Jurnal Sistem Informasi Bisnis 03(2025)
Copyright ©2025, JSINBIS, p-ISSN: 2502-2377, e-ISSN: 2088-3587
On-line: http://ejournal.undip.ac.id/index.php/jsinbis/article/view/71820

Fuzzy Piecewise-objective Programming Approach for Integrated Supplier Selection and Production Planning Problems Considering Discounts and Fuzzy Parameters: the Static Case

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Submitted: March 16th, 2025; Revised: April 17th, 2025;
Accepted: May 15th, 2025; Available Online: Juli 17th, 2025
DOI: 10.21456/vol15iss3pp347-353

Abstract

In the manufacturing and retail sectors, the challenge of supplier selection revolves around efficiently allocating the necessary amount of raw materials to each supplier to minimize procurement costs. Concurrently, production planning focuses on maximizing output. To achieve maximum revenue, decision-makers must make optimal decisions in both areas. This paper introduces a new mathematical model, falling within the fuzzy piecewise programming domain, to support decision-making in supplier selection and production planning. It addresses integrated supplier selection and production planning issues, incorporating discounts and fuzzy factors. The aim is to optimize supply chain performance, ultimately maximizing the production activity profit. The model accommodates scenarios involving multiple raw materials, suppliers, products, and buyers. Through numerical experiments, the effectiveness of the proposed model is evaluated, demonstrating its ability to provide the optimal solution. Thus, it can be readily applied by industry decision-makers and managers.

Keywords: Fuzzy Piecewise Programming; Supplier Selection; Production Planning; Supply Chain Optimization; Discount Consideration

1. Introduction

Manufacturing and retail businesses are constantly seeking ways to optimize their decision-making processes to maximize profitability. Key areas of focus include supplier selection, also referred to as order allocation planning, and production planning. In supplier selection, decision-makers must identify which suppliers to source raw materials or components from and determine the appropriate quantities to meet production needs. Conversely, in production planning, decision-makers must establish the quantities of each product type or brand to manufacture in order to satisfy customer demand. These decisions are driven by the overarching goal of profit maximization. Moreover, decision-makers must navigate various constraints, such as supplier and production capacities, to ensure the chosen actions are feasible.

Extensive research and practical exploration have been conducted on these topics, yielding a variety of approaches to address these challenges. The prevalent approach involves constructing mathematical models, such as optimization models or programming frameworks. However, each model typically addresses these issues with its own set of specifications. For instance, a basic linear programming model introduced by (Ware et al., 2014) facilitates solving supplier selection problems, albeit without incorporating production planning and under the assumption of known parameters. In contrast, (Limi et al., 2024) developed a somewhat more intricate model tailored for managing deteriorating products. Other existing models target specific scenarios, including those involving rapid service demand (Alegoz & Yapicioglu, 2019) analytical hierarchy processes (Manik, 2023) and machine learning techniques (Ali et al., 2023) among others. These models have been primarily tested theoretically and through simulations with randomly generated data. Moreover, practical applications of these models have been demonstrated across various industries, including logistics management (Ghorbani & Ramezanian, 2020) food companies (Hajiaghaei-Keshteli et al., 2023) glove manufacturing (T.M. Joy, 2023) and defense sectors (Güneri & Deveci, 2023) among others.

It is worth noting that the studies referenced above primarily tackled the supplier selection problem in isolation. Similarly, various mathematical models

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have been devised to address production planning challenges, each tailored to the specific problem specifications. For instance, utilized a linear optimization model to tackle production planning in uncertain environments (Wang et al., 2024) while employed nonlinear optimization (Li et al., 2021). Other approaches involved single or multi-objective programming to address production planning under sustainability constraints (Lahmar et al., 2022; Wu et al., 2020; Yazdani et al., 2021; Zarte et al., 2022) mixed integer linear programming for scenarios with nonconstant consumptions (Adrio et al., 2023) and a model predictive control approach for sustainable aggregate planning (May et al., 2023) among others.

Despite the availability of numerous models, each is tailored to specific conditions or requirements. When faced with different scenarios, modifications or entirely new models are often necessary. In this paper, we address the supplier selection and production planning problems considering fuzzy parameters, integrating both activities into a single model capable of managing the flow of raw materials and products. Additionally, the model accounts for discounted pricing structures, where functions such as raw material costs, transportation expenses, and product selling prices may include discounts. Notably, existing literature lacks models tailored to this particular scenario, constituting the primary contribution of this paper. The problem is formulated using fuzzy programming with a piecewise objective function, and numerical experiments are performed to showcase the efficacy of the proposed model.

2. Method

2.1. Problem Setup

Consider a scenario where a manufacturing company plans to produce P product brands using R raw material types sourced from S suppliers or vendors. The flow of these raw materials and products is depicted in Fig. 1. The primary objective is to maximize profitability from this production endeavor, while adhering to specific constraints and limitations outlined in the subsequent sections.

The performance levels of suppliers exhibit variability, encompassing factors such as maximum capacity limits for raw material supply, pricing structures, defect rates, transportation expenses, and reliability in meeting delivery deadlines. This variability adds complexity to the decision-making process concerning raw material procurement.

Moreover, the problem entails considerations of discounts on prices or costs. This involves discounted rates offered by suppliers for raw materials, transportation expenses incurred from carriers, and prices set for products sold to buyers. In this investigation, discounted price functions are assumed to follow piecewise constant functions, where prices become cheaper for higher quantities of raw materials or products, with defined price break levels or points. For detailed technical information, refer to the mathematical modeling section.

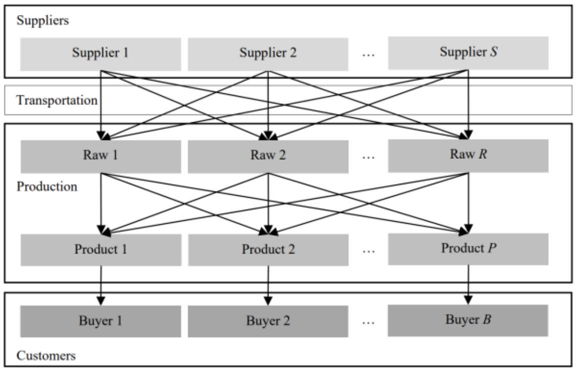

Fig. 1. flow of raw materials and products between suppliers, production units, and buyers

Additionally, suppliers impose restrictions on raw material supply, including limits on the maximum quantity that can be ordered, the potential for a portion of the raw materials to be rejected upon arrival due to damage or subpar quality, and the possibility of some raw materials not being delivered on time, rendering them unusable in production. While maximum capacities are ascertainable, the rates of rejected and late-delivered raw materials remain uncertain. However, it is assumed that historical data are accessible, allowing for the treatment of these uncertain values as fuzzy parameters, with suitable fuzzy distribution functions like the normal or Gaussian distribution. Notably, all decision variables in this study are assumed to be integer-based measurements, necessitating consideration within the model formulation.

2.2 Methodology

The methodology is outlined as a series of problem-solving steps. The initial step has been elaborated on previously. In the subsequent step, four uncertain parameters are taken into account: rates of rejected and tardy delivery of raw materials from suppliers, the rejection rate of products during production, and the demand for products from buyers. Concurrently, the decision variables encompass deciding the number of each raw material type to order from each supplier, planning the production of each product brand using available raw materials, determining the quantity of trucks utilized for raw material transportation, and introducing artificial decision variables to indicate supplier selection for raw material supply.

Following this, discounted price/cost functions and fuzzy distribution functions for the uncertain parameters are formulated. Piecewise constant functions, as elaborated in the mathematical modeling section, are employed for technical elaboration, while

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normal or Gaussian distribution functions, as explained in the numerical experiment results, are utilized. Subsequently, the problem is mathematically modeled, with the objective function aimed at maximizing profit from raw material procurement, production, and product sales. Constraint functions are devised in accordance with the problem's specifications detailed in the preceding section, as described further in the mathematical modeling section.

Proceeding, the optimal decision is determined from the derived mathematical programming. An interior point algorithm, supplemented with branch-and-bound techniques to obtain integer solutions, is employed for this purpose. Finally, the resultant optimal decision is implemented by the decision-maker.

3. Mathematical Model

The supplier selection and production planning problems defined in the previous section are modeled as follows. First, define the following symbols:

indices

- m : type raw material;
- s : index of supplier;
- p : type of product brand;
- b : index of buyer;
- i, j, k : index of discount level;

decision variables:

- X_{ms} : amount of raw material of type m purchased to supplier s;
- O_p : amount of product type p produced by the manufacturer;
- D_s : delivery number to transport raw materials from supplier s to the manufacturer;
- K_s : indicator variable for supplier s whether some raw materials are purchased to the supplier or not; 1 if yes, 0 if not;

prices or costs with discounts:

- $CP_{ms}^{(i)}$: discounted price on discount level i for one unit of raw material m at supplier s;
- $CS_{pb}^{(j)}$: discounted selling price on discount level j for one unit of product brand p sold to buyer b;
- $DT_s^{(k)}$: discounted transportation cost on discount level k for one time of delivery in transporting raw materials from supplier s to the manufacturer;

fuzzy parameters:

- TD_{ms} : rates of raw material type r's defect amount that was ordered to supplier s;
- TL_{ms} : rates of raw material type r's late delivered amount that was ordered to supplier s;
- TD_p : rates of product brand p's defect amount.
- AP_{pb} : amount of product brand p's demand from buyer b.

deterministic parameters:

- CM_s : cost to order raw materials to supplier s;
- PC_p : cost to produce one unit of product brand p;
- SM_{ms} : supplier s's maximum capacity limit in supplying raw material type m;
- MCT : maximum capacity of the truck used in transporting raw materials from suppliers to the manufacturer;
- PL_{ms} : cost to penalize one unit of late delivered raw material type m that was ordered to supplier s;
- PD_{ms} : cost to penalize one unit of defected raw material type m that was ordered to supplier s;
- AM_{mp} : amount of raw material type m that is needed to produced one unit product brand p.

Now, we present the scheme of the discounted prices and costs. It is modeled as piecewise constant functions as follows. The discounted prices for raw materials are formulated as

$$CP_{ms} = \begin{cases} CP_{ms}^{(1)} & \text{if } \; 0 = X_{ms}^{(0)} < X_{ms} \le X_{ms}^{(1)}, \\ CP_{ms}^{(2)} & \text{if } \; X_{ms}^{(1)} < X_{ms} \le X_{ms}^{(2)}, \\ \vdots & \\ CP_{ms}^{(I)} & \text{if } \; X_{ms}^{(I-1)} < X_{ms} \le X_{ms}^{(I)}. \end{cases} \quad (1)$$

Similarly, the discounted transport costs are formulated as

$$DT_s = \begin{cases} DT_s^{(1)} & \text{if } \; 0 = D_s^{(0)} < D_s \le D_s^{(1)}, \\ DT_s^{(2)} & \text{if } \; \mathrm{D}_s^{(1)} < D_s \le D_s^{(2)}, \\ \vdots & \\ DT_s^{(K)} & \text{if } \; \mathrm{D}_s^{(K-1)} < D_s \le D_s^{(K)}. \end{cases} \quad (1)$$

Using the same scheme, the discounted product selling prices are formulated as

$$CS_{pb} = \begin{cases} CS_{pb}^{(1)} & \text{if } \; 0 = AP_{pb}^{(0)} < AP_{pb} \le AP_{pb}^{(1)}, \\ CS_{pb}^{(2)} & \text{if } \; \mathrm{AP}_{pb}^{(1)} < AP_{pb} \le AP_{pb}^{(2)}, \\ \vdots & \\ CS_{pb}^{(J)} & \text{if } \; \mathrm{AP}_{pb}^{(J-1)} < AP_{pb} \le AP_{pb}^{(J)}. \end{cases} \quad (3)$$

As the consequence of the discounted product selling prices defined above, the income (T_{ic}) has also the form of the piecewise function. This is formulated as

$$T_{ic}=\begin{cases}\sum_{p=1}^{P}[CS_{pb}^{(1)}\cdot AP_{pb}] & \text{if } 0=AP_{pb}^{(0)}<AP_{pb}\leq AP_{pb}^{(1)},\\ \sum_{p=1}^{P}[CS_{pb}^{(2)}\cdot AP_{pb}] & \text{if } AP_{pb}^{(1)}<AP_{pb}\leq AP_{pb}^{(2)},\\ \vdots & \\ \sum_{p=1}^{P}[CS_{pb}^{(J)}\cdot AP_{pb}] & \text{if } AP_{pb}^{(J-1)}<AP_{pb}\leq AP_{pb}^{(J)}.\end{cases}$$

Total of seven operational cost components was taken into account. This includes order cost, purchasing cost, delivery cost, penalty cost of late deliveries, penalty cost of defect raw materials, production cost, and penalty cost for defect products. Based on the discounted prices and costs defined above, those cost components are modeled as

$$T_1=\sum_{s=1}^{S}[OC_s\times K_s]$$

$$T_2=\begin{cases}\sum_{m=1}^{M}\sum_{s=1}^{S}[CP_{ms}^{(1)}\times X_{ms}] & \text{if } X_{ms}^{(0)}<X_{ms}\leq X_{ms}^{(1)}\\ \sum_{m=1}^{M}\sum_{s=1}^{S}[CP_{ms}^{(2)}\times X_{ms}] & \text{if } X_{ms}^{(1)}<X_{ms}\leq X_{ms}^{(2)}\\ \vdots & \\ \sum_{m=1}^{M}\sum_{s=1}^{S}[CP_{ms}^{(d_u)}\times X_{ms}] & \text{if } X_{ms}^{(I-1)}<X_{ms}\leq X_{ms}^{(I)}\end{cases}$$

$$T_3=\begin{cases}\sum_{s=1}^{S}[DT_s^{(1)}\times D_s] & \text{if } D_s^{(0)}\leq D_s\leq D_s^{(1)}\\ \sum_{s=1}^{S}[DT_s^{(2)}\times D_s] & \text{if } D_s^{(1)}<D_s\leq D_s^{(2)}\\ \vdots & \\ \sum_{s=1}^{S}[DT_s^{(J)}\times D_s] & \text{if } D_s^{(J-1)}<D_s\leq D_s^{(J)}\end{cases} \quad (4)$$

$$T_4=\sum_{m=1}^{M}\sum_{s=1}^{S}[PL_{ms}\times T_p\times X_{ms}]$$

$$T_5=\sum_{m=1}^{M}\sum_{s=1}^{S}[PD_{ms}\times AP_{pb}\times X_{ms}]$$

$$T_6=\sum_{p=1}^{P}[PC_p\times O_p]$$

$$T_7=\sum_{p=1}^{P}[PDO_p\times DO_p\times O_p].$$

respectively. Based on the formulated income and costs, the expected profit, which needs to be maximized, can now be formulated, this is modeled as the following maximization problem:

$$\max Z=E\left[\sum_{b=1}^{B}[T_{ic}]-[T_1+T_2+T_3+T_4+T_5+T_6+T_7]\right] \quad (5)$$

where $E[\cdot]$ denotes the expectation value. We now present the mathematical modeling parts for the constraint functions based on the problem's specifications and conditions that must be fullfilled. First, the available raw materials should be sufficient to satisfy those that are needed to produce products. This is modeled as

$$\sum_{s=1}^{S}[X_{ms}-TL_{ms}\times X_{ms}-TD_{ms}\times X_{ms}]\geq\sum_{p=1}^{P}[AM_{mp}\times O_p]. \quad (6)$$

Second, the available product amount is expected to be sufficient to satisfy the demand, i.e., the number of the produced products minus defect ones is expected to be larger or at least equal to the demand; this is modeled as

$$O_p-TD_p\times O_p\geq\sum_{b=1}^{B}AP_{pb}]. \quad (7)$$

Third, the total amount of raw materials ordered to supplier s should be not exceeding the total capacity of the trucks used in the delivery; this is modeled as

$$\sum_{m=1}^{M}X_{ms}\leq MCT\times D_s. \quad (8)$$

Fourth, the number of each raw material type ordered to supplier s should be not exceeding the supplier's maximum capacity in supplying the corresponding raw material type. This is modeled as

$$X_{ms}\leq SM_{ms}. \quad (9)$$

The fifth constraint function is the indicator variables calculation to assign when supplier s is selected to supply raw materials. The indicator is set to be one if the corresponding supplier is selected, otherwise it is set to be zero. This is modeled as

$$K_s=\begin{cases}1 & \text{if } \sum_{m=1}^{M}X_{ms}>0,\\ 0 & \text{otherwise;}\end{cases} \quad (10)$$

The last constraint function is the nonnegativity and integer assignments for the decision variables. This is simply modeled as

$$X_{ms},D_s,O_p\geq 0 \text{ and integer.} \quad (11)$$

The optimization problem (5) subject to constraint functions (6)-(11) belongs to probabilistic piecewise linear integer programming since the objective function is a piecewise function and it contains probabilistic parameters. However, the existence of an optimal solution is always guaranteed since the feasible set, as long as not empty, is closed and bounded.

4. Numerical Experiment Results and Discussion

Laboratory-based numerical experiments were undertaken to validate the proposed decision-making support model using randomly generated data. All trials were performed utilizing personal computers equipped with standard specifications.

4.1 Problem's Specification

Consider the supplier selection and production planning problems specified in the previous section where the number of raw material types is three (M1, M2, and M3), the number of suppliers is three (S1, S2, and S3), and the number of product types is also three (P1, P2, and P3). Meanwhile, the number of price break points or discount levels is also three (DL1, DL2 and DL3). The price/cost functions for each discounted price/cost are as follows: the unit price for raw materials ordered to supplier is equal to $CP_{ms}^{(1)}$ if the number of raw materials is less or equal to 50 units, $CP_{ms}^{(2)}$ if the number of raw matrials is larger than 50

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units but not larger than 100 units, and $CP_{ms}^{(3)}$ if it is larger than 100 units. Meanwhile, the unit price for products sell to buyers is equal to $CS_{pb}^{(1)}$ if the number of products is less or equal to 100 units, $CS_{pb}^{(2)}$ if the number of products is larger than 100 units but not larger than 200 units, and $CS_{pb}^{(3)}$ if it is larger than 200 units. And, the one time transportation cost from suppliers to the manufacturer is equal to $DT_s^{(1)}$ if the number of deliveries is only one time, $DT_s^{(2)}$ if the number of deliveries is more than one time but less than 6 times, and $DT_s^{(3)}$ if it is more than 5 times. The values for those discounted prices or costs $CP_{ms}^{(i)}$, $CS_{pb}^{(j)}$ and $DT_s^{(k)}$ with $i, j, k = 1,2,3$ are shown in Table 1 to 3.

Table 1. Discounted prices for raw materials ($CP_{ms}^{(i)}$)

Supplier	Raw material								
	M1			M2			M3		
	DL1	DL2	DL3	DL1	DL2	DL3	DL1	DL2	DL3
S1	25	22	20	15	14	12	18	15	14
S2	24	20	19	14	13	10	20	18	15
S3	24	22	21	12	10	9	19	18	15

Table 2. Discounted prices for products ($CS_{pb}^{(j)}$)

Product	Buyer					
	B1			B2		
	DL1	DL2	DL3	DL1	DL2	DL3
P1	150	120	110	140	120	110
P2	180	150	140	130	120	110
P3	150	115	110	140	120	115

Table 3. Discounted costs of deliveries ($DT_s^{(j)}$)

Supplier	Discount Level		
	DL1	DL2	DL3
S1	75	70	60
S2	70	60	55
S3	65	60	50

Table 4. Other parameters

Parameter	Supplier/raw material/product type		
	S1/M1/P1	S2/M2/P2	S3/M3/P3
Order cost	200	210	230
Penalty cost for rejected raw materials	2	4	4
Penalty cost for late delivered raw materials	3	3	2
Penalty cost for defected products	2	1	2
Production cost	20	25	35
Rates of rejected raw materials (TD_{ms})	$N(0.02,0.005)$		
Rates of late delivered raw materials (TL_{rs})	$N(0.01,0.005)$		
Demands of products from buyers (AP_{pb})	$N(20,5)$		

Table 5. Supplier's Capacity

Supplier	Raw material type		
	M1	M2	M3
S1	600	400	300
S2	400	300	360
S3	300	160	200

5. Results and Discussion

All optimization procedures were conducted using LINGO 20.0 software, employing the primal simplex algorithm as the solver. The algorithm was supplemented with the branch-and-bound scheme to compute integer solutions. The resultant optimal solution, depicting the required quantities of each raw material type to be ordered from each supplier, is illustrated in Figure 3. It's essential to highlight that this optimal solution offers the maximum profit expectation and was derived while considering the uncertainty of fuzzy parameters. In addition, the amount of raw material shipments from suppliers is also illustrated in Figure 4.

It can be seen that all suppliers S1, S2, and S3 were selected to supply raw materials. The number of raw materials ordered to suppliers S1,S2 and S3 was always in the third discount level with more than 100 units for each type. This shows that ordering with lower numbers in the first or second discount level significantly increases the cost and thus was avoided. The number of raw materials ordered at S1 is 89 for M1, 133 for M2, and 263 for M3. The number of raw materials ordered at S2 is 400 for M1, 300 for M2, and 160 for M3. The number of raw materials ordered at S3 is 300 for M1, 360 for M2, and 200 for M3.The number of deliveries of goods made at S1 is 5, the number of deliveries of goods made at S2 is 9, and the number of deliveries of goods made at S3 is 9. Meanwhile, the optimal number of products that should be produced in the production unit is 142 units of brand P1, 145 units of brand P2, and 143 units of brand P3. The maximal profit was expected to be 33072 with income 36434.61 and cost 3362.609.

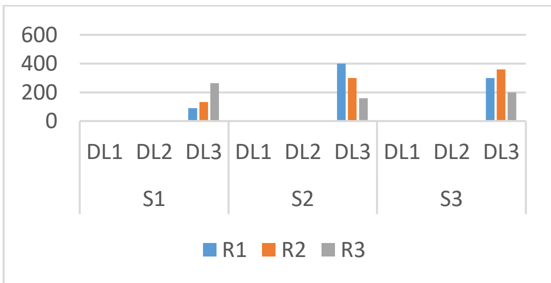

Fig 3. The optimal decision for the number of raw materials to be ordered from suppliers

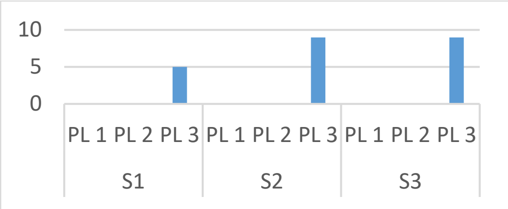

Fig 4. .The number of deliveries of goods from suppliers

The findings suggest that the proposed model effectively addressed the issue, optimizing profit expectations. Drawing from the mathematical model developed and numerical experimentation results, actionable managerial insights emerged. Firstly, the model's versatility was highlighted, capable of accommodating various raw materials and products within specified parameters, with potential minor adjustments. For instance, the utilization of real numbers instead of integers would obviate integer constraints, potentially eliminating the need for the branch-and-bound approach.

Moreover, enhancements to the model were considered, such as incorporating additional operational expenses like production machinery maintenance costs into the objective function. Furthermore, supplementary constraint functions, such as limitations on machine operating hours, budget constraints, and maximum delivery thresholds, could be integrated.

The numerical experiments were conducted on a small scale, yielding swift optimization outcomes within minutes. However, decision-makers must be cognizant of the potential computational challenges inherent in larger-scale scenarios, necessitating longer processing times. Employing high-performance computing resources may mitigate these challenges for timely decision-making.

It's imperative to note that all decisions were formulated and executed based on pre-existing uncertainty, with the profit derived from the optimization model representing an expectation. Subsequent to the resolution of uncertain parameters, the actual profit may diverge from these expectations. Nevertheless, from a mathematical standpoint, leveraging decision support tools under uncertainty remains the optimal strategy for decision-makers.

6. Conclusion

This study introduces a novel decision-making support system tailored for decision makers in manufacturing and retail sectors, designed to tackle supplier selection and production planning challenges amid uncertain probabilities and discounted costs. The approach utilizes fuzzy linear programming with a piecewise objective function. Through numerical experiments employing randomly generated data, the efficacy of the proposed model was demonstrated. Findings indicate that the decision-making support effectively addressed the problem, yielding the maximum expected profit.

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