Supplier Selection and Order Allocation Based on Multi-Criteria Decision-Making Using AHP, Fuzzy TOPSIS, and Multi-Choice Goal Programming to Improve Local Content (TKDN)

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Abstract. PT PLN Pusharlis faces challenges in selecting and allocating suppliers for Control Board components used in Public Electric Vehicle Charging Stations (SPKLU). Inaccurate supplier selection and inefficient order allocation can result in procurement delays and increased operational costs. This study aims to develop an integrated decision-making model that facilitates the selection of the most suitable suppliers and the optimal allocation of orders based on projected demand. The initial phase involves forecasting the demand for Control Board using ARIMA method. The supplier selection and order allocation process then adopt a multi-criteria decision-making framework. The Analytical Hierarchy Process (AHP) is applied to determine the weight of each criterion, suppliers are ranked using the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS), and the final order allocation is optimized through Multi-Choice Goal Programming (MCGP). The evaluation criteria encompass economic performance, ethical compliance, environmental impact, and Local Content Requirement (TKDN). Unlike conventional approaches, the TKDN criterion in this study is developed as a multi-attribute index, incorporating not only the percentage of domestic materials but also local production processes, labor utilization, and technology adoption. The proposed model is expected to support more accurate and support of sustainable SPKLU operations.

Keywords: *ARIMA, AHP, Fuzzy TOPSIS, Multi-Choice Goal Programming, SPKLU, forecasting*

1 Introduction

Electricity demand in Indonesia continues to grow in line with technological advancement and electrification. According to Statistics Indonesia (BPS, 2023), the largest share of electricity consumption comes from households (42%), followed by the industrial (32%) and commercial (18%) sectors. One of the government's strategic initiatives to support energy transition is the development of the national electric vehicle ecosystem, which includes the construction of Public Electric Vehicle Charging Stations (SPKLU). In this initiative, PT PLN

(Persero) Pusharlis plays a key role as a manufacturer of SPKLU units. The production of Control Board components is carried out on a made-to-order basis, making it highly dependent on the timely availability of materials from suppliers. In practice, several recurring issues are encountered, such as delivery delays, specification mismatches, and component shortages. These issues contribute to increased lead time and disruptions in project schedules. Therefore, this study addresses the following key problems:

a. Delays in the procurement of Control Board materials for SPKLU, mainly due to limited availability of raw materials.
b. The absence of a supplier selection and order allocation system that considers multi-dimensional criteria to ensure component availability from suppliers.
c. The lack of a comprehensive Local Content Requirement (TKDN) index that integrates material, labor, process, and technology aspects.

As a solution, this research proposes the development of an integrated decision-making model based on actual demand forecasts.

1.1 Objectives

The objective of this study is to develop an integrated decision-making model for the selection of suppliers and the allocation of orders for Control Board components used in Public Electric Vehicle Charging Stations (SPKLU), manufactured by PT PLN (Persero) Pusharlis. The model integrates demand forecasting, multi-criteria evaluation, and order allocation optimization to support data-driven procurement decisions. The ultimate goal of the model is to ensure optimal supplier allocation that enhances procurement efficiency, supports national sustainability policies, and strengthens the domestic supply chain in the energy sector.

1.2 Research Positioning

Table 1 presents a summary of previous studies related to the topic, highlighting the research gap addressed in this study.

Table 1 Research Positioning

No	Authors	Evaluation Criteria	Methodology							Sensitivity Analysis	Remarks
			Fuzzy	AHP	TOPSIS	BMW	Forecasting	GP	ANP		
1	Chi dan Trinh, (2016)	Evaluation Criteria		✓	✓			✓			Utilizes an integrated approach of AHP, TOPSIS, and Goal Programming for supplier order allocation
2	Menon & Ravi (2022)	Quality, Delivery, Distance, Price, Profile		✓	✓						Employs a combination of AHP and TOPSIS methods, with the final output being a supplier ranking.
3	Chanpuypetch et al. (2024)	Economic, Ethics, Environmental, Social		✓	✓					✓	Applies the AHP–TOPSIS integration method, producing a ranked list of supplier alternatives.
4	Varchandi et al. (2024)	Product, Market, Production, Cost, Environmental	✓		✓	✓				✓	Uses the Best–Mediocre–Worst (BMW) method integrated with Fuzzy TOPSIS, resulting in supplier ranking.
5	Abrian (2016)	Economic, Environmental, Social, Resilience							✓		Implements the Analytic Network Process (ANP) to determine criteria and sub-criteria for supplier selection;
6	Bahar (2025)	Commercial, Quality, Delivery, Local Content	✓	✓	✓		✓	✓		✓	This study introduces a multi-attribute TKDN (local content) index, which includes not only the percentage of domestic materials but also local production processes, labor, and technological contributions.

2 Literature Riview

This section reviews the relevant literature on supplier selection, Multi-Criteria Decision Making (MCDM), fuzzy logic, and sensitivity analysis.

2.1 Supplier Selection

The supplier selection process plays a critical role in supporting the performance of a company's supply chain, particularly in the manufacturing sector. Making the right decision in selecting supplier partners directly affects cost efficiency, product quality, customer satisfaction, and risk mitigation in operations (Monczka et al., 2009; Chopra & Meindl, 2013; Pujawan & Mahendrawathi, 2017). One of the most widely cited early studies in the development of supplier evaluation criteria was conducted by Dickson (1966), who identified 23 important criteria based on a survey of hundreds of purchasing agents. The key criteria highlighted in this study included quality, on-time delivery, and price. Meanwhile, Weber et al. (1991) refined several of these criteria from earlier studies and adapted them to the Just-In-Time (JIT) system context, still emphasizing quality and delivery performance as essential elements in supplier selection. Further research by Stevic (2017) indicated that the evaluation criteria proposed by Dickson and Weber remain highly relevant in modern supply chain management practices.

2.2 Multi Criteria Decision Making (MCDM)

According to Zimmermann (1986) and Kahraman (2015), Multi-Criteria Decision Making (MCDM) is a methodological approach used to address complex problems that involve multiple, often conflicting, criteria. In MCDM, decision-makers evaluate a set of alternatives in order to select the most suitable one and rank them based on their relative performance. MCDM is generally classified into two categories: Multi-Attribute Decision Making (MADM), which deals with discrete alternatives, and Multi-Objective Decision Making (MODM), which involves continuous decision variables. Supplier selection falls under the category of MADM, as it involves conflicting criteria such as cost, quality, delivery time, and others (Ghorabaee et al., 2017). In a study conducted by Ghorabaee et al. (2017), it was found that the Analytical Hierarchy Process (AHP) is the most widely used single-approach technique for supplier selection problems, accounting for 26.77% of usage. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks second with a usage rate of 20.71%, followed by the Analytic Network Process (ANP) at 6.06%. In terms of hybrid approaches, the combination of AHP and TOPSIS is the most commonly applied, with a usage rate of 16.31%, followed by the integration of AHP and Linear Programming (LP) at 13.48%. Other hybrid methods explored in the study include TOPSIS–LP, ANP–TOPSIS, AHP–DEA, and VIKOR-based integrations.

2.3 Fuzzy Logic

Zadeh (1965) introduced fuzzy logic as an approach to handle uncertainty by allowing degrees of membership between 0 and 1. This logic enables a value to be partially true and partially false at the same time, providing a framework for interpreting linguistic data such as the level of importance in supplier selection. One of the most commonly used fuzzy number representations is the Triangular Fuzzy Number (TFN), which is expressed as a triplet (l, m, n), where l represents the lower limit, m the most likely value, and n the upper limit.

3 Results and Discussion

This section outlines the research methodology, including the conceptual model and the methods employed for data processing and analysis.

3.1 Conceptual Model

This study develops a conceptual model designed to systematically and measurably integrate the supplier selection and order allocation processes. This conceptual model serves as the foundation for formulating the mathematical model in the subsequent stages of the research.

a. Structural Aspect
   This research focuses on the selection and allocation of suppliers for Control Board components used in Public Electric Vehicle Charging Stations (SPKLU), which are manufactured by PT PLN (Persero) Pusharlis. Since the production is made-to-order, the accuracy in supplier selection and the optimal allocation of order quantities are critical to ensuring timely production and controlling logistics costs.

b. Functional Aspect
   The proposed model integrates several methods: ARIMA for forecasting the demand of Control Board components, AHP for determining the weight of supplier selection criteria, Fuzzy TOPSIS for ranking supplier alternatives, and Multi-Choice Goal Programming (MCGP) for optimizing order allocation. The supplier evaluation process considers criteria such as economic performance, ethics, environmental impact, and a multi-attribute TKDN index.

c. Decision Variables
   The key decision variables in this model are: the selection of the most suitable suppliers based on preference scores (Fuzzy TOPSIS results), the quantity of order allocation to each supplier (MCGP results), and the proportion of material fulfillment in line with the demand forecasted by ARIMA.

d. Constraints and Limitations
   1) The total demand forecasted by the ARIMA model must be fully satisfied.
   2) The total procurement cost must not exceed the predetermined budget.
   3) The quantity of orders assigned to each supplier must not exceed their maximum capacity.
   4) The minimum Local Content (TKDN) requirement must be met in accordance with applicable regulations.

e. Parameters

The key parameters used in this model include:

1) Historical demand data for Control Board components (input for ARIMA).
2) Weight of supplier selection criteria (derived from AHP).
3) Supplier preference scores (obtained from Fuzzy TOPSIS).
4) Minimum and maximum supply capacity of each supplier.
5) Minimum TKDN threshold required by regulation.

3.2 Flowchart Diagram of Supplier Selection and Order Allocation

This study begins with an initial phase of data collection, which includes both primary and secondary data. The primary data are obtained through the distribution of questionnaires to experts with competencies in procurement, supplier evaluation, and supply chain management, particularly within the electricity industry context. Meanwhile, secondary data are gathered from relevant literature and historical records of material demand for Public Electric Vehicle Charging Stations (SPKLU) from 2021 to 2024. The objective of this phase is to establish both a conceptual and empirical foundation for formulating supplier evaluation criteria and forecasting material demand as a reference for allocation. Once the data are collected, an analysis process is conducted to formulate and validate the evaluation criteria and sub-criteria. This process combines insights from literature reviews with expert assessments. The supplier evaluation criteria consist of: Economic (sub-criteria: quality, delivery, cost, location), Environmental (sub-criterion: eco-design), Ethics (sub-criteria: code of ethics, transparency in accounting and business practices), Local Content (TKDN) (sub-criteria: domestic material content, TKDN certification, local production capacity).

These criteria serve as the foundation for the multi-criteria decision-making process in evaluating supplier alternatives. In parallel, a quantitative forecasting process is carried out based on historical SPKLU data to estimate the demand volume for Control Board components over the next year. This forecast serves as a critical input in the subsequent order allocation optimization process. The first processing stage involves determining the weight of each criterion and sub-criterion using the Analytic Hierarchy Process (AHP), based on expert preference ratings. The output is a set of relative importance weights for all criteria. The second stage entails evaluating supplier alternatives using the Fuzzy TOPSIS method, which addresses uncertainty in qualitative assessments and generates supplier rankings based on closeness coefficients to the ideal solution. The third stage focuses on order allocation using Multi-Choice Goal Programming (MCGP), integrating demand forecasts, supplier capacity constraints, and evaluation scores. The final result is an optimal allocation of orders to each supplier. This result is then subjected to sensitivity analysis to examine the robustness of the model under changing parameters. Finally, a comprehensive analysis and discussion of results is conducted to provide strategic recommendations for more data-driven and measurable procurement decision-making. This overall flowchart is summarized in Figure 1 Supplier Selection and Order Allocation Flowchart.

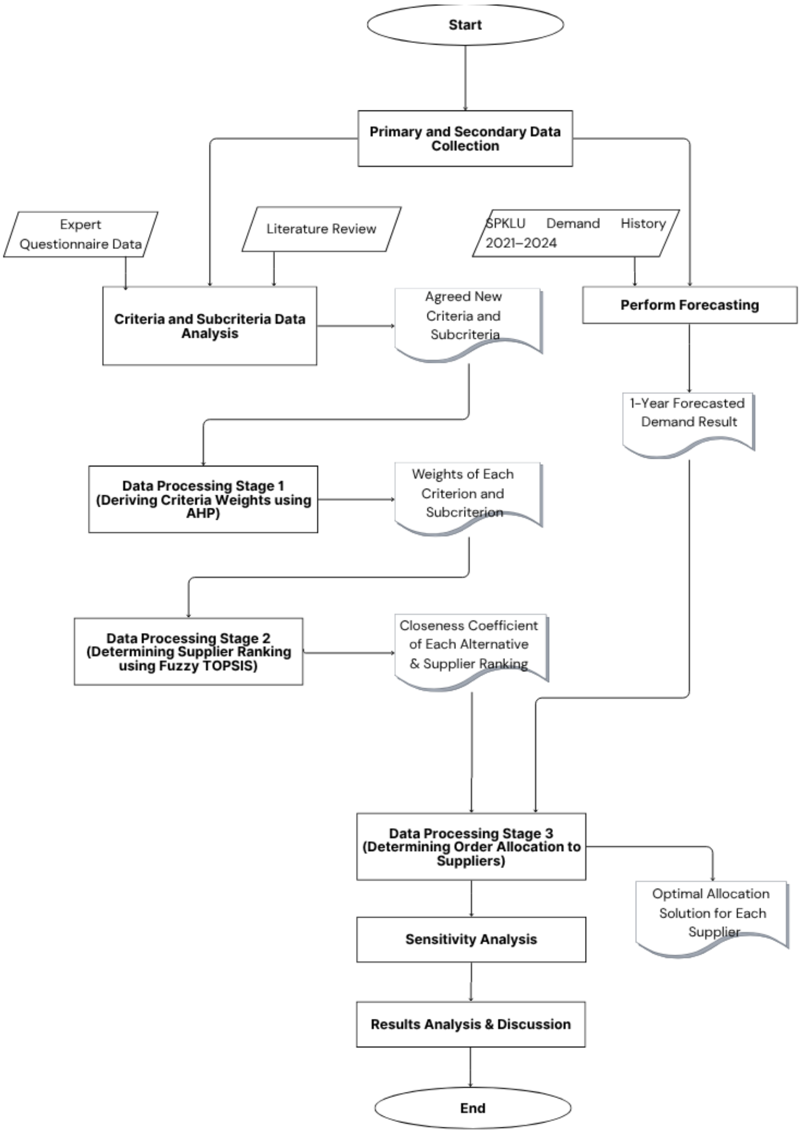

Figure 1 Supplier Selection and Order Allocation Flowchart

3.3 Analytic Hierarchy Process (AHP)

A distinctive feature of the Analytic Hierarchy Process (AHP) lies in its use of pairwise comparisons. The constructed matrix consists of elements evaluated using a numerical scale, where the values are derived from the judgments of decision-makers or subject-matter experts.

According to Chi and Trinh (2016), the AHP procedure involves the following steps:

a. Constructing the Decision Hierarchy
b. Developing the Pairwise Comparison Matrix, as defined in Equation (1):

$$A_{n\times n} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \tag{1}$$

c. Constructing the Normalized Matrix using Equation (2):

$$C_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \tag{2}$$

Where i=1, 2, 3… n, j=1,2,3…n

d. Calculating the Weights from the Normalized Decision Matrix as shown in Equation (3):

$$w_i = \sum_{j=1}^{n} \frac{c_{ij}}{n} \tag{3}$$

e. Calculating the Weighted Sum Vector (Row Matrix) using Equations (4) and (5):

$$E = N^{th}roothvalue/\sum N^{th}roothvalue \tag{4}$$

$$Row\ Matrik = \sum_{j=1}^{n} a_{ij} * e_{j1} \tag{5}$$

f. Calculating the Principal Eigenvalue $\tau\tau max$ through Equation (6):

$$\lambda_{max} = Row\ MatriksE \tag{6}$$

g. Calculating the Consistency Index (CI) with Equation (7)

$$\mathrm{CI} = (\lambda_{max} - n)/(n-1) \tag{7}$$

h. Consistency Ratio (CR) is calculated using Equation (8) to ensure the reliability of the weighting process:

$$\mathrm{CR} = \mathrm{CI}/RI \tag{8}$$

The Consistency Ratio (CR) of the pairwise comparison matrix must be checked to ensure the reliability of the weighting process. If the CR value exceeds 0.1, the pairwise judgments are considered inconsistent, and the weighting process must be repeated until a consistent value of CR ≤ 0.1 is achieved

3.4 Technique For Others Preference by Similarity to Ideal Solution (TOPSIS)

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), introduced by Yoon and Hwang (1981), is a multi-criteria decision-making (MCDM) technique that evaluates alternatives based on their distances from the positive ideal solution and the negative ideal solution using Euclidean distance. This method is considered effective in handling qualitative and subjective data that may arise from differences in expert experience or judgment. TOPSIS has been widely applied in supplier selection research, both in general contexts and those emphasizing sustainability aspects, particularly in industries such as automotive and electronics (Chen et al., 2006; Boran et al., 2009; Memari et al., 2019; Kannan et al., 2014). In addition to being flexible and systematic, TOPSIS has also proven to provide more objective and consistent evaluation results compared to other MCDM methods such as AHP, ANP, and DEMATEL (Lima Junior et al., 2014; Büyüközkan & Ifi, 2012).

The following are the main steps in implementing the Fuzzy TOPSIS method:

a. Determine the number of available alternatives, the criteria used, and the number of experts involved in the evaluation process. In this case, there are *m* alternatives, *n* criteria, and *k* experts.
b. Establish a linguistic rating scale using Triangular Fuzzy Numbers (TFN) to determine the weight of each criterion ($w_j = l_{ij}, m_{ij}, u_{ij}$) and provide an evaluation of each alternative based on the corresponding criteria x_{ij}.
c. Perform the aggregation process of the fuzzy weights for each criterion using Equations (9) and (10) c_j and compile the fuzzy evaluations of alternative A_i, under criterion k_j as assessed by the experts.

$$\tilde{x}_{ij} = \frac{1}{k}\left(\tilde{x}^1{}_{ij} + \tilde{x}^2{}_{ij} + \cdots + \tilde{x}^k{}_{ij}\right); i = .1,2,\ldots,m; j = 1,2,\ldots,n \quad (9)$$

$$\widetilde{w}_{ij} = \frac{1}{k}\left(\widetilde{w}^1{}_j + \tilde{x}^2{}_j + \cdots + \tilde{x}^k{}_j\right); j = 1,2,\ldots,n \quad (10)$$

d. Construct the Fuzzy Decision Matrix using Equation (11):

$$\widetilde{D} = \begin{bmatrix} C_1 & C_2 & \cdots & C_n \\ \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}$$

$$\widetilde{w} = (\widetilde{w_1}, \widetilde{w_2}, \dots, \widetilde{w_n})\, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{11}$$

e. *Construct the normalized Fuzzy Decision Matrix* using Equations (12), (13), and (14):

$$\tilde{R} = [\tilde{r}_{ij}]_{mxn}, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{12}$$

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right) \; where \; u_j^* = \max \, u_{ij} \;, \in G1 \tag{13}$$

$$\tilde{r}_{ij} = \left(\frac{u_j^*}{u_{ij}}, \frac{u_j^*}{m_{ij}}, \frac{u_j^*}{l_{ij}}\right) \; where \; u_j^* = \min \, u_{ij} \;, \in G2 \tag{14}$$

Where G1 represents beneficial criteria, which are maximized, and G2 represents non-beneficial criteria, which are minimized.

f. Construct the fuzzy decision matrix that has undergone normalization and weighting. Since each criterion has a different level of importance, the normalized fuzzy decision matrix is then multiplied by the respective weights of the criteria to obtain the weighted fuzzy decision matrix using Equations (15) and (16):

$$\tilde{V} = [\tilde{v}_{ij}]_{mxn}, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{15}$$

$$\tilde{v} = \tilde{r}_{ij}\, w_j \,, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{16}$$

g. Identify the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS), using Equations (17) and (18):

$$S^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+ \tag{17}$$

$$S^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^- \tag{18}$$

$$\tilde{v}_n^+ = \max\{v_{ij}\} \, dan \; \tilde{v}_n^- = \min\{v_{ij}\}$$

$$where \; \tilde{v}_j \; TFN \; normalized \; and \; weighted, i = 1,2,\dots,m; j = 1,2,\dots,n$$

h. Calculate the distance of each alternative from the Fuzzy Positive Ideal Solution (FPIS) (d^+) & FSIN (d^-) using Equations (19) and (20). The distance between two Triangular Fuzzy Numbers (TFNs) $A_1(l_{1,}m_{1,}u_{1)}$ dan $A_2(l_{2,}m_{2,}u_{2)}$ can be calculated as follows:

$$d(A_1, A_2) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}$$

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), i = 1,2,\dots,m \tag{19}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), i = 1,2,\dots,m \tag{20}$$

i. Calculate the closeness coefficient CCi using Equation (21) and create an alternative sequence After getting d_i^+ dan d_i^-.

$$CCi = \frac{d_i^-}{(d_i^- + d_i^+)}, i = 1,2, \dots, m \quad (21)$$

A higher value of CCi indicates a higher ranking of the supplier, based on the following notations

L	: lowest value (lower bound)
m	: middle value
u	: highest value (upper bound)
G_1	: beneficial criteria, which should be maximized
G_2	: nonbeneficial criteria,which should be minimized
d+d^+d+	: FPIS — Fuzzy Positive Ideal Solution
d−d^-d−	: FNIS — Fuzzy Negative Ideal Solution
CC_i	: closeness coefficient

3.5 Multi Choice Goal Programming (MCGP)

Goal Programming is a decision-making method developed to address problems involving multiple, often conflicting objectives, by enabling the simultaneous pursuit of all goals without the need to sacrifice one objective for another (Jadidi et al., 2015; Jones & Tamiz, 2016). In the context of supplier selection, the decision variables typically refer to order allocations, while the primary objectives include minimizing procurement costs, reducing lead time, and maximizing purchase value, all within the constraints of supplier capacity and demand requirements. Multi-Choice Goal Programming (MCGP) is an extension of this approach, allowing decision-makers to define aspiration levels as discrete values or within specified intervals. This flexibility reflects uncertainty or variations in expert opinions and supports the identification of solutions that satisfy multiple aspiration levels simultaneously in multi-criteria decision-making contexts.

In this stage, the MCGP model is constructed to determine the optimal allocation of orders to selected suppliers. The model is implemented using LINGO optimization software. After obtaining the supplier rankings based on the computed Closeness Coefficient (CCi) from the Fuzzy TOPSIS method, the MCGP model is then formulated as follows (Rouyendegh dan Saputro, 2014, Sari dkk, 2015):

a. Defining Decision Variables
Decision variables are the variables whose values represent the decisions or actions that must be taken in order to achieve an optimal result. In this study, the decision variables are defined as follows:

Xi : the quantity of orders allocated to supplier
Yi : a binary decision variable, where; 1 if supplier i is selected, 0 otherwise

b. Defining the Objective Function using Equation (22):
The objective function in goal programming is always aimed at minimizing the total amount of deviations :
$Min\ Z = d_1^+ + d_1^- + d_2^+ + d_2^- + d_3^+ + d_3^- + d_4^+ + d_4^- + e_1^+ + e_1^- + e_2^+ + e_2^- + e_3^+ + e_3^-$ (22)

c. Defining the Goal for Minimizing Total Procurement Cost using Equation (23):
$\sum_{i=1}^{n} C_i X_i + O_i Y_i + d_1^- - d_1^+ \geq G_{1min}\ atau\ G_{1max}$ (23)

d. Defining the Goal for Maximizing Total Purchase Value using Equation (24):
$\sum_{i=1}^{n} CC_i X_i + d_2^- - d_2^+ \geq G_{2min}\ atau\ G_{2max}$ (24)

e. Defining the Goal for Minimizing Total Delay using Equation (25):
$\sum_{i=1}^{n} P_i X_i + d_3^- - d_3^+ \geq G_{3min}\ atau\ G_{3max}$ (25)

f. Defining the Goal for Minimizing Defective Raw Materials using Equation (26):
$\sum_{i=1}^{n} q_i X_i + d_4^- - d_4^+ \geq G_{4min}\ atau\ G_{4max}$ (26)

g. Demand Constraint is defined using Equation (27):
$\sum_{i=1}^{n} X_i = D$ (27)

h. Capacity Constraint is expressed in Equation (28):
$X_i \leq S_i Y_i\ dimana\ i = 1,2,\dots,n$ (28)

i. Non-Negativity and Integer Constraint are given by Equations (29) and (30):
$X_i \geq 0\ dan\ integer\ i = 1,2,\dots,n$ (29)
$Y_i = 0\ atau\ 1\ ;\ i = 1,2,\dots,n$ (30)

where:
d_1^+, d_1^- : positive and negative deviations from goal j
e_1^+, e_1^- : positive and negative deviations from goal y_i - $g_{imax/min}$
g_i : Aspiration level determined by experts
CC_i : closeness coefficient (from Fuzzy TOPSIS)
C_i : unit cost of raw materials from supplier i
O_i : ordering cost of supplier i
p_i : delay rate of supplier i
q_i : defect rate of raw materials from supplier i
D : total demand
S_i : supply capacity of supplier i

4 Conclusion

This paper proposes an integrated decision-making model for supplier selection and order allocation of Control Board components in SPKLU (Public Electric Vehicle Charging Station) projects developed by PT PLN (Persero) Pusharlis. The model combines forecasting, multi-criteria evaluation, and order allocation optimization simultaneously, incorporating national sustainability considerations through the Local Content Requirement (TKDN) criterion. Unlike conventional approaches that focus solely on price and delivery time, the proposed model introduces a multi-attribute TKDN index that encompasses domestic material contribution, local production processes, utilization of local labor, and technological capabilities. It also considers supply chain resilience and operational efficiency by integrating demand forecasting using the ARIMA method, criteria weighting via the Analytic Hierarchy Process (AHP), and supplier ranking through Fuzzy TOPSIS. The final step involves optimizing order allocation using the Multi-Choice Goal Programming (MCGP) approach. This framework is designed to:

a. Improve procurement efficiency in quantitative terms,
b. Minimize supply delay risks arising from supplier dependency,
c. Strengthen domestic industrial participation by positioning TKDN as a strategic variable.

The proposed model is adaptive and can be adjusted to accommodate operational changes and supply dynamics. In the future, this approach could be further enhanced through the integration of real-time supply chain monitoring systems and applied to other strategic components within the national energy sector.

Declaration of AI Use

Artificial intelligence tools were utilized to assist with grammar correction and typographical review. The manuscript was carefully edited and finalized by the authors, who take full responsibility for its content and conclusions.

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