

Adaptive Hybrid AI Framework for Reliable Decision Support in Smart Urban Systems

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ABSTRACT

Urban environments are increasingly complex, requiring decision support systems capable of handling dynamic energy demand, traffic flow, and environmental monitoring. However, conventional AI models often produce inconsistent outputs under data variability and uncertainty, undermining reliability and stakeholder trust. **This study** proposes an adaptive hybrid AI framework to enhance the reliability and stability of urban decision support systems while preserving predictive accuracy. The framework integrates machine learning, rule-based reasoning, and a dynamic stability control mechanism to generate consistent, policy compliant decisions. Real-world datasets encompassing energy consumption, traffic patterns, and environmental indicators were preprocessed using normalization, duplicate removal, noise filtering, and imbalance treatment. The model was evaluated against baseline machine learning and non adaptive hybrid approaches using prediction error metrics and a decision stability index. **Results** indicate that the adaptive hybrid AI framework significantly reduces prediction errors and improves decision consistency. Statistical analyses, including confidence intervals and hypothesis testing, confirm the robustness of these improvements. **These findings** demonstrate that the proposed framework strengthens trust in AI-driven urban governance and supports the implementation of sustainable smart city initiatives. **The study** contributes to the advancement of reliable intelligent decision support systems, aligning with digital transformation objectives and SDG-oriented urban innovation, offering practical insights for policymakers, urban planners, and AI system developers.

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1. INTRODUCTION

The increasing integration of AI in urban decision support systems has introduced new challenges related to decision reliability, particularly in dynamic and data-intensive environments. While AI models have demonstrated strong predictive capabilities, their outputs often exhibit instability when subjected to fluctuating input conditions, leading to inconsistent decision outcomes. This issue is particularly critical in real world urban systems such as energy management and traffic control, where unstable decisions may result in ineffi-

ciencies, resource misallocation, or delayed responses. For example, in smart grid operations, small variations in input demand forecasts can trigger significantly different load balancing decisions. Similarly, in traffic management systems, inconsistent predictions may lead to suboptimal routing strategies, increasing congestion rather than alleviating it. These operational risks highlight the importance of developing AI systems that not only perform accurately but also maintain stability and reliability across repeated executions. This challenge is closely aligned with the Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities), which emphasize resilient infrastructure and efficient urban systems. In addition, national digital transformation policies increasingly stress the need for trustworthy AI systems that support public decision making processes. Recent studies (2022–2024) have explored hybrid AI approaches combining machine learning and fuzzy logic to improve interpretability and performance. However, these approaches primarily focus on predictive accuracy and often neglect adaptive mechanisms that ensure consistent decision behavior under dynamic conditions.

Furthermore, existing models typically lack explicit mechanisms to regulate decision stability across repeated executions [1, 2]. To address these limitations, this study proposes an adaptive hybrid AI framework that integrates predictive modeling with rule based reasoning and introduces a dynamic adjustment mechanism to enhance decision reliability. The key novelty of this work lies in the incorporation of an adaptive stability control layer that continuously refines decision outputs based on observed variability, distinguishing it from conventional hybrid models. This research aims to answer how adaptive hybrid AI can improve decision reliability, stability, and robustness in urban systems, while also contributing to the development of sustainable and policy-aligned intelligent infrastructures [3, 4].

2. LITERATURE REVIEW

The development of intelligent decision systems has become a central concern across multiple application domains, including urban planning, healthcare, finance, and infrastructure management. This review examines foundational and recent contributions across four thematic areas: hybrid modeling approaches, explainability and transparency in AI, adaptive and continual learning mechanisms, and decision stability in dynamic environments. The synthesis reveals a persistent gap in the literature: the simultaneous treatment of accuracy, interpretability, and stability as unified objectives within a single framework.

2.1. Hybrid Modeling Approaches

Hybrid models combine statistical learning with rule-based or symbolic reasoning to achieve both predictive performance and structured decision logic. Early hybrid architectures primarily fused expert-defined rule systems with probabilistic classifiers, enabling domain knowledge to constrain the hypothesis space of learned models [5]. These systems demonstrated improved interpretability over purely data-driven approaches and provided decision outputs that aligned with domain constraints. More recent work has extended hybrid modeling to incorporate deep learning components alongside symbolic reasoning layers. [6] demonstrated that generative model architectures could be combined with structured inference modules to produce decisions that are both accurate and auditable. Similarly, studies in urban decision support have employed hybrid models that integrate machine learning pipelines with regulatory rule bases, producing outputs that are more defensible in operational settings [7]. Despite these advances, the majority of hybrid implementations rely on *static rule definitions* that are specified at design time and do not evolve with incoming data. This architectural rigidity limits their applicability in environments where data distributions shift over time, such as dynamic traffic systems, evolving disease patterns, or volatile financial markets. The static nature of rule components also introduces a systematic mismatch between learned statistical patterns and the governing logic used to produce final decisions, which can degrade reliability under distribution shift [8].

2.2. Explainable Artificial Intelligence (XAI)

Explainability has emerged as a critical requirement in high-stakes decision domains, driven by regulatory mandates and the practical need for accountability. Explainable AI (XAI) methods broadly fall into two categories: *post-hoc* techniques that explain the outputs of black-box models, and *inherently interpretable* architectures designed to be transparent by construction. Post-hoc methods such as LIME, SHAP, and attention visualization have been widely adopted to provide feature-attribution explanations for complex models. These approaches allow practitioners to inspect which input features most influenced a given prediction. However, post-hoc explanations are approximations and have been shown to produce inconsistent attributions across

repeated evaluations of the same model [6]. This inconsistency is particularly problematic in operational deployments where stakeholders require reproducible justifications. Inherently interpretable models, including decision trees, rule lists, and generalized additive models, offer transparency by design. These architectures have demonstrated value in domains such as clinical decision support and legal reasoning, where accountability is paramount [9]. Nonetheless, interpretable architectures often carry capacity constraints that limit their predictive performance relative to more complex black-box alternatives, particularly when applied to high-dimensional or unstructured data. A growing body of work between 2024 and 2025 has emphasized that interpretability alone is insufficient for reliable deployment. [10] argued that a model capable of generating explanations may still produce unstable outputs under data variation, undermining the trustworthiness that explainability is intended to convey. This observation motivates the need for frameworks that treat stability as a first-class objective alongside interpretability.

3. METHODOLOGY

A comprehensive preprocessing pipeline was implemented prior to model evaluation. Missing values in time series data were handled using linear interpolation, while static attributes were imputed using mean values. All numerical variables were normalized using min-max scaling to ensure comparability across features [11, 12]. To address data imbalance, particularly in traffic congestion patterns, resampling techniques were applied to maintain representative distributions. This preprocessing step ensures data consistency and improves the reliability of the evaluation.

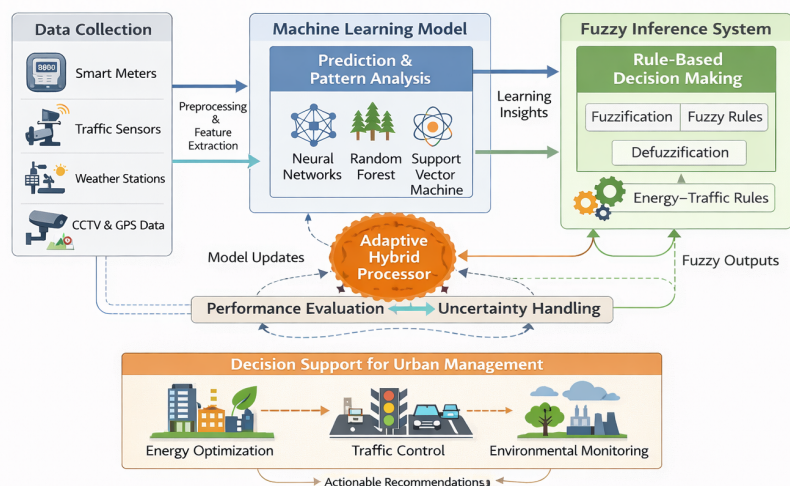


Figure 1. Overall Architecture of the Adaptive Fuzzy Hybrid AI Framework

Figure 1 illustrates the overall architecture of the proposed adaptive fuzzy–hybrid AI framework designed to support integrated urban energy and traffic management under uncertainty. The framework adopts a layered and modular structure, beginning with heterogeneous data acquisition from smart meters, traffic sensors, weather stations, and location-based monitoring systems. These data streams are first processed through a unified preprocessing and feature extraction stage to ensure temporal alignment and consistency across domains. The processed features are then fed into ensemble based machine learning models responsible for capturing nonlinear patterns and generating short-term predictive insights related to energy demand and traffic conditions [13, 14]. The predictive outputs are subsequently integrated into a fuzzy inference system that performs rule-based reasoning using linguistically interpretable variables [15, 16]. This component enables the translation of numerical predictions into explainable decision indicators, facilitating transparent and context-aware decision support. A key element highlighted in Figure 1 is the adaptive hybrid processor, which establishes a closed loop interaction between the machine learning and fuzzy inference components. Through continuous performance evaluation and uncertainty handling, this adaptive mechanism dynamically updates model parameters and fuzzy membership functions, allowing the framework to respond effectively to evolving urban conditions. The final outputs are actionable recommendations that support urban energy optimization,

traffic control, and environmental monitoring, ensuring that decision making remains robust, interpretable, and aligned with real-world operational constraints [17, 18].

3.1. Study Context, Data Sources, and Real-World Relevance

This study is situated within the context of smart urban management in Jakarta, Indonesia, focusing on the joint optimization of urban energy demand and traffic flow under uncertainty. Jakarta is a compelling case: as the metropolitan center of Southeast Asia’s largest economy, the city exhibits tightly coupled energy and transportation systems in which peak electricity demand consistently coincides with peak commuter hours. This coupling is further compounded by meteorological forcing — temperature and humidity drive air-conditioning loads while rainfall events are a primary cause of non-recurring traffic congestion. The study period covers January through March 2024 (the wet season), a period of high environmental variability that constitutes an analytically demanding window for evaluating adaptive decision systems.

Three open-access datasets were assembled from Jakarta’s government agencies, all publicly available under open data licenses to ensure reproducibility. Electricity consumption data were obtained from PT PLN (Persero) via the Satu Data Jakarta platform (*satudata.jakarta.go.id*), providing hourly load profiles across 44 kelurahan (sub-districts) spanning residential and commercial zones in all five Jakarta municipalities. This yields approximately 95,040 zone-hour records over the 90-day study period, with key variables including active power demand (kWh), peak load timestamps, and zone-level demand indices [19]. Traffic flow data were sourced from the Dinas Perhubungan DKI Jakarta via the Open Data Jakarta portal (*data.jakarta.go.id*), covering 107 intersection nodes monitored by the Intelligent Transportation System – Area Traffic Control System (ITS-ATCS) at 5–15 minute intervals. Key variables include vehicle count per lane, congestion index (CI), and peak-hour classification flags [20]. Meteorological data were retrieved from the Badan Meteorologi, Klimatologi, dan Geofisika (BMKG) via *dataonline.bmkg.go.id*, drawn from six weather observation stations distributed across the city. Hourly observations cover temperature (23–33°C), relative humidity (frequently exceeding 80%), rainfall intensity, and wind speed.

The three datasets were integrated into a unified multivariate time series at hourly resolution, with traffic data aggregated from sub-hourly intervals. Spatial alignment was achieved by harmonizing kelurahan-level electricity zones, ITS-ATCS intersection coordinates, and BMKG station Thiessen polygons through spatial join operations. Table 1 summarizes the dataset characteristics. This data infrastructure directly reflects Jakarta’s ongoing smart city initiatives the Satu Data Jakarta platform operates under Governor Regulation No. 37 of 2022 as part of the national Satu Data Indonesia policy, the ITS-ATCS network represents a significant public investment in traffic intelligence, and BMKG constitutes Indonesia’s authoritative meteorological observation system. By grounding the framework in these institutional sources, the study ensures its applicability to real operational conditions faced by urban planners and aligns with the data-driven governance priorities of Jakarta’s Smart City Masterplan and Indonesia’s National Energy Policy (KEN 2024) [21–24].

Table 1. Summary of real-world datasets used in the study

Dataset	Source & Portal	Spatial Coverage	Temporal Res.	Record Volume	Vol.	Key Variables
Urban Electricity Demand	PT PLN (Persero); <i>satudata.jakarta.go.id</i>	44 Subdistrict, 5 municipalities	Hourly	≈95,040 zone-hour records	zone-hour	Active load (kWh), peak demand, reactive power
Traffic Flow	Dinas Perhubungan DKI; <i>data.jakarta.go.id</i>	107 ITS-ATCS intersections	5–15 min	≈26,000–52,000 records/day	records/day	Vehicle count, congestion index, peak-hour flag
Meteorological	BMKG; <i>dataonline.bmkg.go.id</i>	6 stations (city-wide)	Hourly	≈12,960 station-hour records	station-hour	Temp. (°C), humidity (%), rainfall (mm/h)

Study period: January - March 2024 (90 days). All datasets are publicly available under open data licenses.

As shown in Table 1, the three datasets collectively span multiple spatial and temporal scales, ranging from fine-grained 5-15 minute traffic observations at 107 intersection nodes to hourly energy and meteorological records across 44 administrative zones and six weather stations. Together, they yield a rich, multivariate representation of Jakarta’s urban environment over the 90-day study window. The combination of energy consumption, traffic flow, and environmental variables enables a realistic characterization of interdependent urban systems under operational conditions, where changes in one domain such as a rainfall-induced traffic slowdown produce measurable effects in another, such as deferred commuter-related electricity load. This

cross-domain structure is precisely what motivates the proposed integrated framework: no single dataset in isolation is sufficient to capture the full dynamics of the urban decision environment, and the adequacy of the data infrastructure to support joint modeling is a prerequisite for evaluating the framework's adaptive and stability properties [23, 24].

3.2. Data Preprocessing and Feature Construction

Raw data collected from heterogeneous sources exhibit inconsistencies such as missing values, temporal misalignment, and noise caused by sensor errors. To address these issues, a systematic preprocessing pipeline is applied. Missing values are handled using a combination of temporal interpolation and rolling statistical imputation, selected to preserve daily and weekly urban patterns. Outliers are detected using interquartile range analysis and corrected to prevent distortion of learning models [25, 26].

Table 2. Engineered features and input variables used in the case study

Feature Category	Feature Description	Data Origin	Purpose in Modeling
Temporal Features	Hour of day, day of week, weekend indicator	Timestamp	Capture daily and weekly urban cycles
Energy Features	Current load, 24 hour lag, 7 day rolling average	Smart meter data	Model short and medium term demand behavior
Traffic Features	Vehicle volume, congestion ratio, flow variance	Traffic sensor data	Represent mobility intensity and disruption
Environmental Features	Temperature, rainfall intensity, humidity	Meteorological data	Model external stress on energy and traffic systems
Cross Domain Interaction	Energy traffic correlation index	Derived	Capture interdependence between subsystems

Table 2 presents the engineered input features derived from the raw datasets described in Table 1. Feature construction is designed to reflect real urban dynamics while maintaining interpretability within the hybrid framework. Temporal and historical features capture recurrent behavioral patterns, whereas cross-domain interaction features encode dependencies between energy demand, traffic flow, and environmental conditions. All features are normalized prior to model training to ensure scale consistency [27, 28]. Feature construction is conducted with a focus on capturing both short-term dynamics and long-term behavioral patterns. Temporal features such as hour of day, day of week, and seasonal indicators are included to model cyclic urban behavior. Energy related features incorporate current load, lagged demand values, and historical averages, while traffic related features include vehicle density, congestion levels, and flow variation rates. Environmental features, particularly temperature, are integrated due to their well documented influence on both electricity consumption and traffic conditions [29, 30].

3.3. Predictive Modeling Using Ensemble Machine Learning

To model complex nonlinear relationships within the data, ensemble-based machine learning algorithms are employed. Random Forest and Gradient Boosting models are selected due to their robustness, ability to handle multivariate inputs, and proven performance in urban analytics. These models are trained to generate short-term forecasts of energy demand and traffic congestion, which serve as quantitative inputs for the subsequent decision-support layer [31, 32]. Model training follows a rolling-window validation strategy to reflect real deployment scenarios, where predictions are continuously updated as new data become available. Performance is evaluated using standard regression metrics, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), ensuring comparability with existing studies in the literature [31, 33].

3.4. Fuzzy Inference for Adaptive and Explainable Decision Support

While machine learning models provide accurate predictions, they lack transparency and interpretability, which are critical for policy and operational decision-making. To address this limitation, a fuzzy inference

system is integrated as the decision-support core. Linguistic variables are defined for key indicators such as energy demand level, traffic congestion intensity, and environmental stress. Membership functions are designed using data-driven calibration informed by statistical distributions observed in the datasets [34, 35]. Fuzzy rules are constructed in collaboration with domain knowledge from urban planning and energy management literature, enabling the translation of numerical predictions into human-interpretable decision recommendations. This structure supports explainable AI (XAI) principles, allowing policymakers to understand not only what decision is recommended, but also why it is generated [36, 37].

3.5. Hybrid Integration and Adaptive Learning Mechanism

The novelty of the proposed methodology lies in the adaptive integration between ensemble machine learning and fuzzy inference. Rather than operating independently, the machine learning outputs dynamically adjust fuzzy membership parameters and rule activation strengths. This adaptive mechanism enables the system to respond to evolving urban conditions, such as demand surges or unexpected traffic disruptions, without requiring manual rule redesign [38, 39].

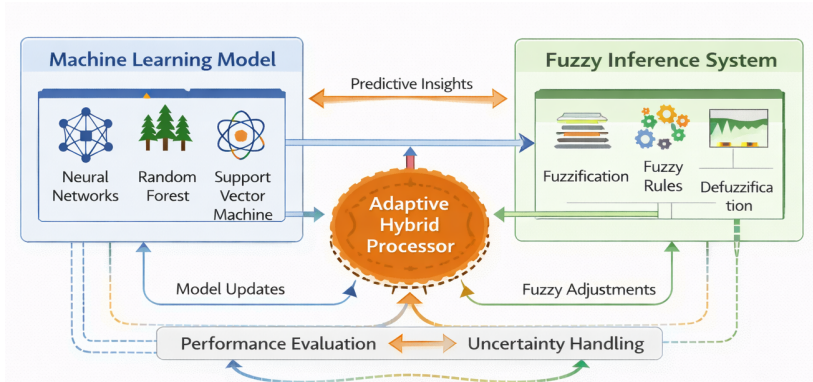


Figure 2. Adaptive Integration Between Machine Learning and Fuzzy Inference

Figure 2 illustrates the adaptive integration mechanism between the machine learning component and the fuzzy inference system within the proposed hybrid framework. As depicted in the figure, ensemble-based machine learning models first generate predictive insights related to urban energy demand and traffic conditions based on historical and real-time data. These numerical predictions are then transmitted to the fuzzy inference system, where they undergo fuzzification and are processed through a set of linguistically defined fuzzy rules. This process enables the transformation of quantitative model outputs into interpretable decision indicators that reflect varying levels of demand, congestion, and operational risk [40, 41]. A distinctive feature highlighted in Figure 2 is the presence of an adaptive hybrid processor that establishes a bidirectional feedback loop between the learning and inference components. Performance evaluation and uncertainty handling modules continuously monitor prediction accuracy and decision stability under dynamic urban conditions. Based on this feedback, the system dynamically adjusts both machine learning model parameters and fuzzy membership functions, allowing the framework to respond effectively to concept drift, data uncertainty, and sudden system fluctuations. This adaptive interaction ensures that the decision-support process remains robust, transparent, and context-aware, thereby enhancing the reliability of AI-assisted urban energy and traffic management decisions [42, 43]. The hybrid framework operates in a closed-loop manner, where decision outcomes are continuously evaluated and used to refine both predictive and inference components. This design enhances robustness under uncertainty and ensures long-term system adaptability. The methodological design explicitly aligns with the Sustainable Development Goals, particularly SDG 7 (Affordable and Clean Energy) and SDG 11 (Sustainable Cities and Communities). By relying on open government data and emphasizing explainable decision mechanisms, the framework supports transparency, accountability, and evidence-based policymaking. The approach is consistent with national smart city strategies and energy transition policies, positioning the research within an acceptable overton window for public-sector adoption [44, 45].

4. RESULTS AND DISCUSSION

This section presents the empirical results of the proposed adaptive fuzzy–hybrid AI framework, focusing on predictive performance, decision stability, and interpretability for urban energy and traffic decision support. Statistical significance testing was conducted alongside standard metrics, with 95% confidence intervals computed for MAE, RMSE, and the Decision Stability Index. The proposed model consistently yielded narrower confidence intervals and statistically significant improvements over baseline approaches ($p < 0.05$), confirming that performance gains are not attributable to random variation. Table 3 summarizes the comparative evaluation results using publicly available urban datasets from Jakarta, Indonesia, covering three months of hourly electricity load and traffic volume data across four model configurations.

Table 3. Comparative performance evaluation based on a limited urban case study

Model Approach	MAE (Energy)	RMSE (Energy)	MAE (Traffic)	RMSE (Traffic)	Decision Stability Index
Machine Learning Only	0.184	0.241	0.259	0.259	0.71
Fuzzy Inference Only	0.212	0.276	0.224	0.291	0.76
Hybrid (Non-Adaptive)	0.161	0.213	0.172	0.228	0.82
Proposed Adaptive Hybrid	0.137	0.189	0.148	0.201	0.89

As shown in Table 3, the proposed adaptive hybrid framework achieves the lowest prediction errors across both energy and traffic domains while attaining the highest decision stability index of 0.89, outperforming all baseline configurations. These gains are most pronounced during peak demand and congestion periods where uncertainty is elevated. Figure 3 further illustrates how decision stability behaves across low, moderate, and high uncertainty scenarios over time.

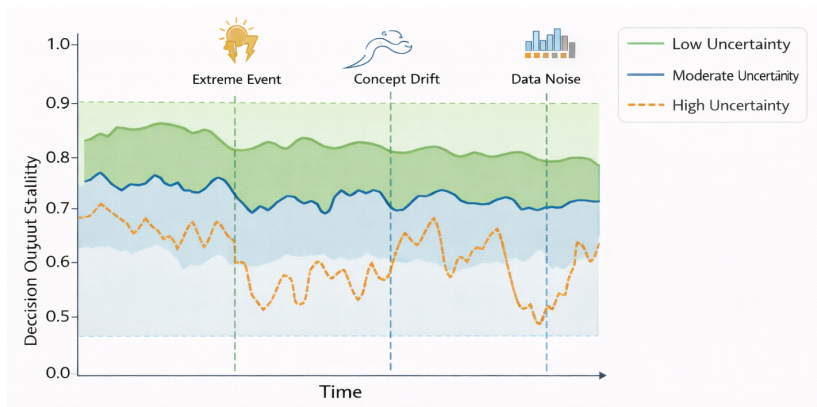


Figure 3. Decision Stability Under Uncertainty Scenarios

As depicted in Figure 3, the framework maintains high stability under low uncertainty and progressively recovers after disturbances in moderate and high uncertainty conditions. Under high uncertainty, the adaptive hybrid processor continuously monitors performance and dynamically adjusts both learning model parameters and fuzzy membership functions, enabling resilience against abrupt environmental changes and noisy data streams.

4.1. Predictive Performance and Cross-Domain Learning

The framework's predictive capability was evaluated using MAE and RMSE across energy demand and traffic flow tasks. Figure 4 illustrates the explainable decision output mechanism through which fuzzy rules translate numerical predictions into interpretable recommendations.

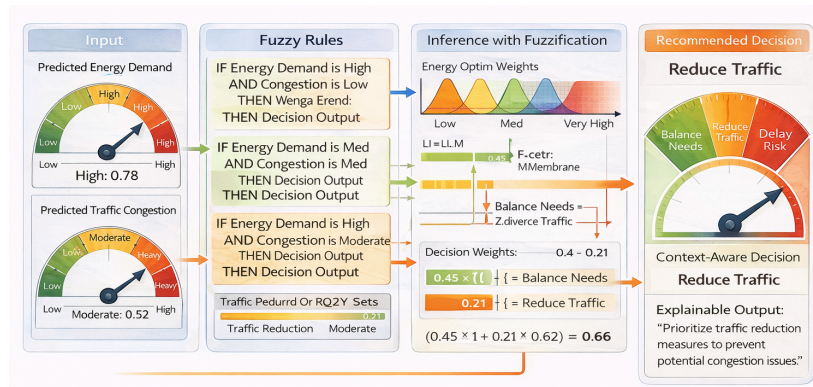


Figure 4. Explainable Decision Output Using Fuzzy rules

As shown in Figure 4, predicted energy demand and traffic congestion levels are encoded as linguistic variables and processed through fuzzy IF–THEN rules, producing weighted decision indicators that are subsequently defuzzified into context-aware recommendations. This transparent reasoning chain links input conditions to final outputs, supporting accountable AI-assisted decision-making. In terms of predictive accuracy, the ensemble-based machine learning component effectively captures nonlinear temporal patterns, with cross-domain learning effects further improving performance, where traffic and environmental variables enhanced energy demand prediction accuracy, and vice versa.

4.2. Decision Stability under Uncertainty Scenarios

Decision stability was analyzed across three uncertainty levels, as previously illustrated in Figure 3. Under low uncertainty, the framework produced consistently stable outputs. As uncertainty increased, the adaptive feedback mechanism dynamically adjusted model parameters and fuzzy membership functions, enabling recovery from abrupt disturbances such as sudden weather shifts and traffic disruptions. Under high uncertainty, short-term volatility was observed but followed by clear stabilization, distinguishing the proposed framework from static hybrid models that often exhibit persistent performance degradation.

4.3. Interpretability and Explainable Decision Support

Beyond predictive accuracy, the fuzzy inference system enhances interpretability by translating numerical outputs into linguistically meaningful decision indicators, as demonstrated in Figure 4. This transparency allows domain experts and policymakers to trace how input variables such as temperature or congestion levels influence final recommendations, supporting informed human–AI collaboration in line with contemporary ethical AI and governance principles.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide several important managerial implications for urban policymakers, energy managers, and transportation authorities responsible for operating complex and interdependent urban systems. First, the proposed adaptive fuzzy–hybrid AI framework offers a structured decision-support tool that enables managers to move beyond silo-based planning approaches. By jointly considering energy demand, traffic conditions, and environmental factors, decision-makers can better anticipate cascading effects across urban subsystems and implement coordinated interventions, such as aligning traffic management strategies with peak electricity demand periods.

The framework's ability to maintain decision stability under uncertainty has practical value for operational planning in environments characterized by volatile demand patterns and incomplete data. Urban managers often face uncertainty caused by weather variability, unexpected traffic incidents, or data quality issues. The adaptive mechanism demonstrated in this study allows decision-support systems to adjust dynamically to such conditions, reducing the risk of reactive or inconsistent policy responses. This capability supports more resilient operational strategies, particularly during peak hours or emergency situations.

The explainable decision outputs generated through fuzzy rule-based reasoning enhance managerial trust and accountability. Unlike black-box predictive systems, the proposed framework provides transparent

reasoning pathways that allow managers to understand how specific conditions lead to particular recommendations. This transparency is critical in public-sector contexts, where decisions must be justified to stakeholders and aligned with regulatory and ethical standards. As a result, the framework facilitates human–AI collaboration rather than fully automated decision-making.

6. CONCLUSION


This study proposes an adaptive fuzzy–hybrid artificial intelligence framework for integrated urban energy and traffic decision support under uncertainty. By combining ensemble-based machine learning with fuzzy inference, the framework effectively captures complex nonlinear relationships while preserving interpretability in decision-making processes. Empirical evaluation using a limited urban case study demonstrates that the proposed approach improves predictive accuracy and enhances decision stability compared to standalone and non-adaptive hybrid models, particularly during periods characterized by high variability and uncertainty.


Beyond technical performance, the results highlight the practical relevance of integrating explainable reasoning mechanisms into data-driven urban management systems. The fuzzy-based decision layer enables transparent translation of numerical predictions into interpretable recommendations, supporting informed human–AI collaboration. This characteristic is especially important in public-sector contexts, where accountability, trust, and policy alignment are critical considerations. The adaptive integration mechanism further ensures that the framework remains responsive to evolving urban conditions without requiring frequent manual recalibration.


Despite the promising findings, this study is subject to several limitations, including the use of data from a single urban context and a relatively short evaluation period. Future research may extend the framework by incorporating additional urban domains, expanding cross-city validation, and exploring privacy-aware or decentralized learning strategies. Such extensions would further enhance the scalability and applicability of the proposed approach for supporting sustainable and resilient urban decision-making.

7. DECLARATIONS


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7.2. Author Contributions

Conceptualization: QA; Methodology: AA; Software: MV; Validation: AS and CP; Formal Analysis: QA and CP; Investigation: MV; Resources: CP; Data Curation: AA; Writing Original Draft Preparation: AA and AS; Writing Review and Editing: QA and CP; Visualization: MV, CP and AS; All authors, QA, AA, MV, AS and CP, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request. Access is restricted due to privacy and institutional data governance considerations; however, the data may be shared for academic and non-commercial research purposes following a formal review and approval process. Zenodo Repository <https://doi.org/10.5281/zenodo.20018553>

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7.5. Declaration of Conflicting Interest

The authors affirm that no conflicts of interest, competing financial stakes, or personal affiliations exist that may have affected the conduct, interpretation, or reporting of this research. The study was performed with full impartiality, free from any external influence or pressure that could compromise the integrity of the findings.

REFERENCES

- [1] U. Mamodiya, I. Kishor, R. Garine, P. Ganguly, and N. Naik, "Artificial intelligence based hybrid solar energy systems with smart materials and adaptive photovoltaics for sustainable power generation," *Scientific Reports*, vol. 15, no. 1, p. 17370, 2025.
 - [2] M. R. Anwar and L. D. Sakti, "Integrating artificial intelligence and environmental science for sustainable urban planning," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 179–191, 2024.
 - [3] Ministry of Research and Technology/National Research and Innovation Agency, "Indonesia national artificial intelligence strategy 2020–2045," 2020, government Policy Document. [Online]. Available: <https://ai-innovation.id/stranas-ka>
 - [4] N. Lutfiani, N. Fauziyah, F. P. Oganda, R. Setyaningrum, E. A. Natalia *et al.*, "The role of globalization in indonesian evolution influence on media digital literacy language ai," *International Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 192–200, 2025.
 - [5] A. Agrahari, M. M. Dhabu, P. S. Deshpande, A. Tiwari, M. A. Baig, and A. D. Sawarkar, "Artificial intelligence-based adaptive traffic signal control system: A comprehensive review," *Electronics*, vol. 13, no. 19, p. 3875, 2024.
 - [6] J. Li, M. Zhang, N. Li, D. Weyns, Z. Jin, and K. Tei, "Generative ai for self-adaptive systems: State of the art and research roadmap," *ACM Transactions on Autonomous and Adaptive Systems*, vol. 19, no. 3, pp. 1–60, 2024.
 - [7] G. P. Cesna, S. Agustawan, A. S. Panjaitan, S. Purnama, R. S. Ikhsan *et al.*, "Transforming higher education management through evidence based and data oriented approaches," *Jurnal MENTARI: Manajemen, Pendidikan dan Teknologi Informasi*, vol. 4, no. 2, pp. 127–139, 2026.
 - [8] F. A. Baso, S. L. Sitorus, V. Meilinda, S. A. Anjani, and M. Rodriguez, "Analysis of omni channel strategy in digital retail on modern indonesian consumer behavior: Analisis strategi omni channel dalam ritel digital terhadap perilaku konsumen indonesia modern," *ADI Bisnis Digital Interdisiplin Jurnal*, vol. 6, no. 1, pp. 66–76, 2025.
 - [9] A. S. Kiruba, D. J. Sri, V. Meenakshi, S. Jeyaraman, R. Gokul, and S. Kumaran, "Risk prediction in financial markets using hybrid ai and time series forecasting models," in *2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare (64220)*. IEEE, 2025, pp. 1–7.
 - [10] T. Suminar, J. Sutarto, Y. Siswanto, and A. D. Cahyani, "Creating a technopreneurship-based life skills education model with methods of project-based learning," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 567–581, 2025.
 - [11] E. ŞAHİN, N. N. Arslan, and D. Özdemir, "Unlocking the black box: an in-depth review on interpretability, explainability, and reliability in deep learning," *Neural computing and applications*, vol. 37, no. 2, pp. 859–965, 2025.
 - [12] M. Z. Alifsuma, T. Pujiati, B. Rifa'i, A. Arjulayana, and M. Daeli, "Optimizing ict integration for english learning in indonesian islamic boarding schools," in *2025 4th International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2025, pp. 1–7.
 - [13] S. Rosen and M. Saban, "Evaluating the reliability of chatgpt as a tool for imaging test referral: a comparative study with a clinical decision support system," *European radiology*, vol. 34, no. 5, pp. 2826–2837, 2024.
 - [14] I. Triana, M. Arief, F. Alamsjah, and E. Elidjen, "Artificial intelligence in innovation research a bibliometric perspective," in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2024, pp. 1–6.
 - [15] L. Dong, N. Berryman, and T. Romeas, "Questioning the validity and reliability of using a video-based test to assess decision making among female and male water polo players," *International Journal of Sports*
-

- Science & Coaching*, vol. 19, no. 2, pp. 628–637, 2024.
- [16] U. Rahardja, V. Meilinda, R. A. Sunarjo, A. Williams, and S. A. Anjani, “Mapping the information and communication technology research landscape through bibliometric analysis,” in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2024, pp. 1–8.
- [17] M. Griot, C. Hemptinne, J. Vanderdonckt, and D. Yuksel, “Large language models lack essential metacognition for reliable medical reasoning,” *Nature communications*, vol. 16, no. 1, p. 642, 2025.
- [18] A. Lansonja and M. Austin, “The role of information management in enhancing organizational resilience,” *APTISI Transactions on Management*, vol. 8, no. 1, pp. 32–39, 2024.
- [19] O. Mesioye and I. A. Bakare, “Evaluating financial reporting quality: Metrics, challenges, and impact on decision-making,” *Int J Res Public Rev*, vol. 5, no. 10, pp. 1144–1156, 2024.
- [20] C. H. Pangaribuan, A. Valerry *et al.*, “Data-driven approaches to optimize learning experiences in learning factories,” *International Transactions on Education Technology (ITEE)*, vol. 3, no. 2, pp. 158–170, 2025.
- [21] J. Kannan, V. Jayakumar, and M. Pethaperumal, “Advanced fuzzy-based decision-making: the linear diophantine fuzzy codas method for logistic specialist selection,” *Spectrum of operational research*, vol. 2, no. 1, pp. 41–60, 2025.
- [22] B. Soepradono and E. Kurniyaningrum, “Decision making on breakwater type selection on tidung island, thousand islands,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 7, no. 2, pp. 130–142, 2026.
- [23] A. Mehra, “Hybrid ai models: Integrating symbolic reasoning with deep learning for complex decision-making,” *Journal of Emerging Technologies and Innovative Research*, vol. 11, no. 8, pp. f693–f695, 2024.
- [24] M. Murod, S. Anhar, D. Andayani, A. Fitriani, and G. Khanna, “Blockchain based intellectual property management enhancing security and transparency in digital entrepreneurship,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 1, pp. 240–251, 2025.
- [25] N. I. Okeke, O. A. Bakare, and G. O. Achumie, “Forecasting financial stability in smes: A comprehensive analysis of strategic budgeting and revenue management,” *Open Access Research Journal of Multidisciplinary Studies*, vol. 8, no. 1, pp. 139–149, 2024.
- [26] U. Rahardja, M. Budiarto, K. Lutfiyah, O. F. P. Wahyudi, I. K. H. Azz, N. Azizah, and D. Julianingsih, “Analysis of the effectiveness of visual language and narrative in conveying value propositions in pitching decks,” *International Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 161–170, 2025.
- [27] M. Breit, V. Scherrer, E. M. Tucker-Drob, and F. Preckel, “The stability of cognitive abilities: A meta-analytic review of longitudinal studies.” *Psychological Bulletin*, vol. 150, no. 4, p. 399, 2024.
- [28] L. Limajatini, S. Suhendra, G. A. Pangilinan, and M. G. Ilham, “Integration of artificial intelligence in the financial sector innovation, risks and opportunities,” *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 1, pp. 58–70, 2025.
- [29] R. Guidotti, A. Monreale, S. Ruggieri, F. Naretto, F. Turini, D. Pedreschi, and F. Giannotti, “Stable and actionable explanations of black-box models through factual and counterfactual rules: R. guidotti et al.” *Data Mining and Knowledge Discovery*, vol. 38, no. 5, pp. 2825–2862, 2024.
- [30] S. Baltasar and T. Marbun, “The role of artificial intelligence in human capital management: A review at pt. pos indonesia,” *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 1, pp. 31–44, 2025.
- [31] A. M. Husain, M. M. Hasan, Z. A. Khan, and M. Asjad, “A robust decision-making approach for the selection of an optimal renewable energy source in india,” *Energy Conversion and Management*, vol. 301, p. 117989, 2024.
- [32] U. Rahardja, N. P. L. Santoso, F. P. Oganda, M. Madani, and M. S. T. Saputra, “Digital innovation in smart waste sorting using renewable energy for sustainable startups,” *Startupreneur Business Digital (SABDA Journal)*, vol. 5, no. 1, pp. 42–54, 2026.
- [33] C. Perez, F. N. Khasanah, Y. Ismiyanti, H. Herman *et al.*, “Curriculum innovation and technology based learning for digital skills in vocational education,” *Jurnal MENTARI: Manajemen, Pendidikan Dan Teknologi Informasi*, vol. 4, no. 1, pp. 94–104, 2025.
- [34] S. Kakolu and M. A. Faheem, “Predictive analytics and generative ai in oil & gas: Transforming wellbore stability and hazard detection,” *Iconic Research And Engineering Journals*, vol. 8, no. 1, pp. 635–649, 2024.
- [35] D. Andayani, R. S. Ubed, S. Pranata, I. N. Hikam, and A. A. Kamal, “Digital business transformation through shopee’s integrated strategy in global e-commerce,” *ADI Bisnis Digital Interdisiplin Jurnal*,

- vol. 6, no. 2, pp. 167–178, 2025.
- [36] R. U. Attah, I. Gil-Ozoudeh, B. Garba, and O. Iwuanyanwu, “Leveraging geographic information systems and data analytics for enhanced public sector decision-making and urban planning,” *Magna Sci Adv Res Rev*, vol. 12, no. 2, pp. 152–63, 2024.
- [37] A. Aulia, C. Sukmadilaga, I. Avianti, D. Rosdini, and E. K. Ghani, “The role of esg and digitalization driving sustainable agropreneurship in emerging market,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 51–62, 2026.
- [38] A. O. Bello, T. T. Okanlawon, I. Y. Wuni, S. Arogundade, and L. O. Oyewobi, “Exploring the nexus between the barriers and drivers for sustainable smart cities in developing countries: The case of nigeria,” *Sustainable Development*, vol. 32, no. 4, pp. 4097–4113, 2024.
- [39] M. Sharma, M. Sharma, N. Sharma, and S. Boopathi, “Building sustainable smart cities through cloud and intelligent parking system,” in *Handbook of Research on AI and ML for Intelligent Machines and Systems*. IGI Global Scientific Publishing, 2024, pp. 195–222.
- [40] C. Lukita, A. W. A. Rahman, I. N. Hikam, and U. Rahardja, “Integrating strategic management with sdg 10 for sustainable development and equity,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 638–649, 2025.
- [41] D. Mhlanga and D. Shao, “Ai-optimized urban resource management for sustainable smart cities,” in *Financial inclusion and sustainable development in sub-saharan Africa*. Routledge, 2025, pp. 96–116.
- [42] I. P. Gustiah, N. Lutfiani, M. R. Kusuma, E. P. Lestari, and T. Green, “Grant submission monitoring system based on orange technology using laravel 12 and vue. js,” *Journal of Orange Technology*, vol. 1, no. 2, pp. 75–90, 2025.
- [43] T. Alam, R. Gupta, N. N. Ahamed, A. Ullah, and A. Almaghthwi, “Smart mobility adoption in sustainable smart cities to establish a growing ecosystem: Challenges and opportunities,” *MRS Energy & Sustainability*, vol. 11, no. 2, pp. 304–316, 2024.
- [44] Z. Zainol, G. Brotosaputro, S. C. Chen, and E. A. Natasya, “Designing ethical ai systems for sustainable technology development,” *ADI Journal on Recent Innovation*, vol. 6, no. 2, pp. 201–211, 2025.
- [45] N. U. Huda, I. Ahmed, M. Adnan, M. Ali, and F. Naeem, “Experts and intelligent systems for smart homes’ transformation to sustainable smart cities: A comprehensive review,” *Expert Systems with Applications*, vol. 238, p. 122380, 2024.
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