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A hybrid governance framework for adaptive and sustainable urban energy management

Renfang Wang [a], Hong Qiu [a,*], Ruyu Liu [b], Huan Huo [c], Xu Cheng [b], Xiufeng Liu [b,*]

[a] College of Big Data and Software Engineering, Zhejiang Wanli University, 315200, Ningbo, China
[b] Department of Technology, Management and Economics, Technical University of Denmark, 2800, Kgs. Lyngby, Denmark
[c] School of Computer Science, University of Technology Sydney, 15 Broadway Ultimo NSW 2007, Australia

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ABSTRACT

Rapid urbanization and escalating energy demands necessitate innovative solutions for sustainable and efficient energy management in smart cities. This paper presents a novel hybrid urban energy governance framework, distinguished by its unique architectural design that orchestrates a synergistic interplay of Multi-Agent Systems (MAS), Internet of Things (IoT), Cloud Computing, and Federated Learning. The framework's core technical novelty lies in its adaptive feedback loop: MAS facilitate decentralized, game-theoretic negotiations among urban areas for resource allocation, informed by real-time IoT data and privacy-preserving demand forecasts generated by Federated Learning. This local intelligence is then dynamically integrated with a cloud-based platform that performs multi-objective optimization (MOO) using evolutionary algorithms to achieve system-wide Pareto-optimal solutions for cost, environmental impact, and energy security. This continuous two-tiered decision-making, balancing local autonomy with global sustainability targets, creates a truly adaptive and resilient governance paradigm. Extensive simulations, using real-world datasets to represent diverse urban scenarios including peak demand and infrastructure challenges, demonstrate the framework's effectiveness in minimizing energy transaction costs, improving forecasting accuracy while ensuring data privacy, and promoting environmental sustainability. This decentralized, adaptive, and secure approach offers a promising pathway for efficient and resilient urban energy management, directly contributing to the development of sustainable smart cities by enhancing energy equity, supporting policy implementation, and optimizing resource use for long-term urban well-being.

1. Introduction

The confluence of rapid urbanization and increasing energy demands presents substantial challenges for energy infrastructure and resource management, with projections indicating approximately 67% of the global population will reside in urban areas by 2050 (Kohlhase, 2013). Smart cities aim to address these challenges by integrating interconnected technologies and sustainable practices (Vasenev et al., 2018). However, traditional centralized energy management systems are often ill-equipped for the complexities of dynamic urban energy demands and the integration of distributed resources, necessitating innovative governance frameworks (Srinivasan et al., 2020).

In this context, 'urban energy governance' refers to the system of rules, processes, and institutions guiding energy-related decision-making within cities, encompassing stakeholder interactions, technology integration, and policies for efficiency, sustainability, and resilience (Alamry & Al-Jashaami, 2024; Downie, 2022). Current systems often suffer from inefficient resource allocation, leading to energy losses (Sharma et al., 2023), and centralized structures that struggle with localized demands and distributed energy integration (Darby, 2020). Furthermore, a lack of transparency and stakeholder trust, coupled with privacy concerns over consumption data, impedes collaborative governance and accurate forecasting (Himdi et al., 2022; Sharma et al., 2023). Existing systems also show limited adaptability to the evolving energy landscape, including renewable energy variability and dynamic demand patterns, which challenges energy security and sustainability goals (Al Mansoori, 2021; Bolwig et al., 2019).

While centralized systems offer certain controls, their rigidity and vulnerability to single points of failure limit their suitability for dynamic smart cities (Levenda, 2018; ur Rehman et al., 2023). Decentralized alternatives like microgrids and distributed energy resources (DERs) provide flexibility but often lack overarching coordination for

* Corresponding authors.
E-mail addresses: wangrf@zwu.edu.cn (R. Wang), qiuhong@zwu.edu.cn (H. Qiu), ruliu@dtu.dk (R. Liu), huan.huo@uts.edu.au (H. Huo), xuche@dtu.dk (X. Cheng), xiuli@dtu.dk (X. Liu).

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city-wide optimization (Meijer & Bolívar, 2016; Singh & Singh, 2024), especially in managing renewable intermittency (Rozhkov, 2024). Advanced technologies such as Multi-Agent Systems (MAS), Internet of Things (IoT), Cloud Computing, and Federated Learning (FL) have shown promise individually (Alam, 2021; Cheng et al., 2022; González-Briones et al., 2018). MAS can facilitate decentralized negotiation (Levenda, 2018), IoT enables real-time monitoring (Marinakis et al., 2015), Cloud platforms offer scalable analytics (Mansouri & Karaca, 2016), and FL allows privacy-preserving collaborative modeling (Chen, 2013). However, their synergistic integration into a comprehensive governance framework remains a key challenge (Pandya et al., 2023; Souza et al., 2024). Many existing integrated systems focus primarily on technical efficiency, often overlooking the nuanced governance mechanisms required for holistic urban sustainability, including equitable resource distribution and alignment with broader urban development policies.

This paper presents a novel hybrid urban energy governance framework that synergistically integrates MAS, IoT, Cloud Computing, and Federated Learning. The core novelty of this framework lies not merely in the combination of these technologies, but in their orchestrated configuration and the unique adaptive feedback loop they establish. This framework models urban areas as intelligent agents negotiating resources via game-theoretic mechanisms, informed by real-time IoT data and privacy-preserved FL-based demand forecasts. Crucially, these decentralized agent decisions are dynamically guided by a central cloud platform performing multi-objective optimization (MOO) to achieve system-wide Pareto-optimal solutions across economic, environmental, and security objectives. This continuous two-tiered decision-making process, balancing local autonomy with global sustainability targets, creates a fundamentally new paradigm for urban energy governance that is both adaptive and resilient. This integrated system architecture targets scalability, fault tolerance, and seamless integration, aiming to drive transformative change by supporting sophisticated decision-making processes that balance economic efficiency, environmental stewardship, and energy security. By enabling decentralized intelligence, leveraging real-time data, providing scalable processing, and ensuring privacy, the framework addresses critical limitations of current systems and facilitates an adaptive, efficient, and citizen-centric approach to urban energy management, crucial for achieving genuinely sustainable and resilient smart cities. This approach has direct implications for urban policy, enabling data-driven strategies for renewable energy integration, demand-side management, and resilient infrastructure planning.

The primary contributions of this research are threefold:

- A novel hybrid governance architecture and problem formulation for urban energy management as a multi-objective optimization problem. This formulation uniquely considers a comprehensive set of objectives critical for sustainability — cost minimization, environmental impact reduction (e.g., CO2 emissions), and energy security — along with realistic operational constraints. Multi-Objective Evolutionary Algorithms (MOEAs) are employed to generate Pareto-optimal solutions, offering policymakers clear trade-offs for sustainable decision-making.
- The implementation of a Federated Learning framework specifically integrated within the governance loop for privacy-preserving energy demand forecasting. This enables collaborative model training across diverse urban areas without sharing sensitive local data, addressing privacy barriers and improving forecasting accuracy through collective intelligence, which is vital for reliable and equitable energy planning.
- The design and simulated validation of a comprehensive decentralized, adaptive, and secure framework for urban energy governance. Its functional novelty stems from the innovative orchestration of MAS for decentralized control and negotiation, IoT for real-time situational awareness, a cloud platform for scalable data aggregation and complex MOEA-based system-wide optimization, and FL for privacy-preserving forecasts. This integration establishes a unique adaptive feedback loop between local agent decisions and global sustainability objectives, providing a robust and intelligent system capable of responding effectively to dynamic urban energy landscapes and supporting sustainable development goals.

The remainder of this paper is structured as follows: Section 2 provides a review of related work. Section 3 presents the proposed framework in detail. Section 4 presents the experimental evaluation, simulation-based case studies, and performance analysis. Section 5 discusses the findings, implications for sustainable urban development and policy, and limitations. Finally, Section 6 concludes the paper and outlines potential directions for future work.

2. Related work

The pursuit of sustainable urban energy management has driven significant evolution in energy systems and governance models. This section reviews literature pertinent to our proposed hybrid framework, focusing on advancements that highlight the need for synergistic integration of technologies and novel governance approaches to meet sustainability objectives. We aim to establish how existing solutions, while valuable, often fall short in providing a holistic, integrated, and deeply sustainable governance paradigm for complex urban energy landscapes, thereby underscoring the necessity and novelty of our proposed approach.

2.1. Advancements in urban energy systems and governance

Urban energy systems are transitioning from centralized models to integrated, smarter, and more decentralized structures like smart grids and microgrids to cope with complex demands and sustainability targets (Altmann et al., 2010; Srinivasan et al., 2020). This transformation involves not only technological shifts but also crucial societal and governance factors. Citizen participation and social innovation are increasingly recognized as vital for successful sustainable energy transitions (Haf & Robison, 2020; Renn et al., 2020), emphasizing the need for governance frameworks that are inclusive and responsive. The proliferation of DERs, while offering sustainability benefits, introduces significant governance complexities, including ensuring fair market access for small producers, managing grid stability with bidirectional flows, and coordinating a multitude of new actors with potentially conflicting objectives (Raskin, 2013). Existing regulatory frameworks are often slow to adapt to these new realities.

Numerous smart grid pilot projects worldwide have demonstrated technological feasibility in areas like advanced metering and demand response (Fang et al., 2011; Gungor et al., 2011). However, many have faced challenges in scaling up due to high investment costs, consumer acceptance issues, and, crucially, a lack of integrated governance models that effectively align technological capabilities with broader urban sustainability policies and stakeholder participation. These initiatives often focus more on technical optimization than on equitable benefit distribution or adaptive policy learning (Hansen et al., 2019; Rogge & Johnstone, 2017). While decentralized solutions enhance flexibility and resilience (Singh & Singh, 2024), their effective coordination across interconnected urban areas, particularly for integrating intermittent renewables and ensuring equitable access, remains a challenge requiring sophisticated governance mechanisms (Meijer & Bolívar, 2016; Rozhkov, 2024). The “3D” trend — decarbonization, decentralization, and digitalization (Küfeoglu et al., 2019) — underscores the need for integrated solutions. However, while digitalization offers powerful tools and decentralization provides structural flexibility, the governance frameworks to effectively steer these elements towards agreed-upon urban sustainability outcomes, balancing diverse stakeholder interests and policy goals, often lag behind technological advancements (Bulkeley et al., 2014). Recognizing these limitations, a growing body of literature emphasizes a socio-technical systems perspective on urban energy transitions (Bridge et al., 2018), highlighting that successful governance requires not just technological solutions but also attention to social practices, institutional capacities, policy coherence, and the active engagement of diverse urban communities (Lazoroska et al., 2021). Our framework seeks to operationalize aspects of this socio-technical approach through its hybrid, participatory-informed design principles. Many existing approaches focus on optimizing specific technical components or single objectives, often lacking a holistic governance perspective that fully integrates technological capabilities with policy goals for broad sustainability outcomes, such as those highlighted by Opitz (2022) in evolving municipal utility models. Current research (Coelho et al., 2017; Zhou et al., 2016) continues to explore novel approaches, yet the challenge of creating truly adaptive, equitable, and participatory energy governance structures persists.

2.2. Role of multi-agent systems in coordinated energy management

MAS offer a powerful paradigm for decentralized decision-making in complex systems like urban energy grids (Roche et al., 2010). By modeling entities as autonomous agents, MAS can manage distributed energy resources and microgrids more effectively than centralized controls, facilitating negotiation and resource allocation (Herath & Venayagamoorthy, 2021; Logenthiran, 2012). MAS have been applied to various energy management tasks, including peer-to-peer (P2P) energy trading in local markets (de Alba et al., 2020; Soto et al., 2021), optimal scheduling of home energy management systems (Khan et al., 2016), and coordinated control of microgrids (Logenthiran, 2012). Game-theoretic approaches, ranging from cooperative bargaining solutions like the Nash bargaining solution (Shen et al., 2021) to non-cooperative models like Stackelberg games or auction mechanisms (Wu et al., 2024), are frequently employed to model agent interactions and incentivize desired behaviors (González et al., 2025). Frameworks like CityLearn (Vazquez-Canteli et al., 2020) further standardize MAS applications for urban energy tasks.

While these applications demonstrate the potential of MAS for decentralized optimization, many existing models operate with simplified assumptions about agent rationality, information availability, or the complexity of the urban environment. Some studies have initiated the integration of MAS with, for instance, IoT data streams for improved situational awareness (Dou et al., 2016). However, the explicit integration of complex, real-time data streams from diverse IoT sources, privacy-preserving forecasting inputs from techniques like FL, and alignment with overarching city-level multi-objective sustainability goals (beyond localized cost or efficiency) often remains a significant challenge. For instance, few MAS frameworks for energy actively consider non-economic objectives such as minimizing local air pollution from energy choices, ensuring equitable distribution of grid service opportunities, or explicitly supporting vulnerable consumer groups as primary drivers in their negotiation protocols (Yao et al., 2023). Consequently, while MAS applications show efficacy in specific contexts, their integration into a broader sustainable governance structure that addresses the multi-objective trade-offs (balancing economic, environmental, and social sustainability pillars) and policy complexities inherent in diverse urban settings remains an active area of research (Leo et al., 2021). Our framework addresses this by embedding MAS negotiations within a system that leverages advanced data analytics and explicitly optimizes for multiple sustainability criteria.

2.3. Leveraging IoT, cloud computing, and federated learning in energy governance

The deployment of IoT sensors and smart meters generates unprecedented volumes of granular data, offering immense potential for optimizing urban energy networks (Simionescu & Strielkowski, 2024). Cloud platforms provide the necessary computational power for storing, processing, and analyzing this data (R. Singh et al., 2024; Tai et al., 2023). Our framework specifically leverages cloud capabilities for large-scale data aggregation from IoT and for executing computationally intensive multi-objective optimization algorithms (MOEAs) that guide system-wide energy allocation decisions. However, effectively translating this data into actionable governance insights involves more than just technical infrastructure; it requires robust data quality management, interoperability standards, and analytical frameworks that can handle uncertainty and complexity in dynamic urban systems (Rathore et al., 2018). Moreover, ensuring secure and ethical data handling, especially when data is aggregated centrally in the cloud, remains a paramount concern for citizen trust and regulatory compliance, potentially hindering the development of truly smart and sustainable cities if not adequately addressed (Ahmed et al., 2022; Gholipour et al., 2012).

Federated Learning (FL) has emerged as a key enabling technology for privacy-preserving machine learning in smart cities (Cheng et al., 2022), with promising applications in energy demand forecasting that mitigate risks associated with sharing raw consumption data (Qiao et al., 2023). While FL addresses data privacy at the model training stage, its integration into a comprehensive governance system requires further consideration. For instance, questions around the ownership of aggregated models, algorithmic fairness across diverse participating entities (e.g., different urban districts with varying data quality or resources), and the mechanisms for using FL-derived insights to inform real-time, decentralized decision-making by entities like MAS agents are still active research areas (Pandya et al., 2023). Current applications often focus on the performance of FL for a specific task (e.g., forecasting accuracy) rather than its role within a multi-layered, adaptive governance architecture that connects privacy-preserved insights to broader policy objectives and operational decisions. While these technologies are powerful, their combined strength for holistic, sustainable governance is often unrealized. IoT provides data, Cloud processes it, and FL can make parts of that processing privacy-preserving. The novelty often lies in how these components are architected into a cohesive governance system that uses their outputs for coordinated, multi-objective decision-making, rather than optimizing individual technological silos.

In summary, while significant progress has been made in advancing individual technologies and decentralized approaches for urban energy management, the literature reveals persistent gaps. There is a clear need for frameworks that move beyond optimizing isolated components or single objectives. The challenge lies in developing truly synergistic integrations that weave these advanced technological capabilities into holistic and adaptive governance models. Such models must be explicitly designed to navigate the complex trade-offs inherent in urban sustainability—balancing economic efficiency not only with environmental protection and energy security, but also with crucial aspects of social equity, citizen participation, and robust policy alignment. Our proposed framework directly confronts this challenge by architecting a hybrid system where decentralized intelligence, real-time data, scalable analytics, and privacy-preserving learning converge to support more effective and comprehensively sustainable urban energy futures.

3. Proposed framework

This section details the architecture and key components of the proposed collaborative urban energy governance framework. The framework's novelty lies in its specific architectural integration of Multi-Agent Systems, the Internet of Things, Cloud Computing, and Federated

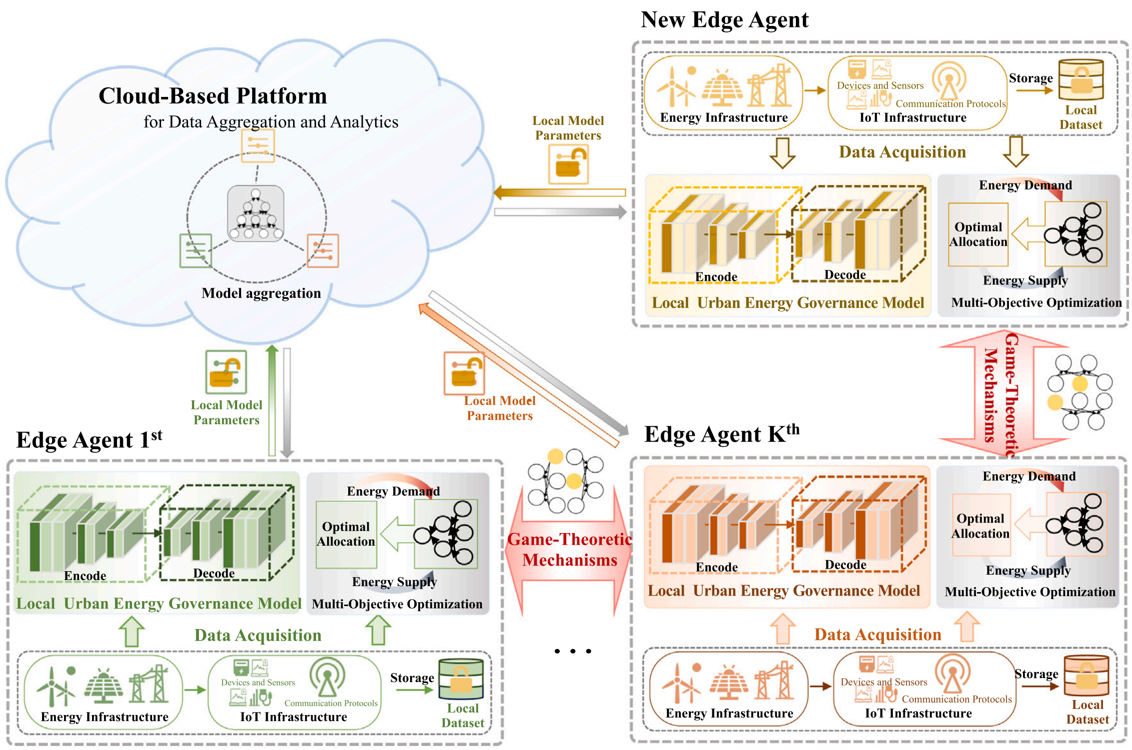

Fig. 1. Architecture of the integrated framework for collaborative urban energy governance. Illustrates the synergistic interplay between MAS for decentralized negotiation, IoT for real-time data, FL for privacy-preserving forecasting, and Cloud for MOO and analytics, forming a cohesive hybrid governance system.

Learning, designed to establish a hybrid governance model that enables efficient, sustainable, and privacy-preserving energy management in smart cities. This model facilitates adaptive decision-making by balancing decentralized agent negotiations with centralized/federated analytics and multi-objective optimization tailored for urban sustainability.

3.1. Overview of the integrated approach

The proposed framework introduces an innovative and comprehensive strategy for tackling the complexities of collaborative urban energy governance. The structure of the integrated framework is depicted in Fig. 1, which highlights the relationships and interactions between its key components: MAS, IoT, Cloud Computing, and Federated Learning. This architecture supports a hybrid governance model where decentralized operational decisions by MAS agents are informed and guided by centralized (or federated) data analytics and strategic optimization.

Central to the framework is the MAS component, which models urban areas as intelligent agents capable of autonomous decision-making and interactions with other agents. These agents are designed to represent their respective urban areas' unique characteristics, energy requirements, and resource constraints. The interactions among agents are facilitated through a negotiation mechanism that enables resource allocation and energy trading. Agents negotiate decentralized, exchanging information and proposals to reach mutually beneficial energy-sharing and resource-distribution agreements. The negotiation process is governed by game-theoretic principles and strategies, ensuring fairness, efficiency, and incentive compatibility. Specifically, the agents employ cooperative game theory concepts, such as the Nash bargaining solution, to determine the optimal allocation of resources and energy trades (de Alba et al., 2020; Shen et al., 2021). This decentralized negotiation capability is crucial for adaptive governance, allowing the system to respond to local conditions while pursuing global objectives defined by the MOO.

The IoT infrastructure is integrated with the MAS and consists of interconnected devices and sensors deployed across urban environments. These IoT devices enable real-time monitoring and control of energy generation, distribution, and consumption, providing a continuous data stream to support decision-making processes (Dou et al., 2016). The data collected by the IoT network is aggregated and processed within a cloud-based platform, which serves as a central hub for data analytics and decision support. The cloud platform leverages advanced computational resources and scalable storage to facilitate efficient data processing, visualization, and the application of optimization algorithms, yielding actionable insights and recommendations (Hao et al., 2019). A Federated Learning framework is also employed to ensure privacy-preserving demand forecasting (Mendes et al., 2024). This approach allows for the collaborative training of forecasting models without directly sharing sensitive data among urban areas. Techniques such as Long Short-Term Memory (LSTM) networks are utilized within the Federated Learning component to produce accurate energy demand predictions while maintaining data privacy and confidentiality (Qiao et al., 2023).

The synergistic integration of these components provides several key advantages and benefits, including decentralization, which supports a decentralized approach to energy governance, enabling urban areas to collaborate and make autonomous decisions based on their local contexts and requirements. Adaptability is achieved through the framework's modular design and the integration of advanced techniques like game theory and machine learning, allowing for real-time adjustments and optimizations in dynamic energy landscapes. Scalability is enhanced by the cloud-based platform and the distributed nature of the IoT and MAS components, accommodating urban growth, increasing energy demands, and the integration of new technologies. Privacy preservation is ensured through the Federated Learning component, addressing concerns related to sharing sensitive energy consumption data among urban areas. The IoT infrastructure enables Real-time monitoring and control, providing continuous monitoring and control of energy generation, distribution, and consumption, which supports proactive decision-making. Finally, the cloud-based platform, combined with advanced analytics and optimization algorithms, facilitates data-driven decision support, leading to informed and efficient resource allocation strategies. This integrated approach overcomes the limitations of systems relying on single technologies by combining decentralized intelligence (MAS), real-time data (IoT), scalable processing (Cloud), and privacy preservation (FL) into a cohesive system designed for the complexities of urban energy management. This hybrid model is particularly suited for urban contexts requiring both local autonomy and system-wide optimization for sustainability goals, potentially informing urban policies on data sharing, market participation, and infrastructure investment.

In addressing the multi-objective optimization problem inherent in urban energy governance, we employ MOEAs. MOEAs are adept at managing conflicting objectives and identifying diverse Pareto-optimal solutions, which assist in trade-off analysis and decision-making (Mauledoux et al., 2015). Our formulation of objectives (cost, environmental impact, security) and constraints is tailored to reflect comprehensive sustainability criteria for urban areas. Including MOEAs within the framework allows for simultaneously optimizing multiple objectives, such as cost minimization, environmental sustainability, and energy security (Guo & Dong, 2024). By utilizing the strengths of MOEAs, the proposed approach helps to identify optimal resource allocation strategies that balance the competing goals of urban energy governance.

The following sections will explore the details of each component, their interactions, and the application of MOEAs within the integrated framework, demonstrating how this approach enhances efficient, sustainable, and collaborative urban energy governance.

3.2. Multi-agent system for urban energy governance

3.2.1. Agent modeling and interactions

In the proposed MAS framework for urban energy governance, each urban area is modeled as an intelligent agent capable of autonomous decision-making and interactions with other agents. These agents are designed to represent their respective urban areas' unique characteristics, energy requirements, and resource constraints. The interactions among agents are facilitated through a negotiation mechanism that enables resource allocation and energy trading. Agents negotiate decentralized, exchanging information and proposals to reach mutually beneficial energy-sharing and resource-distribution agreements. The negotiation process is governed by game-theoretic principles and strategies, ensuring fairness, efficiency, and incentive compatibility. Specifically, the agents employ cooperative game theory concepts, such as the Nash bargaining solution, to determine the optimal allocation of resources and energy trades (de Alba et al., 2020; Shen et al., 2021). This decentralized negotiation capability is crucial for adaptive governance, allowing the system to respond to local conditions while pursuing global objectives defined by the MOO.

Let us consider a set of urban areas $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$, each represented by an agent a_i, where $i \in \{1, 2, \ldots, n\}$. Each agent a_i is characterized by its energy demand d_i, energy supply s_i, and a utility function $u_i(\cdot)$ that quantifies the agent's preferences and priorities. The negotiation process aims to determine an allocation $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, where x_i represents the net energy transfer to agent a_i. The allocation $\mathbf{x}$ must satisfy the following constraints:

$$\sum_{i=1}^{n} x_i = 0 \quad \text{(Energy balance constraint)}$$

$$x_i \leq s_i - d_i \quad \forall i \in \{1, 2, \ldots, n\} \quad \text{(Supply constraint)}$$

The energy balance constraint ensures that the total energy transferred among agents is balanced, while the supply constraint guarantees that no agent can transfer more energy than its surplus supply. To determine the optimal allocation $\mathbf{x}^*$, the agents employ the Nash bargaining solution, which maximizes the product of the agents' utility gains from the negotiated outcome. Mathematically, the Nash bargaining solution is given by:

$$\mathbf{x}^* = \arg\max_{\mathbf{x}} \prod_{i=1}^{n} \left(u_i(x_i) - u_i \right) \tag{1}$$

subject to the energy balance and supply constraints, where $u_i(0)$ represents the utility of agent a_i in the disagreement scenario (no energy transfer). The negotiation process proceeds iteratively, with agents exchanging proposals and counterproposals until the Nash bargaining solution is converged or a predetermined termination condition is met. This iterative process ensures that the agents reach a Pareto-optimal and fair allocation of resources, maximizing the overall utility while respecting individual constraints and preferences (Nash et al., 1950). Using a decentralized MAS with game-theoretic negotiation allows for flexible and autonomous interactions between urban areas, overcoming limitations of rigid centralized systems for resource allocation.

Urban areas can collaborate and engage in energy trading through the MAS framework and the negotiation mechanism, optimizing resource utilization and addressing imbalances in energy demand and supply. The decentralized nature of the system allows for adaptability and scalability, accommodating the dynamic energy landscape and potential changes in urban areas or resource availability. This directly supports policies aimed at fostering local energy markets and community energy initiatives.

3.2.2. Game-theoretic mechanisms for resource allocation

In our proposed collaborative urban energy governance framework, game-theoretic mechanisms are crucial in ensuring fair and efficient resource allocation among participating urban areas. The resource allocation problem is embedded within a broader multi-objective optimization goal: minimizing the Total Energy Governance Costs (TEGC), which uniquely aggregates economic, transmission, and environmental costs. The TEGC encompasses the total energy generation, transmission, and environmental impact costs for each district. Mathematically, this is expressed as:

$$\min \text{TEGC} = \sum_{i=1}^{n} (C_{gen,i} + C_{trans,i} + C_{env,i}) \tag{2}$$

where $C_{gen,i}$ represents the energy generation cost for district i, $C_{trans,i}$ is the energy transmission cost, and $C_{env,i}$ denotes the environmental impact cost. These costs are calculated based on energy production, fuel costs, generation efficiency, transmission distance, line capacity, energy losses, carbon emissions, and other environmental impacts, potentially incorporating carbon pricing policies to reflect true sustainability costs (Stavins, 2020). The total number of districts participating in the collaborative framework is denoted by n.

To ensure the effectiveness, compliance, and sustainability of the system, the optimization problem is subject to a comprehensive set of constraints specifically relevant to urban sustainability: Resource availability constraints limit the available energy resources, including generation capacity, transmission line capacity, and renewable energy generation potential. Operational constraints relate to the limits of the energy system's operations, such as energy storage capacity, charging and discharging rates, and distribution limits. Environmental impact constraints impose limitations on factors like carbon emissions and mandate a minimum percentage of renewable energy usage. Technical constraints ensure the system operates within technical limits, such as voltage levels, frequency stability, and grid stability. In contrast, energy efficiency constraints promote efficient energy use and minimize losses. Finally, scalability constraints ensure that the system can accommodate future growth in energy demand, the number of participating districts, and the integration of new technologies. These constraints ensure that solutions are not only economically optimal but also environmentally responsible and technically feasible for real-world urban deployment.

Fairness, incentive compatibility, and efficient resource utilization are achieved through the Nash Bargaining Solution, a widely adopted concept in cooperative game theory (Li, 2023). This solution provides a unique and Pareto-optimal allocation that satisfies the axioms of individual rationality, feasibility, independence of irrelevant alternatives, and symmetry. Let $\mathcal{U} = \{u_1, u_2, \dots, u_n\}$ denote the set of urban areas participating in the collaborative system, and $\mathcal{V}$ represent the set of feasible allocations satisfying the constraints. The Nash Bargaining Solution is obtained by solving the following optimization problem:

$$\max_{\mathbf{x}\in\mathcal{V}} \prod_{i=1}^{n} \left(u_i(x_i) - u_i(d_i)\right) \tag{3}$$

Here, $\mathbf{x} = (x_1, x_2, \dots, x_n)$ is the allocation vector representing the net energy transfer to each urban area, $u_i(\cdot)$ is the utility function of urban area i, and d_i is the disagreement point for district i, representing the minimum acceptable allocation for that urban area. The utility functions are defined based on cost, renewable energy utilization, and urban area-specific priorities. The Nash Bargaining Solution ensures fairness by maximizing the product of utility gains for all districts, promoting cooperation, and preventing any single urban area from being disadvantaged. It is also Pareto-optimal, meaning no other feasible allocation can improve one district's utility without decreasing another's, ensuring efficient resource utilization.

Example 3.1 (*Resource Allocation Among Three Districts*)**.** Consider three districts participating in the collaborative energy governance system. The objective function, given by Eq. (2), represents the minimization of the TEGC. The specific constraints, based on the categories described earlier, include resource availability constraints (e.g., maximum energy produced and transmission capacity), operational constraints (e.g., maximum and minimum energy distributed, maximum time for energy transfer), environmental impact constraints (e.g., maximum carbon emissions, minimum renewable energy usage), technical constraints, energy efficiency constraints, and scalability constraints. The utility functions for the districts are defined as follows:

$$u_1(x_1) = \alpha_1 \log(x_1 + \beta_1)$$
$$u_2(x_2) = \alpha_2 \log(x_2 + \beta_2)$$
$$u_3(x_3) = \alpha_3 \log(x_3 + \beta_3)$$

where α_i and β_i are parameters representing the preferences and characteristics of each district. The Nash Bargaining Solution is obtained by solving the optimization problem in Eq. (3), subject to the constraints and the feasible set $\mathcal{V}$. The solution $\mathbf{x}^* = (x_1^*, x_2^*, x_3^*)$ represents the optimal allocation of energy resources among the three districts, ensuring fairness, incentive compatibility and efficient resource utilization. This example illustrates how the game-theoretic approach operationalizes the resource allocation process within the MAS framework, enabling decentralized yet coordinated energy sharing.

Through this game-theoretic mechanism for resource allocation, the collaborative urban energy governance framework promotes trust, transparency, and cooperation among participating districts, fostering a sustainable and resilient energy ecosystem. The mechanism's design aims to facilitate equitable participation, a key tenet of sustainable governance.

3.2.3. IoT infrastructure and deployment

The IoT infrastructure enables real-time monitoring and control of energy generation, distribution, and consumption within the proposed collaborative urban energy governance framework. Table 1 provides an overview of the key IoT components employed in the system. Reliable and ubiquitous connectivity across the urban landscape is ensured through selected communication protocols like LoRaWAN, Wi-Fi, NB-IoT, or cellular networks, chosen based on range, bandwidth, power consumption, and existing infrastructure. Deploying edge computing devices like IoT gateways and fog nodes enables localized data processing and analysis, reducing network bandwidth requirements and improving responsiveness (Haseeb et al., 2021). This approach allows for real-time decision-making and optimizations based on local data, enhancing the efficiency and scalability of the IoT infrastructure. Such infrastructure is foundational for evidence-based urban planning and policy verification.

Adhering to industry standards and protocols ensures interoperability among diverse IoT devices, sensors, and systems (Haseeb et al., 2021). Standardization facilitates seamless integration, data exchange, and collaboration among different components of the urban energy governance framework. Implementing robust security measures, including encryption, authentication, and access control mechanisms, is essential to protect the IoT infrastructure from cyber threats and unauthorized access (Haseeb et al., 2021). Privacy-preserving techniques, such as data anonymization and secure communication protocols, safeguard sensitive information and maintain the confidentiality of energy consumption data. The IoT infrastructure should also be designed to accommodate the growing number of connected devices and the increasing volume of data generated. Scalable architectures, such as distributed computing and cloud-based platforms, enable the system to handle the expanding needs of urban energy governance (Ahad et al., 2020). Adaptability to new technologies, protocols, and standards is crucial to ensure IoT deployment's long-term sustainability and evolution.

The IoT infrastructure, with its diverse components and deployment considerations, forms the backbone of the collaborative urban energy governance framework. The IoT infrastructure provides the necessary insights and actionable information to optimize energy generation, distribution, and consumption by enabling real-time monitoring, data collection, and analysis. The integration of edge computing devices and advanced data management and analytics platforms further enhances the capabilities of the IoT infrastructure, enabling efficient and intelligent decision-making processes. The strategic deployment of this robust and secure IoT layer is fundamental for providing the real-time situational awareness needed by the MAS and Cloud Platform for effective energy management, addressing the data acquisition needs highlighted as a challenge in current systems (Rathore et al., 2018). However, deploying IoT infrastructure in urban environments also presents challenges and limitations. These include the need for robust cybersecurity measures to mitigate potential vulnerabilities, seamless interoperability among heterogeneous devices and systems, and the management of large-scale deployments in terms of maintenance, upgrades, and scalability. Addressing these requires careful planning and alignment with municipal technology strategies to ensure equitable access and avoid exacerbating digital divides, a key consideration for sustainable cities.

Addressing these challenges requires ongoing research and development efforts, collaboration among stakeholders, and adopting best practices and standards. By continuously refining and optimizing the IoT infrastructure, the collaborative urban energy governance framework can leverage the full potential of real-time monitoring and control, enabling more efficient, sustainable, and resilient energy management in smart cities.

3.3. Cloud platform for data aggregation and analytics

3.3.1. Cloud architecture and services

The cloud-based platform is the centralized hub for data aggregation, processing, and decision support within the proposed collaborative urban energy governance framework. Designed with key considerations for scalability, fault tolerance, and security, the cloud architecture ensures the system can handle increasing data volumes, maintain high availability, and safeguard sensitive information. This platform leverages a distributed and modular architecture, enabling seamless integration with other components, such as the IoT infrastructure and the MAS. Its role is pivotal in transforming raw data into strategic intelligence for sustainable urban energy planning.

Table 1
Key components of the IoT infrastructure.

Component	Description
IoT devices and sensors	
Smart meters	Intelligent metering devices installed at residential, commercial, and industrial sites for accurate energy consumption monitoring (Liu & Nielsen, 2018).
Environmental sensors	Network of sensors monitoring environmental conditions such as temperature, humidity, and air quality, providing insights for optimizing energy usage and minimizing environmental impact (Ahad et al., 2020).
Renewable energy sensors	Specialized sensors integrated with renewable energy sources like solar panels and wind turbines enable real-time monitoring of energy generation (Ferdous et al., 2016).
Grid sensors	Sensors embedded within the energy distribution grid, monitoring power flow, voltage levels, and other critical parameters to ensure grid stability and reliability (Gungor et al., 2010).
Communication protocols	
LoRaWAN	Low-power, wide-area network protocol designed for long-range, low-power IoT applications, suitable for large-scale deployments in urban environments (Jouhari et al., 2023).
Zigbee	Low-power, low-data-rate wireless protocol for short-range IoT applications, enabling efficient communication among smart meters and sensors (Padma & Erukala, 2023).
Cellular networks (4G/5G)	Leveraging existing cellular infrastructure for IoT connectivity, providing wide coverage and high data rates for critical applications (Huseien & Shah, 2022).

Built on scalable and fault-tolerant infrastructure, the cloud platform specifically utilizes load balancing, auto-scaling, and redundancy techniques to ensure high availability and resilience for large-scale data processing and complex optimization tasks. Its modular design allows horizontal scaling to accommodate growing computational demands from increasing urban areas or higher data granularity. Robust security measures, including encryption, access control mechanisms, and secure communication protocols, protect the confidentiality, integrity, and availability of sensitive energy data (Ahmed et al., 2022), adhering to industry-standard security practices and regulatory compliance requirements.

Integration with the IoT infrastructure is facilitated through secure communication channels and standardized data formats (Ahad et al., 2020). IoT devices and sensors transmit real-time data to the cloud platform, which is ingested, processed, and stored for further analysis and decision support. The cloud platform also seamlessly integrates with the MAS, enabling information exchange and coordination between the agents and the cloud-based decision support system. Agents leverage the cloud platform's analytics capabilities to inform their decision-making processes, while the platform utilizes the agents' negotiated resource allocation strategies to optimize energy governance decisions. The cloud platform's role as a scalable and secure data processing layer is critical for transforming raw IoT data into actionable insights, supporting the complex analytics and optimization required by the framework (Malik et al., 2018). This capability is vital for cities aiming to implement sophisticated energy policies based on comprehensive data analysis.

3.3.2. Decision support and optimization

The cloud-based platform provides decision support and optimization capabilities for the collaborative urban energy governance framework. Leveraging collected data from the IoT infrastructure, forecasting models, and optimization algorithms, the platform derives actionable insights and recommendations (Li et al., 2021). Data visualization, a key component of the decision support capabilities, enables stakeholders to understand the energy landscape comprehensively through interactive dashboards and visual analytics. These visualizations present real-time energy consumption patterns, forecasted demand, resource allocation strategies, and other relevant metrics, facilitating informed decision-making (Wu et al., 2023). Advanced analytics techniques, such as machine learning and predictive modeling, analyze vast amounts of data to identify patterns, trends, and anomalies, optimizing energy governance decisions and improving overall system efficiency (Li et al., 2021).

The platform incorporates optimization algorithms to determine optimal resource allocation strategies and energy trading decisions, considering a comprehensive suite of constraints crucial for sustainable urban systems: resource availability, operational limits, environmental impact, and stakeholder preferences. MOEAs, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) or the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, address the multi-objective optimization problem inherent in urban energy governance (Deb et al., 2002). MOEAs handle conflicting objectives and identify a diverse set of Pareto-optimal solutions, allowing for the simultaneous optimization of multiple objectives like cost minimization, environmental sustainability, and energy security. By leveraging the strengths of MOEAs, the proposed approach helps to identify optimal resource allocation strategies that balance the competing goals of urban energy governance. The objective function for the optimization problem is the minimization of the TEGC, aiming to find Pareto-optimal solutions that minimize TEGC while satisfying various constraints. The ability of the cloud platform to run these computationally intensive MOEAs is essential for finding optimal solutions to the complex multi-objective urban energy governance problem (Ngo et al., 2024). The selection from the Pareto-front can be guided by specific urban sustainability targets or policy priorities, making this a powerful tool for governance.

The platform's decision support capabilities are further enhanced by integrating forecasting models, such as LSTM networks, for energy demand forecasting. Combining forecasted demand with optimized resource allocation strategies, the platform provides comprehensive recommendations for energy governance decisions, ensuring efficient and sustainable energy distribution.

Consider a scenario where the cloud platform identifies an upcoming peak in energy demand based on the LSTM forecasting model. The optimization algorithms can then determine the optimal resource allocation strategy, considering available renewable energy sources, energy storage capacities, and operational constraints. The cloud platform can present this optimized strategy through visual analytics, enabling stakeholders (e.g., urban planners, utility operators) to make informed decisions and implement recommended actions to meet anticipated demand efficiently and sustainably.

3.4. Privacy-preserving energy demand forecasting

3.4.1. LSTM for energy demand forecasting

LSTM networks, a recurrent neural network (RNN), are particularly well-suited for energy demand forecasting because they capture and model complex temporal patterns and long-term dependencies in sequential data (Wang et al., 2023). The LSTM architecture addresses the vanishing gradient problem, common in traditional RNNs, by introducing a gating mechanism that regulates the flow of information through the network (Levy et al., 2018). The mathematical formulation of the LSTM model in our framework is as follows:

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \tag{4}$$

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \tag{5}$$

$$g_t = \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \tag{6}$$

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{8}$$

$$h_t = o_t \odot \tanh(c_t) \tag{9}$$

where i_t, f_t, g_t, and o_t are the input, forget, cell, and output gates' activation vectors, respectively; h_t is the hidden state vector; and c_t is the cell state vector. The weights W and biases b are associated with inputs and hidden states, while σ denotes the sigmoid activation function, and $\odot$ denotes element-wise multiplication.

The LSTM model is trained using historical energy demand data, optimizing weights and biases to minimize the error between predicted and actual energy demand values. This training process involves feeding historical data sequences into the LSTM network and adjusting the model parameters iteratively through backpropagation and gradient descent optimization. LSTM networks offer advantages over traditional time series forecasting methods, such as ARIMA models, by effectively capturing complex temporal patterns and nonlinear relationships. They can model long-range dependencies and handle irregularities or seasonality in energy demand data, making them particularly well-suited for forecasting in urban environments (Siami-Namini et al., 2018). Accurate forecasting is a cornerstone of efficient resource allocation and minimizing energy waste, contributing directly to environmental sustainability.

3.4.2. Federated learning for privacy preservation

Federated Learning is a decentralized machine learning approach that enables collaborative model training while preserving data privacy (Cheng et al., 2022). In the proposed framework, Federated Learning allows urban areas to train an energy demand forecasting model collaboratively without directly sharing sensitive energy consumption data. This addresses a significant barrier to data sharing in smart city applications and aligns with stringent data protection regulations, thereby fostering citizen trust and participation — key elements of social sustainability. This is a key aspect addressing the privacy concerns identified in the Introduction.

The Federated Learning framework maintains a local copy of outfittedhe LSTM model in each urban area, where they independently train their models using local energy consumption data. After a predefined number of training iterations, local model updates, such as weight and bias adjustments, are shared with a central server or co-ordinator. The central server aggregates these updates using secure aggregation protocols like Federated Averaging (Sun et al., 2022), and the aggregated updates are distributed back to the urban areas. This iterative process continues until convergence or a predefined stopping criterion is met.

This framework prioritizes data privacy by keeping raw energy consumption data localized within each urban area. Only model updates, which do not directly expose sensitive information, are exchanged during the collaboration. Secure communication protocols and encryption techniques enhance security, while differential privacy mechanisms provide additional protection. The Federated Learning framework offers numerous advantages for urban energy demand forecasting. Retaining raw data locally addresses data-sharing concerns in different regions. Its decentralized nature facilitates scalability, easily accommodating new urban areas without central data aggregation. The framework also exhibits robustness by relying on aggregated model updates, ensuring the global model remains effective even if individual contributors experience failures or dropouts during training. Leveraging collective knowledge and diverse data sources from multiple urban areas, the framework significantly improves forecasting accuracy compared to isolated local models, contributing to more efficient urban energy governance. Choosing FL over centralized learning models is a deliberate design choice to enable collaborative forecasting without compromising participating urban areas' sensitive energy consumption data, a critical requirement for stakeholder adoption (Shabbir et al., 2024). This ability to leverage diverse data while upholding privacy can build citizen trust and is crucial for developing equitable and widely accepted smart city solutions.

Implementing the Federated Learning framework involves integrating secure communication protocols, model aggregation algorithms, and privacy-preserving mechanisms within the collaborative urban energy governance system. This integration ensures privacy-preserving and scalable training of the LSTM model for accurate energy demand forecasting, enabling informed decision-making and efficient resource allocation within the urban energy governance framework.

3.5. Multi-objective optimization for urban energy governance

The collaborative urban energy governance framework addresses a multi-objective optimization problem where conflicting objectives must be optimized simultaneously, such as cost minimization, environmental sustainability, and energy security. This section details our approach, which is novel in its comprehensive formulation of these objectives and associated constraints tailored to reflect the complex trade-offs inherent in sustainable urban development.

3.5.1. Defining the multi-objective optimization problem

The urban energy governance problem can be formulated as a multi-objective optimization problem, where the objective function comprises multiple weighted objectives. Let $\mathcal{O} = \{O_1, O_2, \ldots, O_k\}$ denote the set of k objectives to be optimized simultaneously. The problem can be expressed as:

$$\min_{\mathbf{x}\in\mathcal{X}} \mathbf{F}(\mathbf{x}) = \left[F_1(\mathbf{x}), F_2(\mathbf{x}), \ldots, F_k(\mathbf{x})\right] \tag{10}$$

where $\mathbf{x}$ is the decision vector, $\mathcal{X}$ is the feasible decision space, and $\mathbf{F}(\mathbf{x})$ is the vector-valued objective function comprising k individual objective functions $F_i(\mathbf{x})$, $i = 1, 2, \ldots, k$. In our framework, these objectives specifically include minimizing total economic costs (generation, transmission), minimizing environmental impact (e.g., CO2 emissions, reliance on non-renewables), and maximizing energy security (e.g., supply reliability, diversity of sources). This comprehensive set distinguishes our approach by directly embedding core sustainability pillars into the optimization. The objectives may represent conflicting criteria, such as cost minimization, environmental impact reduction, and energy security enhancement.

Given the conflicting nature of these objectives, a single solution typically does not exist that optimizes all objectives simultaneously. Instead, the goal is to find Pareto-optimal solutions representing trade-offs between different objectives. A solution $\mathbf{x}_1 \in \mathcal{X}$ Pareto-dominates another solution $\mathbf{x}_2 \in \mathcal{X}$ if and only if:

$$\begin{aligned} &\forall i \in \{1, 2, \ldots, k\} : F_i(\mathbf{x}_1) \le F_i(\mathbf{x}_2) \\ &\quad \text{and} \quad \exists j \in \{1, 2, \ldots, k\} : F_j(\mathbf{x}_1) < F_j(\mathbf{x}_2) \end{aligned} \tag{11}$$

A solution $\mathbf{x}^* \in \mathcal{X}$ is Pareto-optimal if no other solution $\mathbf{x} \in \mathcal{X}$ Pareto-dominates $\mathbf{x}^*$. The set of all Pareto-optimal solutions is known as the Pareto-optimal set, and the corresponding set of objective vectors is the Pareto-optimal front. Presenting this front to urban policymakers allows for informed choices aligned with specific sustainability goals and local priorities.

Algorithm 1: MOEA

Input: Population size N, Generation limit T
Output: A set of non-dominated solutions
$P_0 \leftarrow$ InitializePopulation(N);
Evaluate(P_0);
for $t \leftarrow 1$ **to** T **do**
  $P'_{t-1} \leftarrow$ SelectParents(P_{t-1});
  $O_t \leftarrow$ ApplyGeneticOperators(P'_{t-1});
  Evaluate(O_t);
  $Q_t \leftarrow$ Merge(P_{t-1}, O_t);
  $Q'_t \leftarrow$ NonDominatedSort(Q_t);
  $P_t \leftarrow$ SelectTopN(Q'_t, N);
return ExtractNonDominated(P_T);

3.5.2. Multi-objective evolutionary algorithms

To tackle the multi-objective optimization challenge, we utilize MOEAs, population-based metaheuristic optimization algorithms inspired by Darwinian principles of natural selection. MOEAs resolve multi-objective optimization issues by identifying a diverse array of Pareto-optimal solutions in a single computational run (Coello et al., 2004). This study incorporates renowned MOEA methodologies such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) and the Strength Pareto Evolutionary Algorithm2 (SPEA2) (Sheng et al., 2012). These algorithms leverage unique selection processes, including non-dominated sorting and density estimation, to navigate the search towards the Pareto frontier while preserving solution diversity within the population.

The general procedure of an MOEA involves iterative evolution, where the population is refined through selection, crossover, and mutation operations to generate new solution candidates, as depicted in Algorithm 1. Integrating non-dominated sorting and diversity conservation ensures progression towards the Pareto frontier while maintaining a heterogeneous solution pool.

3.5.3. Constraint handling and objective normalization

The urban energy governance problem involves various constraints, such as resource availability, operational limits, and environmental impacts, as detailed in Section 3.2.2, which are critical for ensuring solutions are practical and sustainable in real urban contexts. To manage these constraints within the MOEA framework, we employ techniques like penalty functions or repair mechanisms. Additionally, objective normalization is crucial in multi-objective optimization as the objectives may have different scales and units. Techniques such as linear scaling or nonlinear mapping ensure that all objectives are treated equally during optimization.

Let $f_i^{\min}$ and $f_i^{\max}$ denote the minimum and maximum values of the ith objective function, respectively. The linear scaling normalization technique transforms the objective values to a common range, typically [0, 1], using the following equation:

$$F_i^{\text{norm}}(\mathbf{x}) = \frac{f_i(\mathbf{x}) - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \tag{12}$$

Other normalization techniques, such as nonlinear mapping or scaling based on user preferences, can also be employed depending on the specific requirements of the urban energy governance problem.

3.5.4. Decision-making and solution selection

The MOEA generates Pareto-optimal solutions representing the trade-offs between conflicting objectives. Decision-making techniques involving stakeholders and decision-makers are used to select a single solution from this set. One approach is to use weighted sum or compromise programming methods, where decision-makers assign weights to different objectives based on their priorities and requirements. The final solution that best satisfies these weighted preferences is the solution. Another approach is to use reference point-based methods, where decision-makers specify a reference point in the objective space and select the solution closest to this point. Visualization techniques, such as parallel coordinate plots or scatter plots, aid decision-makers in understanding the trade-offs between Pareto-optimal solutions and making informed decisions (Nagar et al., 2023). This participatory aspect is vital for aligning technical solutions with broader societal values and urban sustainability policies.

Incorporating multi-objective optimization techniques, constraint handling mechanisms, objective normalization, and decision-making strategies allows the proposed framework to address the complexities of urban energy governance. This enables the identification of optimal resource allocation strategies that balance conflicting objectives and promote sustainable and efficient energy management.

3.5.5. Framework implementation

This section details the practical realization of the proposed urban energy governance framework, integrating various advanced technologies as depicted in Fig. 2. The framework operates on a multi-layered architecture, combining cloud platform services, federated learning, MAS, and IoT infrastructure to achieve efficient and sustainable urban energy management.

The IoT infrastructure forms the foundation, comprising smart meters, environmental sensors, and renewable energy sensors that collect real-time data on energy consumption, environmental conditions, and renewable energy generation. Robust communication protocols like LoRaWAN, Zigbee, and cellular networks ensure reliable data transmission to the cloud platform, facilitating scalable connectivity across urban environments.

The cloud platform serves as the central hub for data aggregation, analytics, and decision support. It leverages load-balancing techniques and robust security measures to process massive datasets from IoT devices. Critical cloud services include advanced analytics and data visualization tools. Within this platform, the federated learning process operates, where local Long Short-Term Memory (LSTM) models trained on individual urban area data are securely aggregated into a global model. This privacy-preserving approach allows for collaborative forecasting without sharing raw sensitive data.

On top of this infrastructure, the Multi-Agent System (MAS) component models urban areas as intelligent agents. These agents utilize the optimized demand forecasts from the federated learning layer to engage in game-theoretic negotiations for decentralized resource allocation. The multi-objective optimization layer, also residing within the cloud, employs evolutionary algorithms to handle the complex trade-offs between competing objectives like cost minimization, environmental impact, and energy security. Constraint handling, objective normalization, and decision-making strategies are integrated to ensure the optimization process yields practical and effective solutions for energy generation, transmission, and consumption.

In summary, the framework's multi-layered approach integrates IoT devices, cloud computing, federated learning, and MAS to create a robust and adaptive system for urban energy governance. This integration facilitates real-time monitoring, data-driven decision-making, and efficient resource allocation, ultimately contributing to the sustainability and resilience of urban energy systems. This holistic integration distinguishes our framework from approaches that focus on individual technologies, enabling a more comprehensive and effective solution for urban energy challenges. The framework is designed for adaptability, allowing for the incorporation of new data sources, analytical techniques, or policy constraints as urban energy systems evolve.

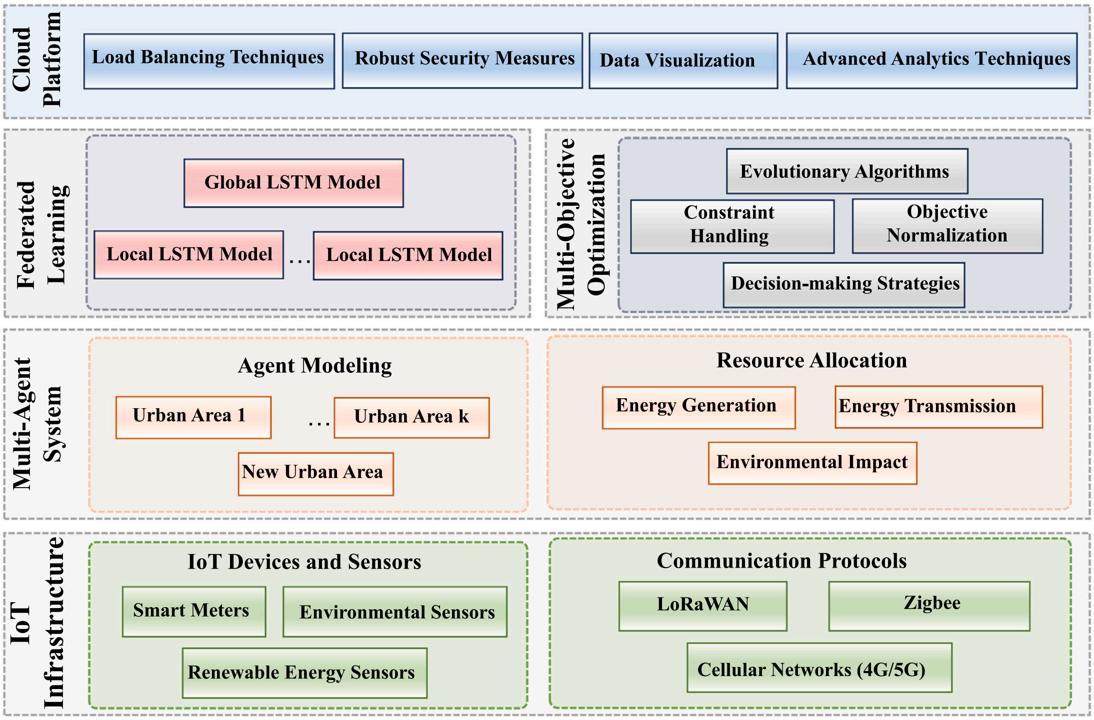

Fig. 2. Component overview of the proposed urban energy governance framework. The framework integrates multiple advanced technologies to achieve efficient and sustainable urban energy management, including IoT devices and sensors, communication protocols, multi-agent systems, federated learning, multi-objective optimization, and cloud platform services. This illustrates the holistic architecture designed for real-world complexity.

4. Evaluation

This section presents a comprehensive evaluation of the proposed collaborative urban energy governance framework. We detail the simulation environment setup, describe the various scenarios used to test the framework's performance under diverse and realistic conditions derived from real-world data characteristics, and analyze the results concerning energy cost reduction, forecasting accuracy, and environmental benefits. The evaluation aims to demonstrate the effectiveness and robustness of the integrated approach, particularly its potential contributions to urban sustainability.

4.1. Simulation setup and scenarios

To evaluate the performance and effectiveness of the proposed collaborative urban energy governance framework, a simulation environment was developed using Python, leveraging libraries such as NumPy for numerical computation, Pandas for data manipulation, and Scikit-learn for machine learning tasks. The simulation environment was designed to emulate the dynamics of urban energy systems, incorporating various scenarios and conditions representative of real-world challenges. These simulations act as virtual pilots, assessing the framework's feasibility and potential impact before large-scale physical deployment. The simulation setup considered a hypothetical urban area of three distinct districts characterized by unique energy consumption patterns and renewable energy generation capacities. The following scenarios were designed to assess the framework's performance under diverse conditions:

Table 2 outlines the key simulation parameters and their values for each defined scenario. These parameters were carefully selected to represent realistic conditions and challenges encountered in urban energy management, allowing for a robust evaluation of the framework's capabilities.

- **Baseline Scenario**: This scenario simulated a traditional, largely uncoordinated energy system, where each district manages its energy resources independently without the proposed framework's collaborative optimization or advanced forecasting. This serves as a benchmark to quantify the improvements offered by our integrated approach.
- **Normal Operation Scenario**: This scenario simulated the typical day-to-day operation of the urban energy system, with average energy demand and supply conditions. This scenario allowed for evaluating the framework's ability to optimize resource allocation, minimize energy transaction costs, and maintain system efficiency under normal operating conditions. The parameters here represent typical load profiles and resource availability for the simulated districts, reflecting average daily variations.
- **Peak Demand Scenario**: This scenario simulated a period of exceptionally high energy demand, such as during a heatwave or a major public event, stressing the energy system's capacity. The Peak Demand Factor of 1.5 was chosen to represent a significant and challenging surge in consumption, approximately 50% above normal levels, reflecting conditions that severely test grid stability. This scenario assessed the framework's ability to effectively handle increased load, maintain system stability, and prevent blackouts by leveraging collaborative resource sharing and optimized energy distribution.
- **Renewable Energy Fluctuations Scenario**: This scenario introduced significant variability in renewable energy generation, reflecting the intermittent nature of solar and wind power. The fixed Renewable Capacity parameter in the table represents the installed capacity, while the simulation introduced temporal fluctuations around this value based on realistic historical or modeled weather patterns specific to urban environments. This scenario evaluated the framework's responsiveness to fluctuating renewable supply, testing its ability to adjust resource allocation dynamically, integrate energy storage, and maintain a reliable energy supply despite intermittency challenges.
- **Infrastructure Failure Scenario**: This scenario simulated a failure or disruption in a critical infrastructure component, such as a transmission line or a power plant. The reduced Transmission Capacity

Table 2
Simulation parameters for different scenarios.

Scenario	Base demand (kWh)	Peak demand factor	Renewable capacity (kWh)	Storage capacity (kWh)	Transmission capacity (kWh)
Baseline	100	1.0	40	20	0.5
Normal operation	100	1.0	40	20	0.5
Peak demand	100	1.5	40	20	0.5
Renewable fluctuations	100	1.0	40	20	0.5
Infrastructure failure	100	1.0	40	20	0.3 (Urban area 1) 0.5 (Urban area 2, 3)
Dynamic pricing	100	1.0	40	20	0.5

for Urban Area 1 (0.3 kWh) compared to others (0.5 kWh) simulates a partial outage or constraint on energy transfer for that district, representing a realistic localized infrastructure issue. This scenario tested the framework's resilience and fault tolerance. It evaluated its ability to maintain a stable energy supply and minimize disruptions in unexpected infrastructure failures, demonstrating its capability to ensure reliable energy governance even under adverse conditions.

- **Dynamic Energy Pricing Scenario**: This scenario introduced time-varying energy prices to capture the economic fluctuations in energy markets. This scenario evaluated the framework's ability to adapt to dynamic pricing and make optimal resource allocation and energy trading decisions based on changing prices. The pricing signals used in the simulation were based on representative profiles of wholesale energy markets, reflecting diurnal or event-driven price changes.

These scenarios comprehensively evaluated the proposed framework's performance across realistic conditions, encompassing regular operation, extreme events, and unexpected disruptions. The results obtained from these simulations provide valuable insights into the framework's ability to optimize urban energy governance, reduce costs, enhance sustainability, and improve system resilience.

4.2. Results and analysis

This section presents and analyzes the key results obtained from the simulation environment, demonstrating the effectiveness of the proposed collaborative urban energy governance framework across various performance metrics and scenarios. The analysis focuses on energy cost reduction, forecasting accuracy, and environmental benefits, directly evaluating the impact of the integrated framework components on key sustainability indicators.

4.2.1. Energy cost reduction

Table 3 presents the TEGC for the overall urban area under various scenarios at hourly intervals. The first "Normal Ops (Uncoordinated)" column represents the traditional, uncoordinated approach. A new "Normal Ops (Centralized Optimized)" column is introduced to simulate a baseline of a more sophisticated, but still centralized, optimization system without the hybrid governance model's decentralized MAS or privacy-preserving FL. The "Normal Ops (Framework)" column shows results using our proposed system. The results demonstrate the effectiveness of the proposed collaborative urban energy governance framework in managing energy transactions and reducing costs compared to the baseline. Under the Normal Operation scenario with the framework active, the TEGC remains consistently low and often significantly lower than the uncoordinated baseline (e.g., 01:00, 05:00), showcasing the framework's efficiency in balancing local generation, storage, and inter-district energy sharing coordinated by the MAS agents using game theory. While the "Centralized Optimized" baseline also shows significant cost reductions compared to the uncoordinated baseline, the "Normal Ops (Framework)" column generally achieves even lower TEGC, particularly during hours with high baseline costs (e.g., 00:00, 01:00, 05:00). This indicates that the hybrid framework's combination of decentralized MAS flexibility and global MOEA optimization, informed by accurate FL forecasts, provides a more granular and adaptive cost management capability than a purely centralized optimization, especially in dynamic conditions. This cost reduction has direct implications for energy affordability, a key component of economic sustainability in cities.

Under normal operating conditions, the framework consistently achieves lower TEGC values, indicating its ability to efficiently manage energy resources by leveraging renewable sources, balancing demand and supply, and coordinating between districts. The scenario with renewable energy fluctuations shows only minimal cost increases, highlighting the framework's adaptability to the inherent variability of renewable energy while maintaining cost efficiency. However, the peak demand scenario presents a significant challenge, resulting in substantially higher TEGC values due to increased demand, particularly at 00:00 (365.87) and other peak hours like 03:00 (127.21) and 13:00 (112.03). This indicates the need for further investigation into the framework's performance and potential mitigation strategies during high-demand periods, possibly through enhanced demand-side management integrated with the MAS negotiation. The significant spikes observed (e.g., at 01:00 and 05:00) in the Uncoordinated Baseline scenario demonstrate the high costs incurred without collaborative optimization, which the framework effectively mitigates in its Normal Operation scenario, showing the value of the integrated approach. The infrastructure failure scenario at 15:00 leads to a dramatic spike in TEGC (2872.28), showcasing the framework's resilience in adapting to the failure and indicating the considerable impact of infrastructure disruptions on energy governance costs. The framework's ability to rapidly reroute energy flows and re-optimize allocation in response to the simulated transmission line failure, supported by real-time data from the IoT infrastructure and decision-making on the Cloud Platform, prevented a complete system collapse. However, it incurred higher transaction costs due to rerouting and increased reliance on potentially more expensive local generation or storage, highlighting the economic impact of such events and the importance of resilient infrastructure for sustainable energy systems. The dynamic pricing scenario introduces notable TEGC fluctuations in response to changing market conditions, especially during the later hours at 14:00 (621.50) and 16:00 (1701.18), demonstrating the framework's responsiveness to dynamic pricing mechanisms. The optimization algorithms within the cloud platform, informed by demand forecasts, successfully adjusted resource allocation strategies based on the fluctuating price signals, influencing decisions on when to buy, sell, or use stored energy to minimize costs in real-time. Such adaptability is crucial for cities participating in volatile energy markets.

In conclusion, the simulation results suggest that the proposed framework offers a promising approach to achieving cost efficiency and sustainable energy governance under normal conditions and renewable fluctuations. However, further research and experimental validation are required to address the challenges posed by extreme peak demand, significant infrastructure failures, and complex dynamic pricing environments to improve the framework's performance, resilience, and adaptability under these challenging conditions. Analyzing these results provides valuable insights into the real-world applicability and robustness of the integrated MAS, IoT, Cloud, and FL components and identifies areas for future algorithmic and system enhancements. The observed cost benefits and operational adaptability contribute to both economic and operational aspects of urban sustainability.

Table 3
TEGC results for varying scenarios (Note: The first 'Normal Ops (Uncoordinated)' column represents the Baseline scenario without the proposed framework; the 'Normal Ops (Centralized Optimized)' column represents a more advanced centralized optimization system; and the 'Normal Ops (Framework)' column shows results with the Proposed Hybrid Framework. TEGC values are indicative units.).

Time	Normal Ops (Uncoordinated)	Normal Ops (Centralized Optimized)	Normal Ops (Framework)	Peak demand	Renewable fluctuations	Infrastructure failure	Dynamic pricing
00:00	114.21	80.00	33.49	365.87	33.43	34.07	75.07
01:00	686.35	150.00	33.20	318.71	34.99	692.08	75.07
02:00	34.76	35.00	34.21	33.37	33.91	33.47	35.11
03:00	32.53	33.00	31.77	127.21	34.36	32.40	32.14
04:00	35.13	34.00	33.70	33.06	354.32	31.97	30.92
05:00	498.96	100.00	35.47	33.47	1119.07	33.60	34.59
06:00	34.12	34.00	34.56	34.87	33.98	31.49	32.77
07:00	34.36	40.00	52.18	38.13	33.81	33.24	33.27
08:00	46.78	40.00	46.78	33.32	84.89	34.32	35.99
09:00	33.70	60.00	154.25	34.48	37.30	33.20	34.67
10:00	35.17	35.00	36.17	33.43	35.06	34.88	34.84
11:00	33.79	34.00	34.53	36.41	34.60	35.85	34.80
12:00	35.25	35.00	34.40	33.50	34.37	34.53	35.84
13:00	37.45	90.00	230.74	112.03	32.47	33.89	379.05
14:00	34.11	50.00	76.29	33.69	33.35	60.32	621.50
15:00	34.10	40.00	35.61	48.84	33.69	2872.28	43.04
16:00	33.41	35.00	33.98	33.94	32.72	33.02	1701.18
17:00	33.30	33.00	33.30	31.22	32.22	35.79	44.38
18:00	33.27	33.00	33.35	33.41	32.19	33.51	33.51
19:00	31.25	31.00	32.20	33.24	31.41	35.07	31.15
20:00	29.79	30.00	32.53	32.38	31.28	32.08	32.12
21:00	33.69	32.00	31.14	34.45	31.87	394.71	30.96
22:00	32.85	32.00	32.85	35.27	32.17	34.69	35.00
23:00	32.42	80.00	223.14	34.66	32.96	33.59	34.32

4.2.2. Forecasting performance

The forecasting performance of the Federated Learning-based LSTM model was rigorously evaluated against traditional centralized models, specifically the Autoregressive Integrated Moving Average (ARIMA) model and a standalone Centralized LSTM model. This evaluation compares the models' accuracy, training time, data transmission overhead, and the impact of increasing the training set size on performance.

The dataset used for this study comprises historical energy consumption records from multiple urban areas, collected and published by UK Power Networks (Networks, 2021). The dataset includes data from 5567 Smart Meters in London, recorded between November 2012 and February 2014, with a granularity of 30 min and expressed in kWh (kW per half-hour). Each time series is associated with a category based on the Classification Of Residential Neighborhoods' (ACORN) standard, segmenting the UK population into different demographic types (Government, 2023). The dataset is enriched with meteorological variables recorded in London and obtained through the DarkSky API. Using such real-world data enhances the relevance of our simulation findings for actual urban environments.

The data was divided into multiple subsets to simulate the federated learning scenario, each representing a different urban area. These subsets served as local datasets, with energy consumption measurements further enriched with weather data and calendar features. This approach allowed us to simulate a range of urban areas (clients) in our experiments (e.g., scaling from 100 to 1000 clients in our communication overhead study) to evaluate the scalability and robustness of the federated learning approach. The training set size (n_{tr}) represents the number of samples used from each simulated urban area during the training phase and was varied to study its impact on model performance.

In the Federated Learning setup, multiple edge devices trained local LSTM models on their respective local data, with model updates aggregated on a central server using the Federated Averaging (FedAvg) algorithm to create a global model (Sun et al., 2022). The baseline models, in contrast, were trained on centralized data without federated updates.

The accuracy of the forecasting models was measured using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics. These metrics were chosen to provide a comprehensive measure of the model's ability to capture temporal patterns and fluctuations in energy demand. The RMSE and MAE values are calculated as follows:

Table 4
Forecasting performance metrics.

Model	RMSE	MAE
Federated LSTM	0.184	0.152
Centralized LSTM	0.215	0.187
ARIMA	0.230	0.213

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{14}$$

where y_i represents the actual energy demand, $\hat{y}_i$ represents the forecasted energy demand, and n is the number of observations.

The results of this evaluation are summarized in Table 4, which compares the RMSE and MAE values for the Federated Learning-based LSTM, ARIMA, and standalone Centralized LSTM models. The Federated Learning-based LSTM model demonstrated superior performance with lower RMSE and MAE values, indicating higher accuracy in forecasting energy demand. This improved accuracy in demand forecasting provides more reliable input for the MAS negotiation and MOEA optimization processes, contributing to better overall energy governance decisions by reducing uncertainties. Enhanced forecasting accuracy directly contributes to environmental sustainability by minimizing energy overproduction and enabling more efficient integration of intermittent renewable sources.

In addition to accuracy, the evaluation also considered training time and data transmission overhead. The training time for each model was recorded and compared, as shown in Fig. 3. The Federated Learning-based LSTM model significantly reduced training time by distributing the computational load across multiple edge devices. This distributed approach resulted in training times nearly invariant to the size of the training set, in stark contrast to the centralized models, where training time increased significantly with larger datasets. This demonstrates the practical scalability and computational efficiency of the

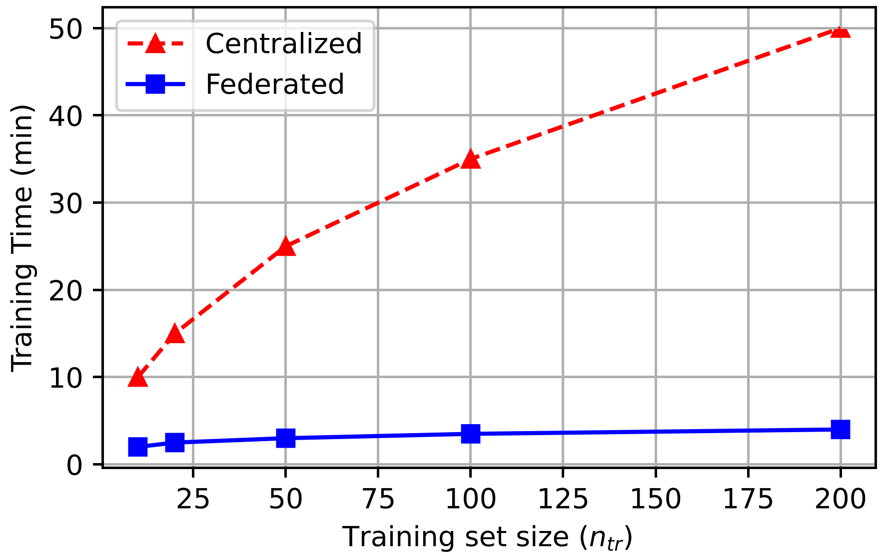

Fig. 3. Training time comparison between Federated LSTM and centralized LSTM models. Highlights the scalability advantage of FL, essential for sustainable large-scale urban deployment.

Federated Learning approach for integrating numerous urban areas into the forecasting process, addressing a key requirement for large-scale deployment. Scalability and efficiency are crucial for the long-term viability and operational sustainability of such frameworks in growing cities.

To further evaluate the robustness of the Federated Learning approach, we compared the forecasting performance between federated and centralized architectures while increasing the training set size. Fig. 4 presents the RMSE values for both architectures as the training set size increases. The results show that the RMSE decreases as the training set size increases for federated and centralized approaches, indicating improved model accuracy with more data. However, the Federated Learning-based LSTM consistently maintains lower RMSE values, demonstrating superior performance. This confirms that the privacy-preserving nature of FL does not compromise forecasting accuracy; instead, it can achieve better performance by collaboratively leveraging data from a wider range of distributed sources without privacy risks, a crucial advantage for urban energy governance. This synergy of privacy and accuracy supports social sustainability by protecting citizen data while enhancing system performance.

Additionally, the communication overhead for federated and centralized architectures was compared as the number of participating urban areas increased. Fig. 5 shows the data transmitted for both approaches. The Federated Learning architecture demonstrated scalability by efficiently managing the communication overhead even as the number of participating areas increased. In contrast, the centralized architecture showed a proportional increase in overhead with the number of areas. This significantly lower communication overhead is a key practical advantage of FL for real-world urban deployments involving diverse data sources, making the system more efficient and less reliant on high-bandwidth networks.

The Federated Learning-based LSTM model achieved superior forecasting performance compared to the traditional ARIMA and standalone Centralized LSTM models. The federated approach enhanced accuracy and significantly reduced training time and communication overhead, making it a viable and efficient solution for real-time energy demand forecasting in urban energy governance frameworks. These results underscore the potential of Federated Learning to improve the efficiency and sustainability of urban energy management systems. Future experiments could explore the impact of data heterogeneity across urban areas on FL performance and investigate advanced FL techniques further to enhance robustness and accuracy in diverse urban settings.

4.2.3. Multi-objective optimization analysis

The proposed framework utilizes MOEAs to solve the urban energy governance problem, which is formulated with conflicting objectives such as minimizing Total Energy Governance Costs (TEGC), reducing environmental impact (e.g., CO_2 emissions), and maximizing energy security (e.g., supply reliability). Unlike single-objective optimization that yields one best solution, MOEAs produce a set of Pareto-optimal solutions (Deb & Gupta, 2005). These solutions represent different trade-offs among the objectives, where no objective can be improved without degrading at least one other objective. This capability is central to sustainable governance, allowing policymakers to navigate complex choices transparently.

Analyzing the Pareto-optimal front obtained from the MOEA provides crucial insights for decision-makers. Fig. 6 illustrates an actual Pareto front generated from our simulations for two objectives (Cost vs. Environmental Impact) in the context of urban energy resource allocation. Each point on the curve represents an optimal resource allocation strategy because no other feasible strategy can achieve lower costs and lower emissions simultaneously. The figure highlights three representative solutions demonstrating the inherent trade-offs in urban energy governance.

Our simulation results reveal distinct resource allocation strategies corresponding to different points on the Pareto front. The simulated Cost-focused solution (e.g., approximately 40 units cost, 150 units emissions) heavily relies on fossil fuels (47.6% coal, 38.0% natural gas) with minimal renewable energy (14.4% solar), achieving the lowest cost but highest environmental impact. The Balanced solution (e.g., approximately 70 units cost, 100 units emissions) distributes resources more evenly across conventional and renewable sources (32.0% coal, 26.8% gas, 17.5% solar, 13.4% wind, 10.3% battery), offering a compromise between economic and environmental objectives. The Environment-focused solution (e.g., approximately 120 units cost, 50 units emissions) prioritizes renewable energy (25.4% solar, 20.2% wind, 15.5% battery) with reduced fossil fuel usage (15.5% coal, 23.3% gas), resulting in the lowest emissions but at a significantly higher cost. Additionally, a Baseline (Unoptimized) point, representing a scenario with higher cost and higher environmental impact (e.g., 130 units cost, 160 units emissions), is shown to illustrate the overall benefit gained from applying the MOEA optimization. These illustrative points, derived from analyzing multiple simulation runs, showcase the tangible decision support offered by the MOEA component.

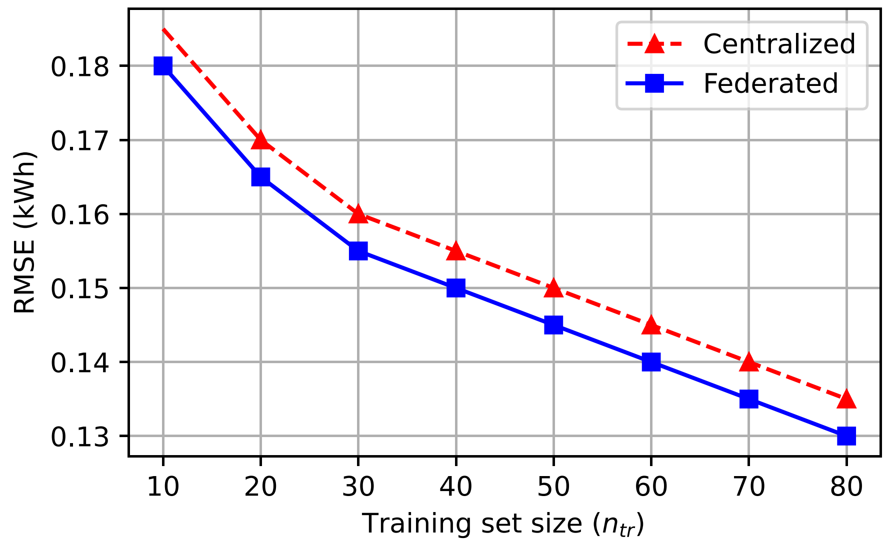

Fig. 4. Forecasting performance comparison between federated and centralized architectures while increasing the training set size n_{tr}. FL-LSTM consistently shows lower error, enhancing reliability for sustainable energy planning.

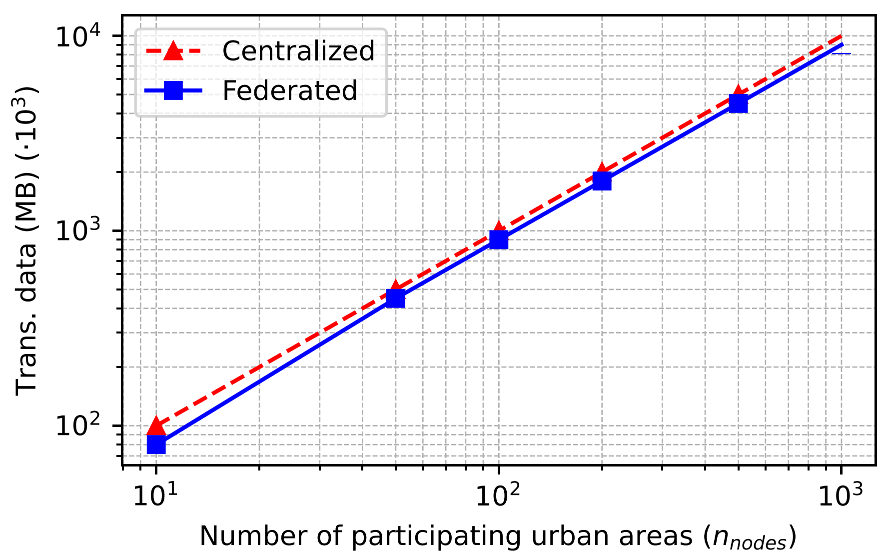

Fig. 5. Communication overhead comparison between federated and centralized architectures as the number of participating urban areas increases. FL's efficiency is vital for practical and sustainable deployment in data-rich urban environments.

The MOEA explored this complex, non-linear solution space defined by the resource allocation decisions of the MAS agents, constrained by factors like energy availability (maximum resource capacities), urban area demands, and renewable generation capacity. Each potential solution was evaluated simultaneously on multiple objectives: cost minimization, emission reduction, and reliability maximization. The reliability scores of 1.80, 2.00, and 2.30 for the three representative solutions demonstrate that environmental benefits also correlate with improved energy security, adding another dimension to the decision-making process. Such multi-faceted optimization is critical for achieving holistic sustainability.

While presenting the full, multi-dimensional Pareto front for all scenarios and time steps is infeasible within this paper, the TEGC results in Table 3 represent the outcome of selecting a specific compromise solution from the generated Pareto set at each time step. This selection can be based on various decision-making criteria the energy managers apply, depending on the prevailing priorities (e.g., prioritizing cost reduction during normal operation or energy security during potential failure events). The effectiveness of the MOEA in identifying a diverse set of high-quality trade-off solutions is a key factor enabling the framework to balance competing goals in real-time energy governance. The parameters of the MOEA, such as population size and number of generations, were tuned during the simulation setup to ensure sufficient solution space exploration and convergence towards a well-distributed Pareto front, providing meaningful options for decision-making in complex urban energy landscapes. This ability to explore and present diverse sustainable pathways is a core strength of the framework for policy support.

4.3. Assessment of environmental benefits: A simulated case study for Chicago

To evaluate the environmental impact and demonstrate the real-world relevance of the proposed collaborative urban energy governance framework, we conducted a simulated case study using historical data. This assessment focuses on carbon emissions reduction and enhanced renewable energy utilization, key indicators of environmental sustainability. The total carbon emissions for both the Baseline Scenario

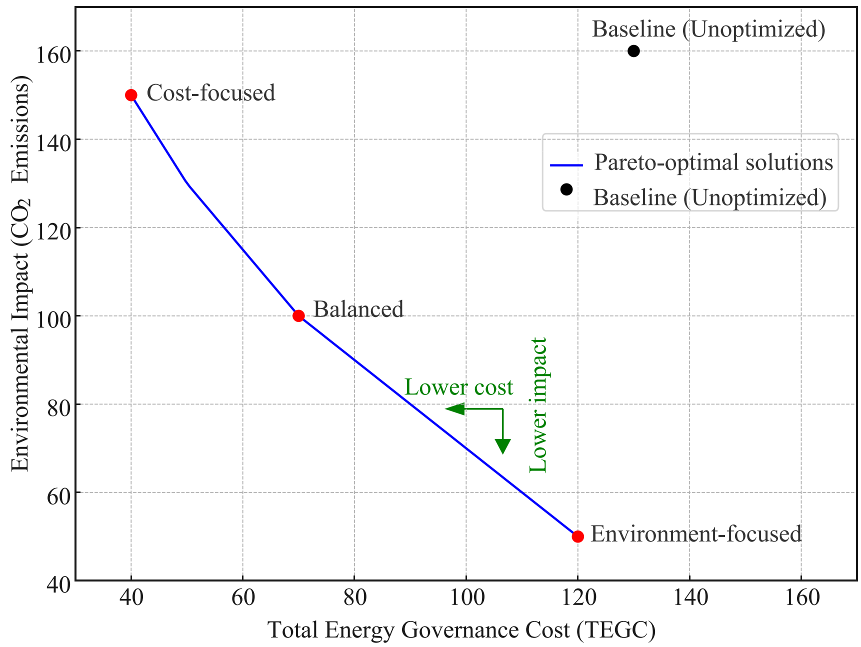

Fig. 6. Simulated pareto-optimal front for urban energy resource allocation showing the trade-off between Total Energy Governance Cost (TEGC) and environmental impact (CO_2 emissions). Three representative solutions derived from simulation outcomes are highlighted: Cost-focused (lowest cost but highest emissions), Balanced (moderate cost and emissions), and Environment-focused (highest cost but lowest emissions). A Baseline (Unoptimized) point is included to show the improvement achievable by the framework. This visualization aids policymakers in selecting strategies aligned with specific urban sustainability targets.

(representing current practices without the framework) and the Framework Implementation Scenario were calculated using the following formula:

$$E_{\text{total}} = \sum_{i=1}^{n} (C_i \cdot E_i) \tag{15}$$

where E_i represents the energy consumption from each energy source, and C_i represents the carbon emission factor for each energy source, obtained from the IEA Emissions Factors 2023 dataset (International Energy Agency, 2023).

The dataset used in this simulated case study is the Chicago Energy Benchmarking dataset (City of Chicago, 2023), which contains energy performance data for municipal, commercial, and residential buildings in Chicago from 2014 to 2019. Using data from a specific city like Chicago allows us to ground our simulations in a concrete urban context, making the findings more tangible for policymakers. The dataset is updated annually as part of the Chicago Energy Benchmarking Ordinance. It features four primary energy sources for our study: Electricity Use, Natural Gas Use, District Steam Use, and District Chilled Water Use. For this study, we divided the data based on ZIP codes into 104 distinct urban areas, each with unique energy consumption patterns and renewable energy generation capacities. The governance algorithm, detailed in Algorithm 2, was employed to optimize energy resource allocation among these urban areas. This optimization process involves evaluating each area's energy demand and supply patterns and strategically allocating resources using game-theoretic principles, specifically Nash negotiation. This ensures that renewable energy sources are utilized to their fullest capacity and energy demands are balanced efficiently and fairly. By prioritizing renewable sources and dynamically adjusting the energy mix based on real-time data and forecasts, the algorithm minimizes reliance on high-emission energy sources, reducing the overall carbon footprint and enhancing energy sustainability. This demonstrates the framework's capability to contribute to decarbonization efforts in urban areas actively. Such contributions are vital for cities striving to meet climate targets like those outlined in the Paris Agreement or local sustainability plans.

The results in Table 5 illustrate the environmental benefits achieved through the proposed framework. For instance, in 2016, the total carbon emissions decreased from an estimated 10,732,893.22 metric tons CO_2 in the Baseline Scenario to 9,867,222.11 metric tons CO_2 in the Framework Implementation Scenario, representing an 8.06% reduction. This reduction is a result of the framework's ability to optimize energy resource allocation, prioritizing renewable energy sources and enhancing energy efficiency, as evidenced by the simultaneous decrease in energy consumption (from 62,028,047,293.7 kBtu to 56,445,523,029 kBtu, a 9.00% reduction) in the same year. On average, over the 6-year period, the framework achieved an approximate 8.44% reduction in CO_2 emissions and a 9.03% reduction in energy consumption for the simulated Chicago context.

Compared to traditional energy governance frameworks, our proposed solution demonstrates superior performance in reducing carbon emissions and improving energy efficiency. The governance algorithm's ability to optimize resource allocation is crucial in these improvements. The results indicate the framework's potential to promote cleaner and more efficient energy systems in urban areas. By integrating advanced technologies such as MAS, IoT, cloud computing, and federated learning, the framework aligns with global efforts to mitigate climate change and enhance energy resilience. Urban planners and policymakers can leverage these findings to implement more sustainable energy practices. The framework's demonstrated capability to significantly lower emissions supports its potential as a tool for cities to meet their environmental targets and contribute to broader climate action goals (e.g., Sustainable Development Goal 13).

The significant reduction in carbon emissions demonstrated in Table 5 is a direct outcome of the framework's multi-objective optimization process, which explicitly includes environmental impact as one of the criteria. The MOEA-based optimization finds solutions on the Pareto front that represent favorable trade-offs, often reducing reliance on carbon-intensive energy sources by efficiently integrating renewables and optimizing energy sharing between districts based on their generation mix. This quantitative analysis validates the framework's potential to contribute significantly to urban sustainability goals and provides a tangible measure of its environmental benefits. Future work

Table 5
Comparative analysis of energy consumption and carbon emissions before and after framework implementation (simulated for Chicago, 2014–2019).

Year	Baseline scenario (kBtu/metric tons CO_2)	Framework implementation (kBtu/metric tons CO_2)	Reduction (%)
2014	23,222,300,090/4,735,656.04	21,032,293,081/4,312,086.60	9.43% (Energy)/8.94% (CO_2)
2015	52,893,208,337/9,171,689.88	48,132,139,670/8,346,236.78	9.00% (Energy)/9.00% (CO_2)
2016	62,028,047,293.7/10,732,893.22	56,445,523,029/9,867,222.11	9.00% (Energy)/8.07% (CO_2)
2017	61,412,358,225/10,540,336.92	55,885,475,202/9,641,369.96	9.00% (Energy)/8.53% (CO_2)
2018	67,542,978,122.8/10,979,352.70	61,464,435,144/10,089,146.23	9.00% (Energy)/8.11% (CO_2)
2019	59,881,459,051.4/9,986,815.32	54,590,273,642/9,186,683.47	8.83% (Energy)/8.01% (CO_2)

Algorithm 2: Governance Algorithm for Collaborative Urban Energy Management

Data: E: Energy consumption data, R: Renewable energy capacities, C: Emission factors
Result: Optimized resource allocation, reduced carbon emissions, increased renewable energy utilization

```
Function GovernanceFramework():
    Input: Load E, R, C;
    Normalize and aggregate E by urban areas;
    Calculate baseline emissions E_baseline = Σ_i (C_i · E_i);
    Initialize: Agents A_i representing urban areas;
    foreach A_i do
        Train local LSTM model on historical E;
        Predict future E_i;
        Send predictions Ê_i to central server;
    Aggregate model updates using Federated Averaging (FedAvg);
    foreach urban area do
        Allocate R first: E_R → A_i;
        Allocate remaining E from least to most carbon-intensive sources;
        Balance allocations using Nash negotiation;
    Calculate post-optimization emissions E_optimized = Σ_i (C_i · Ê_i);
    Output: Optimized energy allocation, reduced carbon emissions, increased renewable energy utilization;
```

could involve a more detailed analysis of the energy source breakdown in the optimized scenario to quantify further the contribution of renewable energy integration to emissions reduction and explore the impact of different carbon pricing policies within the optimization framework.

5. Discussion

This section discusses the implications of the evaluation results and the strengths, limitations, and potential future directions of the proposed collaborative urban energy governance framework. By integrating MAS, IoT, Cloud Computing, and Federated Learning, the framework represents a significant advancement in addressing the complexities of urban energy management. Through extensive simulations using real-world data characteristics and a simulated case study for Chicago, we demonstrated the framework's effectiveness in minimizing energy transaction costs, improving forecasting accuracy, ensuring data privacy, and promoting environmental sustainability. These results validate the core concept of synergistic integration and its potential to enhance urban energy governance compared to traditional or isolated approaches, particularly in fostering sustainable and resilient urban environments.

One of the key strengths of the framework lies in its hybrid governance model, enabling decentralized and adaptive operations. By modeling urban areas as intelligent agents capable of negotiating and allocating resources through game-theoretic mechanisms, the framework facilitates efficient collaboration and decision-making among stakeholders. This decentralized approach is a deliberate choice to overcome the limitations of centralized systems, offering greater flexibility, scalability, and resilience as urban energy landscapes become increasingly distributed with the proliferation of Distributed Energy Resources (DERs) (Panda et al., 2025). The IoT infrastructure for real-time monitoring and control, coupled with a cloud-based data aggregation and analytics platform, provides a robust foundation for data-driven decision support. The continuous stream of real-time data from the IoT layer is crucial for enabling the adaptive decision-making processes within the MAS and the data-intensive optimization performed on the cloud platform. Federated Learning enhances the framework by enabling privacy-preserving demand forecasting, allowing urban areas to collaboratively train models without compromising data confidentiality. Choosing Federated Learning addresses critical privacy concerns associated with sensitive energy consumption data, a significant barrier to data sharing in centralized systems, while still leveraging collective data intelligence to improve forecasting accuracy. The comprehensive optimization problem formulation, which uniquely balances economic, environmental, and security objectives through MOEAs like NSGA-II and SPEA2, ensures that the framework addresses the multifaceted challenges of urban energy governance from a holistic sustainability perspective (Cheraghi & Jahangir, 2023).

The evaluation results highlighted the framework's strong performance under normal operating conditions and its adaptability to renewable energy fluctuations, demonstrating significant energy cost reductions (Table 3) and improved forecasting accuracy (Table 4) compared to baseline and centralized approaches. The simulated Chicago case study also showed a notable reduction in carbon emissions by an average of 8.44% (Table 5), validating the framework's contribution to urban sustainability goals through optimized resource allocation prioritizing cleaner energy sources.

However, the simulations also revealed challenges, particularly during extreme conditions like peak demand and infrastructure failure scenarios. While the framework demonstrated resilience by maintaining system operation, the significant spikes in Total Energy Governance Costs (TEGC) during these events indicate areas for further improvement in handling such stressors. Future work needs to investigate enhanced strategies for resource mobilization, demand response, and fault recovery tailored to extreme conditions to improve resilience and cost-effectiveness during critical events (Taheri et al., 2020). These high-stress scenarios underscore the complex reality of urban systems and the ongoing need for adaptive management strategies.

5.1. Implications for sustainable urban development and policy

The proposed framework presents significant implications for sustainable urban development and the formulation of effective energy policies. Its inherent capability to optimize resource allocation while simultaneously considering environmental and security objectives directly supports the achievement of Sustainable Development Goals

(SDGs), notably SDG 7 (Affordable and Clean Energy) and SDG 11 (Sustainable Cities and Communities). The demonstrated CO2 emission reductions, for example, clearly contribute to SDG 13 (Climate Action). More broadly, the framework empowers urban planners and policymakers by providing sophisticated data-driven tools to promote renewable energy integration; accurate demand forecasting and optimized dispatch mechanisms facilitate higher penetration of renewable sources, even those with intermittent output. It can also enhance energy equity, as achieved cost reductions may translate into more affordable energy, and the decentralized MAS negotiation component offers the potential to incorporate fairness metrics for equitable resource access across diverse urban districts. Furthermore, the framework strengthens data-driven policy-making by offering real-time monitoring and advanced analytics, thereby creating a robust evidence base for designing, implementing, and evaluating critical energy policies such as carbon pricing, energy efficiency mandates, or demand-side management programs. While the system faces challenges during extreme events, its adaptive nature provides a foundational layer for fostering more resilient infrastructure, with the Multi-Objective Optimization capable of explicitly including resilience as a targeted objective. The hybrid architecture also enables new governance models, supporting innovative public–private partnerships or community energy schemes through a transparent and efficient coordination platform. Critically, the integration of Federated Learning addresses significant data governance challenges by offering a practical pathway to leverage sensitive data for public benefit while upholding privacy regulations, which is essential for building trustworthy smart city ecosystems. The framework's scalability, evidenced by FL's efficient management of increasing participants (Fig. 5), indicates its potential applicability across diverse urban contexts. Nevertheless, successful real-world implementation will necessitate overcoming institutional barriers, ensuring digital literacy and equitable access throughout communities to prevent a digital divide, and establishing comprehensive data governance protocols that extend beyond the technical safeguards provided by FL.

5.2. Limitations and future directions

The strategic integration of MAS, IoT, Cloud Computing, and Federated Learning is a core strength that differentiates this framework. While individual technologies have been explored in isolation, their synergistic combination addresses the complex interdependencies inherent in urban energy governance. However, this study, based on simulations, has limitations. Real-world deployment will present further challenges such as imperfect data, communication latencies, and the complexities of integrating with legacy physical infrastructure and existing regulatory frameworks.

Future research should explore several key directions. Integrating blockchain technology can provide enhanced security, transparency, and immutability of energy transactions, particularly for peer-to-peer energy trading within the MAS framework (Soto et al., 2021). Quantum computing techniques can potentially improve the efficiency and quality of solutions for complex optimization problems, offering avenues to tackle larger-scale urban energy networks. Incorporating reinforcement learning into the decision-making process can enable the framework to dynamically adapt and learn from real-time feedback and change environmental conditions. Developing advanced fault tolerance mechanisms and resilience strategies can improve the framework's reliability in the face of uncertainties and disruptions, building upon the insights gained from the infrastructure failure scenario. Expanding the approach to other domains of innovative city management, such as transportation, water management, waste management, and public safety, can lead to a more holistic and integrated approach to smart city governance. Crucially, future work must include pilot deployments in real urban settings to validate the framework under real-world conditions and to engage with stakeholders to refine its governance mechanisms for practical effectiveness and social acceptance. Comprehensive socio-economic impact assessments of the framework can provide valuable insights into its broader implications on energy affordability, job creation, and quality of life for urban residents. Further exploration of the policy levers required to incentivize adoption and ensure equitable outcomes from such advanced governance systems is also essential.

6. Conclusions and future work

The proposed collaborative urban energy governance framework, distinguished by its hybrid architecture integrating Multi-Agent Systems (MAS), Internet of Things (IoT), Cloud Computing, and Federated Learning, represents a significant advancement in urban energy management. The framework addresses key challenges in urban energy governance, including inefficiency, lack of transparency, privacy concerns, and difficulty integrating distributed resources, by leveraging the synergistic combination of these advanced technologies. The framework's core novelty lies in its unique adaptive feedback loop, where decentralized MAS negotiation is continuously informed by privacy-preserving FL forecasts and guided by system-wide multi-objective optimization on the cloud platform. This decentralized and adaptive approach, coupled with advanced multi-objective optimization techniques tailored for sustainability and privacy-preserving demand forecasting, has demonstrated promising results in minimizing energy transaction costs, improving forecasting accuracy, ensuring data privacy, and promoting environmental sustainability. We have evaluated the proposed framework through extensive simulations and a simulated case study using real-world data from Chicago, and the results showed that it effectively reduces energy transaction costs and enhances overall system efficiency across various realistic scenarios, including regular operation, renewable fluctuations, and dynamic pricing. These quantitative achievements, alongside the qualitative benefits of privacy preservation, decentralized control, and explicit sustainability-oriented optimization, underscore the framework's potential to drive positive change in urban energy systems, contributing significantly to the realization of truly sustainable, resilient, and intelligent smart cities.

Future research should address the identified limitations and explore new directions to enhance the framework further. Key areas for future work include improving computational efficiency to handle large-scale implementations involving a greater number of urban areas or higher data granularity, ensuring data quality and availability through robust data validation and imputation techniques, fostering stakeholder adoption and collaboration by developing user-friendly interfaces and demonstrating clear economic and environmental benefits, and integrating the framework with existing legacy systems to ensure interoperability and compatibility. Additionally, navigating the regulatory and policy landscape to ensure compliance with data privacy and security regulations is crucial. Specific avenues for future technical development include exploring more sophisticated MAS negotiation strategies, incorporating real-time adaptation to sudden events, and most importantly, conducting extensive real-world pilot deployments to validate performance in authentic urban environments and refine its socio-technical aspects. By addressing these challenges, the collaborative urban energy governance framework can continue to evolve and make significant contributions to the development of sustainable and intelligent urban energy systems.

CRediT authorship contribution statement

Renfang Wang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Hong Qiu:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Ruyu Liu:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology. **Huan Huo:** Writing – review & editing, Writing – original draft, Methodology. **Xu Cheng:** Writing – review & editing, Writing – original draft, Methodology. **Xiufeng Liu:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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