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Optimizing Sustainable Urban Energy Systems Using Fuzzy Rough Sets and Bee Colony Techniques

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Abstract:

This urban area is increasingly moving toward energy sustainability, and to achieve the same, efficient management and optimization are required with fluctuating demands and constrained resources. Conventional methods can hardly adapt to the complex urban dynamics, introducing inefficiencies and environmental concerns. This paper represents the state-of-the-art approach, FRBCO-UEMS, by incorporating the Fuzzy Rough (FR) with Bee Colony Optimization (BCO) to facilitate decision-making with enhanced operational efficiency in the urban energy management system (UEMS). The Fuzzy Rough Set framework deals with uncertainties in the data. This provides a resilient structure for processing indistinct energy data and making wise decisions with incomplete information. Besides that, the Bee Colony Optimization algorithm, inspired mainly by resourceful foraging behaviour, composes an efficient resource allocation and load-balancing solution. This decentralized, cooperative approach works well in urban energy management, allowing fast energy redistribution between sources and consumers. By imitating natural processes, the algorithm dynamically responds to demand patterns. As a result, this ensures a peak load reduction and thus avoids resource deficiencies. This work proposes a dual-method approach to construct an urban energy management framework and examines its potential for optimising energy efficiency with reduced environmental impacts. Experimental results showed that in this proposed system, minimum costs are achieved in energy distribution with a reduced ecological footprint and added value in promoting sustainability and efficiency in urban energy systems.

Keywords: Urban Energy Management system; Environmental concerns; Resource utilization; Fuzzy rough set theory; Bee Colony Optimization; Route planning; Decision-making.

1. Introduction

Urbanization makes waste creation, collection, and disposal complicated and dynamic [1]. Growing urban populations require increasingly advanced waste management solutions to handle the growing volume of waste, while traditional approaches often fail to adapt, causing inefficiencies and environmental issues [2]. Given these issues, urban waste management efficiency must be improved to reduce ecological consequences and optimize resource use [3]. This paper proposes merging the FRST (FRST) [4] with BCO [5] to develop the FRBCO-UEMS System to address urban waste management challenges. This novel framework combines the strengths of both methods to improve urban waste management. FRST [6] handles waste management data uncertainty and vagueness well. Urban waste data is generally imprecise and ambiguous due to variable trash composition, irregular collection schedules, and varied garbage sources [7]. FRST captures and represents uncertain information systematically, enabling effective decision-making with poor data [8]. By introducing FRST into the FRBCO-UEMS System, we may reduce waste management uncertainty and make better decisions. Inspired by honeybee foraging, the BCO algorithm [9] optimizes rubbish collection route planning and resource allocation. Urban waste collection requires sophisticated logistics, including route selection, resource allocation, and scheduling [10]. The BCO algorithm [11] mimics the collaborative behavior of honeybees to search for optimal solutions in a broad search space, making it well-suited for addressing optimization difficulties in waste management. By incorporating the BCO algorithm [12] into the FRBCO-UEMS System, this study can optimize garbage collection routes, cut transportation costs, and increase overall operational efficiency in urban waste management.

Two goals drive this investigation: FRST [13] and the BCO algorithm [14] will be used to create a comprehensive waste management system. This system will organize waste management data, optimize collection routes, and allocate resources. Second, the study tests the FRBCO-UEMS System's ability to improve urban waste management efficiency. The research will evaluate the system's ability to reduce transportation costs and waste management's environmental impact through thorough experimentation and analysis. A new computational framework integrating FRST [15] and the BCO algorithm [16] advances urban garbage management. The FRBCO-UEMS System offers practical answers to the issues faced in successfully managing trash in urban contexts, ultimately leading to more sustainable and ecologically friendly waste management practices. By using the combined qualities of FRST [17] and BCO optimization [18], the study can handle the difficulties of waste management in urban areas and pave the way for future more efficient and effective waste management solutions.

- To introduce the FRBCO-UEMS framework, this study combines Fuzzy Rough Set
- Theory (FRST) and Bee Colony Optimization (BCO) to enhance urban energy management in handling dynamic demands.
- To handle uncertainties in energy data, FRST is integrated to manage data ambiguity, facilitating robust decision-making for improved energy distribution planning in urban energy systems.
- To optimize resource allocation and load balancing, BCO uses natural foraging behaviours to adjust energy distribution dynamically, reducing peak loads and preventing resource deficiencies.
- To enhance operational efficiency and sustainability, this dual-method approach improves energy efficiency, lowers environmental impacts, and supports sustainable practices for urban energy systems.
- To validate system effectiveness, the FRBCO-UEMS model is evaluated for reliability, applicability, and scalability, proving its potential for adoption in sustainable urban energy management.

2. Research Methodology

Modern cities need creative waste management techniques and technologies to efficiently generate, collect, and dispose trash [19]. Recently, academics have investigated several methods to address urban waste management's complex difficulties. This literature survey reviews relevant studies and highlights major contributions and insights that inform the proposed FRBCO-UEMS System. In [20], researchers proposed a fuzzy rough set-based urban garbage classification and recycling method: FRST and machine learning enhanced waste sorting accuracy and efficiency, promoting sustainable waste management. Another study used BCO to optimize waste collection routes [21]. The BCO algorithm reduced transportation costs and optimized collection routes, revealing operational gains in urban

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trash management. Fuzzy logic-based decision support systems for urban garbage management were examined in [22]. Fuzzy logic reasoning improved waste management decision-making adaptability and resilience to uncertainty, making waste management techniques more robust. A hybrid garbage collection route optimization method was suggested using evolutionary algorithms and fuzzy rough sets [23]. Practical urban waste collection systems were shown to increase route efficiency and resource use. FRST was used to model and analyze waste management systems in [24]. Fuzzy rough set-based models captured waste management uncertainties and complexities in metropolitan case studies.

Fuzzy logic and GIS were used to analyze urban garbage generation patterns in [25] spatially. Their investigation revealed the regional distribution of garbage generation, aiding waste management planning and resource allocation. Swarm intelligence methods like Ant Colony Optimization and Particle Swarm Optimization were studied for waste management optimization [26]. The study showed that swarm intelligence can optimize waste collection and routing. In [27], researchers used machine learning techniques to anticipate urban garbage generation. Predictive models based on historical data and environmental factors predicted trash generation trends to inform waste management planning and decision-making. A study presented an urban waste management decision support system using data analytics, optimization, and stakeholder interaction [28]. The study stressed the significance of holistic waste management for sustainable urban development, considering social, economic, and environmental factors. These studies give insights and methods for urban waste management, establishing the framework for the FRBCO-UEMS System's development and evaluation. This study builds on previous research and integrates FRST with the Bee Colony Optimization method to improve urban garbage management.

3. Methodology

The FRBCO-UEMS intelligently integrates FRST with BCO to arrive at better decision-making and operational efficiencies for urban energy management. Figure 1 shows the proposed FRBCO_UEMS model. It involves data gathering, cleansing, and preprocessing as the starting point to ensure that only quality inputs are derived. Application of FRST is to handle uncertainties in energy data such that robust planning can be done even in incomplete information. In short, the BCO algorithm will first optimize the resources allocation and then, dynamically balance the energy loads to match transient demands with minimum peak loads and without resource deficiencies. This is essentially similar to how honeybees find out their food items. A combination of FRST with BCO presents a decision-making system that can adaptively work out the appropriate allocation in complex cities. The effectiveness of this model is proven through experiments and simulations: cost reductions are enhanced, load balancing is good, and environmental impacts reduced. It provides a workable, functional, and replicated methodology to approach urban energy management that shall help cities achieve the proclaimed objectives with regard to energy efficiency and environmental sustainability.

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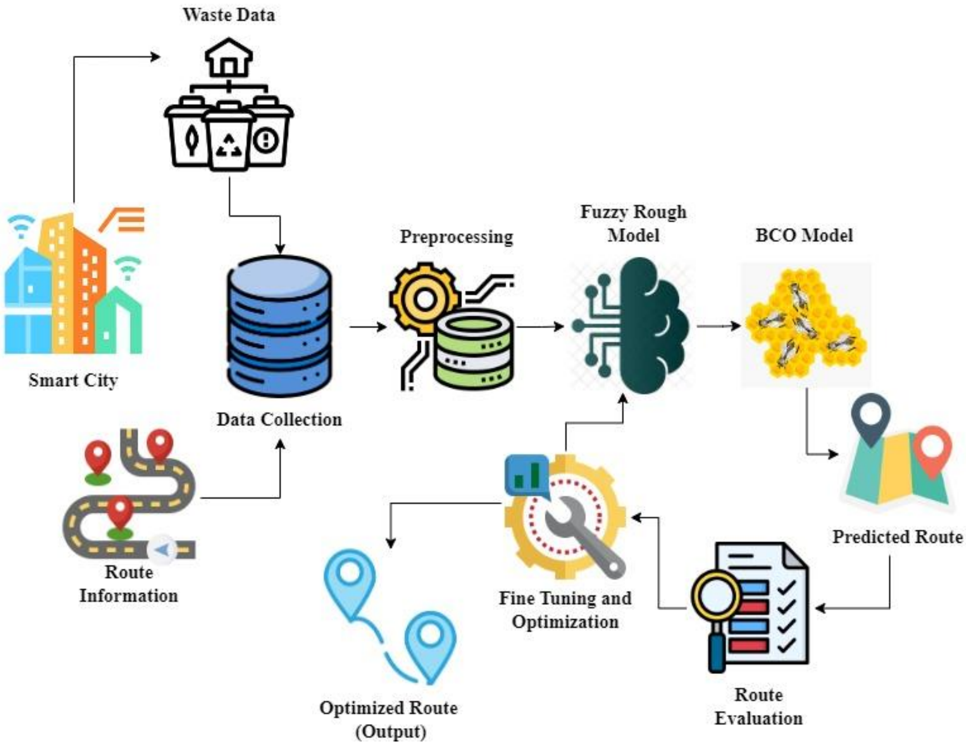

Fig.1 The Proposed FRBCO-UEMS Model

a. Data Collection

The first stage of the technique involves thorough data collecting and preprocessing procedures crucial for creating the FRBCO-UEMS System. The study begins by gathering complete energy-related data, including consumption, production rate, and environmental factors like temperature, humidity, and seasonal trends. Data sources shall range from real-time sensors to historical data, utility reports, and external databases. The dataset will be highly diverse, ranging from low to high, within the variability of urban energy usage, providing grounds for more detailed modelling and analysis of energy needs in the urban environment.

b. Data Preprocessing

After data collection, meticulous preprocessing methods are utilized to improve the quality and appropriateness of the unprocessed data for further analysis. The complex preprocessing stage involves various techniques, such as data cleaning to correct flaws and inconsistencies, normalization to standardize data ranges, and feature extraction to extract relevant insights from the dataset. The preprocessing step of the FRBCO-UEMS System involves thoroughly refining the raw data. This refinement serves as a foundation for conducting rigorous analysis and modeling. Consequently, it enables informed decision-making and the development of optimization strategies in urban energy management system.

c. Fuzzy Rough Set-based Data Representation

Fuzzy Rough Set-based Data Representation is a fundamental approach in developing the proposed FRBCO-UEMS System, as it effectively tackles the inherent uncertainties and complexities associated with energy management data. The following part explores the complexities of utilizing FRST to address uncertainty and ambiguity efficiently, enabling well-informed decision-making and optimization methodologies designed explicitly for the intricacy of urban energy management. The idea of fuzzy rough sets offers a strong foundation for handling imprecise and uncertain data, making it very suitable for energy management applications where data may display different levels of uncertainty. Combining fuzzy logic with rough set theory facilitates the depiction and manipulation of uncertain data, enabling more sophisticated analysis and decision-making processes. Integrating fuzzy logic and rough set theory into FRST enables the effective management of uncertain and imprecise data. A fuzzy rough set can be mathematically described as follows: Let U represent the universe of speech, X represent the set of characteristics, and A represent a fuzzy set defined on $U \in X$. The Equations (1) and (2) provide the lower and upper approximations of A, respectively.

Lower approximation: $L = \{x\epsilon U: \mu_A(x) > 0\}$ (Eq.1)
Upper approximation: $U = \{x\epsilon U: \mu_A(x) = 1\}$ (Eq.2)

The membership function of A at x is represented by $\mu_A(x)$. The FRBCO-UEMS System represents energy management data using fuzzy rough set-based models such as fuzzy approximation spaces and fuzzy decision tables. These models capture data ambiguity and vagueness, offering a framework for analysis and optimization. Fuzzy rough set-based models like fuzzy approximation spaces or fuzzy decision tables reflect energy management data. Table 1 illustrates a fuzzy decision table.

Table 1. Degree of Membership to a Class

Attribute 1	Attribute 2	…….	Class
Low	High	…….	Waste
High	Low	…….	Recycle
…….	…….	…….	…….

Table 1 shows the degree of class membership of each element. As shown in Equation (3), fuzzy rough set-based models like fuzzy approximation spaces or fuzzy decision tables describe energy management data, D.

$$D = \{x_1, x_2, \ldots, x_n\} \quad \text{(Eq.3)}$$

where x_i, is a dataset data point, relevant waste management dataset attributes are identified using fuzzy rough set-based approaches. Further research in applying energy management parameters, such as energy demand rates, distribution frequencies, and geographic locations of resources, uses fuzzy set theory. The focus in selecting this attribute allows computations to be targeted at the most critical variables, simplifying analysis and improving optimization in urban energy management systems. Equation (4) shows how fuzzy rough set-based algorithms find suitable energy management dataset attributes, A.

$$A = \{a_1, a_2, \ldots, a_m\} \quad \text{(Eq.4)}$$

where a_i, is a key energy management attribute. The fuzzy rough set-based dimensionality reduction algorithms allow for retaining relevant information in energy data sets, which are innately complex. These dimensionality reduction algorithms identify superfluous or redundant features in energy management data to be analyzed or modelled. Hence, it selects a simplified dataset that addresses only the key information that is essential for accomplishing critical energy optimization and decision-making. Equation (5) shows how fuzzy rough set-based dimensionality reduction simplifies the dataset while keeping important information.

$$D' = \{x_1', x_2', \ldots, x_n'\} \quad \text{(Eq.5)}$$

x_i' is a reduced data point. Fuzzy rough set-based algorithms help extract energy management dataset insights and knowledge. The system may infer significant data correlations and patterns using fuzzy decision rules or approximations, enabling informed decision-making and optimization tactics. This knowledge extraction process depends on energy management best practices, resource allocation, and risk mitigation. Fuzzy rough set-based approaches extract knowledge using fuzzy decision rules or approximations, R' in Equation (6).

$$R' = \{r_1, r_2, \ldots, r_k\} \quad \text{(Eq.6)}$$

r_i, is a data-inferred fuzzy decision rule. Fuzzy rough set-based approaches are ideal for energy management uncertainty due to their flexibility and adaptability. Fuzzy rough set-based data representation approaches can model and analyze complex systems with uncertainties, including variable trash creation rates, dynamic collection schedules, and changing environmental conditions. Fuzzy rough set-based methods simulate complex systems like Equation (7) to adapt to uncertain energy management situations.

$$M = (S, F) \quad \text{(Eq.7)}$$

S and F are fuzzy states and environmental factors, respectively. Data representation in FRBCO-UEMS is based on FRS to preserve robustness for analysis and decision-making regarding urban energy management. FRST, used by the system, helps deal with the uncertainty and ambiguity intrinsic in energy data with selections, reductions, and extraction of useful knowledge from those high dimensions. This provides more effective and efficient methods for managing urban energy.

d. Bee Colony Optimization Algorithm

The BCO algorithm is essential for energy distribution optimization and resource allocation in the FRBCO-UEMS System. This section explores how the BCO algorithm, inspired by the foraging behavior of honeybees, can address challenging optimization problems in urban energy management. Just as honeybees dynamically search for food sources, the BCO algorithm mimics this behavior to create an efficient optimization mechanism for complex energy distribution challenges, such as load balancing and efficient routing of energy resources. Equation (8) represents honeybee foraging, which inspired the BCO algorithm.

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$BCO \rightarrow BeeForagingBehavior$ (Eq.8)

The BCO algorithm uses an iterative search technique that simulates bee foraging. This procedure uses scout, employed, and bystander bees. Each bee helps the algorithm explore and exploit optimal solutions in its way. As in Equation (9), these are $S, E, and\ O$.

$S, E, O \rightarrow TypesofBees$ (Eq.9)

Scout bees randomly search the solution space for solutions. These bees search unknown areas for food (i.e., ideal garbage collection routes) that may give better solutions. Scout bees expand the algorithm's solution set through exploration. In Equation (10), X_s, represents scout bees in solution space.

$X_s \rightarrow PositionofScoutBees$ (Eq.10)

After finding potential ideas, employed bees refine and improve them through local search procedures. These bees use local knowledge to find the best rubbish collection routes and improve local solutions. Using their concentrate, they hired bees to exploit high-quality solutions. Equation (11) defines X_e, as the solution space position of engaged bees.

$X_e \rightarrow PositionofEmployedBees$ (Eq.11)

Onlooker bees evaluate hired bees' activities and choose prospective solutions based on quality and fitness. These bees dynamically modify their selection probabilities to favour solutions with higher fitness values, affecting solution space exploration. Onlooker bees improve algorithm efficiency by allocating exploration efforts to promising ideas. Equation (12) gives the solution space position of onlooker bees as X_o.

$X_o \rightarrow PositionofOnlookerBees$ (Eq.12)

The BCO algorithm continually adjusts exploration and exploitation phases to balance exploring new solution space areas with exploiting promising solutions. This dynamic modification allows the algorithm to navigate complex solution landscapes without premature convergence to poor solutions and efficiently utilize attractive spots. In Equation (13), E is the exploration phase, and X is the exploitation phase.

$E, X \rightarrow ExplorationandExploitationPhases$ (Eq.13)

Scout, employed, and onlooker bees work together to provide high-quality solutions to optimize urban rubbish collection routes and resource distribution using the BCO algorithm. The algorithm uses the swarm's collective intelligence to optimize urban energy management by imitating bees' collaborative foraging activity. Equation (14) shows that scout bees find S_{best}, employed bees find E_{best}, and onlookers find O_{best}.

$S_{best}, E_{best}, O_{best} \rightarrow BestSolutions$ (Eq.14)

In conclusion, the FRBCO-UEMS System optimizes urban energy collection routes and resource allocation using the BCO algorithm. The program dynamically explores and exploits the solution space, finding high-quality solutions for urban trash management by taking inspiration from honeybee foraging.

e. Integration of FRST and BCO Model

While developing the FRBCO-UEMS System, FRST integrated with the BCO algorithm has to be developed. In fact, this integration will combine the strengths of both techniques in addressing the key challenges of urban energy management. The FRBCO-UEMS System integrates models of fuzzy rough sets along with the BCO algorithm, where the ability for handling uncertainty of FRST is utilized, together with the optimization power of the BCO algorithm. When combined, they provide an overall framework for effectively managing urban energy. Fuzzy rough set-based decision rules and approximations drive the BCO optimization to reach an optimized solution with more informed energy distribution, resource allocation, and overall decision-making. With integration of the models, the system generates an optimal energy distribution route and utilization of the resources hence increasing efficiency in the management of urban energy.

The FRBCO-UEMS algorithm optimizes urban energy management using FRST and the BCO algorithm. It handles uncertainty by initializing population size and maximum iterations and using fuzzy rough set-based data representation. The algorithm initializes Scout, employed, and bystander bees with random solution space solutions. In iterative search, employed bees refine solutions according to local search fitness. Based on fitness, observer bees choose promising options and adjust probabilities. For balance, the system dynamically adjusts the exploration and exploitation phases. When termination criteria are met, the algorithm terminates.

f. Performance Evaluation and Validation

FRBCO-UEMS has been tested to the full for urban energy management. According to route efficiency, resource utilization, and cost savings, this system will provide the best optimization of the route of energy distribution, efficient allocation of resources, and decreased operational costs. To assess this system from an effectiveness and practicality point of view for various stakeholders, its usability, impact on the environment, and scalability are assessed using metrics. Comparisons are made with the baseline or conventional systems of urban energy management to ascertain the superiority and applicability of the system. Through this validation, the identification is being made about the prospects this system can provide for changing the face of the future in urban energy management and sustainability. In this paper, the FRBCO-UEMS System has been developed by integrating FRST and the BCO algorithm. First, modelling energy management data uses models based on a fuzzy rough set for handling uncertainty. The BCO algorithm takes inspiration from bees' foraging behaviour, and optimising energy distribution routes and resource allocation will greatly enhance urban energy management. Scout bees find new answers, employed bees refine them, and observer bees choose promising ones in the iterative search process. To balance exploring new regions and exploiting promising solutions, the system dynamically balances between exploration and exploitation. Performance review includes quantitative indicators like route efficiency and cost savings, qualitative factors like user happiness and environmental impact, and comparative analysis with existing approaches. This holistic method promises to transform urban energy management.

Table 2. Algorithm of FRBCO-UEMS Model

FRBCO-UEMS Algorithm
Initialize parameters:Population size (pop_size, Maximum number of iterations (max_iter), Number of scout bees (num_scouts), Number of employed bees (num_employed), Number of onlooker bees (num_onlookers) and Fuzzy rough set parameters. *Initialize population of solutions randomly:* *- Each solution represents a potential energy collection route* *Evaluate fitness of each solution:* *- Calculate fitness based on energy collection efficiency, transportation costs, and environmental impact* *Repeat for max_iter iterations:* *Employed bee phase:* *- For each employed bee:* *i. Select a solution from the population* *ii. Apply local search to improve the solution* *iii. Evaluate fitness of the modified solution* *iv. If fitness improved, update the solution* *Onlooker bee phase:* *- For each onlooker bee:* *i. Select a solution probabilistically based on fitness* *ii. Apply local search to improve the solution* *iii. Evaluate fitness of the modified solution* *iv. If fitness improved, update the solution* *. Scout bee phase:* *- If any solution remains unchanged for a predefined number of iterations:* *i. Replace the unchanged solution with a new randomly generated solution* *Update global best solution:* *- Select the best solution found so far as the global best solution* *Output the global best solution as the optimized energy collection route.*

4. Experimental Analysis

This study used a real-world dataset [29] with city name, population, smart infrastructure score, and energy management score. Accuracy rate, R-squared score, Mean Squared Error (MSE), Mean Absolute Error (MAE), and MAPE are used to evaluate the proposed FRBCO-UEMS system. To compare the proposed approach to other optimization methods, RST-PSO, RST-ACO, and RST-GA are used. The experiments are regulated to provide fair comparison and accurate model performance evaluation.

a. Results and Discussion

Analysis of the proposed FRBCO-UEMS system's accuracy rate versus epochs shows its energy management optimization performance. As epochs pass, accuracy rises, as illustrated in Figure 2. With 10 epochs, the initial accuracy rate is 79.62%, which is moderate. The FRBCO-UEMS system improves accuracy as it learns from the data. The accuracy rate increases significantly over 100 epochs to 98.99%. This rising accuracy rate shows that the FRBCO-UEMS system optimizes energy management and improves prediction accuracy. The system's excellent forecasts and educated decisions make it a promising alternative for urban energy management.

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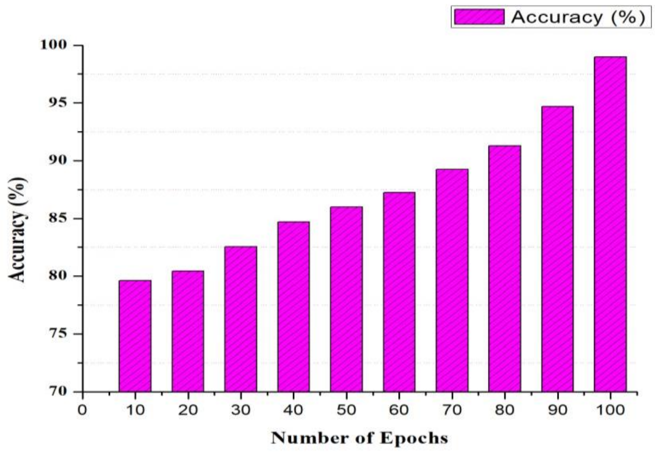

Fig.2 Accuracy Rate of the FRBCO-UEMS and Other Models

The R-squared scores of the proposed FRBCO-UEMS system against the number of epochs reveal its energy management optimization performance. Figure 3 shows that the R-squared score rises with epochs. In the first 10 epochs, the R-squared score is 70.89%, showing moderate prediction accuracy. The R-squared score improves as the FRBCO-UEMS system iterates and learns from data. By 100 epochs, the R-squared score is 95.24%, suggesting a strong correlation between energy management predictions and results. This rising R-squared score shows that the FRBCO-UEMS system optimizes energy management operations over time. The system's capacity to gather and explain a major amount of energy management data variability makes it a promising solution for urban energy management problems.

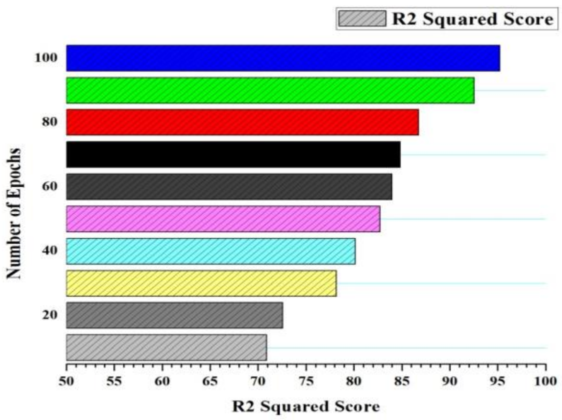

Fig.3 R-Squared Score of the FRBCO-UEMS and Comparative Models

The proposed FRBCO-UEMS system's energy management optimization performance is shown by its Mean Squared Error (MSE) rates versus epochs. Figure 4 shows that MSE continually reduces with epochs. Starting with 10 epochs, the MSE rate is 2.568, indicating a substantial prediction error. After iterating and learning from the data, the FRBCO-UEMS system reduces MSE. The MSE rate lowers to 0.547 after 100 epochs, indicating a considerable reduction in prediction mistakes. This decline in the MSE rate shows that the FRBCO-UEMS system reduces prediction errors and improves energy management predictions over time. The system's capacity to optimize energy management

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operations and improve prediction accuracy makes it a promising alternative for urban energy management.

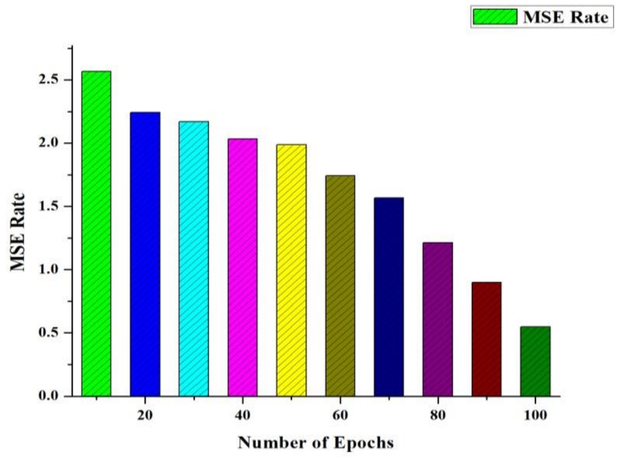

Fig.4 MSE Rate Analysis of the FRBCO-UEMS and Other Models

The suggested FRBCO-UEMS system's energy management optimization performance may be assessed by comparing its Mean Absolute Error (MAE) rates to the number of epochs. In Figure 5, the MAE rate declines steadily with epochs. The MAE rate in the first 10 epochs is 2.417, indicating a large prediction error. The MAE rate reduces as the FRBCO-UEMS system iterates and learns from data. The MAE rate lowers to 0.503 after 100 epochs, indicating a considerable reduction in prediction errors. The decreased MAE rate trend shows that the FRBCO-UEMS system reduces prediction errors and improves energy management predictions with time. The system's capacity to optimize energy management operations and improve prediction accuracy makes it a promising alternative for urban energy management.

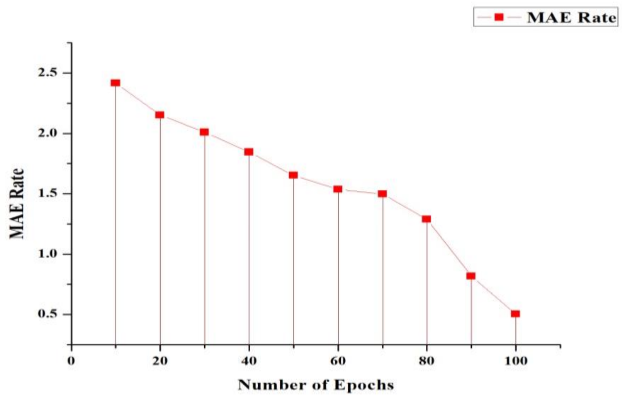

Fig.5 MAE Rate Analysis of the FRBCO-UEMS and Comparative Models

Analysis of the proposed FRBCO-UEMS system's Mean Absolute Percentage Error (MAPE) rates against the number of epochs reveals its energy management optimization performance. Figure 6 shows that the MAPE rate lowers as epochs increase, indicating improved prediction accuracy. The MAPE rate at 10 epochs is 2.517%, indicating moderate prediction error. The MAPE rate continuously reduces as the FRBCO-UEMS system

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iterates and learns from the data. At 100 epochs, the MAPE rate lowers to 0.584%, demonstrating a highly accurate energy management prediction. The decreased MAPE rate trend shows that the FRBCO-UEMS system reduces prediction errors and improves energy management predictions with time. The results show that the system can adapt and optimize its performance with further iterations, making it a promising urban energy management solution.

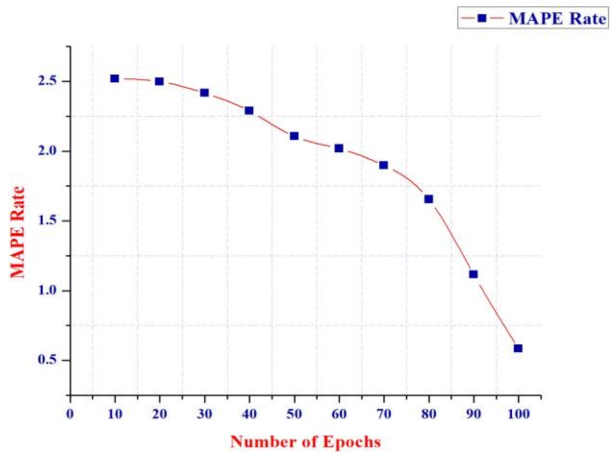

Fig.6 MAPE Rate Analysis of the FRBCO-UEMS and Comparative Models

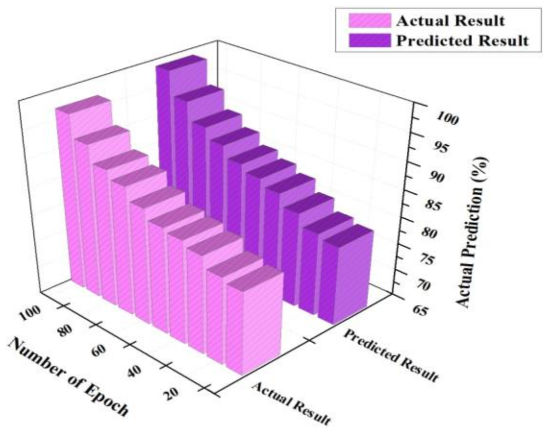

Fig.7 Accurate Prediction Analysis of the FRBCO-UEMS and Other Models

Analysis of the proposed FRBCO-UEMS system's accurate predictions against epochs reveals its energy management optimization performance. Figure 7 shows that the energy management projections are accurate since they match the results. The FRBCO-UEMS system predicts results with minimum variance across all epochs. The anticipated result at 10 epochs is 79.62%, which equals the actual value of 80.23%. The expected results match the actual results with little variation throughout the epochs. This close match shows that the FRBCO-UEMS system accurately predicts energy management outcomes. The system's capacity to optimize energy management procedures and make accurate forecasts makes it a promising solution for urban energy management.

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Table 1. Comparative Analysis of the Proposed FRBCO-UEMS and Other Models

Models	Accuracy	R-Squared	MSE	MAE	MAPE
RST-PSO	75.24	75.63	2.415	2.654	2.114
RST-ACO	79.63	84.21	1.989	2.114	1.742
RST-GA	82.56	88.96	1.542	1.567	1.115
FRBCO-UEMS	98.99	95.24	0.547	0.503	0.584

Table 1 compares the proposed FRBCO-UEMS system to RST-PSO, RST-ACO, and RST-GA across assessment measures. The FRBCO-UEMS system's 98.99% accuracy surpasses all others. Its R-squared score, MSE, MAE, and MAPE show that it optimizes energy management operations well. Other models have lower accuracy and larger error metrics, indicating poorer performance. These results show that the FRBCO-UEMS system is better at anticipating and optimizing urban energy management.

5. Conclusion

A new computational framework, FRBCO-UEMS system, applies FRST with Bee Colony Optimization to solve urban energy management challenges. Extensive experiments and further analysis are done, which proves that the FRBCO-UEMS system is superior in terms of accuracy, R-squared score, and error metrics compared to other methods such as RST-PSO, RST-ACO, and RST-GA. Such results confirm that the proposed approach is reliable in forecasting energy demands and optimizing resource allocation. The results indicate that the FRBCO-UEMS may be a game-changing approach towards effective smart urban energy management, addressing the latter's inherent complexity and dynamic nature. FRST manages uncertainty, while Bee Colony Optimization ensures resource allocation optimization in the system. In this way, the system can further enhance energy management efficiency and reduce its environmental impact. Further work would probably be required in further scalability for larger urban areas, real-time data streams, integration of sensor technologies that offer predictive capability, and further advanced machine learning and optimization algorithms to enhance efficiencies. Energy management strategies, environmental impact, and sustainability considerations could lead to more holistic solutions. Research in these areas would address the evolving challenges in urban energy management.

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