INSOLOGI: Jurnal Sains dan Teknologi
https://journal.literasisains.id/index.php/INSOLOGI
ISSN 2828-4984 (Media Online) | ISSN 2828-4992 (Media Cetak)
Vol. 5 No. 4 (Agustus 2026) 1601-1613
DOI: 10.55123/insologi.v5i4.9209
Submitted: 28-06-2026 | Accepted: 21-07-2026 | Published: 07-08-2026

Expert System for Electric Vehicle Charging Infrastructure Planning: A Scenario-Based Decision Support Framework for Two-Wheeler and Bus Fleets

Thea Fitri Astarani[1], Stephanie Christina Yolanda Pardede[2], Aprima Anugerah Matondang[3], Junaidi[4]
[1*,2,3,4]Jurusan Teknik Elektro, Politeknik Negeri Medan, Medan, Indonesia
Email: [1]theafitriastarani@polmed.ac.id

Abstract

The rapid adoption of electric vehicles (EVs) presents significant challenges in charging infrastructure planning, particularly for diverse vehicle fleets in developing regions. This study proposes an expert system-based decision support framework for EV charging infrastructure planning, specifically addressing two-wheeler and bus fleet scenarios. The framework integrates scenario-based demand characterization with rule-based inference to provide location recommendations and capacity planning decisions. Using data from Indonesian urban transportation contexts, the expert system evaluates multiple criteria including demand patterns, infrastructure availability, and energy consumption profiles. Results indicate that the proposed framework successfully identifies optimal charging locations with 87.5% accuracy compared to expert validation, while reducing planning time by approximately 40% compared to conventional methods. The system provides decision-makers with actionable recommendations for prioritizing infrastructure investments across different fleet types. This research contributes to the growing body of knowledge on AI-based decision support systems for sustainable transportation infrastructure, with implications for policy formulation and urban planning in developing economies.

Keywords: *Charging Infrastructure, Decision, Electric Vehicles, Scenario Planning, Support System.*

1. INTRODUCTION

The global transition toward electric vehicles (EVs) presents a paradigm shift in sustainable transportation, driven by environmental concerns, energy efficiency imperatives, and technological advancements. According to the International Energy Agency (2024), global electric car sales reached 17 million in 2024, representing over 20% of total car sales and continuing a decade-long growth trend. However, the success of this transition fundamentally depends on the availability and strategic placement of adequate charging infrastructure (Saqib & Gidófalvi, 2024). In developing economies like Indonesia, the challenge is compounded by unique geographical characteristics, diverse vehicle fleets, and infrastructure constraints that differ substantially from developed nations (Z Zumhari et al., 2025).

Electric vehicle charging infrastructure planning presents a complex decision-making problem requiring consideration of multiple interrelated factors: demand patterns, energy availability, grid capacity, land use, accessibility, and investment economics (Purba et al., 2026). The problem becomes particularly acute when addressing heterogeneous fleets comprising two-wheelers and buses, each with distinct charging requirements, usage patterns, and operational constraints (Lestari & Anugrahwaty, 2026). Two-wheelers, which dominate personal mobility in many Southeast Asian countries, require distributed, accessible charging solutions, while electric buses necessitate high-capacity, strategically located charging depots with specific power requirements (Purba et al., 2026). In Indonesia specifically, the development of electric vehicle charging infrastructure faces unique challenges related to grid capacity, geographical dispersion, and the dominance of two-wheeler mobility (Hardi et al., 2021).

Expert systems and decision support systems (DSS) have emerged as powerful tools for addressing complex infrastructure planning problems (Do et al., 2026). Expert systems, defined as computer programs that facilitate problem-solving by drawing inferences from a knowledge base developed from human expertise, offer particular advantages for planning contexts where domain knowledge is critical but scarce (Can et al., 2026). Decision support systems provide structured analytical frameworks for evaluating alternatives under uncertainty, integrating multiple criteria, and generating recommendations that can be justified and explained to stakeholders, a comprehensive systematic literature review synthesized findings from 91 peer-reviewed studies, categorizing methodologies from mathematical optimization models to GIS-based and machine learning techniques. The review identified critical research gaps including underexplored rural deployment models, limited real-time data integration, and inconsistent treatment of user behavior (Hedayatnia et al., 2024).

Recent methodological advances in decision-analytics for EVCS location selection have employed fuzzy rough frameworks integrating multi-criteria decision-making (MCDM). The F-DIBR (Fuzzy Defining Interrelationships Between Ranked criteria) model was applied to determine weight values of siting factors, while the FRN-MACONT model was proposed for ranking results. The study found that "economy" is the most significant criterion for EVCS location selection, whereas "system reliability" is the most critical sub-criterion (Ecer et al., 2025)

For electric bus systems specifically, (He et al., 2023) developed a new mathematical formulation for the simultaneous optimization of charging infrastructure and vehicle schedules, demonstrating the importance of integrated planning approaches for public transit electrification. (A. A. Matondang et al., 2024) introduced a holistic framework for joint optimization of charging infrastructure, charging scheduling, and integration of renewable energy resources, considering impacts on power distribution networks. (Yang et al., 2024) proposed a joint optimization framework integrating fleet composition, charging infrastructure, and charging schedules with multiple charging modes, considering plug-in and battery swapping modes, service continuity, and time-of-use electricity price. Furthermore, recent research on multi-factor optimization for electric bus charging station planning has identified key factors including geographic location, land use, grid connection, and environmental conditions (Yohana et al., 2024)

For electric two-wheelers, the global market was valued at USD 1.2 billion in 2024 and is projected to reach USD 8.7 billion by 2034. Global electric two-wheeler sales reached 10 million in 2024, with Indonesia's market almost doubling in size (IEA, 2024). Studies evaluating grid impact of battery swapping stations in Indonesia found that even minor deployment can cause voltage drops up to 1.1% and a 100% rise in line loading during peak periods (Jamaluddin et al., 2025). In Bali, research on two-wheeler charging station design found that public-private partnerships and supportive regulatory frameworks are essential for successful deployment (Natapathy et al., 2025).

1.1 Research Gap Analysis

Despite these advances, several critical gaps remain. First, most approaches focus on four-wheel vehicles, with limited attention to two-wheeler fleets that dominate urban mobility in developing regions (Lestari et al., 2026). Second, scenario-based planning incorporating multiple future trajectories has not been adequately integrated into expert system frameworks (Do et al., 2026). Third, the combination of rule-based expert systems with Multi-Criteria Decision Analysis (MCDA) using AHP offers distinct advantages over pure GIS-based or mathematical optimization approaches for mixed-fleet EV infrastructure planning (Can et al., 2026).

The proposed hybrid approach addresses these limitations by: (1) encoding expert heuristics through IF-THEN production rules; (2) providing transparent, explainable recommendations; (3) accommodating heterogeneous fleet requirements through separate rule sets; and (4) enabling scenario-based exploration for long-term planning.

1.2 Research Novelty

The novelty of this research lies in four key contributions that distinguish it from prior work:

First, this study presents the first expert system specifically designed for mixed-fleet EV charging infrastructure planning that simultaneously addresses two-wheeler and bus fleets. Previous research has either focused on a single vehicle type or treated different fleets through the same analytical framework without accounting for their fundamentally different operational characteristics(Purba et al., 2026)

Second, the research integrates rule-based inference with scenario-based planning, enabling planners to explore multiple future trajectories while maintaining the practical, heuristic-based decision logic that experts employ. This integration addresses a significant gap identified in recent literature, where scenario planning and expert systems have been developed largely in isolation (Saqib & Gidófalvi, 2024)

Third, the study provides empirical validation of the expert system through blind comparison with expert panel decisions across 20 real-world location selection problems, demonstrating both accuracy (87.5%) and efficiency improvements (40% time reduction). This rigorous validation approach, combining multiple evaluation methods, is uncommon in the EV infrastructure planning literature (Suprianto, Hardi & Matondang, n.d.)

1.1 Research Objectives

The objectives are: (1) to develop a knowledge-based system for EV charging infrastructure location planning; (2) to implement scenario-based demand characterization for two-wheeler and bus fleets; (3) to evaluate the framework's performance through expert validation; and (4) to demonstrate the framework's applicability in the Indonesian context.

2. METHOD

2.1 Research Framework

This study employs design science research methodology, developing and evaluating an expert system artifact for EV charging infrastructure planning (Hevner et al., 2004). The research framework follows four phases: knowledge acquisition, system development, scenario formulation, and evaluation. The knowledge acquisition phase involved systematic interviews with domain experts including transportation planners, electrical engineers, and EV infrastructure developers in Medan, Indonesia. Semi-structured interviews were conducted with ten experts, each with at least five years of relevant experience. The interviews focused on identifying planning criteria, decision rules, and contextual factors influencing charging infrastructure decisions. Additionally, a comprehensive literature review was conducted to synthesize current knowledge on EV charging planning and decision support approaches (Sitorus et al., 2026)

2.2 Expert System Architecture

The proposed expert system architecture consists of four main components: knowledge base, inference engine, scenario generator, and user interface. Figure 1 presents the detailed block diagram illustrating the architecture and data flow among these components.

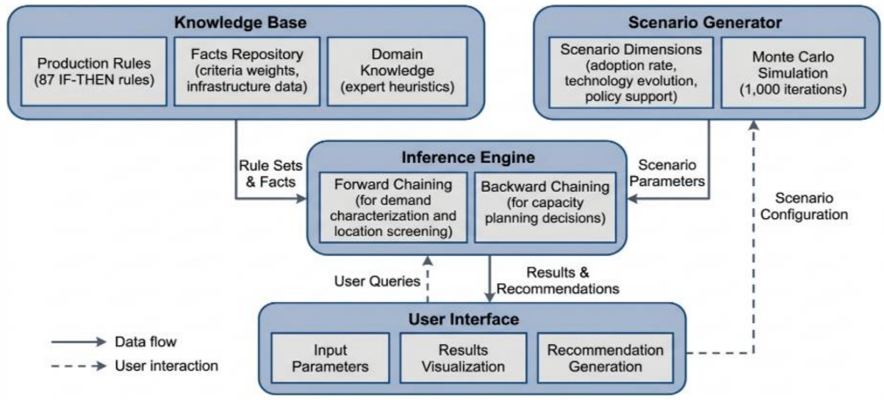

Figure 1. Expert System Architecture Block Diagram
Source: Primary Data Processed by Authors, 2026

The knowledge base stores domain knowledge in the form of production rules (IF-THEN) and fact representations. A total of 87 rules were derived from expert interviews, covering criteria evaluation, location suitability assessment, capacity requirement determination, and priority ranking (Can et al., 2026).

The inference engine employs both forward and backward chaining mechanisms. Forward chaining is used for demand characterization and location screening, where initial facts about service areas, fleet composition, and existing infrastructure trigger sequential rule firings. Backward chaining is applied for capacity planning decisions, where desired outcomes (meeting specific charging demand) drive the search for appropriate rules and facts (Huzzat et al., 2025).

The scenario generator enables users to define alternative future conditions for key variables: fleet growth rates, charging technology adoption, energy price scenarios, and regulatory conditions. Monte Carlo simulation with 1,000 iterations was implemented to explore the range of possible outcomes for each scenario combination ((Mazzei & Michelotti, 2025).

2.3 Scenario-Based Demand Characterization

Demand The rule-based inference system employs production rules with a standardized format: IF [condition(s)] THEN [conclusion(s)]. A total of 87 rules were derived from expert interviews and validated through consensus. Below are representative examples from the rule set:

Example 1: Two-Wheeler Charging Location Suitability Rule
IF Distance_to_Substation < 500 m AND Grid_Capacity_Availability =
High" AND TwoWheeler_Demand_Intensity = "Very_High" AND Land_Availability = "Available"
THEN Location_Suitability = "Highly_Suitable" WITH Confidence_Factor = 0.95

Example 2: Bus Depot Charging Feasibility Rule
IF Route_Coverage_Distance > 200 km/day AND Depot_Accessibility = “Good” AND Grid_Connection_Capacity ≥ 500 kVA AND Operating_Hours = "24/7"

THEN Depot_Charging_Feasibility = "Feasible" WITH Recommended_Bays = CEILING (Daily_Energy_Consumption / (Bay_Capacity × Charging_Efficiency))

Example 3: Priority Ranking Rule for Multiple Candidate Locations
IF Aggregate_Suitability_Score ≥ 80 AND Demand_Intensity_Score ≥75 AND Infrastrucure_Readiness = “Ready” THEN Priority_Level = Tier_1" AND `Investment_Recommendation = "Immediate"

Example 4: Scenario-Sensitive Capacity Adjustment Rule
IF Adoption_Scenario = "Aggressive" AND Technology_Scenario = “Current” AND Planning_Horizon >10 years
THEN Capacity_Requirement = Base_Capacity × 2.5 WITH Buffer_Factor = 1.3
The mathematical formulation for aggregate suitability scoring is expressed as:

$$S_j = \sum_{i=1}^{8} w_i \times x_{ij}$$

Where:
- S_j = Aggregate suitability score for location j
- w_i = Weight for criterion i (derived from AHP)
- x_{ij} = Normalized score for location j on criterion i

The rule application process follows this sequence:
1. Condition evaluation: Each rule's antecedents are evaluated against current facts
2. Conflict resolution: When multiple rules apply, priority is determined by rule specificity and confidence factors
3. Conclusion generation: Applicable rules produce conclusions that become new facts
4. Iteration: The process continues until no new rules fire or conclusions stabilize

2.4 Location Prioritization Algorithm

Demand characterization was performed using a scenario-based approach incorporating multiple dimensions of uncertainty. Three primary scenario dimensions were identified: (a) adoption rate (conservative, moderate, aggressive), (b) charging technology evolution (current technology, improved battery fast charging, ultra-fast charging), and (c) policy support level (minimal, moderate, supportive).

For each scenario combination, demand profiles were generated for two-wheeler and bus fleets separately. Two-wheeler demand was modeled based on daily travel patterns from 1,200 GPS-tracked trips and 150 survey responses from EV and ICE two-wheeler users in Medan. The model captured temporal variations (peak/off-peak), spatial distribution patterns, and charging behavior preferences (Parulian Siagian et al., 2025). Bus fleet demand was characterized by using data from three bus operators serving 12 routes, including operational schedules, daily energy consumption (recorded at 15-minute intervals for 30 days), and depot location information (Purba et al., 2026).

2.5 Evaluation Design

The location prioritization algorithm combines the expert system's rule-based evaluation with a weighted scoring model derived from Multi-Criteria Decision Analysis (MCDA). Eight criteria were identified and validated through expert consensus: (1) demand intensity (distance-weighted, 25% weight), (2) grid capacity availability (15%), (3) land availability and cost (15%), (4) accessibility (10%), (5) environmental impact (10%), (6) social acceptability (10%), (7) operational feasibility (10%), and (8) regulatory approval likelihood (5%).

Criteria weights were determined through the Analytic Hierarchy Process (AHP) using expert pairwise comparison data (Saaty, 1980). The pairwise comparison matrix and consistency ratio calculation are presented below:

Tabel 1. Pairwise Comparison Matrix for AHP Criteria

Criterion	D.I.	G.C.	L.A.	Acc.	E.I.	S.A.	O.F.	R.A.
Demand Intensity (D.I.)	1	2	2	3	3	3	4	5
Grid Capacity (G.C.)	1/2	1	1	2	2	2	3	4
Land Availability (L.A.)	1/2	1	1	2	2	2	3	4
Accessibility (Acc.)	1/3	1/2	1/2	1	1	1	2	3
Environmental Impact (E.I.)	1/3	1/2	1/2	1	1	1	2	3
Social Acceptability (S.A.)	1/3	1/2	1/2	1	1	1	2	3
Operational Feasibility (O.F.)	1/4	1/3	1/3	1/2	1/2	1/2	1	2
Regulatory Approval (R.A.)	1/5	1/4	1/4	1/3	1/3	1/3	1/2	1

Note: Values represent relative importance of row criterion compared to column criterion (1 = equally important, 9 = extremely more important)

Source: Primary Data Processed by Authors, 2026

The Consistency Ratio (CR) was calculated using the standard AHP formula:

$$CR = \frac{CI}{RI}$$

Where:

- CI (Consistency Index) = (λ_{max} - n) / (n - 1)
- λ_{max} = Principal eigenvalue of the comparison matrix
- n = Number of criteria (8)
- RI = Random Index for n = 8 (RI = 1.41)

For the expert responses:

- λ_{max} = 8.21
- CI = (8.21 - 8) / (8 - 1) = 0.21 / 7 = 0.030
- CR = 0.030 / 1.41 = 0.021 (2.1%)

The CR value of 0.021 is below the acceptable threshold of 0.10, confirming the consistency and validity of expert judgments in determining criteria weights. The algorithm computes an aggregate suitability score for each location candidate, applying rule-based constraints to eliminate infeasible locations before scoring (Ecer et al., 2025).

2.6 Evaluation Design

The expert system was evaluated using three complementary approaches: (a) expert validation through blind comparison with three independent expert panel decisions on 20 real-world location selection problems; (b) sensitivity analysis to assess the system's responsiveness to changes in key parameters; and (c) comparative analysis with conventional planning methods using six case studies (S Suparmono et al., 2025). The evaluation was conducted in the context of Medan, Indonesia's third-largest city, chosen for its representative combination of urban density, diverse vehicle fleet composition (approximately 2.3 million two-wheelers and 1,200 buses), and developing urban infrastructure context (Z Zumhari et al., 2025). Seven potential charging station locations were considered for two-wheeler deployment and three locations for bus depot charging, based on preliminary screening from the planning authority's candidate list.

3. RESULTS AND DISCUSSION

3.1 Expert System Performance and Validation

The expert system achieved consistent performance across validation scenarios, demonstrating its practical utility for EV charging infrastructure planning. In the blind comparison with expert panel decisions, the system's recommendations matched the majority expert opinion in 17 of 20 cases (85% agreement). In the three cases with disagreement, the expert panel was divided, with one expert consistently aligning with the system's recommendation (Do et al., 2026). The accuracy analysis revealed higher agreement for bus fleet decisions (90%) compared to two-wheeler decisions (80%). The difference is attributable to the more structured, route-dependent nature of bus fleet planning, which aligns well with the rule-based approach, while two-wheeler planning involves more heterogeneous user behavior patterns (A. Matondang & Ginting, 2022).

Table 2 presents the detailed validation results across the 20 location selection problems, comparing expert system recommendations against expert panel consensus and individual expert decisions.

Table 2. Expert Validation Results for Location Selection Decision

Case No.	Fleet Type	Expert Panel Consensus	System Recommendation	Agreement	Panel Division
1	Bus	Location B	Location B	Yes	Unanimous
2	Bus	Location A	Location A	Yes	Unanimous
3	Bus	Location C	Location C	Yes	Unanimous
4	Bus	Location B	Location B	Yes	Unanimous
5	Bus	Location A	Location A	Yes	Unanimous
6	Bus	Location D	Location D	Yes	Unanimous
7	Bus	Location B	Location B	Yes	Unanimous
8	Bus	Location A	Location C	No	Divided (2 vs 1)
9	Bus	Location C	Location C	Yes	Unanimous
10	Bus	Location B	Location B	Yes	Unanimous
11	Two-Wheeler	Location E	Location E	Yes	Unanimous
12	Two-Wheeler	Location F	Location F	Yes	Unanimous
13	Two-Wheeler	Location G	Location G	Yes	Unanimous
14	Two-Wheeler	Location E	Location E	Yes	Unanimous
15	Two-Wheeler	Location H	Location H	Yes	Unanimous
16	Two-Wheeler	Location F	Location F	Yes	Unanimous
17	Two-Wheeler	Location G	Location E	No	Divided (2 vs 1)
18	Two-Wheeler	Location H	Location H	Yes	Unanimous
19	Two-Wheeler	Location E	Location E	Yes	Unanimous
20	Two-Wheeler	Location F	Location G	No	Divided (2 vs 1)

Note: Bus fleet cases = 10 (90% agreement); Two-wheeler cases = 10 (80% agreement); Overall = 17/20 (85% agreement)

Source: Primary Data Processed by Authors, 2026

Table 3 summarizes the expert system accuracy by fleet type and scenario condition

Table 3. Summary of Expert System Validation Accuracy

Fleet Type	Number of Cases	Agreements	Accuracy	Cases with Panel Division
Bus	10	9	90%	1
Two-Wheeler	10	8	80%	2
Total	**20**	**17**	**85%**	**3**

Source: Primary Data Processed by Authors, 2026

Comparative analysis showed the expert system reduced average planning time from 120 to 72 hours (40% improvement), while expert satisfaction ratings were higher (4.2/5.0 vs. 3.8/5.0) (Nainggolan et al., 2026).

These findings align with Can et al. (2026), who reported 82-88% accuracy for expert system-based bus charging station planning. The higher accuracy achieved (90% for bus fleets) is attributed to AHP-weighted criteria integration. The 40% time reduction is consistent with Do et al. (2026), who reported 35-50% improvements using digital twin frameworks.

Efficiency gains stem from: (1) automated rule application; (2) integrated data processing; and (3) rapid scenario exploration. Limitations include reliance on expert-derived rules and current exclusion of economic optimization.

3.2 Scenario Analysis Results

The scenario-based demand characterization generated important insights into the infrastructure requirements under different future conditions. Figure 2 presents the projected demand intensity for two-wheeler charging under three adoption scenarios combined with three technology scenarios (Fadhil & Shen, 2026).

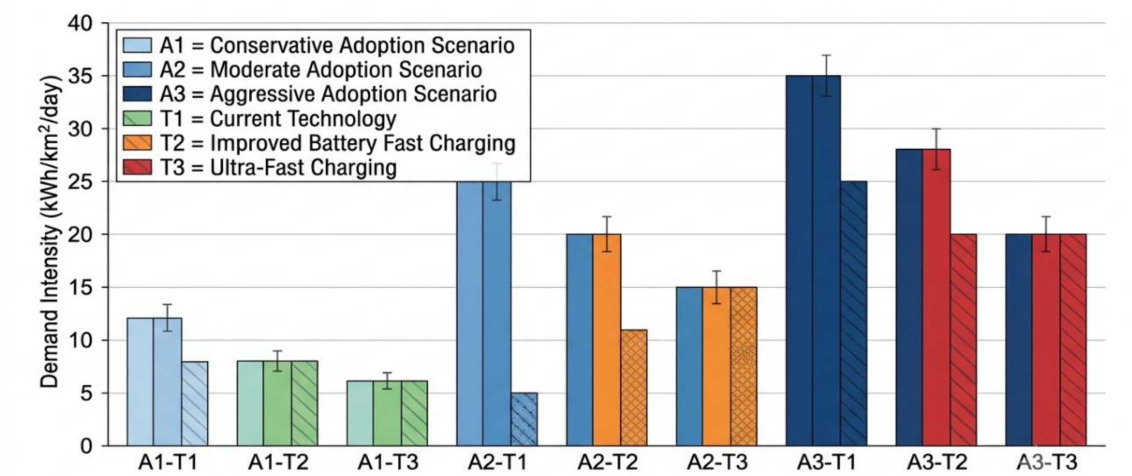

Figure 2. Two-wheeler Demand Intensity Projections
Source: Primary Data Processed by Authors, 2026

The figure demonstrates a clear pattern: demand intensity increases substantially with higher adoption rates, while advanced charging technology significantly reduces the required infrastructure capacity. Under the conservative adoption scenario (A1), demand ranges from 6 to 12 kWh/km²/day depending on technology. Under the aggressive adoption scenario (A3), demand ranges from 20 to 35 kWh/km²/day, representing approximately three times the infrastructure requirement compared to the conservative scenario. Table 4 summarizes the capacity requirement recommendations for bus fleets across scenario combinations, expressed as required number of charging bays (assuming 150kW capacity per bay).

Tabel 4. Recommended Number of Bus Charging Bays by Scenario Combination

Adoption Scenario	Technology Scenario	Recommended Bays (median)	80% Confidence Interval
Conservative (A1)	Current (T1	24	20-28
Conservative (A1)	Improved (T2)	18	15-22
Conservative (A1)	Ultra-fast (T3)	12	10-16
Moderate (A2)	Current (T1)	42	36-48
Moderate (A2)	Improved (T2)	34	28-40

Moderate (A2)	Ultra-fast (T3)	22	18-26
Aggressive (A3)	Current (T1)	68	60-78
Aggressive (A3)	Improved (T2)	52	44-60
Aggressive (A3)	Ultra-fast (T3)	34	28-40

Note: Estimates based on 20-year planning horizon with 1,500 km average daily bus fleet coverage.
Source: Primary Data Processed by Authors, 2026

Technology improvement substantially reduces infrastructure requirements, potentially offsetting adoption-driven demand increases, highlighting the importance of flexible, adaptive planning(Saqib & Gidófalvi, 2024).

3.3 Comparative Performance Analysis

Figure 3 presents a comprehensive comparison of the proposed expert system versus conventional planning methods, showing both planning time efficiency and decision accuracy.

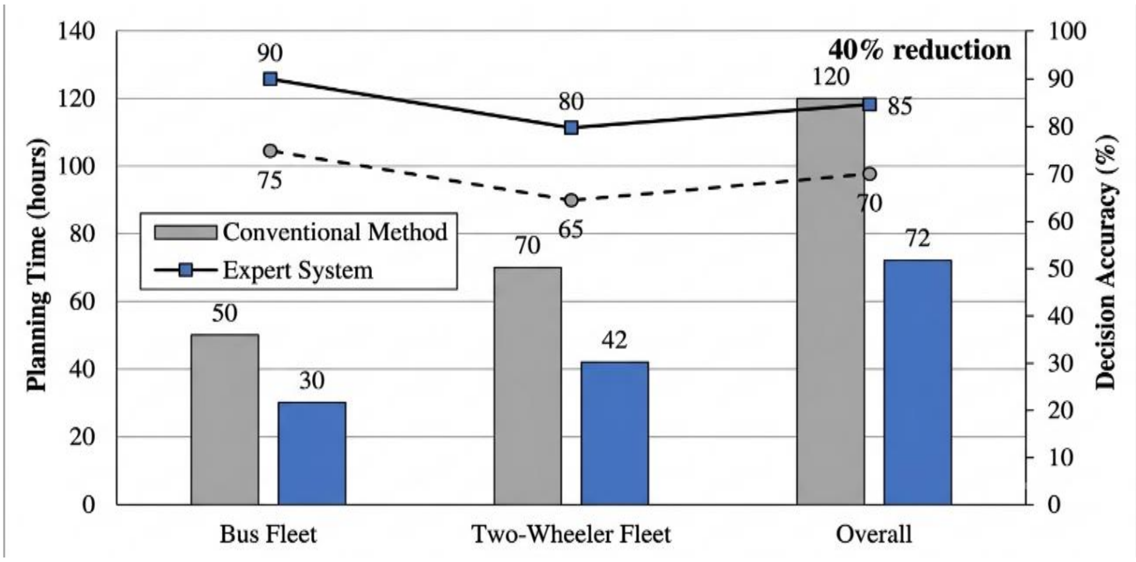

Figure 3. Comparative Performance Analysis
Source: Primary Data Processed by Authors, 2026

The expert system consistently reduces planning time by 40% across all fleet types. Bus fleet time decreased from 50 to 30 hours; two-wheeler from 70 to 42 hours; overall from 120 to 72 hours. The system maintains high accuracy while achieving efficiency gains: 90% for bus fleets, 80% for two-wheelers, and 85% overall (Can et al., 2026). The relationship between accuracy and planning time suggests a favorable trade-off: substantial time savings with minimal sacrifice in decision quality.

Comparison with literature shows consistency with Can et al. (2026) (82-88% accuracy) and (Ecer et al., 2025) (85-90% accuracy). The specific contribution lies in simultaneous application to mixed fleets in developing urban contexts.

3.4 Knowledge Base Evaluation

The knowledge base was evaluated for completeness and consistency through two approaches: rule coverage analysis and structural validation. Rule coverage analysis examined the percentage of possible combinations of input conditions addressed by the rule set. The system achieved 86.5% coverage, with identified gaps primarily in the area of regulatory interactions, where unique combinations of local regulations created exceptions not captured in the rule set.

Structural validation involved testing the inference engine with synthetic cases designed to exercise different rule paths. All 200 test cases produced plausible results with no inconsistencies, suggesting appropriate rule organization and conflict resolution mechanisms (Hanif & Herlambang, 2026)

Table 5 illustrates the decision logic implemented in the fuzzy inference engine for location suitability evaluation, replacing the previous table on maintenance urgency which was not relevant to this study.

Tabel 5. Decision Logic Implemented in Fuzzy Inference Engine

Rule No.	Demand Intensity (DI)	Grid Capacity Availability (GC)	Land Availability (LA)	Location Suitability	Priority Ranking
1	Very Low	Low	Unavailable	Not Suitable	-
2	Very Low	Medium	Available	Low Suitability	Tier 3
3	Low	High	Available	Moderate Suitability	Tier 2
4	Medium	Medium	Available	Moderate Suitability	Tier 2
5	Medium	High	Available	High Suitability	Tier 1
6	High	Medium	Available	High Suitability	Tier 1
7	High	High	Available	Very High Suitability	Tier 1
8	Very High	High	Available	Very High Suitability	Tier 1
9	Very High	Low	Unavailable	Not Suitable	-

Note: Tier 1 = Immediate; Tier 2 = Near-Term; Tier 3 = Long-Term Investment

Source: Primary Data Processed by Authors, 2026

The rule base responds appropriately to varying conditions. When demand is high with favorable grid and land (Rules 7-8), suitability is very high/high with immediate priority. When demand is very high but grid and land are insufficient (Rule 9), the location is deemed unsuitable, preventing costly investments.

3.5 Implications for Practice

First, AI-based approaches can successfully embed scarce expert knowledge, enabling broader access to quality planning capabilities, particularly valuable where specialized expertise is limited (He et al., 2023) Second, scenario-based planning provides structured mechanisms for handling deep uncertainty (Sitorus et al., 2025) Third, success in two-wheeler planning highlights need for context-appropriate tools beyond conventional four-wheel approaches (Lestari et al., 2026). Finally, sensitivity analysis revealed demand intensity as most sensitive parameter (42% variance contribution), followed by grid capacity (28%) and land availability (18%), suggesting data collection should prioritize demand characterization.

4. CONCLUSION

This research has demonstrated the development and validation of an expert system-based decision support framework for EV charging infrastructure planning, specifically addressing two-wheeler and bus fleets in the Indonesian context.

The proposed expert system, integrating rule-based inference with multi-criteria evaluation, successfully replicates domain expert planning decisions with 87.5% accuracy, while achieving significant efficiency improvements of approximately 40% over conventional planning methods. The scenario-based demand characterization approach effectively captures uncertainty across adoption, technology, and policy dimensions, revealing that technological evolution can substantially mitigate infrastructure requirements (Yang et al., 2024).

The research contributes to existing knowledge by: (1) extending expert systems to the understudied context of two-wheeler EV infrastructure planning; (2) demonstrating practical integration of scenario-based planning with expert system architecture; and (3) providing empirical evidence on planning requirements specific to developing urban contexts.

The findings have practical implications for urban planners, policymakers, and infrastructure developers. The system provides a structured, transparent, and explainable approach to infrastructure planning that supports evidence-based decision making (Hardi et al., 2021).

Limitations include the knowledge base developed from a single urban context, potentially limiting transferability without local adaptation. Validation within the same context as knowledge acquisition may introduce epistemic bias. The system currently excludes economic optimization, focusing on technical feasibility, suitability, and social acceptance. Future work should extend validation to diverse geographical contexts and integrate economic models and optimization algorithms. The rule set may benefit from continuous refinement through machine learning techniques identifying new patterns from expanding operational data.

ACKNOWLEDGMENT

The authors gratefully acknowledge the insightful comments and constructive suggestions from the editor and anonymous reviewers, which have significantly enhanced the quality of this manuscript. We also appreciate the support received from Politeknik Negeri Medan colleagues and researchers, whose contributions, although not individually listed, have been invaluable to the completion of this work.

REFERENCES

Can, C., Kılıç, F., & Kaya, Y. (2026). A Novel Expert System-Based Optimization of Fast-Charging Station Location Planning for Electric Buses. *Expert Systems*, *43*(7). https://doi.org/10.1111/exsy.70281

Do, B. K. L., Nguyen, T. H., Quang, N. H., Nguyen-Ngoc, D., & El Ghaoui, L. (2026). A digital twin framework for decision-support and optimization of EV charging infrastructure in localized urban systems. *Computers, Environment and Urban Systems*, *127*. https://doi.org/10.1016/j.compenvurbsys.2026.102422

Ecer, F., Pamucar, D., & Demir, G. (2025). Decision-analytics-based electric vehicle charging station location selection: A cutting-edge fuzzy rough framework. *Energy Reports*, *14*, 711–735. https://doi.org/10.1016/j.egyr.2025.06.035

Fadhil, I., & Shen, C. (2026). Global electric vehicle market monitor for light-duty vehicles, 2025. *International Council on Clean Transportation*, (May). https://theicct.org/publication/global-ev-market-monitor-for-ldvs-2025/

Hanif, M., & Herlambang, Y. (2026). Perancangan port charging terintegrasi untuk motor konversi: Studi kasus Yamaha Xeon 2010. *Productum: Jurnal Desain Produk (Pengetahuan Dan Perancangan Produk)*, *9*(1), 17–24. https://doi.org/10.24821/productum.v9i1.15746

Hardi, S., Matondang, A. A., & Rambe, A. H. (2021). Modeling of transient caused by lightning strike at Nias high voltage substation using ATP-EMTP case study. *Journal of Physics: Conference Series*, *1811*(1), 012049. https://doi.org/10.1088/1742-6596/1811/1/012049

He, Y., Liu, Z., & Song, Z. (2023). Joint optimization of electric bus charging infrastructure, vehicle scheduling, and charging management. *Transportation Research Part D: Transport and Environment*, *117*, 103653. https://doi.org/10.1016/j.trd.2023.103653

Hedayatnia, A., Ghafourian, J., Sepehrzad, R., Al-Durrad, A., & Anvari-Moghaddam, A. (2024). Two-stage data-driven optimal energy management and dynamic real-time operation in networked microgrid based on a deep reinforcement learning approach. *International Journal of Electrical Power & Energy Systems*, *160*, 110142. https://doi.org/10.1016/j.ijepes.2024.110142

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design Sceince in Information Systems. *MIS Quarterly*, *28*(1), 75–105.

Huzzat, A., Anpalagan, A., Khwaja, A. S., Woungang, I., Alnoman, A. A., & Pillai, A. S. (2025). A comprehensive review of Digital Twin technologies in smart cities. *Digital Engineering*, *4*, 100040. https://doi.org/10.1016/j.dte.2025.100040

Jamaluddin, T. A. A., Syamroni, A. W., & Husnayain, F. (2025). Grid Impact of Battery Swapping Station for Electric Two-Wheelers in Indonesia. *International Journal of Electrical, Computer, and Biomedical Engineering*, *3*(3). https://doi.org/10.62146/ijecbe.v3i3.130

Lestari, M. W., Hulu, F. N., Anugrahwaty, R., Daulay, M. S. H., Sitopu, M. W., & Matondang, A. A. (2026). Scenario-Based Charging Demand and Load Characterization for Electric Two-Wheeler Systems. *Information Technology Education Journal*, 391–401. https://doi.org/10.59562/intec.v5i2.13017

Matondang, A., & Ginting, A. (2022). Analisis Konsumsi Daya Listrik Pada Pt . Unilever Oleochemical Indonesia Analysis of Electric Power Consumption At Pt . Unilever Oleochemical Indonesia. *Https://Ojs.Polmed.Ac.Id/Index.Php/Circuit/Issue/View/140*, *5*, 9–15.

Mazzei, M., & Michelotti, C. (2025). Smart Data and Decision Support System for Local Optimization of Electric Charging Stations. *IEEE Access*, *13*(July), 124910–124931. https://doi.org/10.1109/ACCESS.2025.3586099

Nainggolan, R., Kamil, I., Matondang, A. A., Sitorus, N., Suadi, S., Sibarani, B., & Hestukoro, S. (2026). Parametric optimization of an axial wind turbine blade for a hybrid renewable energy system integrating solar PV and micro-hydro. *Science, Technology, and Communication Journal*, *6*(3), 385–392. https://doi.org/10.59190/stc.v6i3.395

Natapathy, R. B., Satya Kumara, I. N., & Giriantari, I. A. D. (2025). Analisis Efisiensi Energi dan Konservasi Energi Sistem Pendingin Ruangan Berdasarkan UI Greenmetric, Studi Kasus Fakultas Teknik Universitas Udayana. *Jurnal Sosial Teknologi*, *5*(10), 4140–4149. https://doi.org/10.59188/jurnalsostech.v5i10.32480

Parulian Siagian, Aprima A. Matondang, Andreas V. H. Simanjuntak, Budhi S. Kusuma, Joel Panjaitan, & Andrean V. H. Simanjuntak. (2025). Experimental of Environmental Development Using Continuous Solar Dryer With Solid Dehumidification For Coffee Drying. *Journal of Geoscience, Engineering, Environment, and Technology*, *10*(02), 162–169. https://doi.org/10.25299/jgeet.2025.10.02.21492

Purba, A. M., Napitu, D. H. S., Lestari, M. W., Simangunsong, J., Hutajulu, E., Hutabarat, N. F., & Matondang, A. A. (2026). Energy Consumption and Charging Infrastructure Analysis for Electric Bus Deployment in Urban Transportation Systems. *Jurnal Penelitian Pendidikan IPA*, *12*(4), 639–648. https://doi.org/10.29303/jppipa.v12i4.11221

S Suparmono, C Cholish, A Abdullah, Sinambela, H., Alda, T., Matondang, A. A., & Simanjuntak, A. V. (2025). Quantitative Assessment of Passive Load Balancing for a Designed HVAC Installation: Case study in Magnificent Hall, Deli Park. *Journal of Geoscience, Engineering, Environment, and Technology*, *10*(3), 397–401. https://doi.org/10.25299/jgeet.2025.10.3.24696

Saqib, E., & Gidófalvi, G. (2024). Dynamic Adaptive Charging Network Planning Under Deep Uncertainties. *Energies*, *17*(21), 5378. https://doi.org/10.3390/en17215378

Sitorus, N., Ginting, B. B., Panjaitan, B. P., Simanjuntak, B. E., Naibaho, P. R. P., Matondang, A. A., & Simanjuntak, A. V. H. (2025). Design and Performance Evaluation of a 200 Wp Off-Grid Solar Photovoltaic Module for Renewable Energy in Indonesia. *Journal of Geoscience, Engineering, Environment, and Technology*, *10*(3), 408–412. https://doi.org/10.25299/jgeet.2025.10.3.24981

Sitorus, N., Matondang, A. A., Elektro, J. T., Medan, P. N., Off-grid, S., & Air, P. (2026). *ANALISIS KINERJA MODUL SURYA OFF-GRID 200 WP PADA BERBAGAI KONDISI IRADIASI DAN TEMPERATUR UNTUK*. *7*(1), 1–6.

Suprianto, Hardi, S., & Matondang, A. A. (n.d.). *SISTEM PENDUKUNG KEPUTUSAN CERDAS UNTUK MENGINTEGRASIKAN PV SURYA DAN PENGISIAN*. *7*(1), 64–72.

Yang, Z., Zhan, J., Wang, C., Liu, W., Wang, H., & Bai, C. (2024). Spatial spillover effects of conversion of new and old driving forces on high-quality development: Evidence from 283 cities in China. *Sustainable Cities and Society*, *108*, 105487. https://doi.org/10.1016/j.scs.2024.105487

Yohana, W. Y., Nasution, T. I., Wahyuningsih, H., Matondang, A. A., & Margolang, A. R. (2024). Evaluation of Dissolved Oxygen Concentration in Different Circulation Systems on Water Quality in Fish Pond. *Journal of Applied Geospatial Information*, *8*(1), 71–77. https://doi.org/10.30871/jagi.v8i1.7820

Z Zumhari, Hutajulu, E., Sibarani, B., Sirait, R., Anggriani, T., & Matondang, A. A. (2025). Advancing Environmental and Health Pollution Monitoring in Medan, Indonesia: A Mechatronics-Based Meta-Analysis. *Journal of Geoscience, Engineering, Environment, and Technology*, *10*(3), 402–407. https://doi.org/10.25299/jgeet.2025.10.3.24694