Scientia Iranica E (2014) 21(6), 2307–2314

Sharif University of Technology
Scientia Iranica
Transactions E: Industrial Engineering
www.scientiairanica.com

A new robust fuzzy approach for aggregate production planning

D. Rahmani[a,*], **A. Yousefli**[b] **and R. Ramezanian**[a]

a. *Department of Industrial Engineering, K.N. Toosi University of Technology, Tehran, Iran.*
b. *Department of Industrial Management, Imam Khomeini International University, Qazvin, Iran.*

Received 30 May 2012; received in revised form 3 January 2013; accepted 22 September 2014

KEYWORDS
Aggregate production planning;
Robust optimization;
Fuzzy programming;
Fuzzy entropy.

Abstract. Aggregate production planning is a medium-term production plan that determines the production plan for satisfying fluctuating demand. In this paper, a robust approach is used to formulate aggregate production planning, in which some parameters, such as production cost and customer demand, are fuzzy variables. The concept of entropy is used to reduce the sensitivity of noisy data and to obtain a more robust aggregate production plan, based on the proposed model. Finally, a numerical example is presented to explain the model solution. In addition, the robustness of the proposed model solution is compared with other classical fuzzy programming approaches.

1. Introduction

Aggregate Production Planning (APP) is an activity used to determine an aggregate plan for production systems in advance of 3 to 18 months, so that the total cost is kept to a minimum. The quantity of subcontracted products, regular and overtime hours of labor, numbers to be hired and fired, and amounts of inventory and backorder are determined in each period.

A comprehensive survey for aggregate production planning has been presented in [1], which has studied the models and solution methods for APP. Due to APP being NP-hard, some meta-heuristic methods have been developed to solve these problems [2-4].

In order to model uncertainty in a real production environment, some parameters, such as cost and demand, are uncertain and fluctuate in the planning horizon. Some approaches have been used to reduce the uncertainty of the production environment. Stochastic programming is a technique that is applied to stochastic aggregate production planning. In this method, stochastic variables with probability functions are used to represent uncertain parameters [5-7]. Fuzzy programming is another approach to incorporate uncertainty into aggregate production planning. Some studies have proposed Fuzzy Linear Programming (FLP) models for APP [8-12]. Multi product aggregate production planning with fuzzy demands and fuzzy capacities has been presented in [13]. Wang and Fang [14] implemented a genetic-based approach for APP with fuzzy variables and within a family of inexact solutions. Researchers have considered APP with multiple objectives in fuzzy environments [15,16]. Yan et al. [17] proposed a fuzzy programming model for lot sizing in a production planning problem. In their proposed model, unit profit, capacity and demand are considered fuzzy variables. They used a GA algorithm based on fuzzy simulation to solve the problem.

In the literature, some researchers have used strong approaches to extenuate uncertainty. Robust optimization is an approach that is effective in reducing the sensitivity of uncertain parameters. This

*. *Corresponding author.*
E-mail addresses: drahmani@kntu.ac.ir (D. Rahmani); Yousefli@soc.ikiu.ac.ir (A. Yousefli); Ramezanian@kntu.ac.ir (R. Ramezanian)

approach has been developed to find admissible and desirable solutions for any possible events of uncertain agents. The robust approach has been developed in operation research, using a concept called the robust counterpart [18]. Robust optimization has been used to formulate aggregate production planning in uncertain environments [19,20], and an agent-based web service approach has been presented to increase the robustness of the experimental results across diverse uncertainties in the production environment [21].

The existence of uncertain parameters in production planning problems makes the attaining of robust solutions more valuable than obtaining optimal solutions that ignore this uncertainty. In fact, for some systems, managers prefer to have a production plan that will be robust in any possible event in the future, even if it does not have an optimum production cost. This fact shows that it is essential to develop an approach which will be efficient for any system, where the robustness of the solution is important, in addition to the total cost of production for their managers. In fact, for such systems, not only a solution should be with minimum total cost, but also the fluctuation in real scenarios should be low. This paper presents a new approach towards the robustness of a solution.

In this paper, a robust aggregate production planning model is developed to minimize the total cost of production. To provide a more realistic model, we assume that some parameters, such as cost and demand, are fuzzy variables. We use the concept of fuzzy entropy in the proposed robust model because it can show a degree of uncertainty. We show that our model is insensitive to uncertain parameters.

The rest of this paper is organized as follows. In Section 2, the primary fuzzy aggregate production planning is proposed. In Section 3, the definition of expected value and entropy are described. In Section 4, the novel proposed robust fuzzy model is demonstrated. In Section 5, the computational results are presented, and, finally, Section 6 provides conclusions of the research.

2. Fuzzy aggregate production planning

This paper has concentrated on multi-period and one-product systems in which some parameters, i.e. regular time production cost, overtime production cost, subcontracting cost, and demand at each period, are uncertain. These uncertain parameters are fuzzy variables with triangular membership functions. For example, customer demand is a fuzzy variable, $\tilde{D}_t = (D_{lt}, D_{mt}, D_{rt})$, in which D_{lt}, D_{mt} and D_{rt} denote the smallest possible value, the most promising value, and the largest possible value, respectively. They describe a fuzzy event. The parameters and variables are as follows.

2.1. Model variables

P_t : Regular time production in period t (units);

O_t : Overtime production in period t (units);

B_t : Backorder level in period t (units);

S_t : Subcontracting volume in period t (units);

H_t : Number of workers hired in period t (man-days);

L_t : Number of workers laid off in period t (man-days);

W_t : Workforce level in period t (man-days);

I_t : Inventory of product in period t (units).

2.2. Model parameters

$\tilde{D}_t = (D_{lt}, D_{mt}, D_{rt})$: Demand of product in period t (units);

$\tilde{P}_t = (p_{lt}, p_{mt}, p_{rt})$: Regular time production cost per unit of product in period t (\$/units);

$\tilde{o}_t = (o_{lt}, o_{mt}, o_{rt})$: Overtime production cost per unit of product in period t (\$/units);

$\tilde{s}_t = (s_{lt}, s_{mt}, s_{rt})$: Subcontracting cost per unit of product in period t (\$/units);

h_t: Inventory cost per unit of product in period t (\$/units);

b_{it}: Backorder cost per unit of product in period t (\$/units);

hr_t: Cost to hire one worker in period t (\$/man-days);

l_t: Cost to layoff one worker in period t (\$/man-days);

w_t: Labor cost in period t (\$/man-days);

W_0: Initial workforce level (man-days);

I_0: Initial inventory level of product in period t (units);

M_t: Regular time machine capacity in period t (machine-hours);

b: Hours of machining per unit of product;

β_t: Ratio of regular machine capacity available for use in overtime in period t;

α_t: Ratio of regular-time workforce available for use in overtime in period t;

δ: Working hours of labor in each period (man-hour/man-day);

a: Hours of labor per unit of product (man-days/unit);

$W_{t\max}$: Maximum labor level available in period t (man-days);

$S_{t\max}$: Maximum subcontracted volume available of product in period t (units).

And the primary model is as follows:

$$\mathrm{Min}Z = \sum_{t=1}^{T} \tilde{p}_t P_t + \tilde{o}_t O_t + \tilde{s}_t S_t + hr_t H_t + l_t L_t + w_t W_t + h_t I_t + b_t B_t. \quad (1)$$

Subject to:

$$P_t + O_t + S_t + I_{t-1} - I_t + B_t - B_{t-1} = \tilde{D}_t \qquad \forall t, \quad (2)$$

$$aP_t \leq \delta W_t \qquad \forall t, \quad (3)$$

$$aO_t \leq \delta \alpha_t W_t \qquad \forall t, \quad (4)$$

$$bP_t \leq M_t \qquad \forall t, \quad (5)$$

$$bO_t \leq \beta_t M_t \qquad \forall t, \quad (6)$$

$$W_t = W_{t-1} + H_t - L_t \qquad \forall t, \quad (7)$$

$$W_t \leq W_{t\max} \qquad \forall t, \quad (8)$$

$$S_t \leq S_{t\max} \qquad \forall t, \quad (9)$$

$$P_t, O_t, S_t, H_t, L_t, W_t, I_t, B_t \geq 0 \qquad \forall t. \quad (10)$$

Constraint (2) is relevant to market demand. Since total demand may be greater than the total resource capacity, the last period backorder can be non-zero. Constraints (3) and (4) correspond to workforce capacity constraints at regular time and overtime at each period. Constraint (5) ensures that the quantity of regular time production does not exceed available machine capacity. Constraint (6) is relevant to overtime machine capacity constraints. Constraint (7) ensures that the workforce in period t is equal to the summation of the workforce in the previous period and the change of workforce level. Constraints (8) and (9) are relevant to the maximum defined level for the workforce level and subcontracting variable in any period.

3. Expected value and entropy of a fuzzy variable

Assume that $\tilde{A}$ is a fuzzy variable with Membership Function (MF) denoted as $\mu(\alpha)$, with triangular form in a fuzzy interval. The expected value has been computed as [22]:

$$E(\tilde{A}) = a_0 + \frac{1}{2}\int_{a_0}^{+\infty} \mu(a)da - \frac{1}{2}\int_{-\infty}^{a_0} \mu(a)da. \quad (11)$$

Fuzzy entropy is a significant index in measuring fuzzy information. It evaluates the degree of fuzziness between two fuzzy sets. This concept is a prevalent measure of randomness. Different researchers have proposed various definitions of fuzzy entropy. In this paper, we use the following formulation [8]:

$$H(\tilde{A}) = -\int_{-\infty}^{+\infty} \Big(\mu(a)\mathrm{Ln}\mu(a) + (1-\mu(a))\mathrm{Ln}(1-\mu(a))\Big) da. \quad (12)$$

4. Robust fuzzy aggregate production planning formulation

In this section, a robust aggregate production planning model is developed to minimize the total cost of production, which is insensitive to uncertain parameters.

The proposed approach considers the "robustness" of the solution in addition to the total cost of production. In fact, the total cost of production is a classical measure and the robustness of the solution is a performance measure. We call a solution "robust" if it is insensitive to uncertain parameters.

At the beginning of the planning horizon, some parameters are uncertain, and fuzzy numbers and their real values in the future are unclear. In fact, there are many real scenarios that will occur in the future, and only in the execution time of the plan will the real amounts of uncertain parameters and real scenarios be determined. It is clear that any possible scenarios in the future will cause different values of real total cost. If a model can provide a solution in which, for any scenarios, the fluctuations and variations in real total cost are low, then the model is robust.

Since the objective function includes some fuzzy parameters, it can be defined as a single fuzzy variable. In fact, the objective function can be considered a fuzzy stochastic variable. So, we redefine the objective function in terms of the expected value and entropy of this variable. Regarding the fact that uncertain variables are triangular fuzzy numbers, a new triangular fuzzy number, $\tilde{R}_t = (R_{lt}, R_{mt}, R_{rt})$, can be defined as follows:

$$R_{lt} = p_{lt}P_t + o_{lt}O_t + s_{lt}S_t + hr_tH_t + l_tL_t + w_tW_t + h_tI_t + b_tB_t \qquad \forall t, \quad (13)$$

$$R_{mt} = p_{mt}P_t + o_{mt}O_t + s_{mt}S_t + hr_tH_t + l_tL_t + w_tW_t + h_tI_t + b_tB_t \qquad \forall t, \quad (14)$$

$$R_{rt} = p_{rt}P_t + o_{rt}O_t + s_{rt}S_t + hr_tH_t + l_tL_t + w_tW_t + h_tI_t + b_tB_t \qquad \forall t. \quad (15)$$

So, objective function (1) is equal to:

$$\mathrm{Min}Z = \sum_{t=1}^{T} \tilde{R}_t. \quad (16)$$

As already shown, robust optimization is an approach that is effective in reducing the sensitivity of uncertain parameters. This approach has been developed to find admissible and good solutions for any possible events of uncertain agents in the future.

The concept of entropy is used in our robust model to reduce the fluctuation of uncertain parameters, because it can show the degree of uncertainty of these parameters. In fact, a fuzzy variable with lower entropy has a lower degree of uncertainty. In the objective function, such variables cause an insensitive solution to be made against any possible scenarios in the future. We define our robust objective function based on the expected value and entropy of fuzzy variable, $\tilde{R}_t$. So, in the robust model, the objective function, Z', is defined as follows:

$$\text{Min}Z' = \sum_{t=1}^{T} \left(E(\tilde{R}_t) + \lambda H(\tilde{R}_t)\right). \tag{17}$$

The expected value of $\tilde{R}_t$ leads to obtaining the near optimal solution efficiently and the entropy attempts to measure the degree of uncertainty of the fuzzy parameters. According to the minimization of the objective function, this definition causes the variations and sensitivity of uncertain parameters to reduce. Thus, the total cost is robust for any possible events in the future. Eqs. (18) and (19) show the statements of the expected value and the entropy of $\tilde{R}_t$. These equations were solved and Eqs. (20) and (21) show their final results:

$$E(\tilde{R}_t) = R_{mt} + \frac{1}{2}\int_{R_{mt}}^{R_{rt}} \frac{R_{rt}-R_t}{R_{rt}-R_{mt}} - \frac{1}{2}\int_{R_{lt}}^{R_{mt}} \frac{R_t-R_{lt}}{R_{mt}-R_{lt}} dR_t \qquad \forall t, \tag{18}$$

and also:

$$\begin{aligned} H(\tilde{R}_t) = &-\int_{R_{lt}}^{R_{mt}} \frac{R_t-R_{lt}}{R_{mt}-R_{lt}} \text{Ln}\left(\frac{R_t-R_{lt}}{R_{mt}-R_{lt}}\right) dR_t \\ &+\int_{R_{mt}}^{R_{rt}} \frac{R_{rt}-R_t}{R_{rt}-R_{mt}} \text{Ln}\left(\frac{R_{rt}-R_t}{R_{rt}-R_{mt}}\right) dR_t \\ &+\int_{R_{lt}}^{R_{mt}} \left(1-\frac{R_t-R_{lt}}{R_{mt}-R_{lt}}\right) \\ &\times \text{Ln}\left(1-\frac{R_t-R_{lt}}{R_{mt}-R_{lt}}\right) dR_t \\ &+\int_{R_{mt}}^{R_{rt}} \left(1-\frac{R_{rt}-R_t}{R_{rt}-R_{mt}}\right) \\ &\times \text{Ln}\left(1-\frac{R_{rt}-R_t}{R_{rt}-R_{mt}}\right) dR_t \qquad \forall t. \end{aligned} \tag{19}$$

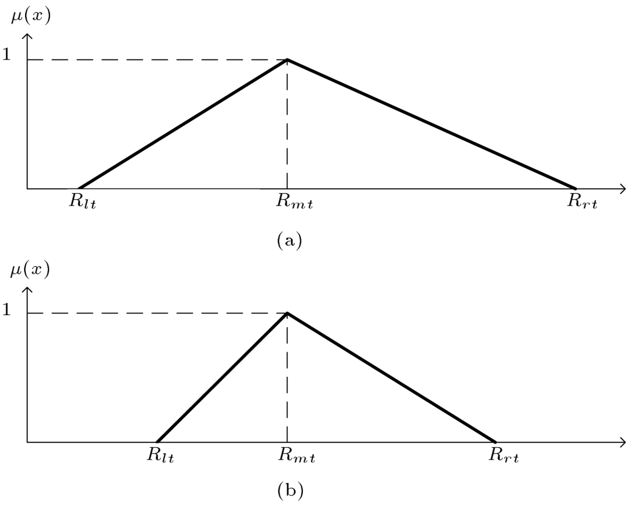

Figure 1. The comparison of robustness between two triangular fuzzy numbers.

After solving these terms, we have:

$$E(\tilde{R}_t) = \frac{1}{2}R_{mt} + \frac{1}{4}\left(R_{lt}+R_{rt}\right) \qquad \forall t, \tag{20}$$

$$E(\tilde{R}_t) = \frac{1}{2}\left(R_{rt}-R_{lt}\right) \qquad \forall t. \tag{21}$$

Based on Eq. (21), the entropy in the triangular fuzzy number is the interval between two points, R_{rt} and R_{lt}. So, in Figure 1, it is shown that the triangular fuzzy number (b) has a lower value of entropy than the triangular fuzzy number (a). Then, based on definition, fuzzy number (b) is more robust than fuzzy number (a). In other words, in the proposed approach, minimization of the entropy of decision variable, $\tilde{R}_t$, causes a more robust solution.

In Eq. (17), λ is the coefficient of robustness in the objective function, such that a greater amount of this coefficient leads to an increase in the importance of the robustness of the solution. The significance of total cost maybe be reduced and an undesirable solution may be obtained, so, a suitable amount for this coefficient is required. This coefficient is determined by decision makers, such as system managers.

As depicted earlier, the market demand of a product is a fuzzy number, so, we can defuzzify it in a demand constraint, classically, which causes this constraint to linearize. Eventually, our proposed model can be stated as follows:

$$\text{Min}Z' = \sum_{t=1}^{T}\left(\frac{1}{2}R_{mt}+\frac{1}{4}(R_{lt}+R_{rt})+\frac{\lambda}{2}(R_{rt}-R_{lt})\right). \tag{22}$$

Subject to:

$$P_t + O_t + S_t + I_{t-1} - I_t + B_t - B_{t-1}$$

Table 1. Triangular fuzzy variables.

Period (t)	Difuzzied demand (unit)	Fuzzy regular time production cost ($/unit)	Fuzzy over time production cost ($/unit)	Fuzzy subcontracting cost ($/unit)
1	1500	(30,70,140)	(70,100,195)	(180,220,320)
2	1800	(35,80,190)	(75,140,185)	(225,285,295)
3	1700	(32,75,180)	(70,130,190)	(210,280,300)
4	1900	(35,80,175)	(70,130,185)	(230,255,310)
5	1650	(33,80,190)	(80,150,200)	(220,275,330)
6	1900	(32,80,170)	(75,145,195)	(220,290,295)

Table 2. Certain costs and machine parameters.

Period (t)	Inventory cost ($/unit)	Backorder cost ($/unit)	Max subcontract (unit)	Machine capacity	Machine ratio
1	24	1000	200	2500	0.4
2	24	1200	250	1800	0.3
3	24	1280	250	2200	0.3
4	24	1300	250	2000	0.3
5	24	1300	250	2000	0.4
6	24	1350	270	2050	0.4

Table 3. Labor relevant costs and parameters.

Period (t)	Hiring cost ($/man-day)	Layoff cost ($/man-day)	Labor cost ($/man-day)	Max work force (man-day)	Work force ratio
1	145	150	112	700	0.3
2	145	150	112	700	0.3
3	145	150	120	750	0.3
4	145	155	120	750	0.3
5	145	155	120	800	0.3
6	145	155	120	800	0.3

$$= \frac{1}{4}\left(D_{lt} + 2D_{mt} + D_{rt}\right) \qquad \forall t, \tag{23}$$

$$aP_t \leq \delta W_t \qquad \forall t, \tag{24}$$

$$aO_t \leq \delta \alpha_t W_t \qquad \forall t, \tag{25}$$

$$bP_t \leq M_t \qquad \forall t, \tag{26}$$

$$bO_t \leq \beta_t M_t \qquad \forall t, \tag{27}$$

$$W_t = W_{t-1} + H_t - L_t \qquad \forall t, \tag{28}$$

$$W_t \leq W_{t\max} \qquad \forall t, \tag{29}$$

$$S_t \leq S_{t\max} \qquad \forall t, \tag{30}$$

$$P_t, O_t, S_t, H_t, L_t, W_t, I_t, B_t \geq 0 \qquad \forall t. \tag{31}$$

5. Computational results

We consider a hypothetical production system with a multi-period and a single product. Our proposed model must determine a production plan for 6-months. The regular time production costs, overtime production costs, subcontracting costs, and customer demand are triangular fuzzy numbers. Tables 1 and 2 present the given values for 6 working periods. The initial workforce consists of 750 man-days and, at regular time per worker, there are 8 working hours. Machining and labor times are $a = 2$ and $b = 2.5$, respectively, and, also, the coefficient of robustness is $\lambda = 10$. Other data are detailed in Table 3.

Our proposed formulation of robust APP is a linear programming model, so, we used LINGO8 software to solve this problem efficiently. The result of this package is shown in Table 4.

5.1. Classic approach

In the classical approach, the objective function is just based on the expected value of the fuzzy stochastic variable. In fact, in this approach, the robustness and, thus, the entropy, is not considered, and the classical method is used to define the objective function, which is based on the concept of expected value. So, the objective function in the classical approach is as follows:

$$\text{Min}Z = \sum_{t=1}^{T} \left(\frac{1}{2} R_{mt} + \frac{1}{4} (R_{lt} + R_{rt}) \right). \tag{32}$$

5.2. The robustness of proposed model

We considered the robustness of our proposed model compared to the classical approach. For this purpose, the illustrated problem is solved based on the proposed model, and the classical approach, and their solutions are obtained. So, these approaches are used to obtain the solutions as the production plans for the future. Note that at the beginning of the planning horizon, some parameters are uncertain and are fuzzy numbers. Just in the execution time of the plan, the real amounts of uncertain parameters will be determined. The real state of the system, with real occurred parameters, in execution time, must be determined to demonstrate the robustness of the proposed model. For this purpose, we simulated some possible real future scenarios that may occur after executing the production plan. So, 10 hypothetical scenarios that could occur in the real state of the system are generated at 2 periods. In each scenario, we generated a random number for each triangular fuzzy parameter that is included in its support interval. In fact, a random number is generated for each uncertain fuzzy parameter that illustrates the real amount of that parameter that may occur in the future. Each scenario is a possible state of the system that may exist in future reality. So, in each simulated scenario, all parameters have given certain amounts, so the real value for total cost can be calculated. In fact, the real value of total cost in the future is based on the following equation:

$$\text{Total cost} = \sum_{t=1}^{T} \Big(p_t P_t + o_t O_t + s_t S_t + hr_t H_t + l_t L_t + w_t W_t + h_t I_t + b_t B_t \Big). \tag{33}$$

In this equation, the amounts of parameters are given, and the two different solutions are determined, based on the proposed model and the classical approach. So, the total cost for each scenario is calculated for two approaches. The results obtained from solving the 10 generated scenarios are shown in Table 5.

In Table 5, the mean value is an expected value of ten amounts of total costs, and the variation is the difference between the largest and smallest values of the total costs in each row. The results illustrate that our proposed model generates a more robust solution for any possible future scenarios. Figure 2 shows that the values of the total cost for different scenarios are closer to each other than those values for the classical approach. In fact, the variation and fluctuation in the amount of total costs for different scenarios in the proposed robust approach is smaller than the classical

Table 4. Production plan by Lingo.

	Period (t)					
	1	**2**	**3**	**4**	**5**	**6**
Regular time production	1250	900	1100	1000	1000	1025
Over time production	500	270	330	300	400	410
Subcontracting products	200	200	250	250	250	270
Inventory	450	20	0	0	0	0
Backorder	0	0	0	350	350	540
Hiring level	0	0	0	0	73	11
Layoff level	229	177	0	0	0	0
Workforce level	521	344	344	344	417	428

Table 5. The results of total cost for 10 generated possible scenarios ($\lambda = 10$).

	Scenarios										**Mean value**	**Variation**
Total cost of proposed model	1292004	1319515	1299004	1329013	1310914	1319345	1292004	1317 689	1322456	1289457	1309140.1	39556
Total cost of classical approach	1326506	1252007	1349906	1187002	1218765	1198965	1325467	1198797	1187004	1339994	1258441.3	162904

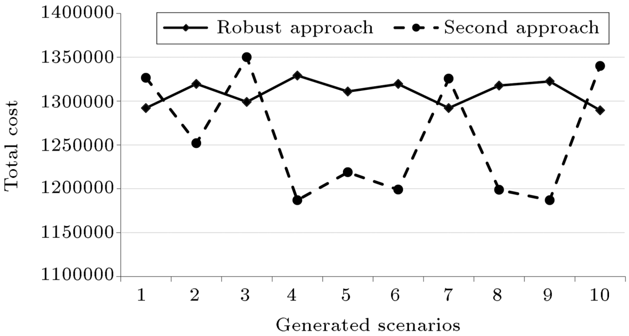

Figure 2. The comparison of solutions robustness between two approaches.

approach. The curve of total cost in the proposed method follows a more robust trend, but the fluctuation in the curve of the total cost for the classical approach is very high. As shown in Table 5 and Figure 2, the mean value of total cost in the robust approach is larger than the classical approach. This problem shows that the proposed approach is efficient for any system and that the robustness of the solution is important, in addition to the total costs of production, for their managers. In fact, for such systems, having a solution with minimum total cost is not adequate, but the fluctuation in real scenarios should be low. Nevertheless, it should be noted that it is possible, for some levels of λ, that the robust model may create a solution that has minimum value for the mean value of total cost, and minimum value for variations, simultaneously.

We should mention that the proposed model will certainly create a robust solution with minimum variation in the future, because of minimizing the entropy. But, minimization of the term of the mean value of the real total cost is dependent on λ, and this coefficient will be determined by system managers.

6. Conclusion

In this paper, a different interpretation of the robust optimization approach is presented. We proposed a robust aggregate production planning model with fuzzy parameters to minimize the total cost of production that is insensitive to uncertain parameters. We used the concept of entropy in our robust model to reduce the fluctuation of uncertain parameters and expected value to obtain the near optimal solution efficiently.

A hypothetical example was implemented to achieve the proposed model solution. Finally, the robustness of the proposed model solutions was compared with other fuzzy approaches, and the results showed that our robust model could generate a more robust solution for any possible future scenarios.

This paper concentrated on multi-period and one-product systems to show the efficiency of the proposed robust model well. For future research, the proposed method can be used for more practical models in production planning, and real-world cases can be conducted.

References

1. Nam, S.J. and Ogendar, N.R. "Aggregate production planning - A survey of models and methodologies", *European Journal of Operational Research*, **61**, pp. 255-272 (1992).
2. Kumar, G.M, and Noorul Haq, A. "Hybrid genetic-ant colony algorithms for solving aggregate production plan", *Journal of Advanced Manufacturing Systems (JAMS)*, **1**, pp. 103-111 (2005).
3. Hsu, H.M. and Lin, Y.J. "Fuzzy logic control of aggregate production planning using genetic algorithms", *International Journal of Industrial Engineering: Theory Applications and Practice*, **6**, pp. 325-333 (1999).
4. Luca, D.A. and Termini, A. "Definition of non-probabilistic entropy in the setting of fuzzy sets theory", *Information and Control*, **20**, pp. 301-312 (1972).
5. Bakir, M.A. and Byrne, M.D. "Stochastic linear optimization of an MPMP production planning model", *International Journal of Production Economics*, **55**, pp. 87-96 (1998).
6. Escudero, L.F., Kamesam, P.V., King, A.J. and Wets, R.J.B. "Production planning via scenario modeling", *Annals of Operations Research*, **43**, pp. 309-335 (1993).
7. Kazemi Zanjani, M., Nourelfath, M. and Ait-Kadi, D. "A stochastic programming approach for production planning in a manufacturing environment with random yield", CIRRELT, 58 Working Document, Québec, Canada (2007).
8. Türkşe, I.B. "A review of developments in fuzzy system models: Fuzzy rule basesto fuzzy function", *Scientia Iranica D*, **18**(3), pp. 522-527 (2011).
9. Wang, R. and Fang, H. "Aggregate production planning in a fuzzy environment", *International Journal of Industrial Engineering*, **7**(1), pp. 5-14 (2000).
10. Lee, Y.Y. "A fuzzy linear programming approach to aggregate production planning", *Journal of the Chinese Institute of Industrial Engineers*, **10**(1), pp. 25-32 (1993).
11. Dai, L., Fan, L. and Sun, L. "Aggregate production planning utilizing a fuzzy linear programming", *Journal of Integrated Design and Process Science*, **7**, pp. 81-95 (2003).
12. Fazel Zarandi, M.H., Moattar Hosein, S.M., Bastani, S. and Mohebi, A. "A fuzzy intelligent information agent architecture for supply chains", *Scientia Iranica*, **15**(5), pp. 623-636 (2008).
13. Fung, R., Tang, J. and Wang, D. "Multiproduct aggregate production planning with fuzzy demands and fuzzy capacities", *IEEE Transactions on Systems,*

Man, and Cybernetics Part A: Systems and Humans, **33**, pp. 302-313 (2003).

14. Wang, D. and Fang, S. "A genetics-based approach for aggregate production planning in a fuzzy environment", *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, **5**, pp. 636-645 (1997).
15. Wang, R. and Fang, H. "Aggregate production planning with multiple objectives in a fuzzy environment", *European Journal of Operational Research*, **133**, pp. 521-536 (2001).
16. Wang, R. and Liang, T. "Application of fuzzy multi-objective linear programming to aggregate production planning", *Computers and Industrial Engineering*, **46**, pp. 17-41 (2004).
17. Yan, W., Zhao, J. and Cao, Z. "Fuzzy programming model for lot sizing production planning problem", *Lecture Notes in Artificial Intelligence*, **36**(13), pp. 285-294 (2005).
18. Mulvey, J.M., Vanderbei, R.J. and Zenios, S.A. "Robust optimization of large-scale systems", *Operations Research*, **43**, pp. 264-281 (1995).
19. Leung, S.C.H. and Wu, Y. "A robust optimization model for stochastic aggregate production planning", *Production Planning and Control*, **15**, pp. 502-514 (2004).
20. Kazemi Zanjani, M., Ait-Kadi, D. and Nourelfath, M. "Robust production planning in a manufacturing environment with random yield: A case in sawmill production planning", *European Journal of Operational Research*, **201**(3), pp. 882-891 (2010).
21. Kwon, O., Imb, G.P. and Lee, K.C. "An agent-based web service approach for supply chain collaboration", *Scientia Iranica*, **18**(6), pp. 1545-1552 (2011).
22. Marano, G.C. and Quaranta, G. "Fuzzy-based robust structural optimization", *International Journal of Solids and Structures*, **45**, pp. 3544-3557 (2008).

Biographies

Donya Rahmani received her BS degree from Bu-Ali Sina University, Tehran, Iran, and MS and PhD degrees from Iran University of Science and Technology, Tehran, Iran, all in Industrial Engineering. She is currently Assistant Professor of Industrial Engineering at K.N. Toosi University of Technology, Tehran, Iran, and is reviewer of several international journals. Her research interests include production planning, robust optimization, dynamic scheduling and operations research.

Amir Yousefli holds a BS degree from Kurdistan University, Iran, and MS and PhD degrees from Iran University of Science and Technology (IUST), Tehran, Iran, all in Industrial Engineering. He is currently Assistant Professor of Industrial Engineering at Imam Khomeini International University (IKIU), Tehran, Iran. His research interests include fuzzy optimization and decision making, stochastic decision making, stochastic inference engines, uncertain management, artificial intelligence and location-allocation models. Dr. Yousefli is author of several papers on fuzzy decision making in fuzzy environments, applications of stochastic controllers in mathematical programming and optimization models and other applications of uncertain decision making. He is reviewer of several international journals.

Reza Ramezanian received BS, MS and PhD degrees, all in Industrial Engineering, from Iran University of Science and Technology, Tehran, Iran, and is currently Assistant Professor of Industrial Engineering at K.N. Toosi University of Technology, Tehran, Iran. His research interests include operation research, stochastic optimization, production planning, dynamic lot-sizing and scheduling theory and applications.