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Research Paper

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DESIGNING FLOUR SUPPLIER AND ORDER ALLOCATION SYSTEM USING MULTI-OBJECTIVE LINEAR PROGRAMMING

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ABSTRACT. MSME XYZ, an artisan bakery business, faces challenges in meeting the demand for flour, its primary raw material, due to supply uncertainty, which amounts to up to 5% of the total demand. This issue results in missed production targets and a risk of declining product quality credibility. To address this problem, this study designs a supplier selection and order allocation (SSAO) system using the analytical hierarchy process (AHP), simple additive weighting (SAW), and multi-objective linear programming (MOLP) methods. The purpose of this research is to reduce the percentage of unfulfilled flour fulfilment at UMKM XYZ through order allocation planning based on the results of supplier performance evaluation. AHP is employed to determine the weights of supplier evaluation criteria, SAW is used to rank suppliers based on these weights, and MOLP is applied to optimize order allocation across four objective functions: minimizing delivery delays, minimizing quantity shortages, minimizing rejected products, and minimizing unmet demand. The proposed system demonstrates significant improvements: reducing delivery delays from 8 to 2 days, decreasing quantity shortages to 1 kg, lowering the total number of rejected products from 25 kg to 11 kg, and reducing the unmet demand rate from 5% to 2%. The SSAO system proves effective in improving raw material procurement efficiency and supporting the continuity of MSME XYZ's production processes within the agro-industry value chain.

INTRODUCTION

In the food industry, the availability of high-quality and consistent raw materials is a key factor in maintaining production quality and operational efficiency. Wheat flour is a primary raw material in the bakery industry and plays a crucial role in determining the texture, flavor, and final quality of the products. The central role of flour as a raw material is also evident in various other types of flour processed from agricultural products (Anwar *et al*., 2017). As a processed raw material derived from agricultural produce (wheat), wheat flour contributes to extending the agricultural value chain by linking the upstream (wheat farmers) and downstream (processed food industry) (Cappelli and Cini, 2021). Therefore, it is important to ensure efficient management of raw materials throughout the value chain to minimize their impact and maintain the sustainability of flour derivative products (Zuhria *et al*.,2021). As noted by (Ozaydin and Direk, 2022), the bakery sector is an integral part of the agro-industry, an agriculture-based industry that transforms farm produce into value-added products. The agro-industry plays a strategic role in increasing the added value of agricultural commodities, extending the agro-industrial supply chain, raising farmers' incomes, creating new employment opportunities, and strengthening national economic growth (Rosminah *et al*., 2024). Agro-industrial supply chain management involves several members of the supply chain that are integrated from upstream to downstream in a sustainable manner, with key aspects to consider including performance, added value, risk, and transparency (Putri *et al*., 2020). Consequently, the availability and management of raw materials, such as flour, are critical factors in ensuring

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the sustainability of the national agro-industry (Aulia Arifin *et al*., 2024).

MSME XYZ, an artisan bakery business established in 2021 in Bandung, is one of the downstream agro-industry actors that heavily depends on the availability of flour as its main raw material. Alongside business growth and the opening of new branches in several strategic locations, such as Kemang, Rawamangun, and Bintaro, the company has faced increasing challenges in maintaining a consistent flour supply. The main issue encountered is the mismatch between the quantity of flour requested and the actual supply fulfilled by suppliers. The data show that the actual demand and delivery of flour by suppliers to each outlet is inconsistent. All outlets require the same amount of flour, which is 120 kg. However, in reality, the Bandung outlet only received 118 kg, the Kemang outlet 108 kg, the Rawamangun outlet 112 kg, and the Bintaro outlet 108 kg. All outlets experienced unmet flour demand, with figures exceeding the company's maximum tolerance threshold of 3%. The primary causes of this shortfall were rejected products due to damaged packaging during delivery and distribution delays, particularly at outlets located in high-traffic areas such as Kemang and Bintaro. According to (Serina, 2023), this uncertainty in raw material procurement poses a risk to the continuity of production processes, undermines the company's credibility, and may result in financial losses due to decreased sales revenue.

Therefore, this study explicitly aims to design a decision support system for supplier selection and order allocation to reduce the percentage of unmet flour demand, improve efficiency in procurement, and support the continuity of production at MSME XYZ. Unlike previous studies that applied AHP, SAW, and MOLP mainly for supplier selection from manufacturers to suppliers, this research focuses on the allocation from suppliers to the company (MSME XYZ). This distinction highlights a different perspective in the supply chain, where the challenge lies in ensuring reliable raw material procurement at the downstream level (Pasaribu *et al*., 2023). By integrating AHP, SAW, and MOLP, this study not only evaluates supplier performance but also optimizes order allocation, thereby addressing a research gap that has not been sufficiently explored in previous studies.

RESEARCH AND METHODS

According to (Anatan and Ellitan, 2018), the stages of supplier selection include fulfilment of needs for new suppliers, formulation of decision criteria, pre-qualification, final supplier selection, and monitoring of selection results. By following these stages, this research applies the analytical hierarchy process (AHP), simple additive weighting (SAW), and multi-objective linear programming (MOLP) methods. AHP is chosen because it allows the determination of criterion weights through structured pairwise comparisons, which has been widely applied in previous supplier evaluation studies. SAW is employed because it is a simple yet effective method to convert these weights into supplier performance scores through weighted summation. MOLP is used because it can optimize order allocation by considering multiple conflicting objectives simultaneously, such as delivery time, shortages, quality, and demand fulfilment. Therefore, the integration of these three methods ensures accurate supplier selection and optimal allocation of procurement orders.

Both primary and secondary data were used in this study to bolster the analysis. Questionnaires with performance evaluation criteria discussions and prioritizing were administered to selected respondents through selective sampling, and these comprised the primary data. In the meantime, supplier performance records, historical multi-sourcing data, and firm demand fulfilment data are examples of secondary data. The AHP was used to process the primary data to create criterion weights using consistency tests and pairwise comparisons. The SAW technique then used these weights to assess supplier performance ratings. To identify the best order allocation by reducing delivery time, shortages, reject rates, and unmet demand, the MOLP model was finally combined with the supplier scores and company demand data. With the implementation of this system, UMKM XYZ will be able to improve the reliability of raw material supply, and procurement planning can be performed more effectively to obtain quality products on time to meet market demand. The sequential integration of these three approaches involves AHP establishing the relative weights of each evaluation criterion, SAW using these weights to produce supplier performance scores, and MOLP optimizing order allocation based on supplier ranking results. Figure 1 presents the systematic design of this research.

In the design process using the analytical hierarchy process (AHP), the initial step involves calculating the priority vector to determine the weights of the supplier performance evaluation criteria based on the responses collected through the questionnaire (Wulandari *et al*., 2023).

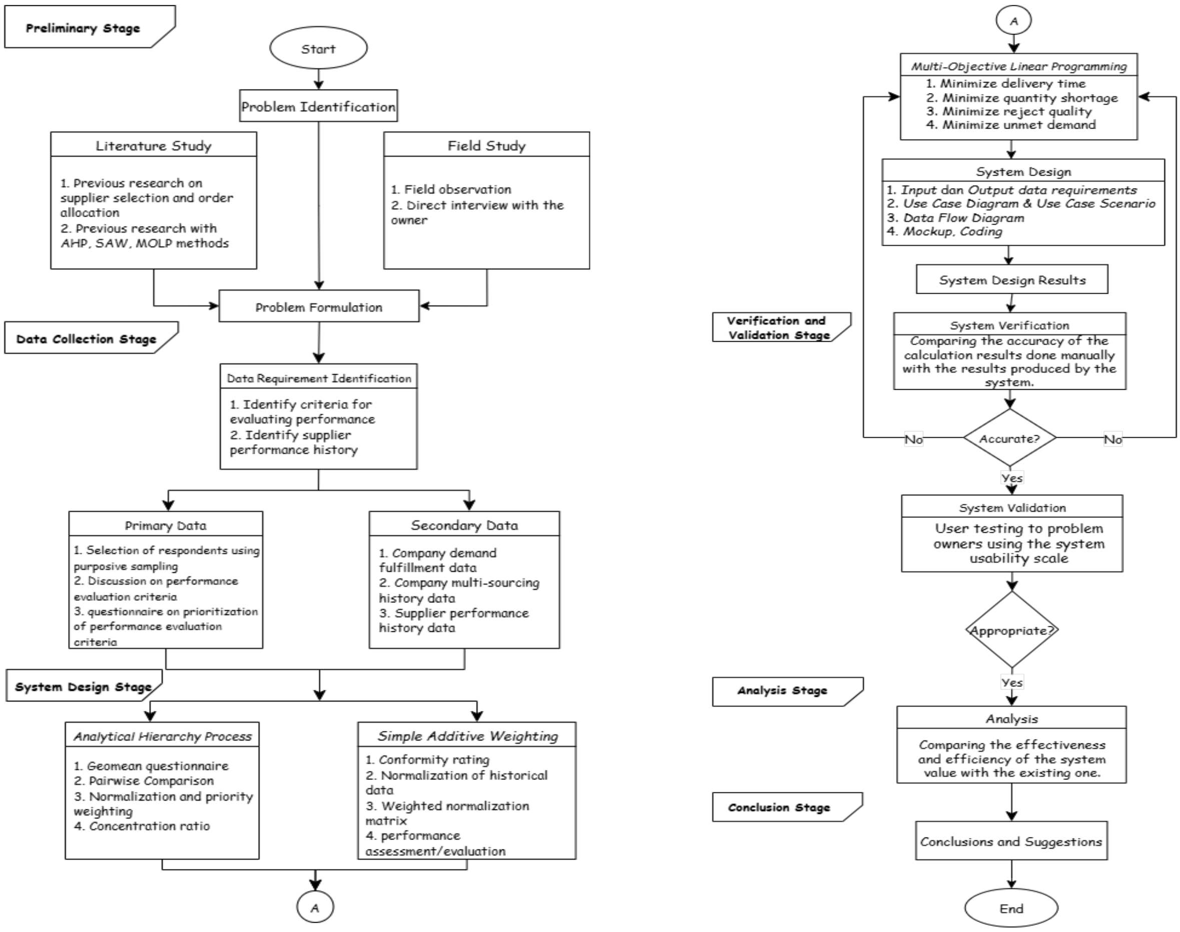

Figure 1. Design systematics of this research

Subsequently, the results of the AHP analysis are processed using the simple additive weighting (SAW) method to generate performance evaluation scores for all supplier alternatives (Sopian and Ermatita, 2021). According to (Sopian and Ermatita, 2021), the simple additive weighting (SAW) method is a weighted summation approach. The core principle of the SAW method is to calculate the weighted sum of the performance scores of each alternative across all criteria. Once all suppliers are qualified, the data are further processed using the multi-objective linear programming (MOLP) method, which aims to determine the values of the decision variables within the linear programming model (Anna, 2018). Through the MOLP method, it is possible to minimize delivery time, minimize quantity shortages, minimize the number of rejected products, and generate an order allocation for each supplier that minimizes unmet demand. Consequently, the integration process proceeds in a methodical manner: the AHP supplies the priority weights, the SAW converts them into thorough supplier performance evaluations, and the MOLP utilizes these ratings as input to create the best possible order allocation plan.

RESULTS AND DISCUSSIONS

Analytical Hierarchy Proses (AHP)

The performance evaluation criteria were selected through consultations with relevant stakeholders and were based on established references related to order fulfillment performance. Drawing upon criteria defined by subject matter experts and professionals with expertise in the field, a decision hierarchy was constructed to systematically decompose the complex problem into subsystems, elements, and sub-elements, thereby enhancing clarity and analytical precision (Ngubane *et al*., 2024). The resulting hierarchical structure is presented in Figure 2.

In distributing the questionnaire to respondents, the assessment scale used in the AHP pairwise comparison matrix followed the classification presented in Table 1 (Wulandari *et al*., 2023).

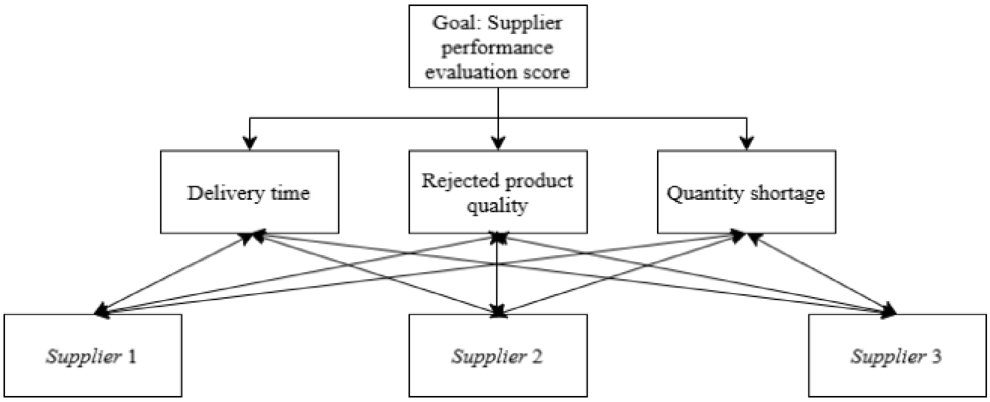

Figure 2. Hierarchical structure

Table 1. Rating scale in the AHP pairwise comparison matrix

Intensity	Definition
1	Both elements are equally important.
3	One element is slightly more important than the other.
5	One element is more important than the other.
7	One element is clearly more important than the other.
9	One element is absolutely more important than the other.
2,4,6,8	Values between two adjacent considerations.

In this study, to obtain the assessment results from each respondent, calculations were performed using the geometric mean method (Wulandari *et al*., 2023). The geometric mean can be calculated using the following equation, with the results presented in Table 2.

$$G = \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$$

where:
G = geometric mean
n = total respondent
x = assessment result

A pairwise comparison was conducted to compare two elements and assess and assign weights to the criteria and alternatives in the decision-making process (Ramik, 2020). Table 3 presents the results of the pairwise comparison calculation. After the pairwise comparison matrix is calculated, the priority vector is determined. The normalized principal eigenvector is referred to as the priority vector. Because it has been normalized, the sum of all elements in the priority vector is 1. The priority vector represents the relative weights among the elements being compared (Ginting *et al*., 2023). The steps for calculating the normalization and priority vector values are as follows. Table 4 presents the normalization results, and Table 5 shows the priority vector results. First, normalization is conducted.

$$w_i = \sum_{i=1}^{n} \frac{a_{ij}}{n}$$

Where:
Wi = weight value
$\frac{a_{ij}}{n}$ = normalized row matrix

Next, the priority vector is calculated as follows:

$$Nw_{ij} = \frac{w_{ij}}{\sum_{i=1}^{n} q_i}$$

Where :
Nw_{ij} = weight value N
w_{ij} = weight value total of the matrix column values A A
q_i = total of the matrix column values A

The final step involves calculating the eigenvalue and the maximum eigenvalue.

$$\lambda_i = \sum_{i=1}^{n} \frac{a_{ij}}{w_i}$$

Where:
λ_i = eigenvalue for the i-th criterion where a_{ij} an element of the pairwise comparison matrix between criteria i and j.
w_i = priority weight of the i-th criterion
n = number of criteria

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Table 2. Geometric mean result

Criteria	Respondents			Geomean	Criteria
	1	2	3		
Delivery time	1.00	1.00	1.00	1.00	Reject quality
Reject quality	2.00	2.00	1.00	1.58	Quantity shortage
Quantity shortage	0.33	0.33	0.50	0.37	Delivery time

Table 3. Pairwise comparison result

Criteria	Delivery Time	Reject Quality	Quantity Shortage
Delivery time	1.00	1.00	2.70
Reject quality	1.00	1.00	1.58
Quantity shortage	0.37	0.63	1.00
Total	2.37	2.63	5.28

Table 4. Normalization result

Criteria	Delivery Time	Reject Quality	Quantity Shortage	Amount	Priority Vector	Eigen Value (λ)
Delivery time	0.42	0.38	0.51	1.31	0.438	0.97
Reject quality	0.42	0.38	0.30	1.10	0.37	1.04
Quantity shortage	0.16	0.24	0.19	0.59	0.20	0.99

$$\lambda_{max} = \sum_{i=1}^{n} \frac{\left(\frac{a_{ij}}{w_i}\right)}{n}$$

Where:

λmax = eigenvalue for the i-th criterion.
a_{ij} = element of the pairwise comparison matrix between criteria i and j.
w_i = priority weight of the i-th criterion
n = number of criteria

Table 5. Priority weight results for the criteria

Assessment Criteria	Priority Vector
Delivery time	43%
Reject quality	37%
Quantity shortage	20%

According to the results of the sensitivity analysis, Supplier 1 is always the best option across all weight fluctuation scenarios. When the weights of quantity shortage, rejection quality, and delivery time are altered by ±10%, the rankings of Suppliers 2 and 3 do not change, but their scores do. This suggests that the outcomes of supplier selection are stable and unaffected by slight variations in the AHP weights. Table 6 presents the sensitivity analysis.

Simple Additive Weighting

After determining the weights for the supplier performance evaluation criteria, the next step is to assign a suitability rating to each alternative for each criterion and then convert these ratings into fuzzy numbers (Setiadi *et al.,* 2018). In this study, the evaluation criteria were categorized into four levels: very poor, poor, good, and very good. Table 7 presents the performance classification based on this index. The historical performance data of suppliers, based on the evaluation criteria obtained from the company's document analysis, are presented in Table 8.

Based on the supplier performance historical data, the next step is to assign performance ratings to each supplier according to their performance, as shown in Table 9. After determining the performance ratings for each criterion, the next step is to form the decision matrix (X) from the rating table of the suitability of each alternative for each criterion (Setiadi *et al*., 2018).

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Table 6. Sensitivity analysis results of criteria weights

Scenario	Delivery	Reject	Shortage	Score S1	Score S2	Score S3	Ranking
Baseline	0.43	0.37	0.20	1.000	0.736	0.808	S1 > S3 > S2
Delivery +10%	0.45	0.35	0.19	1.000	0.733	0.802	S1 > S3 > S2
Delivery -10%	0.40	0.39	0.21	1.000	0.739	0.814	S1 > S3 > S2
Reject +10%	0.41	0.39	0.19	1.000	0.734	0.815	S1 > S3 > S2
Reject -10%	0.45	0.35	0.21	1.000	0.739	0.801	S1 > S3 > S2
Shortage +10%	0.42	0.36	0.22	1.000	0.741	0.807	S1 > S3 > S2
Shortage -10%	0.44	0.38	0.18	1.000	0.731	0.809	S1 > S3 > S2

Table 7. Performance index

Performance	Delivery Time	Quality Reject	Quantity Shortage	Performance Index
Very poor	(>5)	(>5)	(>5)	1
Poor	(3-4)	(3-4)	(3-4)	2
Good	(1-2)	(1-2)	(1-2)	3
Very good	0	0	0	4

Table 8. Supplier performance historical data

Criteria	Unit	Supplier 1	Supplier 2	Supplier 3
Delivery time history	Days	2	3	3
Reject quality history	%	1%	3%	2%
Quantity shortage history	%	0%	0%	1%

Table 9. Supplier performance rating

Supplier	Delivery Time	Reject Quality	Quantity Shortage
Supplier 1	3	3	4
Supplier 2	2	2	4
Supplier 3	2	3	3
MAX	3	3	4

The results of the normalized matrix are presented in table X, which was obtained using the benefit equation.

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{Max_{ij}(x_{ij})} & If\ j\ is\ a\ benefit\ attribute \\ \dfrac{Min_{ij}(x_{ij})}{x_{ij}} & If\ j\ is\ a\ cost\ attribute \end{cases}$$

Where:

r_{ij} = normalized performance rating value
x_{ij} = actual value of each criterion attribute
Max (X_{ij}) = maximum value for each criterion
Min (X_{ij}) = minimum value for each criterion

Table 10. Normalized matrix

Supplier	Delivery Time	Reject Quality	Quantity Shortage
Supplier 1	1.00	1.00	1.00
Supplier 2	0.67	0.67	1.00
Supplier 3	0.67	1.00	0.75
Priority Vector	43%	37%	20%

The normalized matrix is multiplied by the weight of each criterion and then summed to obtain the maximum value, which represents the best alternative (Ai) (Sopian and Ermatita, 2021). The results of the weighted normalized matrix are presented in Table 11, which was obtained using the following equation:

$$V_i = \sum_{j=1}^{n} W_j\ x\ r_{ij}$$

Where:

V_i = ranking value for each alternative
W_j = weight value for each criterion
r_{ij} = normalized performance rating value

Table 11. Results weighted normalized matrix

Supplier	**Delivery Time**	**Reject Quality**	**Quantity Shortage**	**Performance Evaluation Score**	**Ranking**
Supplier 1	0.43	0.37	0.20	1.00	1
Supplier 2	0.29	0.25	0.20	0.73	3
Supplier 3	0.29	0.37	0.15	0.81	2

The final ranking score is obtained by summing the results of the multiplication between the normalized matrix I and the weight vector (Sopian and Ermatita, 2021), resulting in performance evaluation scores for each supplier, as presented in Table 12. If an iteration is performed with an input exceeding the maximum threshold, the supplier is assigned a score of 0.7. Therefore, if a supplier's final score is below or equal to the minimum standard (≤ 0.7), they are not recommended to proceed in the selection process. In this study, all suppliers scored above the minimum standard, allowing the research to advance to the order allocation stage using the multi-objective linear programming method.

Table 12. Supplier performance evaluation

Supplier	**Evaluation Score**
Supplier 1	1.00
Supplier 3	0.81
Supplier 2	0.73

Multi-Objective Linear Programming

In developing the model, the formulation adopted refers to the study by (Anna, 2018). The multi-objective linear programming (MOLP) model includes the following constraint functions:

1. Demand constraint: The total order for each type of raw material allocated to suppliers must match the quantity required by the company.

$$\sum_{j}^{n} X_{ij} = \forall D_i$$

2. Minimum order constraint – Each supplier is required to receive raw material orders in quantities not lower than the predetermined minimum threshold.

$$X_{ij} \geq Q_{i\,|min} \forall i, j$$

3. Maximum order constraint: The quantity of raw material ordered from each supplier must not exceed the established maximum limit.

$$X_{ij} \geq Q_{i\,|min} \forall i, j$$

4. Non-negativity constraints – X_{ij} Decision variables must be greater than or equal to zero and not negative.

$$X_{ij} \geq 0, \forall i, j$$

5. Target fulfilment constraints – Total unmet demand should be less than 3%.

$$Z_4 \leq 3\%, \forall i, j$$

Where:

X_{ij}	= quantity of item i ordered from supplier j
D_i	= quantity of item i required
$Q_{i\,min}$	= minimum order quantity
$Q_{i\,max}$	= maximum order quantity

The MOLP model formulated in this study has 4 objectives, including:

1. Minimizing Delivery Time.
2. Minimizing Quantity Shortages.
3. Minimizing Reject Quality.
4. $Min\ Z_4 = \sum_i^m \sum_j^n (Z_2 + Z_3) \div D_i$ Minimizing Unmet Demand

Where:

X_ij	=	quantity of item i ordered from supplier j
T_{ij}	=	the delivery time for item i from supplier j
q_{ij}	=	the shortage in quantity of item i from supplier j.
d_{ij}	=	the quantity of rejected items i from supplier j.

Table 13 presents the data on the limitations of the supplier's capabilities obtained through interviews and document analysis of UMKM XYZ in September 2024, which will be used as input in the MOLP method calculation.

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Table 13. Supplier capability constraint data

Criteria	Unit	Supplier 1	Supplier 2	Supplier 3
Price	IDR/Kg	28,000	25,000	24,000
Maximum capacity	Kg	1000	1000	1000
Minimum order	Kg	100	100	100
Delivery time history	Days	2	3	3
Order history	Kg	490	500	660
Quantity shortage history	Kg	-	-	1
Reject history	Kg	2%	5%	4%

Table 14 presents the company's historical order allocation data, which is used as input for the quantity of required goods and for comparison between the existing planning and the system-generated planning results.

Table 14. Order allocation history

Order allocation (Kg)	Supplier 1	Supplier 2	Supplier 3
	200	350	250

Table 15 presents the order allocation determined directly by the company through the direct appointment of suppliers with strong relationships with the company, without considering target achievement. Table 14 also shows that the percentage of unmet demand in the existing planning is 5%, indicating that the level of demand fulfillment still exceeds the maximum target threshold set at 3%.

Table 15. Output allocation history

Data	Unit	Value
Needs	Kg	800
Delivery time	Kg/Days	100/8
Quantity shortage	Kg	1
Reject	Kg	25
Unfulfilled Demand	%	5%

Subsequently, Table 16 and Table 17 present the comparison results of the allocation outputs for each objective, following data processing using the Add-In Solver in Microsoft Excel, considering the objective functions and constraints. All combinations met the target when the company set the target percentage of unmet demand at 3%. Among the four optimization objectives, the most suitable solution is obtained from Z2 (minimize quantity shortage), which results in the lowest shortage of 0.5 kg, reject of 8 kg, and unmet demand of 1%. These outcomes demonstrate significant improvements compared to the existing allocation and confirm that the MOLP-based allocation under Z2 provides the most efficient and reliable result, as illustrated in Figure 3.

System Design

The information system design in this study employs the rapid application development (RAD) method, a software development model that follows a linear sequential phase and focuses on a development cycle that takes a short period. The RAD approach was chosen because of its several advantages, including shorter development cycles, high flexibility, increased user involvement, and the ability to minimize the likelihood of errors (Nurman and Kusuma, 2021). Table 18 presents the input data that will be used for processing in the supplier selection and order allocation systems.

Subsequently, Table 19 presents the data generated as the output of the supplier selection system and order allocation. The user design phase focuses on creating a user interface that connects the user with the system, including layout, icons, colors, buttons, and user interactions. In this phase, a use case diagram is created, as shown in Figure 4, to illustrate the relationship between the actor (owner) and the system. Table 20 to Table 23 present the use case scenarios, which illustrate in detail the interaction between the actor and the system flow.

Table 16. Objective output comparison

Objective	Unit	Z1	Z2	Z3	Z4
Delivery time (Z1)	Kg/Days	400/1	400/1	400/1	400/1
Quantity shortage (Z2)	Kg	1	0,5	1	1
Reject quality (Z3)	Kg	11	8	11	11
Unfulfilled demand (Z4)	%	1,5%	1%	2%	1,5%

Table 17. Objective output comparison analysis

Objective	Result
Z1 (Minimize delivery time)	The solver produces outputs that meet the target constraints. The oder allocation combination for objective Z1 resulted in an estimated delivery time of 400 Kg/Days, an estimated quantity shortage of 1 kg, an estimated quality reject of 11 kg, and an estimated percentage of unmet demand of 1.5%.
Z2 (Minimize quantity shortage)	The solver produces outputs that meet the target constraints. The combination of oder allocation for objective Z2 produces an output of estimated delivery time of 400 Kg/Days, estimated quantity shortage of 0,5 kg, estimated quality reject of 8 kg, and estimated percentage of unmet demand of 1%.
Z3 (Minimize reject quality)	The solver produces outputs that meet the target constraints. The oder allocation combination for objective Z3 resulted in an estimated delivery time of 400 Kg/Days, an estimated quantity shortage of 1 kg, an estimated quality reject of 11 kg, and an estimated percentage of unmet demand of 2%.
Z4 (Minimize unfulfilled demand)	The solver produces outputs that meet the target constraints. The oder allocation combination for objective Z1 resulted in an estimated delivery time of 400 Kg/Days, an estimated quantity shortage of 1 kg, an estimated quality reject of 11 kg, and an estimated percentage of unmet demand of 1.5%.

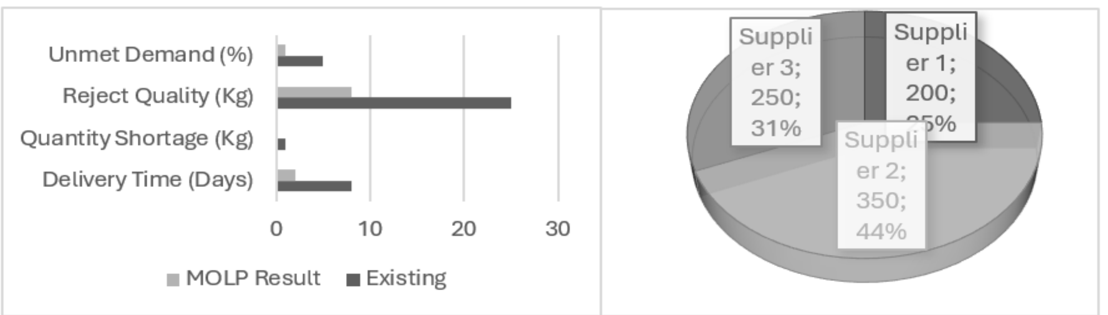

Figure 3. Comparison and allocation chart

Table 18. System input

No	Data	Unit	No	Data	Unit
1	Item requirement	Kg	6	Order quantity history	Kg
2	Supplier name	-	7	Delivery time history	Days
3	Item price	IDR	8	Quality reject history	Kg
4	Maximum order capacity	Kg	9	Quantity shortage history	Kg
5	Minimum order capacity	Kg	10	Preference weight importance	%

Table 19. Output system

No	Data	Unit
1	Minimization of delivery time	Kg/Days
2	Minimization of reject quality	Kg
3	Minimization of quantity shortage	Kg
4	Minimization of unmet demand	%

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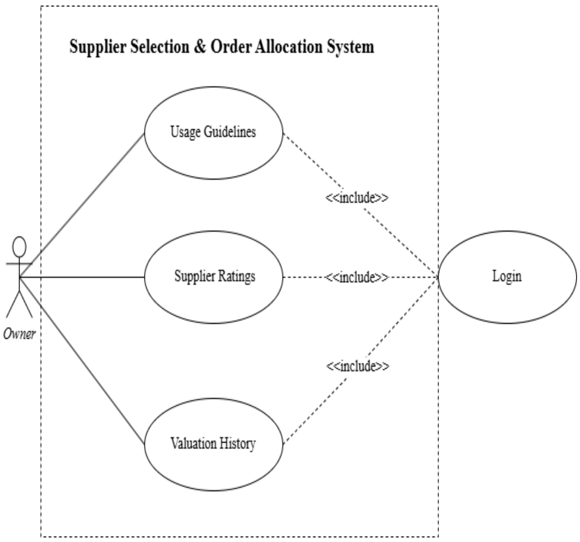

Figure 4. Usecase Diagram

Table 20. Use case scenario login

Element	Description
Use case	Login
Actor	Owner
Description	Owner performs login process to access the system
Before state	Owner enters user data
After state	System verifies data and displays home page
Event flow	1. Owner selects the user guide menu 2. The system displays the user guide page
Include	-
Assumption	Owner login successfully

Table 21. User guide use case scenario

Element	Description
Use case	User guide
Actor	Owner
Description	Owner accesses user guide on SSAO system
Before state	Owner accesses user guide
After state	System displays user guide
Event flow	1. Owner logs into the SSAO system (Include: Login) 2. The system verifies and displays the dashboard 3. Owner selects the user guide menu 4. The system accepts the request and loads the guide page 5. The system displays the user guide content 6. Owner reads the information in the guide
Include	Login
Assumption	Owner successfully accesses the user guide

Table 22. Supplier evaluation usecase scenario

Element	Description
Use case	Supplier Assessment
Actor	Owner
Description	Owner accesses the supplier assessment feature in the SSAO system
Before state	Owner is in the system and wants to conduct a supplier assessment
After state	The system successfully displays the supplier assessment results
Event flow	1. Owner logs into the SSAO system (Include: Login) 2. The system verifies credentials and displays the main dashboard 3. The owner selects the supplier assessment menu 4. The system displays the assessment form page 5. Owner fills in and sends the supplier assessment form 6. The system processes the sent assessment data 7. The system displays the results of the supplier assessment to the Owner
Include	Login
Assumption	Owner successfully accesses the user guide

Table 23. History evaluation use case scenario

Element	Description
Use case	Valuation History
Actor	Owner
Description	Owner accesses the assessment history in the SSAO system
Before state	Owner accesses the assessment history feature
After state	System displays assessment history data
Event flow	1. Owner logs into the SSAO system (Include: Login) 2. The system displays the main dashboard 3. The owner selects the assessment history menu 4. The system displays the assessment history page 5. The owner observes the previous assessment result data
Include	Login
Assumption	Owner successfully accesses the user guide

According to (Rahman *et al*., 2021), a data flow diagram (DFD) is a representation of a logical data or process model that illustrates the sources and destinations of data, the flow of data into and out of the system, data storage locations, the processes that generate the data, and the interactions between data and associated processes. Figure 5 presents the Level 0 DFD of the supplier selection and order allocation system implemented at MSME XYZ.

Subsequently, after the Level 0 data flow diagram (DFD) has been defined, the next step is to present the Level 1 DFD as part of the system design. The purpose of the Level 1 DFD is to provide a more detailed understanding of the overall system. Figures 6–9 illustrate the Level 1 DFDs for processes one through four.

During the construction phase, the platform used to develop this system is application-based. This medium was chosen to facilitate a more user-friendly and accessible interface. During the construction phase, the platform used to develop this system was application-based. This medium was chosen to facilitate a more user-friendly and accessible interface. Figure 10 is a diagram of user interactions.

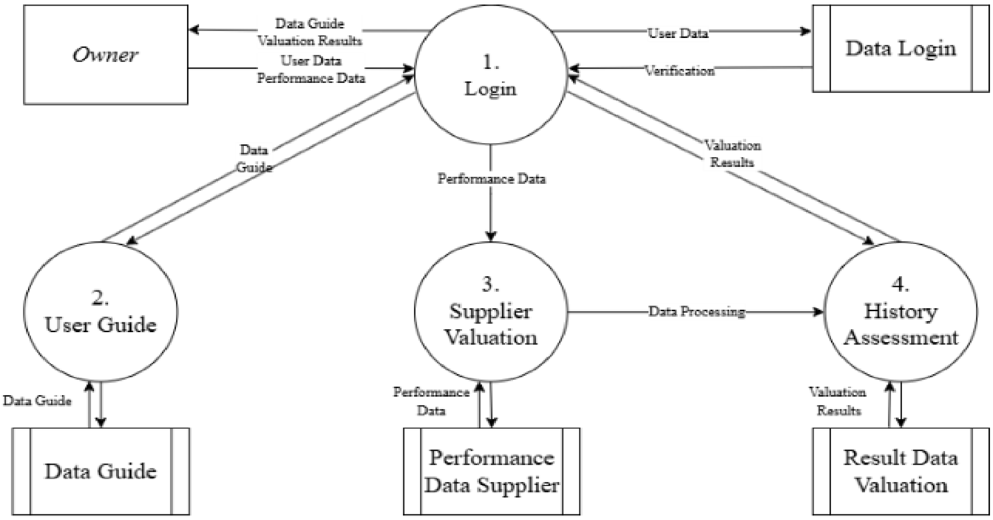

Figure 5. Level 0 data flow diagram (DFD)

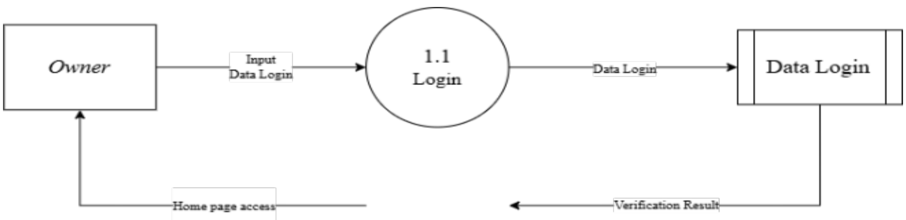

Figure 6. Level 1 data flow diagram – Process 1

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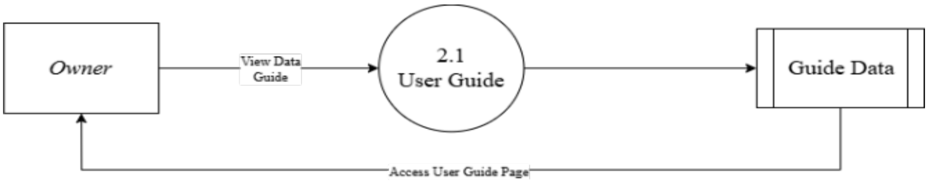

Figure 7. Level 1 data flow diagram – Process 2

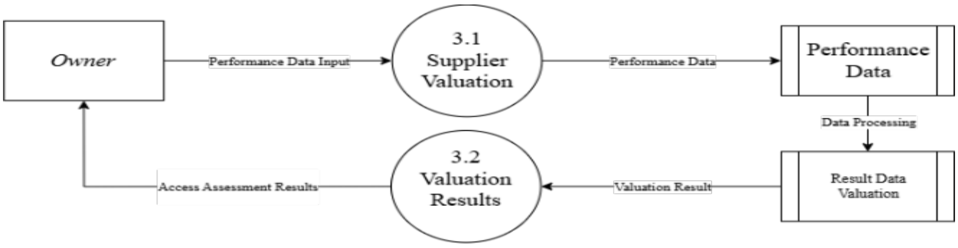

Figure 8. Level 1 data flow diagram – Process 3

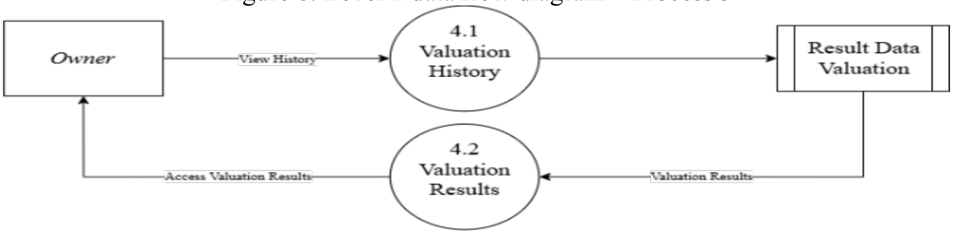

Figure 9. Level 1 data flow diagram – Process 4

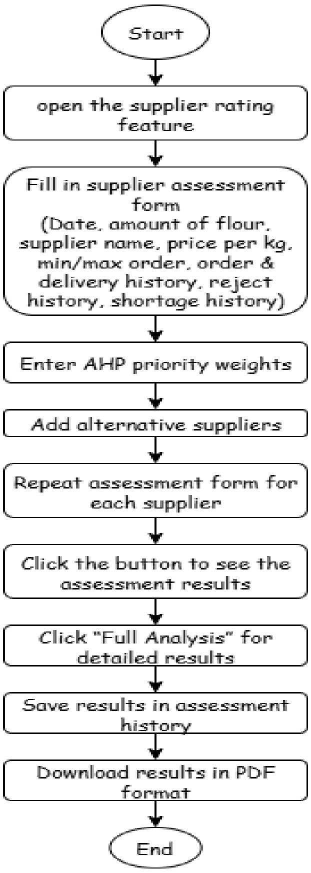

Figure 10. User interactions flowchart

Figure 11 shows the login interface. The login process functions as an authentication mechanism, requiring users to enter a valid username and password to gain access to the system.

Figure 11. Login interface

Figure 12 shows the homepage interface. The homepage is the first screen displayed after a user successfully logs in. On this page, users can access various features and information available within the system.

 DOI: https://doi.org/10.24961/j.tek.ind.pert.2026.36.1.12

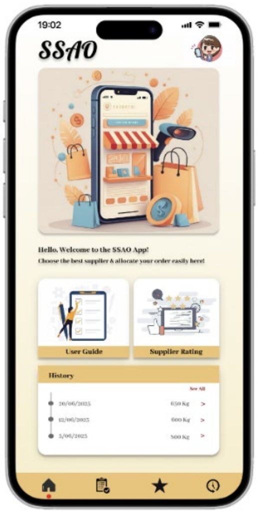

Figure 12. Home interface

Figure 13 shows the user guide interface. The user guide page contains essential information that users must understand before conducting the supplier evaluation.

Figure 13. The user guide interface

Figure 14 presents the supplier evaluation page. The supplier evaluation page is used to initiate the assessment process by filling out the required data form.

Figure 15 presents the evaluation results page. The evaluation results page displays information about the optimal order allocation and supplier performance evaluation results. Figure 16 shows the complete analysis page. The complete analysis page contains detailed information related to all four objectives of the system.

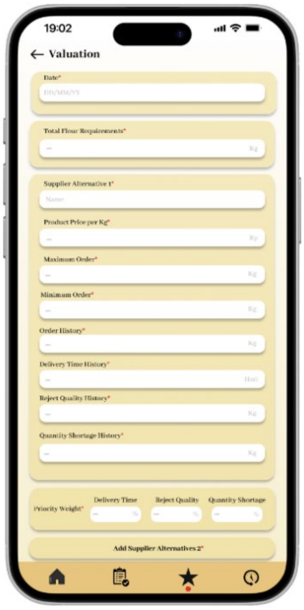

Figure 14. Supplier evaluation interface

Figure 15. Evaluation Result Interface

Figure 16. Complete analysis interface

Table 24. Usability testing result

Metrics	Owner	Staf Purchasing 1	Staf Purchasing 2	Average
Task success rate	100%	100%	100%	100%
Time on task (seconds)	215	242	221	226
Error rate	0	0	0	0

Figure 17 shows the history interface. The history feature allows users to easily reopen and modify data inputs from previously conducted calculations.

Figure 17. History interface

During the application testing phase, usability testing was conducted with three participants: the owner, purchasing staff 1, and purchasing staff 2. The task involved determining order allocation using the designed application. According to (Puspito, 2024), the three main parameters used for scenario testing are as follows: (1) success rate, which refers to the task success rate; (2) error rate, which refers to the frequency of user errors; (and 3) time on task, which refers to the time spent completing the task. Table 24 presents the results of the scenario testing based on these parameters.

The owner, purchasing staff 1, and purchasing staff 2 successfully completed the tasks with a 100% success rate and zero errors (0% error rate). Overall, the usability testing showed excellent results, with perfect task completion and no issues encountered during the process. After the task testing was completed, the next step was to distribute the System Usability Scale (SUS) questionnaire to objectively measure the system's usability from the users' perspective. The results of the questionnaire responses were then compiled using the SUS method, followed by analysis and comparison with values on the acceptability graph, adjective rating, and SUS score percentile rank (Mardi Suryanto *et al.*, 2022). Table 25 presents a summary of the questionnaire scores obtained from the SUS responses provided by the users. To clarify the usability results, the SUS evaluation was conducted by referring to the adjective rating categories, which were then interpreted within the acceptability range.

This process provides an indication of whether the system is acceptable to users. Figure 18 presents the adjective rating graph and the acceptability range based on SUS scores (Mardi Suryanto *et al.*, 2022).

Table 25. System usability scale (SUS) score

	Usability Scale Value
Owner	90
Staf purchasing 1	85
Staf purchasing 2	87.5
Average	87.5

Based on the average SUS score of 87.5, the system can be categorized as 'Excellent' in the adjective ratings and 'Acceptable' within the acceptability range. This result indicates that the system is considered very easy to use and satisfactory for users. In addition, the system is also well-received and does not cause significant obstacles when used. The system does not require urgency for improvement because users have felt that the system is optimal enough.

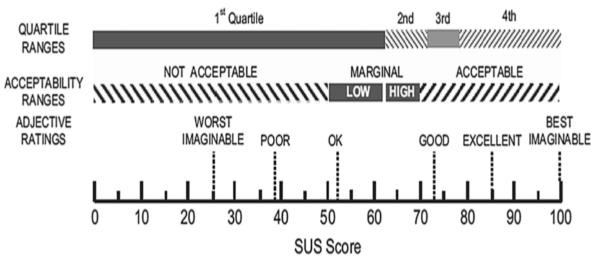

Figure 18. Adjective ratings and acceptability range

CONCLUSSIONS AND RECOMMENDATIONS

Conclusions

MSME XYZ faces problems in supplier selection and order allocation for flour raw materials that are not optimal, resulting in ineffective demand fulfillment performance. The problem is indicated by the high average delivery time of 8 days, the number of raw material quantity shortages of 1 kg, rejected products reaching 25 kg, and the percentage of unmet demand of 5%. Through this research, a decision support system for supplier selection and order allocation is designed using the analytical hierarchy process (AHP), simple

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additive weighting (SAW), and multi-objective linear programming (MOLP) methods. The AHP method was used to determine the weight of the criteria, with results of 43% for delivery time, 37% for rejected product quality, and 20% for quantity shortage. Furthermore, the SAW method was used to evaluate three alternative suppliers and resulted in Supplier 1 as the best choice with the highest score. Finally, the MOLP method was applied to optimize order allocation with the aim of minimizing delivery time, quantity shortage, quality product rejects, and unmet demand. The results of the system implementation showed significant improvements, with the delivery time successfully reduced to 2 days, the quantity shortage dropping to 0.5 kg, the number of rejected products decreasing to 8 kg, and the percentage of unmet demand reduced to 1%. This achievement even exceeded the company's target of setting a maximum unmet demand limit of 3%. The system was then tested through usability measurement, and the results showed an average SUS score of 87.5. This value indicates that the system category adjective ratings are ‘excellent’ and ‘acceptable’ in the acceptability range; therefore, the system is considered very easy to use and satisfying for users. However, this system still has several limitations. The number of alternative suppliers is restricted to three, the assessment can only be conducted by one respondent, and the assessment criteria are limited to those predefined in the system. In addition, the system cannot automatically eliminate suppliers with poor evaluation scores and only minimizes objectives without allowing users to set specific target thresholds. These limitations should be addressed in future research to improve the flexibility and applicability of the system.

Recommendations

It is recommended to add criteria relevant to the management of perishable product inventory, such as moisture, temperature, or shelf life, to reduce the risk of stock shortages or overstocking. In addition, to improve accuracy and reduce uncertainty in quality assessment, it is advisable to implement more variables in the fuzzy system, allowing it to adapt more dynamically to changes in product conditions.

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