Supplier selection in rank order using fuzzy ahp and fuzzy molp with sensitivity analysis

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Abstract. Supply chain management (SCM) plays a great role in any company, a good SCM requires a good selection of all its components. One of the components is the raw material supplier selection that needs to consider both tangible and intangible factors in each supplier. Therefore, we can use fuzzy AHP which uses an intangible approach and fuzzy MOLP which uses a tangible approach. In this paper, we aim to use both methods to get the rank order of the best suppliers from all 5 suppliers in a woodworking company. The result shows that both methods can work together as the rank order from both methods gives the same result. However, sensitivity analysis is done in case both methods give different rank order. Sensitivity analysis shows that change in criteria from 10% to 100% make a variance in fuzzy AHP from 0% to 30% while fuzzy MOLP from 75% to 100%. That means fuzzy AHP is more robust than fuzzy MOLP. We also found that fuzzy AHP is influenced heavily by the expertise of the expert as two experts give different results while fuzzy MOLP is more objective-oriented using real data. These results suggest that each Method has its own characteristics that must be put into mind when we use it.

1. Introduction
The supply chain process of any company has a long flow ranging from upstream to downstream processes. Therefore, it requires a good supply chain management (SCM). SCM is influenced by the location selection and quality of goods, so the appropriate selection is required in order to provide maximum profit for the company [1]. One of the most used selections in the supply chain processes is the selection of raw material suppliers. The factors used to determine the selection are: the infrastructure used, policy-maker preferences, as well as other universally-universal constrains [2][3].

The selection of suppliers becomes one of the most important activities in SCM, considering the selection of suppliers can affect the quality of goods produced and even affect the performance of the supply chain of existing organizations [4][5]. Knowing the importance of this supplier selection, a certain method can be used to provide the best solution. Transportation models are often used to provide solutions to multi-objective selection. The transportation model focuses on the lowest cost and demand available that the results can be applied instantly. One of the applications of transportation models is using a linear programming method to determine the selection of the best warehouse locations in one of the regions in Pakistan [6]. From the results of the study, the best trade-off selection of warehouses is used with the lowest cost and highest demand fulfillment [6].
Transportation models include some methods that can be applied directly in the field. The problem though, that the transportation model often focuses solely on the selection based on the lowest cost and demand alone (tangible) that many intangible factors are ignored [7]. These intangible factors turned out to give a considerable effect on the field that made the transportation models less optimal. To overcome these problems, another supporting method is required to help select the best raw material supplier. The proper method used for the selection with many alternatives is multi-criteria Decision Making (MCDM) [8]. MCDM uses mathematical procedures and computational calculations to determine the best solution from alternatives that have many constraints [9]. MCDM can be used to help the transportation model in determining the selection of raw materials suppliers.

MCDM has many methods, such as AHP, TOPSIS, ELECTREE, and VIKOR. Looking at the complexity of variables and the constraints commonly used in supplier selection, the AHP method with the hierarchy is able to divide the problems into simpler cases to make it easier to solve. However, AHP methods are rated less than optimal in the selection of solutions with uncertain attributes. Fuzzy usage is required in MCDM methods such as AHP in solutions relying on trade-off models such as Supplier selection [10]. Therefore, fuzzy usage is also required in the AHP method to help provide the best solution. AHP with Fuzzy is already widely used to solve the SCM problem. One of the applications is the research from [11].

The case study used in this paper is the selection of the supplier Albasia Woods in a woodworking company. The results of this paper will be used to help the company to choose the best suppliers.

2. Methods

In this paper, we analyze the best suppliers using fuzzy AHP and fuzzy MOLP methods based on a dataset from case study findings. Then, we use sensitivity analysis to determine the more suitable method to choose in case there are differences in rank order between fuzzy AHP and fuzzy MOLP.

Fuzzy MOLP model used in this paper is based on [12] and modified some of the elements in order to change the allocation into the rank order.

| Suppliers  | Volume (M3) | Fuel cost (Rp) | Incentive (Rp) | Truck volume (M3) | Time (minutes) | Distance (km) |
|------------|-------------|----------------|----------------|-------------------|----------------|---------------|
| Bawang     | 15,042      | 243529         | 5961           | 1750              | 1040           | 20            |
| Wonotunggal| 15,127      | 388062         | 11937          | 1691              | 1338           | 79            |
| Talun      | 14,981      | 436580         | 13428          | 1660              | 1670           | 93            |
| Tulis      | 13,442      | 410705         | 13739          | 1643              | 1606           | 83            |
| Sumowono   | 14,666      | 348951         | 1046           | 1644              | 1337           | 56            |

The models of fuzzy MOLP used in this paper as follows:

a) Make Models of MOLP
b) Convert the attributes of MOLP into fuzzy MOLP using given \( \alpha \) used in the calculations.
c) Convert the numbers into crisp ones using multiplication between \( \alpha \) and the numbers and then normalize them
d) Change the parameters of the constraint from allocating the resources into rank-based order
e) Solve the fuzzy MOLP using ordinary Linear Programming

The fuzzy AHP model used in this paper is based on [13]. The models of fuzzy MOLP used in this paper as follows:

a) Make the pairwise comparison between the alternatives and the attributes
b) Convert the pairwise in fuzzy numbers using \( \alpha \)-fuzzy cuts
c) Solve the fuzzy eigenvalue for each matrix
d) Check the Consistency Ratio (CR) and make sure the CR is <0.1

e) Multiply each attribute and the evaluation matrix to obtain the priority weights each alternative

f) Rank the alternatives based on the order

Sensitivity analysis is performed by changing the one parameter while keeping the others in its original value, then see if there is any change in the rank order before and after the change. The number used for changing the parameter is 10% to 100%. The data used for the calculations is a dataset from the history data of each supplier from a woodworking company. The criteria and the sub-criteria used in this paper are based on data available from the company. The data is shown in table 1.

3. Result and discussion

3.1. Fuzzy MOLP

3.1.1. Make the models. The first step is to make a model for the problems, there are 6 sub-criteria based on figure 1, we use the same number of criteria with fuzzy AHP to make it easier for comparison. Therefore, there are six objectives as follows:

Maximize (K2): 14666X1+13442X2+14981X3+15127X4+15042X5

Minimize (K4): 243529X1+388062X2+436580X3+410705X4+348951X5

Maximize (K5): 5961X1+11937X2+13428X3+13739X4+1046X5

Maximize (K3): 1750X1+1691X2+1660X3+1643X4+1644X5

Minimize (K6): 1040X1+1338X2+1670X3+1606X4+1337X5

Minimize (K1): 20X1+79X2+93X3+83X4+56X5

From table 1, there are five alternatives as bawang (X1), winotunggal (X2), talun (X3), tulis (X4), and sumowono (X5)

3.1.2. Convert the models into Fuzzy MOLP. The second step is to convert the number into fuzzy MOLP. By giving each number with \( \alpha \). Then, turn the fuzzy models into crisp numbers by multiplying \( \alpha \) with the numbers. \( \alpha \) used in this calculations is 0.5

3.1.3. Change the parameters into rank-based orders. After the numbers are turned into crisp ones, the next step is to change the parameters so that the alternatives will get rank instead of allocation. The parameters that got changed are as follows:

\[ S.T \]
\[ 0 < X1 \leq 5 \]
\[ 0 < X2 \leq 5 \]
\[ 0 < X3 \leq 5 \]
\[ 0 < X4 \leq 5 \]
\[ 0 < X5 \leq 5 \]
\( X1 <> X2 <> X3 <> X4 <> X5 \)
3.1.4. Solve with ordinary linear programming. After the parameters got changed, then the models can be solved using ordinary simplex Linear programming and the result then normalized. Finally, we sum all the normalized number respective to their suppliers. The supplier with the highest number got rank 1 and then goes on until rank 5. The solving is handled with an application program that is shown in figures 3.

3.2. Fuzzy AHP

3.2.1. Data modelling. The first step of fuzzy AHP is making a hierarchical structure that can break the criteria into sub-criteria, thus making it easier to solve.

![Fuzzy AHP hierarchical model](figure 1)

Figure 1. Fuzzy AHP hierarchical model.

From figure 1, there are four main criteria: distance, volume, cost, and time. While distance and time do not have any sub-criteria, volume and cost consist of production volume (K2) and truck volume (K3) for volume and fuel cost (K4) and driver’s incentive (K5) for cost.

3.2.2. Data weighting. The second step for AHP is determining the weights for each criterion, sub-criteria, and alternatives with the pair-wise comparison. Those weighting processes are handled with an application program, which is shown in figure 2.
Figure 2. Weighting processes using the application program.

The result from the application, each criterion, sub-criteria, and alternatives are shown in table 2, table 3, and table 4. Then, the pairwise result is converted into $\alpha$-fuzzy cuts to change it into fuzzy models. $\alpha$ used in this calculation is 0.5. Solve the $\alpha$-fuzzy cuts from each number to get the weights. The weights are shown in table 3 and table 4. Based on table 2, table 3 and table 4, it is shown that all CR is under 0.1 so the weighting processes are considered consistent. Now that all calculations are consistent, we can move to the last step of the calculations.

Table 2. Criteria weighting.

| No | Criteria | Weight |
|----|----------|--------|
| 1  | Distance | 0,25   |
| 2  | Volume   | 0,25   |
| 3  | Cost     | 0,25   |
| 4  | Time     | 0,25   |

$\text{CR} = 0$

Table 3. Weighting for sub-criteria.

| Criteria   | Sub criteria | Weights |
|------------|--------------|---------|
| Distance (K1) | -            | 0,431   |
| Volume     | Production (K2) | 0,3048  |
|            | Truck (K3)   | 0,085   |
| Cost       | Fuel (K4)    | 0,0639  |
|            | Incentives (K5) | 0,0397  |
| Time (K6)  | -            | 0,049   |

$\text{CR} = 0,09$
### Table 4. Weighting for evaluation rating.

| Alternatives | weights (Each criterion) |
|--------------|--------------------------|
|              | K1 | K2  | K3  | K4  | K5  | K6  |
| Bawang       | 0,646 | 0,213 | 0,211 | 0,396 | 0,37 | 0,598 |
| Wonotunggal  | 0,1 | 0,195 | 0,323 | 0,236 | 0,151 | 0,125 |
| Talun        | 0,083 | 0,206 | 0,174 | 0,131 | 0,18 | 0,099 |
| Tulis        | 0,06 | 0,27 | 0,137 | 0,12 | 0,18 | 0,072 |
| Sumowono     | 0,11 | 0,115 | 0,155 | 0,117 | 0,119 | 0,106 |

CR = 0,05

3.2.3. **Alternative Rank Order.** Rank order for the alternative is done by using the equations from [13] as follows:

\[
\text{Ranking} = \sum_{i=1}^{t} (\text{attribute weight} \times \text{evaluation rating perk})
\]

Using the equations above, the rank order using the fuzzy AHP method is done by the application program which is shown in figure 3. As seen in figure 3, both methods have the same rank order, so we need to run another calculation using a different expert on pairwise comparison in order to make the rank order different. Using the same calculations, we can see the result in figure 4.

![Figure 3. The rank order of the supplier.](image)

![Figure 4. The rank order of supplier with a different expert.](image)

3.3. **Sensitivity analysis**

Sensitivity analysis will be performed on the fuzzy method of fuzzy AHP and fuzzy MOLP to find out which method is more sensitive to changes. Sensitivity analysis is useful in case both methods have different rank order. The process of sensitivity analysis will be done in a different way between AHP
and MOLP. For AHP, sensitivity analysis will be done by changing the weighted value of one of the criteria by 10% to 100% while other criteria will have the same value. Changing the weight value has the detail as: 10%, -10%, 20%, -20%, 30%, -30%, 50%, -50%, 100%, -100%. As for the MOLP, it will be done by changing the value of one of the alternatives with the same detail as AHP. Once the value is changed it will be known whether changing the value will change the rank order. The method which the least change in rank order can be said to be more robust.

3.3.1. Comparing changes between fuzzy AHP and Fuzzy MOLP. After using sensitivity analysis on both methods, now we can compare changes between both methods to see which one is more robust than the other. The comparison table is shown in table 5. Table 5 shows that fuzzy AHP is much more robust than fuzzy MOLP. On 10% and -10% change, fuzzy AHP has no change in rank order while Fuzzy MOLP has a rank order change of 9 out of 12 groups which means a change of 75%. For 20% and -20% change, fuzzy MOLP is further gained additional changes to 10 groups which means the percentage rises to 85% while fuzzy AHP did not gain additional changes. At 30% and -30% change, the fuzzy MOLP is further gain additional changes to 12 groups which means the percentage rose to 100% or all the group’s rank-order changes while fuzzy AHP did not gain additional changes. At 50% and -50% change, the fuzzy MOLP is already at 100% changes While fuzzy AHP finally gain additional changes with 1 group rank of 6 groups or with a percentage increase to 15%. At 100% and -100% change, the fuzzy is already at 100% changes while fuzzy AHP further gained additional changes into two groups or with a percentage increase to 30%. From the analysis above, we can conclude that fuzzy AHP is more robust to change than fuzzy MOLP. The percentage change from fuzzy AHP is in line with the findings of [14] which concludes that AHP has a relatively small percentage of change.

| Change of criteria of | Number of changes | Percentage of changes |
|----------------------|-------------------|-----------------------|
|                      | Fuzzy AHP | Fuzzy MOLP | Fuzzy AHP | Fuzzy MOLP |
| 10%                  | 0         | 9          | 0%        | 75%       |
| -10%                 | 0         | 9          | 0%        | 75%       |
| 20%                  | 0         | 10         | 0%        | 85%       |
| -20%                 | 0         | 10         | 0%        | 85%       |
| 30%                  | 0         | 12         | 0%        | 100%      |
| -30%                 | 0         | 12         | 0%        | 100%      |
| 50%                  | 1         | 12         | 15%       | 100%      |
| -50%                 | 1         | 12         | 15%       | 100%      |
| 100%                 | 2         | 12         | 30%       | 100%      |
| -100%                | 2         | 12         | 30%       | 100%      |

On the other hand, fuzzy MOLP relies heavily on the criteria values of each alternative which means if the gap between values is very small, fuzzy MOLP will be very sensitive to changes. However, fuzzy AHP relies heavily on the expert decision as fuzzy AHP only use the pairwise result as the only source of data which means if the expert does not understand the real condition on the subject, then the results obtained will not give the right rank order but only the subjectivity of the expert as seen on figure 3 and figure 4. We can see that expert 1 in figure 3 has the same rank order as MOLP while expert 2 has a different rank order. Expert 1 is more experienced than expert 2 as expert 1 is the top manager and expert 2 is the production manager. On the other hand, fuzzy MOLP uses the history data of criteria and alternatives which reflect the real conditions; thus, the result will give the most objectives solution to the problem.
4. Conclusions
From the findings and analysis in the previous section, we can conclude this paper with several conclusions, that fuzzy AHP and fuzzy MOLP have a very distinct characteristic, fuzzy AHP is very robust to criteria change as change from 10% to 100% only give variance from 0%-30%, but very vulnerable to inexperienced expert as two experts used in this study gives different result. On the other hand, while the robustness relies heavily on the data of each alternative as change from 10% to 100% give variance from 75% to 100%, the result from fuzzy MOLP is much more accurate than fuzzy AHP as it uses real data, both methods give the same rank order of supplier selection, but if the result is different, sensitivity analysis must be done with consideration of each method’s characteristic, fuzzy AHP and fuzzy MOLP have distinct approach to solve the problem. But, if the result of both methods is the same, then most likely the result is the best solution available.

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