{16}$$

$$Dem_{cqt} > (1 - \delta) \cdot AvgDem_{cqt} \tag{17}$$

5- Non-negativity constraints

$$Qsp_{tqsp}, Qpd_{tqpd}, Qdc_{tqdc}, Qprod_{tqp}, Qinv_{tqd}, Ym_{mpt}, Xp_{pt}, Xd_{dt} \geq 0 \quad \forall \mathrm{f, d, c} \tag{18}$$

6- Integer constraints are shown in equation (19)

$$\frac{Qsp_{tqsp}}{Batch\ size}, \frac{Qpd_{tqpd}}{Batch\ size}, \frac{Qdc_{tqdc}}{Batch\ size}, \frac{, Qprod_{tqp}}{Batch\ size}, Ym_{mpt} \text{ are integers} \quad \forall \mathrm{t, q, p}, d, c \tag{19}$$

7- Binary constraints for the plants and distribution centers locations

$$Xp_{pt}, Xd_{dt} \text{ are binary} \quad \forall \mathrm{t, p}, d \tag{20}$$

4. Computational results

A set of experiments are designed and conducted to study the effectiveness of the proposed model. The assumed supply chain design input data are given in Table 1. The proposed model is solved using FICO Xpress Optimization software. Robust optimization and goal programming modules are used to design the supply chain and analyze experiments results at different conditions. All assumed goal programming objectives are given the same weight. Disruption cost was the primary objective followed by the investment cost and the contribution.

Table 1 Data set for numerical example

Parameter	Value
No. of potential suppliers (s)	3

No. of potential plants (P)	4
No. of potential DCs (D)	4
No. of customers (C)	5
No. of Periods (T)	4
No. of products (Q)	2
Production Modules	Module A and Module B
Module A capacity	q1=100 , q2 =150
Module B capacity	q1=200 , q2 =220
Investment cost per period for Module A	3000
Investment cost per period for Module B	4500
Cost of opening Plant (P) per Period	50 000
Cost of opening DC (d) per Period	20 000
$Pcap_{\mathrm{p}}$, $Dcap_{\mathrm{d}}$	6000
Interest Rate	10%
Unit Price	q1=150 , q2=160
Production cost	q1=20 , q2=30
Transportation cost per unit per period	10
Holding Cost per unit per period	10
Over-capacity cost per unit per period	30
Penalty cost per unit per period	30
Customer mean demand during the first period	500 Unit
Increase in customer demand per period	100 unit
Variability range in demand	± 10%

5.1 The effects of the Demand Variability on the supply chain network design

The aim of this experiment is to study the effect of the demand disruptions on the supply chain network design. The results shown in Table (2) indicate that the supply chain design changes every period with the increase in average demand and demand range of variation.

Two cases are considered. The first case is the supply chain design with deterministic demand while the second case is considering the variability in the demand as a disruption. For each period the design is given as the number of plants and the number of modules installed in each plant. For example P1(17A, 14B) indicates that plant 1 is open and 17 module of type A and 14 module of type B are installed. Also D1, D2 indicates that two distribution centers are opened.

Table 2 Results of the generated test problems

Design at $\delta = 0$	**Design at $\delta = 0.1$**
Period 1:P1(17A, 14B), D1, D2	**Period 1:**P1(14A, 13B), D1, D2
Period 2:P1(18A, 15B), D1, D2	**Period 2:**P1(18A, 15B), D1, D2
Period 3:P1(18A, 15B), P2(0, 7B), D1, D2	**Period 3:**P1(18A, 15B), D1, D2
Period 4:P1(18A, 15B), P2(5A, 8B), D1, D2	**Period 4:**P1(18A, 15B), P2(9A, 3B), D1, D2

5.2 The effects of the Demand Variability

This experiment is to study the effect of the demand variability range on the different cost elements. The results shown in Table 3 indicate that the cost elements vary considerably with demand variability ranges. For these test problems all the parameters were kept fixed and δ is the only variable. It is evident that in general all financial results slightly increase up to demand variation of 1% and then decrease except shortage and over production and holding costs. It is worth mentioning that when optimizing the model by Integer Programming with no demand variation (no disruption) same results given for δ =0 were obtained.

Table 3 Results of the generated test problems at different demand variability ranges at w/sp = 0.2

Parameter	$\delta = 0$	$\delta = 0.001$	$\delta = 0.005$	$\delta = 0.01$	$\delta = 0.05$	$\delta = 0.1$
Revenue	4,030,000	4,036,200	4,051,700	4,055,650	3,899,000	3,691,500
Investment cost	703, 394	702,843	701,140	699,879	646,931	622717

Transportation cost	780,000	781,200	784,200	785,050	754,200	714000
Over-production cost	0	2,400	8,400	12,750	13,980	13560
Shortage cost	0	-	60	3,000	64,800	144000
Holding cost	2800	3,000	3,080	3,000	17,680	7160
Variable Cost	1,432,800	1,435,200	1,440,780	1,442,350	1,402,680	1,318,660
Contribution	2,597,200	2,601,000	2,610,920	2,613,300	2,496,320	2,372,840
Total cost	2,136,190	2,138,040	2,141,920	2,142,230	2,049,610	**1,941,380**
Profit	1,893,810	1,898,160	1,909,780	1,913,420	1,849,390	1,750,120

5.3 The effects of the demand variability range

The third set of experiments were conducted to study the effect of changing the different cost elements with the range of demand variability at different ratios between the losses per unit due to shortage or over production “w” and the selling price per unit “sp”. Three ratios are considered 0.2, 1 and 2. The results for the different cost elements are shown in Figure 2. In these experiments, the average demand is kept constant at 500 per customer per period for different time periods. The total profit and contribution were found to decrease with the increase in demand variability, the higher the ratio of “w/sp” the lower the rate of decrease. Profit and contribution may decrease to negative values (loss) especially at high values of “w/sp”. On the other hand, the total cost has an opposite behavior with “w/sp”. Investment cost was found to decrease with increasing range of demand variation, but insensitive to “w/sp”. The total cost and has inverse trend as it increases with increasing demand variation. The increase rate is higher the higher “w/sp”.

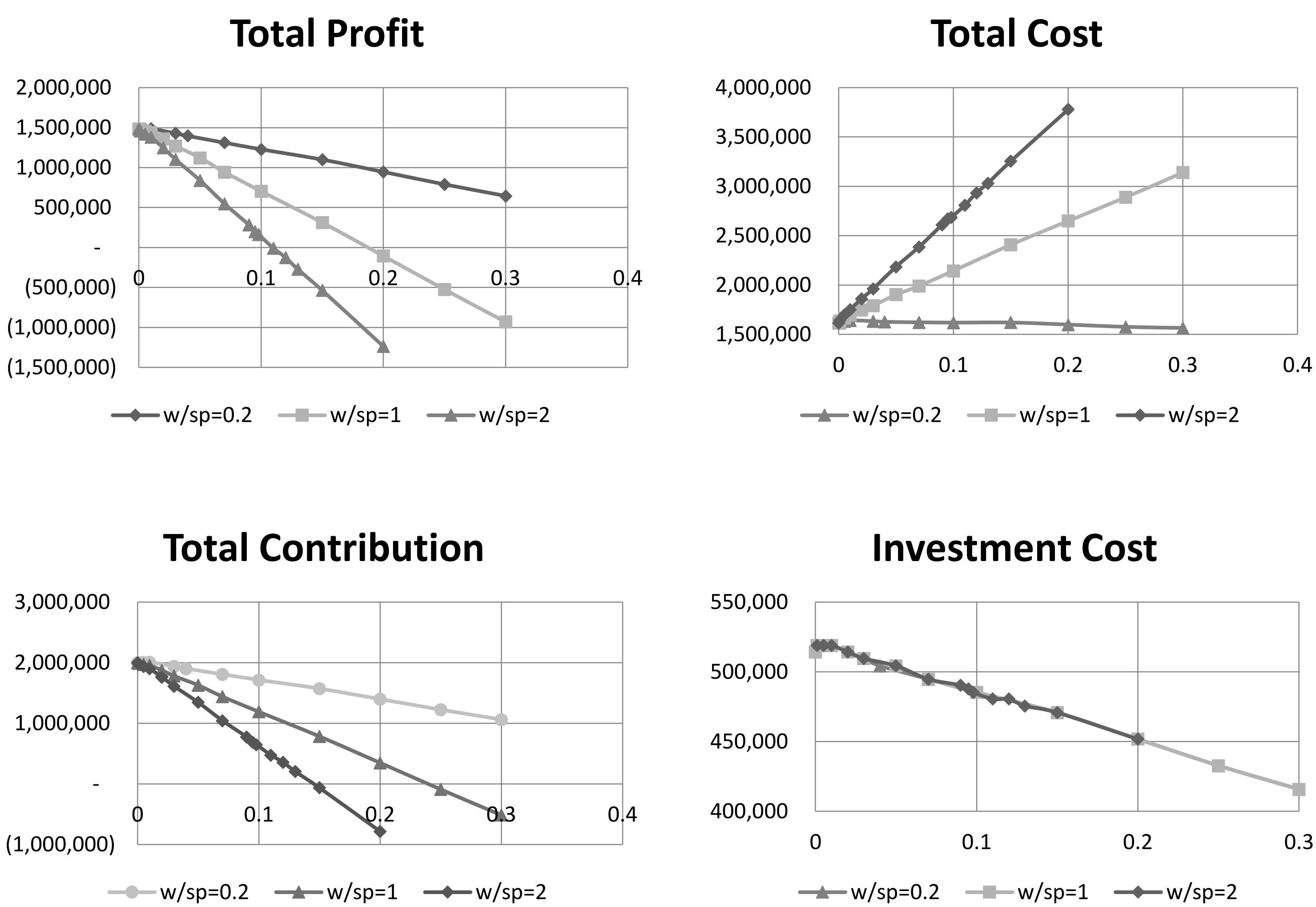

Figure 2: effect of Variability range

5.4 The effect of interest rate

The fourth experiment is to study the effect of the interest rate. All the parameters are fixed and interest rate " r" changes from 0 to 25%. The results in Figure 4 show that the total cost and investment cost decrease with interest rate while the profit increases. This is due to the fact that, at each period, the model opens plants or adds production farcicalities to the existing plants as required satisfying the demand and its variation. The investment cost represented by the present worth should decrease with the increase of interest rate.

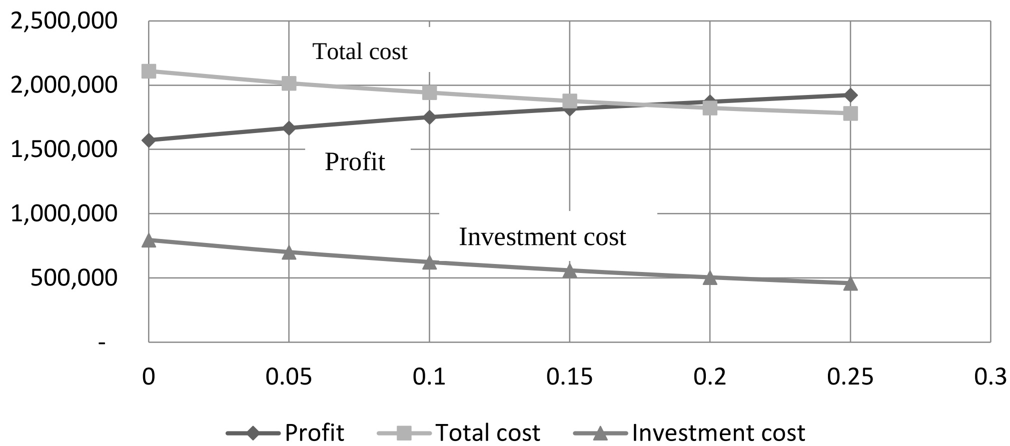

Figure 3: effect of interest rate

5. Conclusion

The proposed model is capable to consider continuous installment of production modules as the demand increases with time and this has reduced considerably the investment cost represented by the present worth.

The results of robust optimization showed that as the demand variability increases the disruption cost increases and by virtue the contribution decreases. However, the results obtained were conservative so as to lead to minimum disruption cost compared with the no disruption case.

The ratio between the losses due to shortage/over-production and the selling price has a significant effect on the contribution and the total cost. The higher the value of this ratio is the higher the cost and the lower the contribution. However this ratio had no effect on the investment cost as the investment cost decrease with the increase in the demand variability.

It was also proved that incase where the interest rate are high, the higher the saving in investment if the installments are made on time of demand requirement.

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