Dynamic Supplier Selection and Its Optimal Strategy Considering Full Truck Load and Fuzzy Demand using Fuzzy Expected Value-Based Programming

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Abstract: - This article proposes a linear integer optimization model incorporating fuzzy parameters to find the optimal solution for a dynamic supplier selection problem with uncertain demand. The uncertain demand value is represented using a fuzzy variable. A fuzzy expected value-based linear optimization solver is used to address the optimization problem, to minimize the total cost under fuzzy demand values. Several computational experiments were conducted to evaluate and analyze the model. The results show that the proposed model effectively identifies the optimal suppliers for each product. Additionally, the model determines the optimal purchase volumes for each product type from the selected suppliers, leading to the minimal total expected cost.

Key-Words: - dynamic supplier selection problem (DSSP), full truck load, fuzzy demand, fuzzy parameters, linear programming, order allocation, supply chain management.

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1 Introduction

A manufacturing company commonly faces supplier selection problems that involve determining the optimal or best suppliers from several possible alternatives. The optimal decision must satisfy the demand constraints and provide the best quality of purchased products or services to the manufacturer, [1]. In large business organizations, the supplier selection process often involves multiple products, multiple periods, and multiple suppliers, while maintaining quality and lead time. This is known as a Dynamic Supplier Selection Problem (DSSP) [2], [3] whereas a simpler problem is referred to as the Traditional Supplier Selection Problem (TSSP). The main difference between them is that the DSSP approach is more realistic than the TSSP due to its consideration of parameter dynamics over time, [4], [5].

The impact of transportation costs on DSSP is very significant, [6]. When a buyer splits orders among multiple suppliers, the delivery quantities from the suppliers to the buyer result in higher transportation costs. However, many researchers addressing supplier selection problems do not consider transportation costs in their proposed models. They usually include transportation costs within the product price. Therefore, including transportation costs when determining order quantities in DSSP is important to improve efficiency in the supply chain process, [7].

The demand value at the present time in a supplier selection problem is commonly known with certainty, but future demand is typically uncertain. The optimal decision on which supplier to select and the quantities to order from each supplier under uncertain demand is clearly more challenging. For certain demands, most researchers have used mathematical models to minimize total cost, [8], [9]. There are several other approaches to solving supplier selection problems, such as risk-optimizing approaches, integrated supplier selection, inventory management, and risk management, [10], [11], [12]. For supplier selection problems considering uncertain parameters, several research papers have been developed, most of which were solved using stochastic programming, [13], [14], [15], [16].

In uncertainty theory, an uncertain value can be approached in two ways: through frequency generated by samples (historical data or trials) and belief degrees evaluated by the .decision-maker, [17]. The frequency approach uses probability theory and is applicable when samples are available, as they can be used to determine the probability distribution. Unfortunately, in many cases, no samples are available to estimate the probability distribution. In such cases, belief degree theory can be used to estimate the uncertain value of a variable. The simplest form of the belief degree approach is by using a fuzzy variable. An uncertain value can be represented by a membership function defined by the decision maker. If an optimization problem contains at least one fuzzy variable (or parameter), then fuzzy programming can be used to solve it.

Fuzzy programming offers a powerful method for handling optimization problems with fuzzy variables. All forms of optimization, such as linear programming, quadratic programming, and general nonlinear programming, can be handled when they involve fuzzy parameters, [18], [19]. A general model of fuzzy linear optimization can be interpreted as a linear optimization problem in which some or all of the parameters are fuzzy variables or fuzzy numbers. There are several special cases: (1) the objective is crisp, (2) some or all constraints are crisp, (3) some or all constraints are soft constraints or a combination of these. In this paper, type (3), where the objective function is crisp and some constraints are soft constraints, will be used to select the optimal supplier when the demand value is fuzzy. To solve this, we can use the fuzzy expected value-based approach, [17].

In this article, we propose a mathematical model for dynamic supplier selection with a full truckload transport scheme under uncertain demand values in a linear fuzzy optimization framework. The fuzzy expected value-based approach is used to solve the minimization problem. Numerical experiments will be presented to demonstrate how the problem is solved using the proposed approach.

2 Materials and Methods

The developed model considers the multi-product, multi-supplier, and multi-period cases. We introduce the notations used in the model below:

indices:

P : Set of product sets

S : Set of suppliers

T : Set of time periods

Decision variables:

X_{tsp} : Amount (unit) of product p purchased from supplier s in time period t

Z_{ts} : The binary number that represents whether the supplier s is charged for order cost at period t, it will be 1 if yes or 0 if not

W_s : Binary number representing whether supplier s is chosen as a new supplier (1) or not (0)

S_{ts} : The number of truck that delivers product from supplier s in period t

i^+_{tp} : Inventory level of product p in time period t

i^-_{tp} : Shortage level of product p in time period t

Parameters:

UP_{sp} : Unit price of product p at supplier s in each time period

TC_s : FTL cost from supplier s to the buyer in each time period

NC_s : Cost occurs when a new supplier is selected to be contracted.

SOC_{tp} : Cost of shortage unit product p in time period t

C : Full truck load maximum capacity

D_{tp} : Demand value (unit) of product p in period t

SC_{tsp} : Maximum capacity of supplier s to supply product p in period t

l_{sp} : Late on delivery rate (in percentage) of ordered product from suppliers of product p

de_{sp} : Percentage of rejected product p from supplier s

P^l_p : Penalty cost for late delivery of product p in each time period

P^d_p : Penalty cost for defective product p

O_s : Cost that occurred while ordering products from supplier s

h_p : Cost for storing a unit product p per one time period

MS_{tp} : Maximum warehouse capacity to store product p in time period t

ϕ_{tp} : Service level value of supplier in time period t for product p. The value $(1-\phi)$ means the proportion of unsatisfied demand.

Figure 1 shows the solution procedure implemented in this study. In the first 3 steps, the DM has a significant role especially since he has to define the membership function value for each fuzzy parameter. This defining process is using intuition from the DM based on his experience.

Let $\tilde{D}_{tp}$ be the fuzzy variable of the demand value of product *p* in review period *t*. The solution must satisfy the demand value, meaning the total purchased product must be greater than or equal to the demand. However, if the demand is uncertain and represented by a fuzzy variable, the purchase quantity must be greater than the fuzzy variable of the demand. This condition can be referred to as a not-well-defined problem since the feasible set does not produce a crisp value. As a result, the optimal strategy cannot be determined as a crisp value. To address this, the authors approach the crisp value of the fuzzy demand by using the fuzzy expected value. In fact, there are several formulas to calculate the expected value of a fuzzy number. Our proposed approach used the expectation value defined in [20] where in any time period *t* and for each product *p*, the expectation of $\tilde{D}_{tp}$ is given by:

$$E\left[\tilde{D}_{tp}\right]=\int_0^{\infty} Cr\left\{\tilde{D}_{tp}\geq r\right\}dr-\int_{-\infty}^{0} Cr\left\{\tilde{D}_{tp}\leq r\right\}dr \quad (1)$$

provided that at least one result of these two integral terms is finite where $Cr[\cdot]$ is denoting the credibility value.

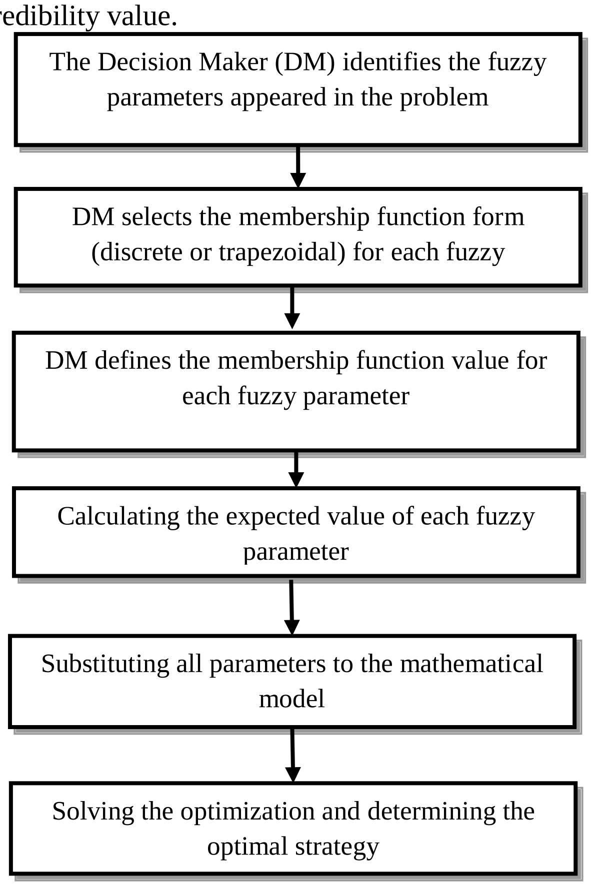

Fig. 1: The solution procedure

The formula can be used to calculate the expectation of any fuzzy number according to its membership function. For a special case where the discrete fuzzy number/variable ξ having the membership function given by:

$$\mu_\xi(x)=\begin{cases}\mu_1, \text{ if } x=x_1\\ \mu_2, \text{ if } x=x_2\\ \vdots\\ \mu_m, \text{ if } x=x_m\end{cases} \quad (2)$$

with x_1, x_2, …, x_m distinct and $x_m > x_{m-1} > \cdots > x_2 > x_1$, the expectation of ξ will be

$$E[\xi]=\sum_{i=1}^{m} w_i x_i \quad (3)$$

where

$$w_i=\tfrac{1}{2}\left(\max_{1\leq j\leq i}\mu_j-\max_{1\leq j<i}\mu_j+\max_{i\leq j\leq m}\mu_j-\max_{1<j\leq m}\mu_j\right) \quad (4)$$

for $i=1,2,\ldots,m$. For a trapezoidal fuzzy number $\tilde{T}=(a,b,c,d)$, the expectation value is

$$E\left[\tilde{T}\right]=\frac{a+b+c+d}{4}. \quad (5)$$

In the supplier selection problem with fuzzy demand that we are discussing, the objective is to minimize the total procurement cost, with constraints to satisfy the fuzzy demand and other related conditions. The mathematical model is as follows:

$$\begin{aligned}\min Z=&\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{p=1}^{P}X_{tsp}\cdot UP_{sp}+\sum_{t=1}^{T}\sum_{s=1}^{S}O_s\cdot Z_{ts}\\&+\sum_{t=1}^{T}\sum_{s=1}^{S}NC_s\cdot W_s+\sum_{t=1}^{T}\sum_{p=1}^{P}h_p\cdot i_{tp}^{+}\\&+\sum_{t=1}^{T}\sum_{p=1}^{P}SOC_p\cdot i_{tp}^{-}+\sum_{t=1}^{T}\sum_{s=1}^{S}TC_s\cdot S_{ts}\\&+\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{p=1}^{P}P_p^{d}\cdot de_{sp}\cdot X_{tsp}\\&+\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{p=1}^{P}P_p^{l}\cdot l_{sp}\cdot X_{tsp}\end{aligned} \quad (6)$$

Subject to:

$$\begin{aligned}&i_{(t-1)p}^{+}-i_{tp}^{+}+\sum_{s=1}^{S}X_{tsp}+\sum_{s=1}^{S}l_{ps}X_{(t-1)sp}\\&-\sum_{s=1}^{S}l_{ps}X_{tsp}-\sum_{s=1}^{S}d_{ps}X_{tsp}-i_{(t-1)p}^{-}\\&+i_{tp}^{-}\geq E\left[\tilde{D}_{tp}\right],\forall t\in T,\forall p\in P;\end{aligned} \quad (7)$$

$$\frac{i_{tp}^{-}}{(1-\phi_{tp})}\leq E\left[\tilde{D}_{tp}\right],\forall p\in P,\forall t\in T; \quad (8)$$

$$\left\lceil \frac{\sum_{p=1}^{P} X_{tsp}}{C} \right\rceil \le S_{ts}, \forall s \in S, \forall t \in T; \quad (9)$$

$$X_{tsp} \le SC_{tsp}, \forall p \in P, \forall s \in S, \forall t \in T; \quad (10)$$

$$\sum_{p=1}^{P} X_{tsp} \le M \cdot Z_{ts}, \forall s \in S, \forall t \in T; \quad (11)$$

$$i_{tp}^{+} \le MS_{tp}, \forall p \in P, \forall t \in T; \quad (12)$$

$$\sum_{t=1}^{T} Z_{ts} \le M \cdot W_s, \forall s \in S; \quad (13)$$

$$X_{tsp}, i_{tp}^{+}, i_{tp}^{-} \text{ integer}; \quad (14)$$

$$Z_{ts}, W_s \in \{0,1\}. \quad (15)$$

The objective function Z represents the total operational cost whereas constraints (7)-(15) can be explained respectively as follows. The first constraint is used to manage the inventory and for demand satisfaction. The second one is the service level requirement whereas the third one is the full truck load condition. The fourth to the ninth constraints respectively represent the supplier capacity, ordering cost, storage capacity, new supplier indicator, integer constraint, and binary constraint for the decision variables.

3 Results and Discussion

3.1 Results

In this section, we evaluate the optimization model (6) using data given in Table 1, Table 2, Table 3, Table 4, Table 5 and Table 6. We consider three products, four suppliers over a planning horizon of ten periods. Table 1 provides the unit price (UP_{tsp}) that is offered by each supplier. Table 2 shows the supplier capacity of each supplier. Table 3 presents parameter values related to products i.e. the values of storage capacities, defect penalties, late delivery penalties, holding costs, and shortage costs. Table 4 provides parameter values related to suppliers that consist of ordering costs, contract costs and transportation costs. Defect rates at all supplier are shown in Table 5. Table 6 presents late rates at all suppliers.

Table 1. Unit price for all time periods

Supplier	Products		
	P1	P2	P3
S1	40	82	61
S2	42	83	62
S3	41	82	62
S4	41	81	61

Table 2. Supplier capacity for all time periods

Supplier	Products		
	P1	P2	P3
S1	1200	400	750
S2	1000	350	650
S3	950	300	800
S4	900	450	850

Table 3. Product's parameter value for all periods

Parameter	P1	P2	P3
Storage capacity (unit)	1200	1000	1000
Defect penalty ($)	1	2	1
Late delivery penalty ($)	0.5	0.01	0.02
Holding cost ($)	0.2	0.8	0.4
Shortage cost ($)	1	1	2

Table 4. Suppliers' parameters in all periods

Supplier	Ordering cost	Contract cost	Transportation cost
S1	12	45	120
S2	10	50	120
S3	14	45	120
S4	12	40	120

Table 5. Defect rates in all time periods

Supplier	P1	P2	P3
S1	0.04	0.02	0.03
S2	0.04	0.04	0.00
S3	0.04	0.00	0.05
S4	0.03	0.02	0.05

Table 6. Late rates in all periods

Supplier	P1	P2	P3
S1	0.02	0.01	0.03
S2	0.00	0.04	0.05
S3	0.02	0.00	0.00
S4	0.04	0.03	0.02

Example 1 (Discrete membership function). Suppose a manufacturer faces a supplier selection problem involving three products: P1, P2, and P3, and four suppliers: S1, S2, S3, and S4, where the demand value for all products is uncertain. Assume that the decision-maker deals with uncertainty in demand values, which can be represented by fuzzy variables, with the membership functions being discrete and defined by:

$$\mu_{\tilde{D}_{t=1,4,p=1,2,3}} = \begin{cases} 0.25 \text{ if } \tilde{D}_{tp} = 480; 0.40 \text{ if } \tilde{D}_{tp} = 490; \\ 0.70 \text{ if } \tilde{D}_{tp} = 510; 1.00 \text{ if } \tilde{D}_{tp} = 530; \\ 0.90 \text{ if } \tilde{D}_{tp} = 550; 0.88 \text{ if } \tilde{D}_{tp} = 570; , \\ 0.75 \text{ if } \tilde{D}_{tp} = 590; 0.60 \text{ if } \tilde{D}_{tp} = 610; \\ 0.50 \text{ if } \tilde{D}_{tp} = 630; 0.45 \text{ if } \tilde{D}_{tp} = 650; \end{cases}$$

$$\mu_{\tilde{D}_{t=2,5,p=1,2,3}} = \begin{cases} 0.25 \text{ if } \tilde{D}_{tp} = 130; 0.40 \text{ if } \tilde{D}_{tp} = 140; \\ 0.70 \text{ if } \tilde{D}_{tp} = 150; 1.00 \text{ if } \tilde{D}_{tp} = 160; \\ 0.90 \text{ if } \tilde{D}_{tp} = 170; 0.88 \text{ if } \tilde{D}_{tp} = 180; \\ 0.75 \text{ if } \tilde{D}_{tp} = 190; 0.60 \text{ if } \tilde{D}_{tp} = 200; \\ 0.50 \text{ if } \tilde{D}_{tp} = 210; 0.45 \text{ if } \tilde{D}_{tp} = 220; \end{cases},$$

$$\mu_{\tilde{D}_{t=3,p=1,2,3}} = \begin{cases} 0.25 \text{ if } \tilde{D}_{tp} = 370; 0.40 \text{ if } \tilde{D}_{tp} = 395; \\ 0.70 \text{ if } \tilde{D}_{tp} = 410; 1.00 \text{ if } \tilde{D}_{tp} = 430; \\ 0.90 \text{ if } \tilde{D}_{tp} = 450; 0.88 \text{ if } \tilde{D}_{tp} = 460; \\ 0.75 \text{ if } \tilde{D}_{tp} = 465; 0.60 \text{ if } \tilde{D}_{tp} = 475; \\ 0.50 \text{ if } \tilde{D}_{tp} = 480; 0.45 \text{ if } \tilde{D}_{tp} = 490; \end{cases},$$

$$\mu_{\tilde{D}_{t=6,9,p=1,2,3}} = \begin{cases} 0.22 \text{ if } \tilde{D}_{tp} = 430; 0.58 \text{ if } \tilde{D}_{tp} = 440; \\ 0.65 \text{ if } \tilde{D}_{tp} = 460; 0.75 \text{ if } \tilde{D}_{tp} = 480; \\ 1.00 \text{ if } \tilde{D}_{tp} = 500; 0.99 \text{ if } \tilde{D}_{tp} = 520; \\ 0.62 \text{ if } \tilde{D}_{tp} = 540; 0.50 \text{ if } \tilde{D}_{tp} = 560; \\ 0.35 \text{ if } \tilde{D}_{tp} = 580; 0.25 \text{ if } \tilde{D}_{tp} = 600; \end{cases}$$

$$\mu_{\tilde{D}_{t=7,10,p=1,2,3}} = \begin{cases} 0.25 \text{ if } \tilde{D}_{tp} = 80; 0.54 \text{ if } \tilde{D}_{tp} = 90; \\ 0.60 \text{ if } \tilde{D}_{tp} = 100; 0.72 \text{ if } \tilde{D}_{tp} = 110; \\ 0.85 \text{ if } \tilde{D}_{tp} = 120; 0.92 \text{ if } \tilde{D}_{tp} = 130; \\ 1.00 \text{ if } \tilde{D}_{tp} = 140; 0.85 \text{ if } \tilde{D}_{tp} = 150; \\ 0.75 \text{ if } \tilde{D}_{tp} = 160; 0.40 \text{ if } \tilde{D}_{tp} = 170; \end{cases},$$

$$\mu_{\tilde{D}_{t=8,p=1,23}} = \begin{cases} 0.10 \text{ if } \tilde{D}_{tp} = 320; 0.54 \text{ if } \tilde{D}_{tp} = 345; \\ 0.72 \text{ if } \tilde{D}_{tp} = 370; 0.75 \text{ if } \tilde{D}_{tp} = 380; \\ 1.00 \text{ if } \tilde{D}_{tp} = 400; 0.90 \text{ if } \tilde{D}_{tp} = 410; \\ 0.80 \text{ if } \tilde{D}_{tp} = 415; 0.65 \text{ if } \tilde{D}_{tp} = 425; \\ 0.52 \text{ if } \tilde{D}_{tp} = 430; 0.45 \text{ if } \tilde{D}_{tp} = 440. \end{cases}.$$

We solved (6) for 10 time periods in LINGO® 17.0 with a daily used personal computer with the Operating System Windows 8, RAM 4 GB, and Processor AMD A6 2.7 GHz. The solution or the optimal decision obtained by the calculation is shown in Figure 2 (Appendix). It describes the optimal solution, which specifies the amount of each product that the manufacturer should purchase from each corresponding supplier to achieve the minimum expected total cost. For example, in period 1, P1 is supplied with 423 units by Supplier 1, 70 units by Supplier 3, and 71 units by Supplier 4. For P2, the orders in period 1 are split as 51 units to Supplier 1, 4 units to Supplier 2, and 121 units to Supplier 3. Orders for P3 are fulfilled with 126 units from Supplier 1, 326 units from Supplier 2, and 8 units from Supplier 3. The total cost for this solution is \$ 613,468.

Example 2 (Trapezoidal membership function). For this example, let $\tilde{D}_{tp}$ be the fuzzy demand value with a trapezoidal membership function illustrated by Figure 3 (Appendix) where the values of $a_{tp}, b_{tp}, c_{tp}, d_{tp}$ are given in Table 7. By evaluating the optimization problem (6) over 10 time periods, where the demand is represented by a trapezoidal membership function shown in Figure 3 (Appendix), we derive the optimal strategy illustrated in Figure 3 (Appendix). The optimal strategy consists of the unit volumes of all products that the manufacturer should order from each supplier in each time period (1, 2, …, 10) to achieve the minimum expected total cost. From Figure 4 (Appendix), we can see that in time period 1, 273 units of product P1 and 1 unit of product P2 should be purchased from Supplier 1, 180 units of P3 must be purchased from Supplier 2, and 1 unit of P1 and 76 units of P2 must be purchased from Supplier 4. The optimal strategies for each subsequent time period (2, 3, …, 10) can be obtained from Figure 4 (Appendix). The expected total cost for all time periods is 259,288.

3.2 Discussion

From the two examples, we can draw several interpretations. In the first example, the decision maker needs to specify certain discrete demand values where the membership values are positive, while other discrete demand values have membership values of zero. In the second example, the decision maker must determine the membership values of the demand, which are assumed to follow a line segment in the corresponding piecewise linear trapezoidal function. The first example, which uses a discrete membership function, is easier to apply since the decision maker only needs to determine the demand and its membership values. In contrast, the second example requires the decision maker to specify the lower bound with a membership value of 0, the mid-lower bound and mid-upper bound with membership values of 1, and the upper bound with a membership value of 0 in the trapezoidal function. This means that the membership values for demand between these points are not decided by the decision maker, as they will follow the trapezoidal function shown in Figure 3 (Appendix). Consequently, this approach may not fully represent the real conditions of the problem.

Table 7. Trapezoidal membership functions of $\tilde{D}_{tp}$

Period	Product	Trapezoidal fuzzy membership function for $\tilde{D}_{tp}$ i.e. $\mu_{\tilde{D}_{tp}} = (a_{tp}, b_{tp}, c_{tp}, d_{tp})$				Expectation Value $E[\tilde{D}_{tp}]$
		a_{tp}	b_{tp}	c_{tp}	d_{tp}	
1	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
2	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
3	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
4	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
5	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
6	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
7	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
8	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
9	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170
10	P1	100	200	250	350	225
	P2	40	60	70	120	72.5
	P3	50	150	200	280	170

4 Conclusion

A dynamic supplier selection problem with a full truckload transport scheme and fuzzy demand was considered. A fuzzy expected value-based approach for fuzzy optimization was formulated and successfully used to determine the optimal decisions and calculate the optimal product volumes that the manufacturer should purchase from the selected suppliers for all time periods. The solution procedure involves the following steps: first, the decision maker (DM) identifies the fuzzy parameters; second, the DM defines the membership function values for each fuzzy parameter; third, the expectation for all fuzzy parameters is calculated; fourth, these values are substituted into the formulated model; and finally, the corresponding linear programming problem is solved using LINGO. Two numerical examples were considered. For all given problems, the proposed approach successfully obtained the optimal decisions, i.e., the optimal product volumes for all time periods from each supplier were determined with minimal expected total cost. The decision maker can then use and apply these optimal decisions to the manufacturing system.

References:

[1] M. Qasim, K. Y. Wong, and Komarudin, "A review on aggregate production planning under uncertainty: Insights from a fuzzy programming perspective," *Eng Appl Artif Intell*, vol. 128, p. 107436, 2024, doi: https://doi.org/10.1016/j.engappai.2023.107436.

[2] N. R. Ware, S. P. Singh, and D. K. Banwet, "A mixed-integer non-linear program to model dynamic supplier selection problem," *Expert Syst Appl*, vol. 41, no. 2, pp. 671–678, 2014, doi: 10.1016/j.eswa.2013.07.092.

[3] F. Firouzi and O. Jadidi, "Multi-objective model for supplier selection and order allocation problem with fuzzy parameters," *Expert Syst Appl*, vol. 180, 2021, doi: 10.1016/j.eswa.2021.115129.

[4] M. T. Ahmad and S. Mondal, "Dynamic supplier selection model under two-echelon supply network," *Expert Syst Appl*, vol. 65, pp. 255–270, 2016, doi: 10.1016/j.eswa.2016.08.043.

[5] Ö. Karakoç, S. Memiş, and B. Sennaroglu, "A Review of Sustainable Supplier Selection with Decision-Making Methods from 2018 to 2022," *Sustainability*, vol. 16, no. 1(125), pp. 1–51, Dec. 2023, doi: 10.3390/su16010125.

[6] S. Aouadni, I. Aouadni, and A. Rebaï, "A systematic review on supplier selection and order allocation problems," *Journal of Industrial Engineering International*, vol. 15, no. 1, pp. 267–289, 2019, doi: 10.1007/s40092-019-00334-y.

[7] J. A. Ventura, B. Golany, A. Mendoza, and C. Li, "A multi-product dynamic supply chain inventory model with supplier selection, joint replenishment, and transportation cost," *Ann Oper Res*, vol. 316, no. 2, pp. 729–762, 2022, doi: 10.1007/s10479-021-04508-z.

[8] S. Islam, S. H. Amin, and L. J. Wardley, "Supplier selection and order allocation planning using predictive analytics and multi-objective programming," *Comput Ind*

Eng, vol. 174, p. 108825, 2022, doi: https://doi.org/10.1016/j.cie.2022.108825.

[9] H. Kaur, M. Gupta, and S. P. Singh, "Integrated model to optimize supplier selection and investments for cyber resilience in digital supply chains," *Int J Prod Econ*, vol. 275, p. 109338, 2024, doi: https://doi.org/10.1016/j.ijpe.2024.109338.

[10] W. Chen and Y. Zou, "An integrated method for supplier selection from the perspective of risk aversion," *Appl Soft Comput*, vol. 54, no. Supplement C, pp. 449–455, 2017, doi: https://doi.org/10.1016/j.asoc.2016.10.036.

[11] M. Y. Jaber, J. Peltokorpi, and T. L. Smunt, "The lot size problem and the learning curve: A review of mathematical modeling (1950's -2020)," *Appl Math Model*, vol. 105, pp. 832–859, 2022, doi: https://doi.org/10.1016/j.apm.2022.01.007.

[12] S. Chen, R. Berretta, A. Clark, and P. Moscato, "Lot Sizing and Scheduling for Perishable Food Products: A Review," in *Reference Module in Food Science*, Elsevier, 2019. doi: https://doi.org/10.1016/B978-0-08-100596-5.21444-3.

[13] P. Amorim, E. Curcio, B. Almada-Lobo, A. P. F. D. Barbosa-Póvoa, and I. E. Grossmann, "Supplier selection in the processed food industry under uncertainty," *Eur J Oper Res*, vol. 252, no. 3, pp. 801–814, 2016, doi: https://doi.org/10.1016/j.ejor.2016.02.005.

[14] Y. Li, M. Liu, F. Saldanha-da-Gama, and Z. Yang, "Risk-averse two-stage stochastic programming for assembly line reconfiguration with dynamic lot sizes," *Omega (Westport)*, vol. 127, p. 103092, 2024, doi: https://doi.org/10.1016/j.omega.2024.103092

[15] I. Slama, O. Ben-Ammar, S. Thevenin, A. Dolgui, and F. Masmoudi, "Stochastic program for disassembly lot-sizing under uncertain component refurbishing lead times," *Eur J Oper Res*, vol. 303, no. 3, pp. 1183–1198, 2022, doi: https://doi.org/10.1016/j.ejor.2022.03.025.

[16] I. Slama, O. Ben-Ammar, D. Garcia, and A. Dolgui, "Two-stage stochastic program for disassembly lot-sizing under random ordering lead time," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 1363–1368, 2022, doi: https://doi.org/10.1016/j.ifacol.2022.09.580.

[17] B. Liu, *Uncertainty Theory*. in Springer Uncertainty Research. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015. doi: 10.1007/978-3-662-44354-5.

[18] J. C. Figueroa–García, G. Hernández, and C. Franco, "A review on history, trends and perspectives of fuzzy linear programming," *Operations Research Perspectives*, vol. 9, p. 100247, 2022, doi: https://doi.org/10.1016/j.orp.2022.100247.

[19] N. Karimi, M. R. Feylizadeh, K. Govindan, and M. Bagherpour, "Fuzzy multi-objective programming: A systematic literature review," *Expert Syst Appl*, vol. 196, p. 116663, 2022, doi: https://doi.org/10.1016/j.eswa.2022.116663.

[20] B. Liu and Y. K. Liu, "Expected value of fuzzy variable and fuzzy expected value models," *IEEE Transactions on Fuzzy Systems*, vol. 10, no. 4, pp. 445–450, 2002, doi: 10.1109/TFUZZ.2002.800692.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.

APPENDIX

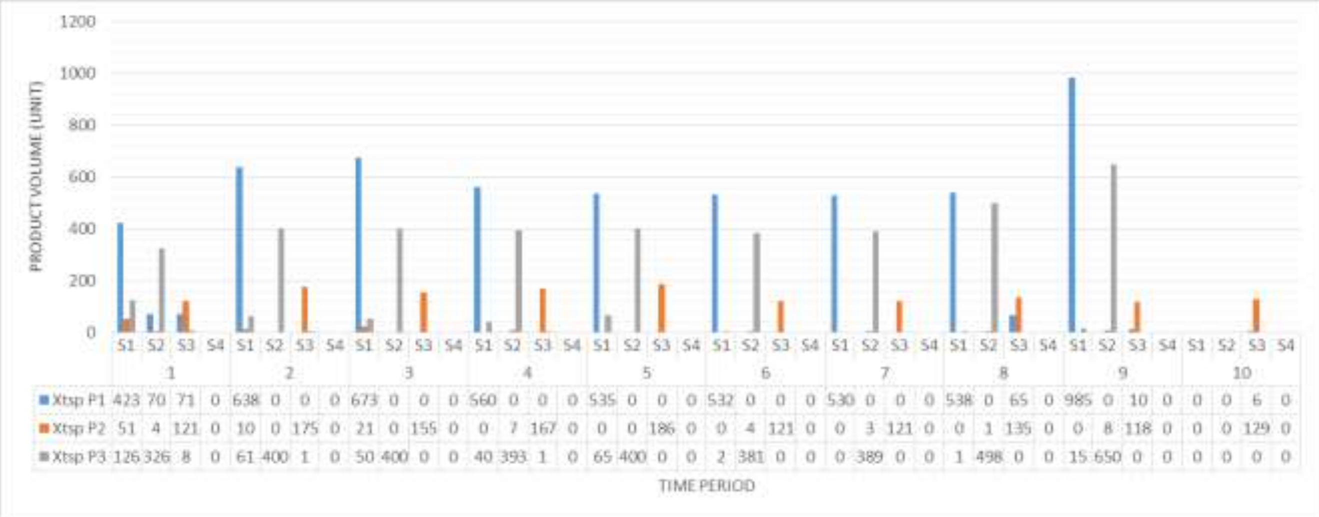

Fig. 2: Optimal product volume for time periods 1 to 10

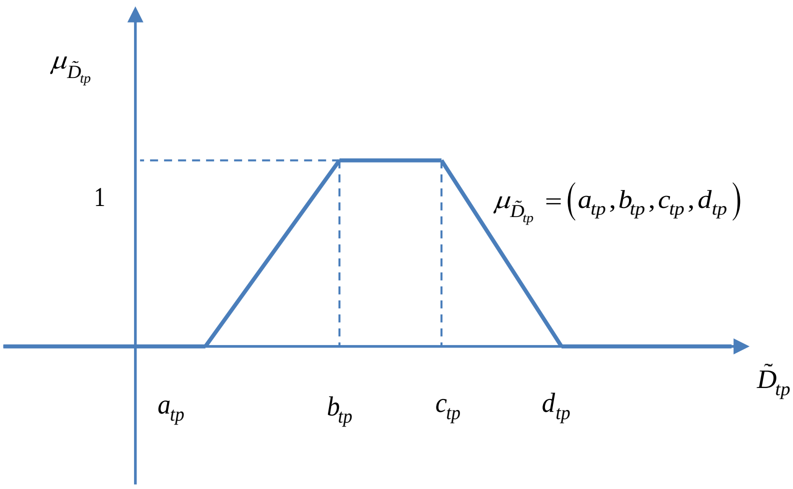

Fig. 3: Trapezoidal membership function $\mu_{\tilde{D}_{tp}} = (a_{tp}, b_{tp}, c_{tp}, d_{tp})$

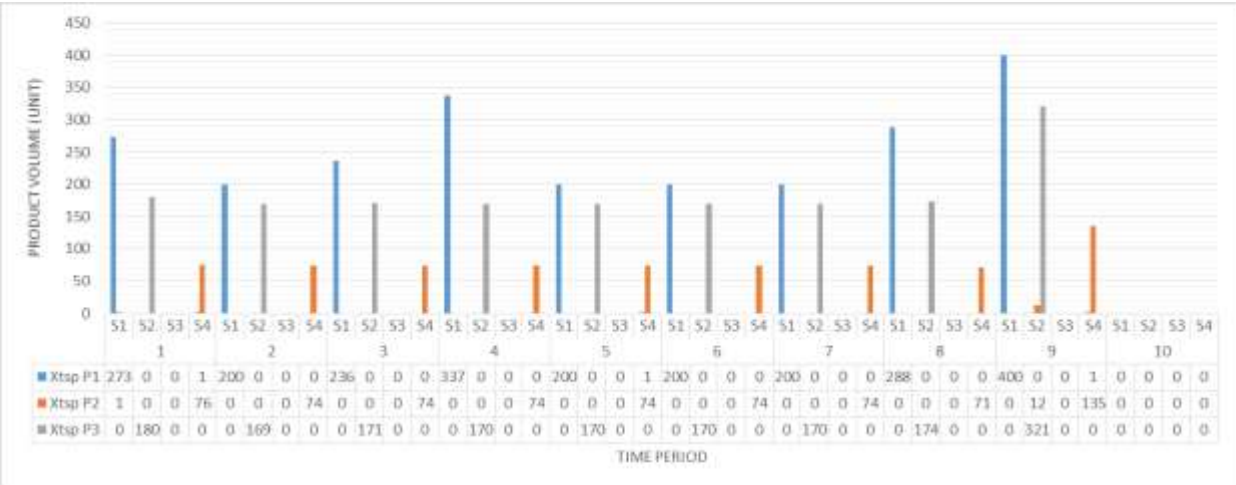

Fig. 4: Optimal product volume for Example 2