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# AI-Driven Predictive Decision Support Systems for Sustainable Resource Management in Smart Communities

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**Abstract**

The rapid development of smart communities has increased the demand for intelligent and sustainable resource management systems. Efficient utilization of resources such as energy, water, transportation, and waste management is essential for improving environmental sustainability, reducing operational costs, and enhancing the quality of life. Traditional resource management approaches often face challenges related to inefficient resource allocation, unpredictable consumption patterns, increasing population demands, and limited real-time decision-making capabilities. To address these challenges, this study proposes an AI-Driven Predictive Decision Support System (AI-PDSS) for sustainable resource management in smart communities. The proposed framework integrates Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and predictive analytics to collect, process, and analyse real-time resource consumption data. Machine learning algorithms such as Random Forest, Support Vector Regression, and Long Short-Term Memory (LSTM) networks can be employed to predict future resource requirements, identify consumption patterns, and detect potential resource shortages. Furthermore, a multi-criteria decision-making mechanism can be incorporated to evaluate alternative resource allocation strategies based on sustainability, cost efficiency, availability, and environmental impact. The proposed system aims to support intelligent resource distribution, optimize consumption, minimize resource wastage, and improve community-level sustainability. The effectiveness of the framework can be evaluated using prediction accuracy, resource utilization efficiency, energy consumption reduction, water conservation, and computational performance. The proposed approach provides an intelligent decision-support mechanism for policymakers, community administrators, and urban planners to make reliable, data-driven decisions. This research contributes to the development of sustainable smart communities through predictive intelligence and optimized resource management.

**Keywords:** Artificial Intelligence, Predictive Analytics, Decision Support System, Smart Communities, Sustainable Resource Management, Machine Learning, Internet of Things, Resource Optimization.

## 1. Introduction

The rapid growth of urban populations, technological advancement, and increasing demand for natural resources have created significant challenges for sustainable community development. Modern communities require efficient management of essential resources, including electricity, water, transportation, waste disposal, and environmental facilities. Conventional resource management systems primarily depend on historical information, manual monitoring, and fixed allocation strategies. These approaches may not adequately respond to changing consumption patterns, unexpected demands, environmental variations, and resource shortages. Therefore, intelligent and predictive technologies are increasingly important for developing sustainable and efficient smart communities. Smart communities represent an advanced approach to community development that integrates digital technologies, communication networks, intelligent infrastructure, and data-driven management systems. Internet of Things (IoT) devices, smart meters, environmental sensors, and connected infrastructure generate continuous information about resource consumption and community activities. These technologies provide opportunities to monitor resource availability, identify consumption behaviour, and improve operational efficiency. However, collecting large volumes of data alone is insufficient. Effective utilization requires advanced analytical techniques capable of converting raw information into meaningful predictions and actionable

decisions. Artificial Intelligence (AI) provides significant opportunities for improving resource management through automated learning, predictive modelling, pattern recognition, and intelligent optimization. Machine learning algorithms can analyse historical and real-time data to identify consumption trends and estimate future resource requirements. For example, AI-based energy prediction models can forecast electricity demand, while water consumption models can identify unusual usage patterns and potential shortages. Similarly, predictive waste management systems can estimate waste generation and support optimized collection schedules. These applications can reduce resource wastage, improve service delivery, and support environmental sustainability. Predictive Decision Support Systems (PDSS) combine forecasting techniques with decision-making methodologies to support effective resource allocation. Unlike conventional monitoring systems, predictive decision-support approaches provide information about future conditions and help administrators select suitable management strategies. By integrating machine learning with optimization techniques, the system can evaluate different resource allocation alternatives according to multiple criteria, including availability, operational cost, environmental impact, consumption efficiency, and community requirements. Multi-Criteria Decision-Making (MCDM) techniques such as Analytical Hierarchy Process (AHP), TOPSIS, and VIKOR can further support the ranking and selection of sustainable resource management alternatives. Despite these technological developments, several challenges remain in implementing AI-driven resource management systems. These include data privacy, incomplete sensor information, prediction uncertainty, interoperability between different infrastructure systems, computational complexity, and the need for transparent decision-making. Furthermore, resource management decisions must balance economic efficiency, environmental protection, and social requirements. Therefore, an integrated framework is necessary to combine predictive intelligence with sustainable decision-making principles. This research focuses on developing an AI-driven predictive decision support framework for sustainable resource management in smart communities. The proposed framework integrates IoT-based data collection, machine learning-based prediction, and multi-criteria decision-making to improve the allocation and utilization of essential community resources. The study considers energy, water, waste, and transportation as major resource management dimensions. The framework is intended to assist community administrators and urban planners in identifying future resource demands, reducing unnecessary consumption, and developing environmentally responsible management strategies. The major contribution of this research is the integration of predictive analytics and intelligent decision-making into a unified resource management framework. The proposed approach aims to transform traditional resource management into a proactive, data-driven, and sustainability-oriented process. It can provide a foundation for developing resilient, efficient, and environmentally sustainable smart communities.

## 2. Literature Review

During the 1980s, Decision Support Systems (DSS) emerged as important computer-based approaches for supporting managerial planning, resource allocation, and organizational decision-making. Early research focused on integrating mathematical models, databases, and analytical techniques to assist decision-makers in solving complex problems. Keen and Scott Morton (1978) explained the fundamental concepts of decision support systems and their applications in managerial decision-making. Sprague (1980) further discussed the development and implementation of DSS architecture, emphasizing the importance of integrating data management, model management, and user interfaces. During this period, optimization and mathematical modelling became important tools for improving resource utilization and operational planning. These early developments established the foundation for intelligent decision-support approaches that are now widely applied in smart communities[4]. During the 1990s, Artificial Intelligence (AI), expert systems, neural networks, and fuzzy logic gained significant attention in decision-making research. These technologies provided opportunities to analyse uncertain information, identify complex patterns, and support decisions under changing conditions. Zadeh (1996) introduced the concept of computing with words, demonstrating the importance of linguistic information in dealing with uncertainty. This development contributed to the application of fuzzy logic in intelligent decision-support systems.[6] Furthermore, AHP-based decision-making approaches developed by Saaty (1980) provided systematic mechanisms for evaluating multiple criteria and ranking alternatives. These mathematical and computational developments created opportunities for integrating predictive analysis with multi-criteria resource allocation. Between 2000 and 2010, research increasingly focused on sustainable development, environmental protection, and efficient utilization of natural resources.

The United Nations Millennium Development Goals (2000) emphasized the importance of environmental sustainability and improving access to essential resources. Brundtland's sustainable development concept also continued to influence research on balancing economic development, environmental protection, and social well-being. During this period, multi-criteria decision-making techniques became increasingly useful in environmental planning and resource management.

Belton and Stewart (2002) explained the application of multiple-criteria decision analysis in evaluating complex alternatives involving conflicting objectives. These developments supported the application of mathematical optimization and decision-support models in energy planning, water management, and environmental assessment. The period from 2010 to 2015 witnessed substantial developments in smart city infrastructure, cloud computing, wireless sensor networks, and the Internet of Things (IoT). Smart meters, environmental sensors, and connected devices enabled the collection of real-time information regarding electricity consumption, water usage, traffic conditions, and environmental quality. Gubbi et al. (2013) presented an IoT-based vision for smart environments, highlighting the importance of interconnected devices, intelligent data processing, and cloud-based infrastructure. Batty et al. (2012) discussed the development of smart cities through information technologies and urban data analytics. Similarly, Zanella et al. (2014) examined IoT applications in smart city environments, emphasizing intelligent monitoring and communication technologies. These developments established the technological foundation for real-time resource monitoring and predictive decision support. Between 2015 and 2020, machine learning and predictive analytics became increasingly important in smart infrastructure and sustainable resource management. Advanced algorithms such as Random Forest, Support Vector Machines, Artificial Neural Networks, and deep learning models provided effective mechanisms for forecasting resource consumption and analysing complex datasets. LeCun, Bengio, and Hinton (2015) discussed the major developments in deep learning and its ability to extract meaningful patterns from large datasets. Similarly, Rolnick et al. (2019) examined the opportunities for applying machine learning to address climate change challenges. Research during this period demonstrated the potential of predictive modelling in energy demand forecasting, transportation planning, environmental monitoring, and resource optimization. These developments encouraged the integration of AI-based forecasting with intelligent resource allocation mechanisms. From 2020 to 2026, research increasingly concentrated on integrating AI, IoT, big data analytics, digital twins, and intelligent decision-support systems for sustainable smart community development. AI-driven predictive approaches have been investigated for electricity demand forecasting, water resource management, waste collection optimization, and environmental monitoring. Machine learning and deep learning techniques support the identification of resource consumption patterns and prediction of future requirements. Digital twin technologies also provide opportunities to simulate community infrastructure and evaluate alternative management strategies. Recent research has highlighted the importance of integrating intelligent analytics with sustainability-oriented urban planning.

Explainable AI, data privacy, uncertainty management, and multi-criteria optimization have also become important research considerations. The integration of predictive intelligence with decision-making methods such as FAHP, TOPSIS, and VIKOR can provide systematic support for evaluating resource allocation alternatives. Recent developments have demonstrated the importance of combining predictive analytics, intelligent optimization, and real-time monitoring for sustainable resource management. AI-based decision-support systems are increasingly being considered for integrated energy, water, waste, and transportation management. Morain et al. (2024) reviewed artificial intelligence applications in water consumption assessment and highlighted the potential of machine learning approaches for understanding water demand and consumption patterns [12]. Research published by Wang et al. (2026) further examined AI applications in water regulations, pollution control, drinking water management, and infrastructure regulation [13]. These studies indicate that AI can provide valuable analytical support for resource management, although practical implementation requires reliable datasets, independent model validation, and appropriate sustainability evaluation. The application of AI in smart communities also requires consideration of uncertainty and multiple conflicting objectives. For example, reducing electricity consumption should not negatively affect community services, while minimizing water usage must maintain adequate water availability. Therefore, integrating fuzzy mathematical models with predictive algorithms can improve decision-making under uncertain conditions. A hybrid framework combining LSTM forecasting, Interval Type-2 Fuzzy AHP, and TOPSIS can be considered for predicting resource demand, determining sustainability criteria weights, and ranking resource allocation alternatives. Such an integrated approach can support intelligent planning, efficient resource distribution, environmental protection, and long-term community sustainability.

### 2.1.Research Gap

The literature from 1980 to 2026 demonstrates the evolution of decision-support systems from conventional computer-based managerial tools to intelligent, AI-driven predictive platforms. However, the following research gaps remain:

1. Limited integration of multiple resources, including energy, water, waste, and transportation, within a unified framework.

2. Insufficient integration of real-time IoT monitoring with machine learning-based demand forecasting.
3. Limited consideration of uncertainty in predictive resource allocation.
4. Need for combining AI prediction with fuzzy multi-criteria decision-making techniques.
5. Insufficient evaluation of economic, environmental, and social sustainability simultaneously.
6. Need for explainable, reliable, and computationally efficient decision-support mechanisms.

**2.2.Research contribution:** The present study aims to develop an integrated AI-driven predictive decision support system using IoT, machine learning, and fuzzy multi-criteria optimization. The framework will predict future resource requirements and recommend suitable resource allocation strategies for sustainable smart community development.

**3,Proposed Work**

The proposed research develops an AI-Driven Predictive Decision Support System (AI-PDSS) for sustainable resource management in smart communities by integrating Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), predictive analytics, and Multi-Criteria Decision-Making (MCDM) techniques. The primary objective is to improve the allocation, monitoring, and utilization of essential community resources, including energy, water, transportation, and waste management. Initially, historical and real-time resource consumption data are collected from IoT sensors, smart meters, environmental monitoring devices, and community infrastructure. The collected data are preprocessed using data cleaning, missing-value treatment, normalization, and feature extraction techniques to improve data quality and prediction accuracy. In the next stage, machine learning algorithms such as Random Forest (RF), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) are employed to analyse historical consumption patterns and predict future resource requirements. These algorithms identify variations in resource demand, consumption trends, and potential resource shortages. The predictive performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (\(R^2\)). Based on the predicted resource requirements, a multi-criteria decision-making mechanism is developed to evaluate alternative resource allocation strategies. The decision-making process considers resource availability, operational cost, consumption efficiency, environmental impact, and community demand. The TOPSIS method is applied to rank alternative resource management strategies according to their relative closeness to the ideal solution.

Furthermore, an optimization mechanism is incorporated to identify suitable resource distribution strategies while satisfying resource availability, budget, and community requirements. The final system generates intelligent recommendations for energy conservation, water management, waste reduction, and transportation optimization. Continuous IoT monitoring enables the system to update resource consumption information and improve future predictions. The proposed framework aims to minimize resource wastage, improve operational efficiency, reduce environmental impact, and support sustainable decision-making in smart communities.

**3.1.Proposed Work Algorithm:**

**Step 1: Data Collection:** Collect historical and real-time resource consumption data from IoT sensors and smart meters.

**Step 2: Resource Identification:** Identify the major resources, including energy, water, waste, and transportation.

**Step 3: Data Preprocessing:** Clean the collected data and perform normalization and missing-value treatment.

**Step 4: Feature Extraction:** Extract relevant features influencing resource consumption patterns.

**Step 5: Dataset Division:** Divide the dataset into training, validation, and testing subsets.

**Step 6: Model Selection:** Apply Random Forest (RF), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) algorithms.

**Step 7: Model Training:** Train the selected machine learning models using historical resource consumption data.

**Step 8: Demand Prediction:** Predict future resource requirements for each resource category.

**Step 9: Performance Evaluation:** Evaluate prediction accuracy using MAE, RMSE, MAPE,

**Step 10: Criteria Identification:** Identify sustainability criteria, including cost, availability, efficiency, and environmental impact.

**Step 11: Decision Matrix:** Construct a decision matrix for different resource allocation alternatives.

**Step 12: TOPSIS Application:** Apply TOPSIS to calculate weighted values and identify ideal solutions.

**Step 13: Alternative Ranking:** Calculate closeness coefficients and rank resource allocation alternatives.

**Step 14: Resource Optimization:** Select optimal resource allocation strategies based on predicted demand and available resources.

**Step 15: Decision Support:** Generate intelligent recommendations for sustainable resource management.

**Step 16: Continuous Monitoring:** Update resource consumption data using real-time IoT information and repeat the prediction process.

**Step 17: Termination:** Stop the algorithm after generating the final resource allocation recommendations.

**3.3 Mathematical Formulation**

**1. Predictive modelling**

The future resource demand is estimated as:

$$\hat{R}_{t+1} = f(X_t, X_{t-1}, \dots, X_{t-n})$$

**2. Mean Absolute Error (MAE)**

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|R_i - \hat{R}_i\right|$$

**3.Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_i - \hat{R}_i\right)^2}$$

**4.TOPSIS closeness coefficient**

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

where (D_i^+) and (D_i^-) represent the distances from the positive and negative ideal solution

**3.4. Results and Discussion**

The proposed AI-Driven Predictive Decision Support System (AI-PDSS) provides an integrated framework for improving sustainable resource management in smart communities. The framework combines IoT-based data collection, machine learning prediction models, and TOPSIS-based multi-criteria decision-making to support intelligent resource allocation. The proposed system considers four major resource categories: energy, water, waste management, and transportation. By analysing historical and real-time consumption data, the system can identify demand patterns, estimate future resource requirements, and generate appropriate resource management recommendations. The application of Random Forest (RF), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) algorithms provides alternative approaches for predicting resource consumption. RF can identify relationships between different consumption factors, while SVR can model nonlinear demand patterns. LSTM can capture temporal dependencies in historical resource consumption data. The predictive performance of these models is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (\(R^2\)). These evaluation measures help

identify the most suitable prediction model for different resource categories. Furthermore, the integration of TOPSIS supports the evaluation and ranking of alternative resource allocation strategies. The decision-making process considers important sustainability criteria, including resource availability, operational cost, consumption efficiency, environmental impact, and community demand. The TOPSIS closeness coefficient helps identify the most suitable allocation alternative by measuring its distance from the positive and negative ideal solutions. This approach supports balanced decision-making by considering economic, environmental, and operational requirements simultaneously. The proposed framework is expected to improve resource utilization by identifying unnecessary consumption, predicting potential shortages, and recommending efficient distribution strategies. For energy management, predictive analysis can support demand forecasting and energy conservation. In water management, consumption prediction can help identify unusual usage patterns and improve water distribution. In waste management, demand estimation can support optimized collection schedules. Similarly, transportation prediction can assist in improving route planning and reducing unnecessary fuel consumption. Overall, the proposed AI-PDSS provides a systematic approach to transforming conventional resource management into an intelligent, predictive, and sustainability-oriented process. Continuous IoT monitoring and periodic model updating can further improve the reliability of resource demand predictions and decision-making recommendations.

## 4. Conclusion and Future Work

This research proposes an AI-Driven Predictive Decision Support System (AI-PDSS) for sustainable resource management in smart communities. The proposed framework integrates Artificial Intelligence, Machine Learning, Internet of Things, predictive analytics, and Multi-Criteria Decision-Making techniques to improve the efficient utilization of essential community resources. Random Forest, Support Vector Regression, and Long Short-Term Memory algorithms are considered for predicting future resource requirements based on historical and real-time consumption information. Furthermore, the TOPSIS method is incorporated to evaluate and rank alternative resource allocation strategies based on resource availability, operational cost, consumption efficiency, environmental impact, and community demand. The proposed framework addresses important research gaps associated with conventional resource management approaches, particularly limited real-time monitoring, inefficient resource allocation, uncertain demand patterns, and the lack of integrated sustainability evaluation. By combining predictive intelligence with multi-criteria decision-making, the system provides a structured mechanism for supporting energy conservation, water management, waste reduction, and transportation optimization. The framework can assist policymakers, community administrators, and urban planners in making informed decisions and developing sustainable smart community infrastructure.

Future research will focus on implementing the proposed AI-PDSS framework using real-time datasets collected from smart communities. Advanced deep learning algorithms, including Transformer-based models and hybrid LSTM approaches, can be investigated to improve prediction performance. Interval Type-2 Fuzzy AHP and TOPSIS can also be integrated to handle uncertainty in sustainability criteria and resource allocation decisions. Furthermore, digital twin technology can be incorporated to simulate different resource consumption scenarios and evaluate alternative management strategies. Explainable AI techniques can improve transparency and provide understandable recommendations to decision-makers. Finally, the proposed framework can be implemented and validated in a real-world smart community environment to evaluate its effectiveness in reducing resource wastage, improving operational efficiency, and achieving long-term environmental sustainability.

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