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Third-Party Logistic Selection for Logistic Aggregator Company using Multi-Criteria Decision Making

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Abstract: The customer of Aggregator Company for Logistics (ACL) faces a problem when creating an order in the aggregator logistics platform. They have difficulty making an order as there are a lot of third-Party Logistic (3PL) alternatives available but they do not have any references for which 3PL they should select. This study helps the customer to choose the best 3PL by determining the suitable criteria. The study's objective is to build a Multi-Criteria Decision-Making (MCDM) model for 3PL assessment based on historical data. To construct the model in doing the assessment, a combined model based on the Fuzzy Analytic Hierarchy Process (F-AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) Was methodically operated. F-AHP was used to weigh the criteria and TOPSIS functioned to rank and score the 3PL alternatives. Sensitivity analysis is also performed to verify the robustness of the proposed model. This study was taken place in one of the Indonesian ACLs and the model could be beneficial for Indonesian ACL in evaluating, selecting, and recommending the best 3PL partner.

Keywords: 3PL Selection, MCDM, F-AHP, TOPSIS, Aggregator Logistics

Introduction

The increase in digitization has affected various business activities, including the company's business model, by enabling new forms of collaboration between companies and leading to new product and service offerings (Rachinger *et al*., 2018). The collaboration is also helped by developing Information and Communication Technologies (ICT) that enable companies to exchange products and services (Laya *et al*., 2016). Aggregation is one of the business models that emerges because of the ease of exchanging products and services. The aggregation business model is a business model with an intermediary company between the service provider and the customer. The intermediary company gives additional value by offering new services based on existing services under their platform (Laya *et al*., 2016).

In the logistics industry, third-Party Logistics (3PL) is an external company that provides logistic services to other companies or an individual (Yang, 2014). 3PL usually partners with an Aggregator Company for Logistics (ACL), so its services can be used by a broader range of customers and increase 3PL's number of orders. ACL practically collects product information from more than one 3PL partner. Then, it sells the products to its customers using its platform. ACL usually generates revenue from the commission given by its 3PL partner.

In the logistics industry, third-Party Logistics (3PL) is an external company that provides logistic services to other companies or an individual (Yang, 2014). 3PL usually partners with an Aggregator Company for Logistics (ACL) and collects product information from more than one 3PL partner. Then, it sells the products to its customers using its platform. ACL usually generates revenue from the commission given by its 3PL partner.

Since the ACL only acts as an aggregator and does not provide any new product to the customer, its main challenge is how to give the best user experience and keep them using its platform. One way to increase ACL's customers' experiences is by helping them to select the available 3PL alternatives. When customers input detailed information about their order (e.g., route and other information needed), they need a formal model to choose or recommend the best 3PL based on historical data and mathematical calculation.

In the last couple of years, there are many works related to the 3PL selection applied in many industries; such as pharmacy (Singh *et al*., 2017), cement (Sasananan *et al*., 2016), electronics (Prakash and Barua, 2016), marble (Ecer, 2018), agriculture (Yazdani *et al*., 2017; Yadav *et al*., 2020), chemical (Sremac *et al*., 2018) and logistics (Jovčić *et al*., 2019). But, none of them specifically discuss the aggregator business model or ACL.

Moreover, the 3PL selection process is a complex multi-criteria decision making, as the criteria considered depend on the industry and the business problem (Singh *et al*., 2017). In the ACL case, the criteria being used must represent the company and customers' needs. The selected 3PL must be the one that gives the highest revenue to the ACL and provides the best last-mile experience for the ACL's customers.

This study tried to address the problem, specifically in one ACL, by determining the suitable criteria and MCDM model. The criteria were determined by a literature study and direct interviews with the company. Since there are few studies about aggregator business models, this study is expected to be a reference to understand the suitable criteria for selecting 3PL for aggregator business models, specifically in the logistics industry.

The MCDM model was built based on a combination of currently available MCDM methods. The model developed combines the F-AHP and TOPSIS methods. F-AHP was used to give weight to each criterion that has been determined and TOPSIS functioned to rank and score the 3PL alternatives.

Finally, this study can be a novel academic reference for other researchers in building and implementing the official MCDM model in the aggregator business model. Then, the proposed model can be used for the company to evaluate, select and recommend their 3PL partner formally.

3PL

3PL is an external company that provides logistic services to other companies or individuals, typically on a contract basis (Yang, 2014). The emergence of 3PL was initially driven by business competition in several industries. Companies must continuously seek ways to design new products, manufacture them and distribute them efficiently and effectively to the end customers. Thus, to reduce costs, some companies are starting to outsource one or more of their logistics functions to the 3PL. The 3PL has more resources and experience in warehousing, distribution, and transportation to provide more efficient and cheaper logistics services (Yang, 2014).

In the e-commerce industry, the role of 3PL is still relatively significant even though some e-commerce already has their own logistics services. For example, Amazon still uses 3PL services such as FedEx, UPS, and DHL during peak seasons such as year-end holidays and prime days in July. They also use 3PL for simple orders that do not require complex processes that require these orders to be processed on their own logistics platform (Poncea *et al*., 2020).

Aggregator Business Model

The aggregator business model is a business model in which companies partner with other companies and collect information about their partners' products and services, then sell the products and services under their brand or platform (Gu *et al*., 2019). Typically, the aggregator company does not have manufacturing and warehousing capabilities. The aggregator company relies on its capabilities on leverages its extensive marketing network to create customer pools.

In Fig. 1, the aggregator company provides products or services to its customer based on products and services provided by its partner. The aggregator company usually generates revenue from the commission given by its partner. So, the income earned by aggregator companies is influenced by the amount of commission they get and the number of orders they generate.

3PL Selection

There were many studies about 3PL selection between 2016-2020. Sasananan *et al*. (2016) studied the best parameter to make a 3PL selection in the cement industry in India. Based on that research, the five best criteria successfully determined are the cost of service, compatibility with the customers, quality of services, the reputation of the vendor, and performance measurement. Prakash and Barua (2016) conducted research in the electronics industry. They combined the Fuzzy Analytic Hierarchy Process (F-AHP) and the visekriterijumsko kompromisno rangiranje (VIKOR) model to assess the 3PL alternatives. They evaluated the proposed model by discussing it with related industries. They said their model is useful based on the criteria they determined.

Singh *et al*. (2017) researched 3PL selection in the pharmaceutical industry in India. They combined F-AHP and fuzzy technique for order of preference by similarity to ideal solution (Fuzzy TOPSIS) in the 3PL assessment. Based on their research, the criteria defined were cost, infrastructure and facilities, customer service, network management, material handling capabilities, quality control, and inspection, process automation, innovation and effectiveness of cold chain processes, IT application, and flexibility.

Furthermore, Ecer (2018) used the AHP method to weigh and evaluate the criteria based on Distance from Average Solution (EDAS) as ranking or scoring models in the marble industry. Based on their research, the best 3PL selection criteria in the marble industry were cost, relationship, services, quality, information system, flexibility, delivery, professionalism, financial position, location, and reputation.

Yazdani *et al*. (2017) conducted a study about 3PL selection in the agriculture industry. They combined the Quality Function Deployment (QFD) and TOPSIS models to assess the alternatives. They evaluated their model

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using sensitivity analysis. The sensitivity analysis showed that by giving ten different weight values, the model gave a similar order for the best 3PL provider.

Moreover, Sremac *et al*. (2018) proposed a new model called rough step-wise weight assessment ratio analysis (Rough SWARA) and rough weighted aggregated sum product assessment (Rough WASPAS) to make a 3PL selection on the chemical industry. Rough SWARA was used for weighting criteria, while Rough WASPAS is used to rank or score. They evaluated their model using sensitivity analysis and compared it with currently available models i.e., EDAS, MABAC, and TOPSIS.

Based on sensitivity analysis, the result of recommended 3PL was similar even though they input different weigh of criteria. It could be concluded that the outcome of the 3PL selection between each model is significantly correlated.

Jovčić *et al.* (2019) proposed a new model called Fuzzy Inference System (FIS) built based on Wang-Mendel's method to determine fuzzy rules and the F-AHP method to determine the criteria. They studied 20 logistic companies in the Czech Republic and Poland. They compared their proposed model with TOPSIS and got a cumulative error of 1.991 for 20 3PL selections. So, they concluded that their model has a similar performance to TOPSIS.

Yadav *et al.* (2020) conducted a study about determining the best parameter to make a 3PL selection on the agriculture industry in India. They used the F-AHP model to solve the problem. There were four criteria and nine sub-criteria that they studied. Based on their research, the top 5 criteria for 3PL selection in the agriculture industry were privacy protection, congestion, overload issue, scalability of services, logistic support, and data quality.

Fig. 1: Aggregator business model

In summary, AHP is the most used model to weigh the criteria, while TOPSIS is the most used model to do the assessment. Six studies used AHP and two studies used TOPSIS. Additionally, two studies also compare their new proposed model with TOPSIS. Therefore, we combined both models in this study to make the 3PL selection. We also added fuzzy logic in AHP to handle uncertain and vague experts' opinions.

Materials and Methods

There are five stages in this study, as shown in Fig. 2. In the first stage, we interviewed the Indonesian ACL representatives to get a deeper understanding of the existing case and problems. These interviews were conducted to answer several questions, such as why the company needs to eliminate the 3PL selection process, the current 3PL selection process, and the criteria that need to be considered in the 3PL selection.

After conducting the interview, the next step was constructing the decision parameters based on the interview and literature study. As we said earlier, the parameters should represent the company and customer's needs. The third stage in this study was the data collection process. There were two types of data that we collected in this stage. The first is the relative importance value for each criterion and the other is the 3PL and its criteria value. For the first data, we interviewed industry experts to get their perspectives on the relative importance value of our selected parameters. While the 3PL criteria value were collected through direct observation of the company databases. Data collected depend on the selected parameters in the previous stages. We collected all order data from 1 October 2020 to 31 March 2021 in the selected route from the Indonesian ACL.

The following stage of the study was designing the model. In this study, a Unified Modeling Language (UML) consisting of 2 diagrams (i.e., activity diagram and class diagram) was operated methodically. UML is a modeling language operated scientifically to speak the constructed model to the typical reader in an easy way (Hartanto and Utama, 2020). The activity diagram illustrates the sequence of activities in the model being built (Rachmat and Utama, 2020). Then, the class diagram shows the interconnected class in the model (Utama *et al*., 2020). Finally, the last stage in this study was constructing the model. The model developed combines the F-AHP and TOPSIS methods. F-AHP was used to give weight to each criterion that has been determined and TOPSIS functioned to rank and score the 3PL alternatives.

F-AHP

Saty originally proposed AHP in 1980. The AHP method compares criteria or alternatives to a criterion in a natural, pair-wise mode. The AHP is the most popular MCDM model because it can understand the problem from various levels using a hierarchical structure (Luthra *et al*., 2013). The other advantage of AHP is that this method can consider many parameters simultaneously, the consistent ratio can track inconsistent judgment and it can be applied to any organization at any level of expertise (Sasananan *et al*., 2016).

Saaty (1980) formulated a scale from 1 to 9 to determine the level of importance of each criterion. The value of importance for each criterion comes from the expert's opinion. Since the expert's opinion is uncertain and vague, Zadeh (1965) developed a fuzzy set theory to deal with this inaccuracy of human expert opinion.

F-AHP is a combination between fuzzy set theory and the AHP method by using fuzzy numbers in the calculation process to replace the original value (Ayhan, 2013). Fuzzy numbers are seen as a fuzzy subset of real numbers and a fuzzy number A on R is expressed as $A = [(x, \mu_A(x)), x \in R]$, where $\mu_A(x)$ is the membership function and $\mu_A(x)$: R [0,1]. The main operation rules for two fuzzy numbers are as follows:

$$(p_1, r_1, s_1) \oplus (p_2, r_2, s_2) = (p_1 + p_2, r_1 + r_2, s_1 + s_2) \quad (1)$$

$$(p_1, r_1, s_1) \otimes (p_2, r_2, s_2) = (p_1 p_2, r_1 r_2, s_1 s_2) \quad (2)$$

$$(p_1, r_1, s_1)^{(-1)} = (1/s_1, 1/r_1, 1/p_1) \quad (3)$$

To transform the lingusitic variables into fuzzy numbers, Table 1 is utilized. The step of F-AHP calculation are described as follows:

1. Construct $n \times n$ pairwise comparison matrix
2. Change the scale to a triangle fuzzy number based on Table 1
3. If there is more than one comparison matrix, aggregate the value using fuzzy geometric mean (r) e using Eq. (4) to form one comparison matrix
4. Calculate fuzzy geometric mean (r) for each parameter mean using Eq. (5); where d_e is fuzzy number; i = 1,2 ,...m; and j = 1,2,...,n
5. Calculate fuzzy weight (w) using Eq. (5); e where r is the fuzzy geometric mean for each e parameter
6. Convert fuzzy triangular number to crisp value by calculating the center of the area to get weight (M) using Eq. (6); where lw is the lower value of fuzzy weight (w); mw is the middle value of the fuzzy weight $(\tilde{w})$, and uw is upper value of fuzzy weight $(\tilde{w})$
7. Normalized weight (N) using Eq. (7); where M is the weight for each parameter.

$$\tilde{r}_1 = \sqrt{\prod_{j=1}^{n} \tilde{d}_{ij}} \quad (4)$$

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\tilde{r}_1 \oplus \tilde{r}_2 \oplus ... \oplus \tilde{r}_n\right)^{(-1)} \quad (5)$$

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \quad (6)$$

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \quad (7)$$

TOPSIS

TOPSIS is an MCDM method proposed by Hwang and Yoon in 1981 to find the best alternative by choosing the closest distance to the positive ideal solution (optimal solution) and having the furthest distance from the negative ideal solution (non-optimal solution) (Ginting *et al*., 2017). Figure 3 shows an example of the spatial distribution of alternatives where A^+ and A^- are the optimal and non-optimal solutions respectively. The symbols $A_1, A_2, ...,$ *and* A_m are the available alternatives, and $K_1, K_2, ...,$ and K_n are the criteria considered in the selection process.

This method is a widely accepted MCDM model because this method is sound logic, considers ideal and non-ideal solutions and the calculation process can be computed easily (Kim *et al*., 1997). Some researchers combine the TOPSIS method with fuzzy logic if the research requires the use of linguistic variables in the criteria (Singh *et al*., 2017). The steps of TOPSIS are described as follows:

1. Create decision matrix
2. Normalized decision matrix using Eq. (8); where X is the original value for each parameter
3. Calculated weighted normalized (y) decision matrix using Eq. (9); where w is weight; and r is a normalized value
4. Find the ideal best (y^+) and ideal worst (y^-) value
5. Calculate the euclidean distance from the ideal solution (D^+) and ideal worst solution (D^-) using Eq. (10) and (11); where y is the normalized value; y^+ is the ideal best solution, and y^- is the ideal worst solution
6. Calculate decision value (V) using Eq. (12); where D^+ is the distance from the ideal best solution; and D^- is the distance from the ideal worst solution:

$$\tilde{r}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} X_{ij}^2}} \quad (8)$$

$$y_{ij} = w_{ij} r_{ij} \quad (9)$$

$$D+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_{ij}^+\right)^2} \quad (10)$$

$$D^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_{ij}^-\right)^2} \quad (11)$$

$$V_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (12)$$

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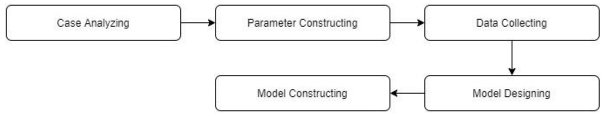

Fig. 2: Research stages

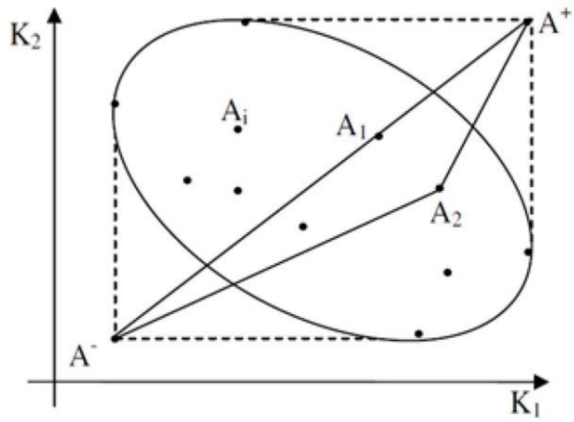

Fig. 3: Alternate distance from an optimal and non-optimal ideal solution

Table 1: F-AHP scale

Scale	Linguistic variable	Triangle fuzzy number
1	Equally important	(1,1,1)
2	Intermediate value	(1,2,3)
3	Weakly Important	(2,3,4)
4	Intermediate value	(3,4,5)
5	Fairly Important	(4,5,6)
6	Intermediate value	(5,6,7)
7	Strongly Important	(6,7,8)
8	Intermediate value	(7,8,9)
9	Important	(9,9,9)

Results and Discussion

Parameterization

Based on a literature study and direct interviews with the ACL, three criteria with five sub-criteria (i.e., on-time score, complain score, a commission from 3PL, shipment cost, and promised time delivery) are considered as parameters to evaluate 3PL alternatives. All of those parameters can be seen in Table 2. The influence diagram in Fig. 2 shows the interconnection between all parameters in the constructed model. On-time score and complaint score are dependent parameters determined based on other parameters. On-time scores are determined by points collected and total order, while complaint scores are determined by total order with a complaint and total order. The influence diagram in Fig. 4 also shows the sub-model that involves constructing the primary model. Three models are being used (i.e., fuzzy logic, AHP, and TOPSIS). Fuzzy logic is used since there are linguistic variables in determining the parameters' relative importance value. AHP is used to weigh the parameters, while TOPSIS ranks and scores the alternatives. In the end, the influence diagram shows the primary model's objective. The objective of the constructed model is to maximize the decision value of recommended 3PL based on the best 3PL alternative.

Constructed Model

The class diagram in Fig. 5 shows the interconnected class in the constructed model. The constructed model consists of 11 classes (i.e., 3PL, TOPSIS, F-AHP, AHP, Fuzzy Logic, Fuzzy Rule, Membership Function, Triangular MF, Trapezoidal MF, Curve MF, and decision). The class 3PL describes the 3PL information and its criteria value. The classes TOPSIS and F-AHP will be the center of model operation. In class TOPSIS will perform 6 calculation such as normalizeData(), calculateWeightedNormalization(), getBestWorstVal(), calculateEuclideanDistance(), calculateDecisionValue() and showBestAlternative().

The F-AHP class is an empty class that combines operations between the AHP and Fuzzy Logic classes. In the AHP class there are 4 AHP operations such as setPairWiseMatrix(), calculateGeometricMean(), calculateWeight() and normalizedWeight(). Meanwhile, in the Fuzzy Logic class, it will perform 2 operations, including fuzzify() and defuzzify(). To perform fuzzy operations in the Fuzzy Logic class, another class is needed such as Fuzzy Rule, Membership Function, Triangular MF, Trapezoidal MF, and Curve MF. The detail of each calculation process is explained in the activity diagram in Fig. 6.

Experimental Results

Based on the collected data, we create a comparison matrix based on the relative importance value for our parameters. There is three comparison matrix from 3 experts' ratings. Then we aggregate all of them using the geometric mean. The aggregation result can be seen in Table 3. After that, we calculate the fuzzy geometric mean for each parameter using Eq. (1) to get the average value:

$$
\begin{aligned}
\tilde{r}_{(OS)} &= \Big(\sqrt[5]{1*3.17*1.26*3.17}, \\
&\quad \sqrt[5]{1*4.22*3.98*1.71*4.22}, \\
&\quad \sqrt[5]{1*5.24*5.04*2.29*5.24}, \Big) \\
&= (2.05, 2.61, 3.16)
\end{aligned}
$$

$$
\begin{aligned}
w_{(OS)} &= (2.05, 2.61, 3.16) \otimes \left(\frac{1}{7.38}, \frac{1}{5.91}, \frac{1}{4.65}\right) \\
&= \left(2.05 * \frac{1}{7.38}, 2.61 * \frac{1}{591}, 3.16 * \frac{1}{4.65}\right) \\
&= (0.28, 0.44, 0.68)
\end{aligned}
$$

After we get the fuzzy weight, then we convert the fuzzy number to a crisp value by calculating the center of the area using Eq. (3):

$$M_{(OS)} = \frac{(0.28 + 0.44 + 0.68)}{3}$$
$$= 0.467$$

Then, the last step in the F-AHP calculation process is to normalize the weight using Eq. (4):

$$N_{(OS)} = \frac{0.467}{(0.467 + 0.094 + 0.172 + 0.212 + 0.128)}$$
$$= 0.435$$

The calculation result for all of those calculation processes can be seen in Table 4. At this point, we can see that the On-time Score (OS) has the highest weight followed by Commission (CM), Shipment Cost (SC), Complain Score (CS), and Time Delivery (TD).

After we got the normalized weight for each parameter, we began the TOPSIS calculation process. Our original parameters data can be seen in Table 5. There are six 3PL alternatives with five parameters value each. The first step is to normalize the data using Eq. (5). The result of the normalized value can be seen in Table 6:

$$\tilde{r}_{(OS,3PLA)} = \frac{0.93}{\sqrt{0.93^2 + 0.78^2 + \ldots + 1.11^2}}$$
$$= \frac{0.93}{2.25}$$
$$= 0.41$$

Next, we calculate the weighted normalized value using Eq. (6) based on the previous normalized weight and normalized parameters value. The result of the weighted normalized value can be seen in Table 7:

$$y_{(OS,3PLA)} = 0.435 * 0.41$$
$$= 0.18$$

Then, we determine the ideal best and ideal value for each parameter. The ideal best value for OS and CM is the highest value while for CS, SC and TD is the lowest value. After that we calculate the euclidean distance from each value to its best and worst ideal value using Eq. (7) and (8):

$$D^+_{(3PLA)} = \sqrt{(0.17 - 0.23)^2 + \ldots + (0.20 - 0.23)^2}$$
$$= \sqrt{0.013}$$
$$= 0.115$$

$$D^-_{(3PLA)} = \sqrt{(0.18 - 0.11)^2 + \ldots + (0.22 - 0.11)^2}$$
$$= \sqrt{0.009}$$
$$= 0.096$$

The last, we calculate the decision value based on euclidean distance using Eq. (9):

$$V_{3PLA} = \frac{0.096}{0.096 + 0.115}$$
$$= 0.455$$

3PL with the highest decision value is the best 3PL alternative. Based on our calculation, the best 3PL alternative is 3PL F followed by 3PL C, 3PL E, 3PL A, 3PL B, and 3PL D.

Sensitivity Analysis

Sensitivity analysis is a technique for observing how the ranking order of 3PL providers behaves when the criteria weights are switched. The strategy to operate sensitivity analysis in this study is to switch two criteria while the others are constant. For example, in the first test weight of OS is switched with CS, then in the next test weight of CS is switched with CM, and so on. Therefore, five different sets of weights are tested for the TOPSIS model. All test scenarios can be seen in Table 8 and 9.

The change in the final ranking for each test can be seen in Table 10. 3PL F remains the best alternative for all test scenarios, followed by 3PL C and 3PL E in second and third place. The result shows that the proposed framework is robust and less influenced by experts' ratings.

Table 2: 3PL selection criteria

Criteria	Sub-criteria	Description	Goals
Performance	On-time Score (OS)	It is an assessment of how disciplined 3PL is to deliver goods within the time frame, they have promised	Max
Performance	Complain Score (CS)	represents the number of complaints related to problems related to the 3PL in certain routes	Min
Firm revenue	Commission from 3PL (CM)	The amount of commission given by the 3PL party for every order made through the logistics aggregator platform	Max
Cost	Shipment Cost (SC)	Cost that must be borne by consumers to use 3PL delivery services for certain routes and types of services	Min
Service	Promised Time Delivery (TD)	The maximum time limit promised by 3PL for the package to arrive at the destination city	Min

Table 3: Aggregation of relative importance value

	OS	CS	CM	SC	TD
OS	(1.00, 1.00, 1.00)	(3.17, 4.22, 5.24)	(2.88, 3.98, 5.04)	(1.26, 1.71, 2.29)	(3.17, 4.22, 5.24)
CR	(0.19, 0.24, 0.31)	(1.00, 1.00, 1.00)	(0.44, 0.58, 0.79)	(0.25, 0.33, 0.50)	(0.50, 0.69, 1.00)
CM	(0.20, 0.25, 0.31)	(1.26, 1.71, 2.29)	(1.00, 1.00, 1.00)	(0.87, 1.22, 1.59)	(1.10, 1.44, 1.82)
SC	(0.44, 0.58, 0.79)	(2.00, 3.00, 4.00)	(0.63, 0.82, 1.14)	(1.00, 1.00, 1.00)	(1.00, 1.44, 2.00)
TD	(0.19, 0.24, 0.31)	(1.00, 1.44, 2.00)	(0.55, 0.69, 0.91)	(0.50, 0.69, 1.00)	(1.00, 1.00, 1.00)

Table 4: F-AHP calculation

Parameters	Fuzzy geometric means	Fuzzy weight	Weight	Normalized weight
OS	(2.05, 2.61, 3.16)	(0.28, 0.44, 0.68)	0.467	0.435
CS	(0.40, 0.50, 0.66)	(0.05, 0.09, 0.14)	0.094	0.087
CM	(0.75, 0.95, 1.18)	(0.10, 0.16, 0.25)	0.172	0.160
SC	(0.89, 1.16, 1.49)	(0.12, 0.20, 0.32)	0.212	0.198
TD	(0.55, 0.70, 0.89)	(0.08, 0.12, 0.19)	0.128	0.120

Table 5: Parameters original value

	OS	CS	CM	SC	TD
3PL A	0.93	0.024	0.08	20,000	2.00
3PL B	0.78	0.009	0.10	30,750	2.13
3PL C	1.20	0.000	0.18	11,000	4.00
3PL D	0.55	0.005	0.10	36,000	2.00
3PL E	0.77	0.000	0.05	23,666	2.00
3PL F	1.11	0.000	0.15	12,000	3.00

Table 6: Parameters normalized value

	OS	CS	CM	SC	TD
3PL A	0.41	0.92	0.28	0.34	0.31
3PL B	0.35	0.35	0.35	0.52	0.33
3PL C	0.53	0.00	0.62	0.19	0.62
3PL D	0.25	0.18	0.35	0.61	0.31
3PL E	0.34	0.00	0.17	0.40	0.31
3PL F	0.49	0.00	0.52	0.20	0.47

Table 7: Weighted normalized value

	OS	CS	CM	SC	TD
3PL A	0.18	0.08	0.04	0.07	0.04
3PL B	0.15	0.03	0.06	0.10	0.04
3PL C	0.23	0.00	0.10	0.04	0.07
3PL D	0.11	0.02	0.06	0.12	0.04
3PL E	0.15	0.00	0.03	0.08	0.04
3PL F	0.22	0.00	0.08	0.04	0.06

Table 8: TOPSIS Final Calculation

	D+	D−	Decision Value	Rangking
3PL A	0.115	0.096	0.455	4
3PL B	0.117	0.081	0.407	5
3PL C	0.037	0.183	0.831	2
3PL D	0.155	0.080	0.340	6
3PL E	0.116	0.106	0.477	3
3PL F	0.030	0.166	0.849	1

Table 9: Test for sensitivity analysis

	WOS	WCS	WCM	WSC	WTD
Test 1	0.435	0.087	0.160	0.198	0.120
Test 2	0.087	0.435	0.160	0.198	0.120
Test 3	0.435	0.160	0.087	0.198	0.120
Test 4	0.435	0.087	0.198	0.160	0.120
Test 5	0.435	0.087	0.160	0.120	0.198

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Table 10: Sensitivity analysis ranking outcomes

	Test 1	Test 2	Test 3	Test 4	Test 5
3PL A	4	6	6	5	4
3PL B	5	5	4	4	5
3PL C	2	2	2	2	2
3PL D	6	4	5	6	6
3PL E	3	3	3	3	3
3PL F	1	1	1	1	1

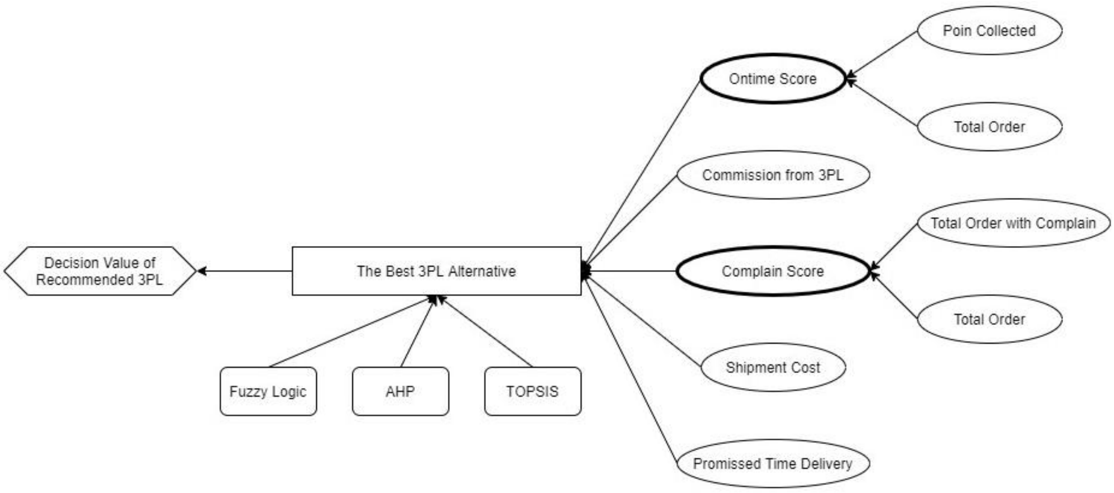

Fig. 4: Influence diagram

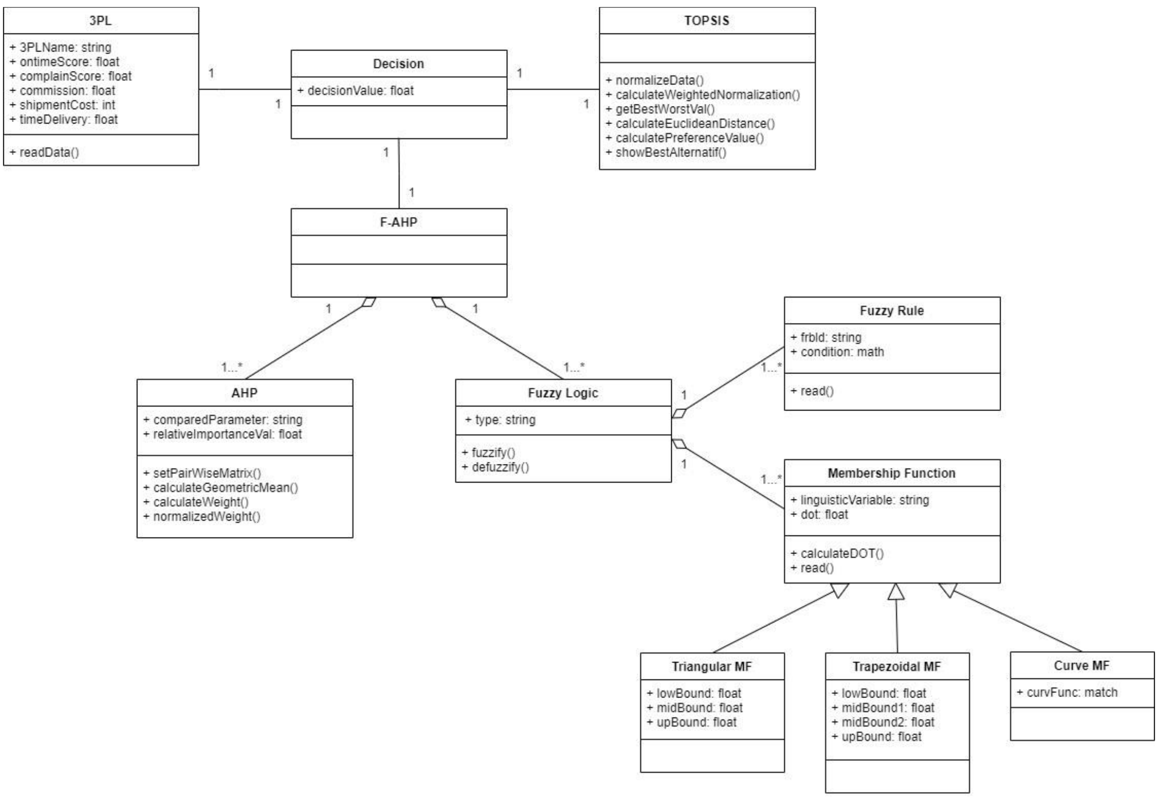

Fig. 5: Class diagram

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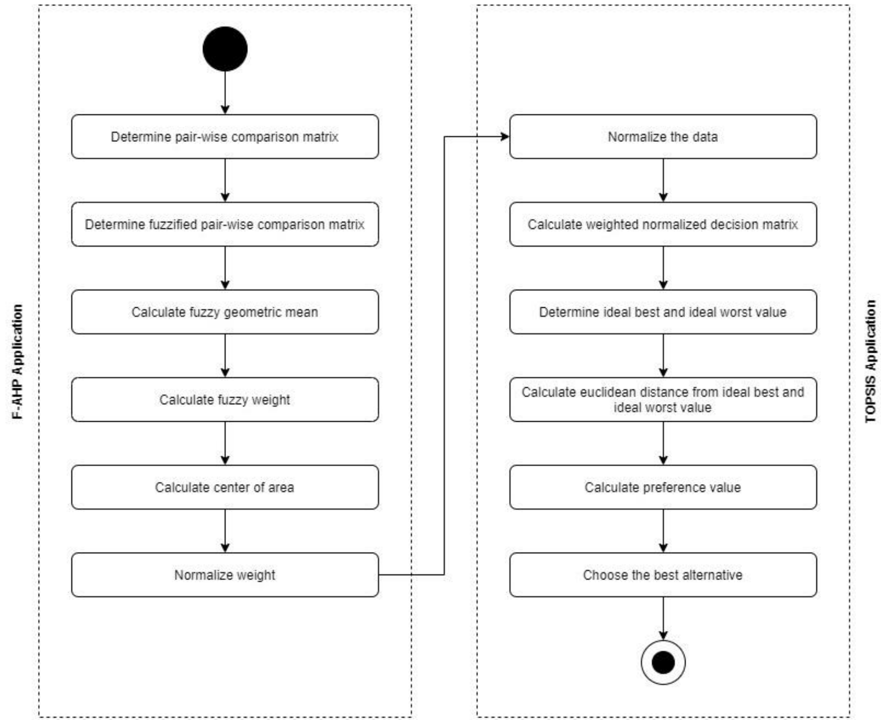

Fig. 6: Activity diagram

Conclusion

An MCDM model was successfully created on the aggregator logistics case. 5 parameters (i.e., on-time score, complain score, a commission from 3PL, shipment cost, and promised time delivery) can be considered on the 3PL assessment in an aggregator logistics company. Those parameters already covered the aggregator company and the customer's needs. The constructed model combined F-AHP and TOPSIS to evaluate the 3PL alternatives. Using fuzzy in AHP can eliminate the uncertainty judgment from an industry expert to the relative importance value of our parameters.

This constructed model can be used in an aggregator logistic company's platform by being implemented in the back-end process of order creation. This model will help to recommend or choose the best 3PL service for their customer. By implementing this model, the customer does not need to choose a 3PL service when creating an order. This will shorten the flow of order creation. This model can also help the aggregator company evaluate its 3PL partner by knowing which 3PL is performing better. So when the aggregator company wants to make a strategic partnership, they know which 3PL they will go to.

Future research in this area is still interesting. In a specific route, 3PL may have more than one service that can be offered to the customer. Because of the data limitation, we cannot analyze or include the customer preferences of service in the model. It will be interesting if there is any study that can include that perspective to understand the customer better.

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Author's Contributions

Muhammad Khakim Hidayad: Contribute to defining the research problem, collecting the data, developing the model, and writing the paper.

Ditdit Nuegraha Utama: Supervising the research by providing suggestions in the development of the model and reviewing the final manuscript.

Ethics

This manuscript substance is the authors' original work and has not been previously published somewhere else. Authors already read and approved the manuscript and no potential ethical issues are immersed.

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