

A Geoanalytical Framework for Forecasting Urban Electricity Consumption in Smart City Systems*

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Abstract

This paper proposes a geoanalytical framework for forecasting urban electricity consumption in smart city systems, combining spatio-temporal modeling with machine learning techniques. The approach integrates temporal consumption patterns with spatial dependencies between urban zones through the use of a weight matrix and spatial aggregation mechanisms. A mathematical model is developed to construct enriched feature representations that capture both local dynamics and inter-zone interactions. The framework is implemented as a modular system including data preprocessing, spatial modeling, predictive analytics, and geospatial visualization. A prototype system based on gradient boosting (CatBoost) is designed to support real-time forecasting and analysis. The experimental evaluation is conducted on a dataset reflecting realistic urban energy consumption patterns, incorporating temporal dynamics and modeled spatial structure. The results demonstrate that the proposed approach outperforms baseline and non-spatial models in terms of MAE, RMSE, and MAPE metrics. In particular, the inclusion of spatial dependencies significantly improves forecasting accuracy and robustness. The findings confirm that the integration of geoanalytical methods and machine learning provides an effective solution for urban energy forecasting. The proposed framework can be applied in smart city decision-support systems and offers potential for further development in spatio-temporal analytics.

Keywords

geoanalytical framework; urban electricity consumption; smart city systems; spatio-temporal modeling; spatial aggregation; machine learning; CatBoost; energy forecasting; geospatial analysis; anomaly detection, Smart City

1. Introduction

Rapid urbanization and the increasing complexity of modern energy systems have made efficient management of electricity consumption a critical challenge for smart city development. Urban infrastructures are becoming increasingly dependent on data-driven decision-making, where accurate forecasting of energy demand plays a key role in ensuring system stability, optimizing resource allocation, and reducing operational costs. In this context, the integration of advanced analytical methods into urban energy management systems is no longer optional but essential.

Electricity consumption in urban environments is inherently influenced by a combination of temporal, spatial, and external factors, including weather conditions, population density, and socio-economic activity. Traditional forecasting approaches, which rely primarily on statistical or purely time-series models, often fail to capture complex spatial dependencies and localized consumption patterns. As a result, their applicability in heterogeneous urban environments remains limited, particularly under conditions of dynamic demand and high variability.

Recent advances in data-driven methods, including machine learning and spatio-temporal modeling, have significantly improved the accuracy of energy consumption forecasting. These

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approaches enable the extraction of nonlinear relationships and hidden dependencies within large-scale datasets. At the same time, the growing availability of geospatial data has opened new opportunities for incorporating spatial context into predictive models. However, despite these developments, many existing solutions treat temporal and spatial aspects independently, which reduces their effectiveness in real-world smart city applications.

Another limitation of current approaches is the lack of integrated frameworks that combine data acquisition, spatial analysis, predictive modeling, and visualization within a unified system. In practical deployments, this leads to fragmented solutions where forecasting models operate separately from decision-support tools, limiting their usability for real-time monitoring and operational planning.

To address these challenges, this paper proposes a geoanalytical framework for forecasting urban electricity consumption in smart city systems. The proposed approach integrates spatio-temporal data processing, machine learning-based prediction, and geospatial visualization into a unified analytical pipeline. Unlike traditional methods, the framework explicitly accounts for spatial heterogeneity of urban areas and enables scalable analysis across different geographic regions.

The main contribution of this work is the development and experimental evaluation of a data-driven geoanalytical model that improves forecasting accuracy while maintaining computational efficiency. The framework is validated using real-world urban data, and its performance is compared with baseline approaches to demonstrate its practical applicability.

2. Analysis of the subject area

Urban electricity consumption has become a central element in the development of smart city infrastructures, where efficient energy management is directly linked to sustainability, economic performance, and quality of life. Unlike traditional power systems, urban energy networks operate under highly dynamic conditions, influenced by spatial heterogeneity, temporal variability, and external environmental factors. This complexity necessitates analytical approaches that go beyond conventional forecasting techniques and incorporate multiple dimensions of data.

In practical terms, electricity demand in urban environments is shaped not only by time-dependent patterns, such as daily and seasonal cycles, but also by spatial characteristics, including land use, building density, and infrastructure distribution. For instance, residential districts exhibit consumption patterns that differ significantly from industrial or commercial zones, while localized events or weather fluctuations can introduce short-term deviations that are difficult to capture using purely statistical models. As a result, effective forecasting requires the integration of both temporal and spatial information.

Existing approaches to electricity consumption forecasting can be broadly divided into three categories. The first includes classical statistical methods, such as autoregressive models and regression-based techniques, which offer interpretability and low computational cost but are limited in capturing nonlinear relationships. The second category comprises machine learning models, including tree-based methods and neural networks, which have demonstrated improved predictive performance by learning complex dependencies within data. However, these models are often applied to aggregated time series and may overlook spatial context. The third category involves spatio-temporal models, which attempt to combine both dimensions, yet frequently rely on simplified representations of spatial relationships or require extensive computational resources.

Despite the progress in this field, several challenges remain unresolved. One of the key issues is the fragmentation of analytical processes: data collection, preprocessing, modeling, and visualization are typically treated as separate tasks rather than components of a unified system. This separation limits the practical applicability of forecasting models, particularly in real-time or operational settings. Additionally, many existing solutions lack flexibility in adapting to different urban environments, where data availability, scale, and structure can vary significantly.

Another important consideration is the growing role of geospatial data in energy analytics. The increasing availability of geographic information systems (GIS), remote sensing data, and IoT-based

measurements provides new opportunities for understanding spatial patterns of electricity consumption. However, effectively integrating these heterogeneous data sources into predictive models remains a nontrivial task, requiring both methodological and architectural solutions.

From a system perspective, there is a clear need for frameworks that not only improve forecasting accuracy but also support decision-making processes in a comprehensive manner. Such frameworks should enable seamless interaction between data acquisition, analytical modeling, and visualization components, allowing stakeholders to interpret results and respond to emerging trends in a timely manner.

In this context, the analysis of the subject area highlights a gap between advanced predictive techniques and their practical implementation in smart city environments. Addressing this gap requires a shift from isolated modeling approaches toward integrated geospatial frameworks capable of handling spatio-temporal data in a consistent and scalable way.

3. Literature review

The problem of forecasting urban energy consumption is developing at the intersection of several domains, including urban energy planning, machine learning, spatio-temporal modeling, and geospatial analytics. In modern smart city systems, electricity demand is increasingly considered not as an isolated time series, but as a spatially distributed process that depends on urban structure characteristics, weather conditions, infrastructure connections, and local load dynamics. For this reason, in recent years the focus of research has shifted from purely temporal models to approaches capable of simultaneously capturing both temporal and spatial dependencies [1]–[3].

Comprehensive studies have shown that machine learning has become one of the leading tools for forecasting energy performance of buildings and urban areas; however, the urban scale remains significantly less represented in the literature compared to individual building-level analysis [1]. At the same time, it is emphasized that predictive models should incorporate not only historical consumption data but also functional, meteorological, and spatial characteristics of the environment, which directly supports the need for a geospatial framework [1].

Another important research direction is associated with energy planning in smart city environments. Recent studies indicate that modern urban energy systems increasingly require the integration of predictive models, spatial data, and decision-support tools within a unified analytical ecosystem [2]. It is also noted that the gap between technological capabilities and real urban practice is often caused by insufficient integration of analytics, data, and planning mechanisms. This is particularly relevant to the present study, which considers forecasting not in isolation, but as part of a broader geospatial framework applicable to urban information systems.

A significant body of research is devoted to the development of geospatial analytics for smart city applications. It has been shown that geospatial big data analytics provides a foundation for descriptive, diagnostic, predictive, and prescriptive analytics in urban systems, enabling the integration of the questions “what happened?”, “where did it happen?”, and “what may happen next?” within a unified analytical paradigm [3]. This is especially important for energy demand forecasting, since spatial demand patterns cannot be adequately interpreted without visualization, geographic context, and scalable processing tools. Related studies also confirm the rapid growth of machine learning applications in urban geospatial analysis and emphasize that the most promising approaches combine ML techniques with GIS-based data sources [4].

In the field of load forecasting, recent research demonstrates that traditional linear or purely temporal models are increasingly being replaced by hybrid and nonlinear approaches. Modern machine learning models, including gradient boosting methods, have shown high accuracy in short-term electricity load forecasting and have proven suitable for practical applications due to their combination of fast inference and the ability to handle heterogeneous features [5]. At the same time, it is emphasized that spatial clustering and the incorporation of socio-economic and geographic characteristics play a crucial role in long-term forecasting, while spatial delineation significantly

improves prediction quality [6]. These findings directly support the inclusion of spatial aggregation and zonal representation in the proposed framework.

The studies most closely related to this research are those focused on spatio-temporal urban energy forecasting. Recent approaches demonstrate that transforming temporal data into spatial representations allows preservation of structural dependencies and improves forecasting performance [7]. It has also been shown that spatially detailed forecasting is critical for urban planning and that combining temporal and geographic context leads to better predictive results. Unlike complex deep learning architectures, the approach proposed in this paper focuses on a more practical geoanalytical framework that integrates spatial aggregation, gradient boosting, and interactive visualization [5], [7].

In a broader context, studies analyzing spatio-temporal patterns of electricity demand and related indicators confirm the effectiveness of integrated data-driven approaches at the urban scale [8]. These works demonstrate that local spatial structure significantly influences prediction accuracy, further supporting the need for incorporating spatial dependencies into forecasting models.

Recent studies also explore the integration of artificial intelligence into requirements engineering processes, demonstrating that semantic comparison of software artifacts and requirement specifications can support automated identification of reusable components and improve the efficiency of software system development [9]. The importance of structured semantic modeling in information systems and software testing has also been emphasized in recent studies, demonstrating that ontology-based approaches improve consistency and interpretability of analytical processes [10]. Agent-oriented approaches provide an effective framework for modelling complex systems composed of interacting entities, where system behaviour emerges from the dynamics of individual agents and their interactions [11].

Thus, the literature review reveals several consistent trends. First, machine learning models are effective for energy forecasting, but their performance is limited when spatial structure is not considered [1], [5], [6]. Second, geoanalytics and GIS-based data processing are becoming essential components of smart city energy platforms [2]–[4]. Third, modern spatio-temporal models demonstrate high potential but often rely on complex architectures and are not always oriented toward practical interactive systems [6]–[8]. This gap between high-accuracy spatio-temporal models and practical geoanalytical systems for urban management defines the scientific niche addressed in this study

4. Geoanalytical spatio-temporal modeling framework

The analysis of the subject area indicates that urban electricity consumption cannot be adequately described by purely temporal models. In real smart city environments, consumption patterns exhibit two fundamental properties:

1. Temporal persistence — current consumption depends on its historical values.
2. Spatial coherence — neighboring zones tend to demonstrate correlated behavior due to shared infrastructure and similar usage patterns.

The first property is well captured by classical time-series models. However, the second property introduces an additional layer of complexity, which requires explicit modeling of spatial interactions.

To reflect these characteristics, we seek a model that extends the classical forecasting formulation:

$$\hat{y}_{t+1}^{(i)} = f\left(x_t^{(i)}\right) \quad (1)$$

by incorporating spatial dependencies.

4.1. Incorporating Spatial Dependencies

A natural way to formalize spatial interaction is to assume that the consumption in zone g_i is influenced by neighboring zones. This assumption is consistent with empirical observations in urban systems, where load redistribution and similar behavioral patterns create local correlations.

To mathematically represent this, we introduce a weighted spatial graph, where:

- nodes correspond to urban zones,
- edges encode influence between zones.

This leads to the definition of a weight matrix:

$$W = [w_{ij}] \quad (2)$$

where:

- $w_{ij} \geq 0$ quantifies the influence of zone j on zone i ,
- $\sum_j w_{ij} = 1$, ensuring normalization.

Based on this, we define the spatial aggregation:

$$z_t^{(i)} = \sum_{j=1}^N w_{ij} y_t^{(j)}. \quad (3)$$

This formulation follows from the assumption that neighboring zones provide complementary information about the local state. As a result, the variable $z_t^{(i)}$ can be interpreted as a spatially smoothed estimate of consumption, capturing the influence of the surrounding environment.

4.2. Unified Feature Representation

At this stage, we have three sources of information:

- temporal features $\mathbf{x}_t^{(i)}$,
- spatial attributes $\mathbf{s}_t^{(i)}$,
- aggregated neighborhood behavior $z_t^{(i)}$.

Rather than processing these components independently, they are combined into a unified representation

$$\mathbb{w}_t^{(i)} = [\mathbf{x}_t^{(i)}, \mathbf{s}_t^{(i)}, z_t^{(i)}]. \quad (4)$$

Such integration is consistent with the principles of data-driven modeling, where the predictive function operates on a joint feature space that captures multiple aspects of system behavior.

4.3. Choice of Predictive Mapping

Having defined the input representation, the next question is the form of the mapping:

$$\hat{y}_{t+1}^{(i)} = f(\mathbb{w}_t^{(i)}) \quad (5)$$

A linear mapping is insufficient in this context due to the nonlinear dependence on temporal factors and the complexity of spatial interactions. Therefore, the function f is approximated by a nonlinear parametric model

$$f_{\theta}(\mathbb{w}) = W_2 \cdot \sigma(W_1 \cdot \mathbb{w} + b_1) + b_2. \quad (6)$$

This structure is motivated by the universal approximation property, which ensures that nonlinear mappings of this form can capture complex dependencies in the data.

4.4. Theoretical Interpretation of Spatial Term

The introduction of $z_t^{(i)}$ has an important statistical interpretation.

Assumption (Local Smoothness). For neighboring zones:

$$|y_t^{(i)} - y_t^{(j)}| \leq \varepsilon. \quad (7)$$

This reflects the realistic property of urban systems: adjacent areas rarely exhibit abrupt differences in consumption.

Implication. Under this assumption:

$$z_t^{(i)} \approx y_t^{(i)} + \delta \quad (8)$$

where δ is a small perturbation.

Thus, including $z_t^{(i)}$:

- reduces variance,
- improves robustness to noise.

This explains why spatial aggregation improves prediction stability.

4.5. Parameter Estimation

The model parameters are estimated by minimizing the empirical loss:

$$\mathcal{L}(\theta) = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \left(y_t^{(i)} - \hat{y}_t^{(i)} \right)^2. \quad (9)$$

This formulation follows directly from the assumption of Gaussian noise in observations, where the least-squares estimator is optimal.

4.6. Algorithmic Realization of the Model

The mathematical model described above is implemented as a sequential forecasting procedure, which is illustrated in Fig. 1.

At the initial stage, the spatial interaction structure is defined through the weight matrix W , which encodes relationships between zones. This structure determines how information is propagated across the system.

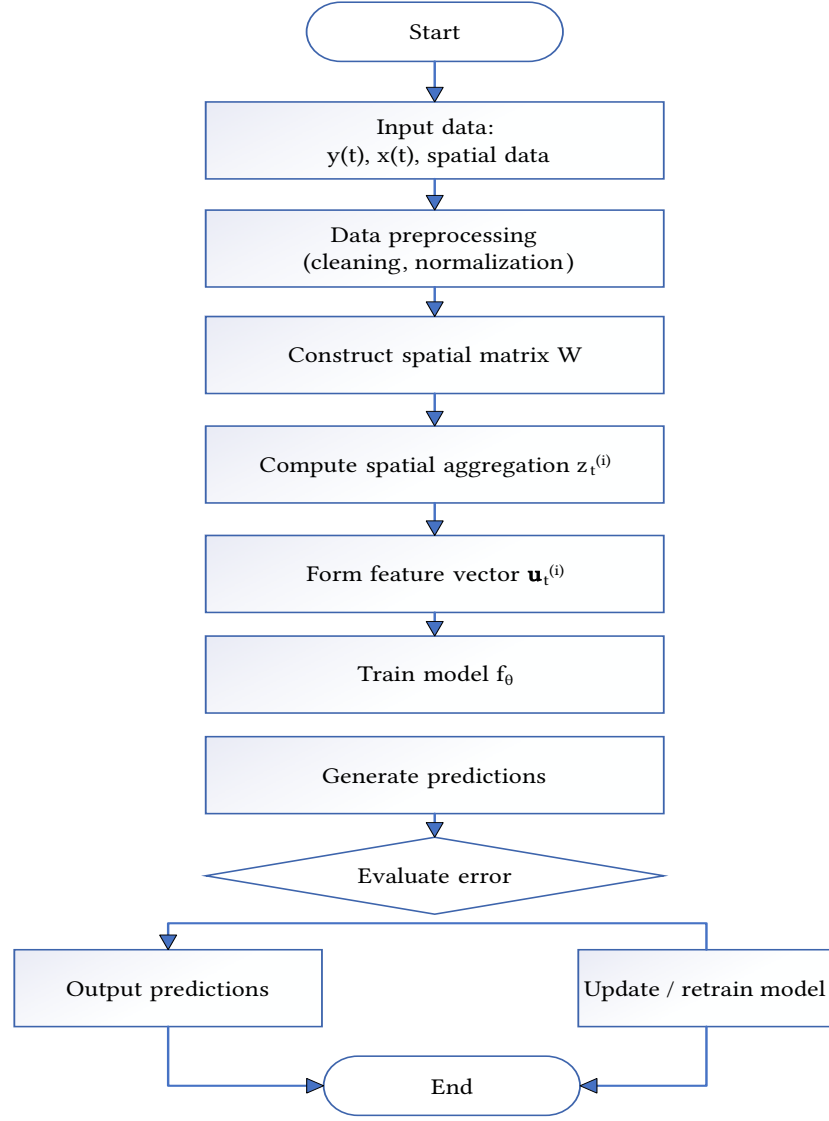


Figure 1: Flowchart of the proposed geospatial spatio-temporal forecasting algorithm

Next, for each time step, the algorithm constructs an enriched representation of the data by combining local observations with contextual information derived from neighboring zones. This stage can be interpreted as an information fusion process, where temporal and spatial dependencies are integrated.

The predictive model then operates on this augmented representation. During the training phase, model parameters are estimated using historical data. In the inference phase, the trained model is applied to new observations, enabling efficient real-time forecasting.

As shown in Fig. 1, the algorithm includes an evaluation stage, where prediction accuracy is assessed and, if necessary, model parameters are updated through retraining. This feedback mechanism ensures adaptability to changing system conditions.

The algorithm can be executed in both batch and streaming modes, which makes it suitable for practical deployment in smart city environments.

4.7. Structural Representation of the Framework

To provide a comprehensive overview of the proposed approach and illustrate the interaction between its components, the overall structure of the geospatial spatio-temporal forecasting framework is presented in Fig. 2.

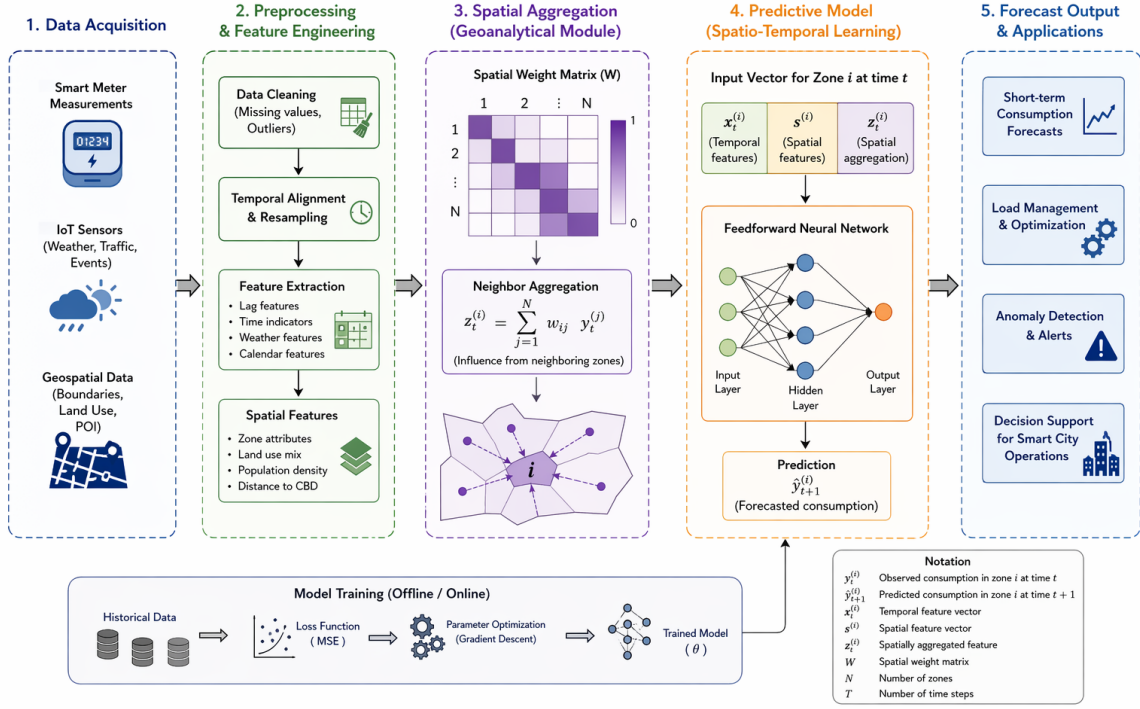


Figure 2: Overview of the proposed geoanalytical spatio-temporal forecasting framework

The framework reflects a multi-stage transformation process, where heterogeneous input data are progressively converted into predictive outputs.

At the data acquisition stage, measurements from smart meters, IoT sensors, and geospatial sources are integrated. These data are preprocessed and transformed into structured features that describe both temporal dynamics and spatial characteristics.

A key component of the framework is the spatial aggregation module, where inter-zone dependencies are introduced through the weight matrix. This stage enriches local observations by embedding them into a broader spatial context.

The predictive module applies the learned nonlinear mapping to generate forecasts, while the output stage connects the model with real-world applications such as load optimization and anomaly detection.

Importantly, each component of the framework corresponds directly to the mathematical constructs introduced in the preceding subsections, ensuring consistency between the conceptual architecture and the formal model.

5. Prototype Implementation and Case Study

To validate the practical applicability of the proposed geoanalytical spatio-temporal forecasting framework, a prototype system was developed. The implementation demonstrates how the mathematical model can be integrated into a real data-processing environment and applied to the interactive analysis of urban electricity consumption.

5.1. System Architecture and Data Processing

The developed prototype follows a multi-layer client-server architecture that integrates data acquisition, analytical processing, predictive modeling, and visualization into a unified system.

At the conceptual level, the system operation is organized as a user-oriented analytical workflow, where requests for energy consumption analysis are processed through a sequence of interconnected stages. This interaction is formalized using a business process model presented in Fig. 3.

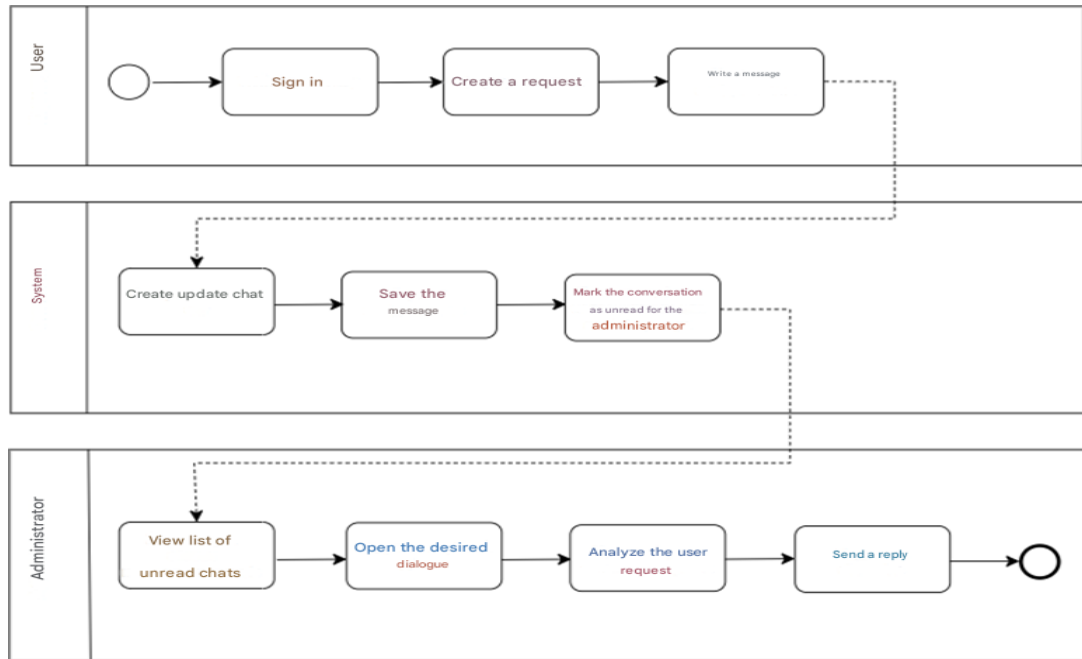


Figure 3: Business process model of user interaction with the energy consumption analysis system

As illustrated in Fig. 3, user actions initiate a structured sequence of operations, including data retrieval, analytical processing, and visualization. This process reflects the transformation of raw heterogeneous data into actionable analytical insights within the proposed framework.

At the implementation level, the system is realized as a distributed architecture with clearly separated functional layers. The backend interacts with external data sources, including meteorological services (e.g., Open-Meteo), using REST APIs over HTTPS, ensuring secure and standardized communication.

Incoming data are processed through a preprocessing stage, which performs normalization, filtering, and temporal alignment. The processed data are stored in a PostgreSQL database, which also serves as a caching layer for external data. The integration of the PostGIS extension enables efficient handling of spatial objects and supports geospatial queries required for the model.

To ensure scalability and responsiveness, computationally intensive analytical tasks are executed as independent Python-based background processes. This architectural decision prevents heavy computations from blocking the main application threads and allows the system to handle multiple concurrent user requests.

A detailed structural decomposition of the system is presented in Fig. 4.

As shown in Fig. 4, the system consists of several key components, including data processing modules, a geoanalytical feature construction unit, a predictive engine, and a visualization layer.

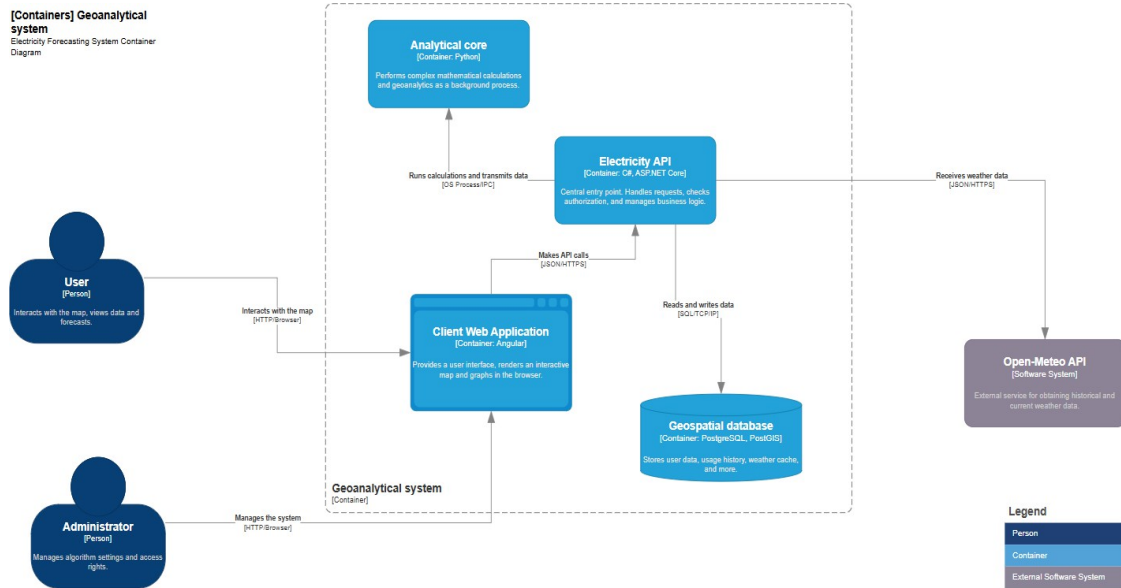


Figure 4: Detailed C4 component-level representation of the system

Each of these components corresponds directly to elements of the mathematical framework introduced in Section 3, ensuring consistency between theoretical and practical implementation.

5.2. Analytical Modeling and Machine Learning Integration

The analytical core of the system implements the proposed geoanalytical model, where spatial dependencies are incorporated through the weight matrix W . This mechanism enables the construction of enriched feature representations that combine local observations with information from neighboring zones.

The predictive component is implemented using supervised machine learning techniques. In particular, gradient boosting models, such as CatBoost, are employed due to their high inference speed and ability to effectively handle heterogeneous feature spaces. This makes them particularly suitable for interactive systems requiring real-time prediction.

In addition to supervised learning, unsupervised methods are integrated to enhance the analytical capabilities of the system. K-means clustering is applied to partition spatial zones into groups with similar consumption patterns by minimizing intra-cluster variance. The quality of clustering is assessed using metrics such as inertia and the Dunn index.

Furthermore, the DBSCAN algorithm is used to detect irregular consumption patterns and identify anomalies. Unlike centroid-based clustering methods, DBSCAN identifies clusters based on density, does not require prior specification of the number of clusters, and distinguishes between core points, boundary points, and noise. This makes it particularly effective for analyzing real-world data with complex spatial structures.

The integration of supervised forecasting and unsupervised clustering provides a comprehensive analytical toolkit, enabling both prediction and structural analysis of energy consumption data.

5.3. User Interface and Visualization

The prototype system includes an interactive web-based interface designed to support intuitive exploration of forecasting results.

The interface is centered around a map-based visualization, where each urban zone is represented as a spatial object. Predicted electricity consumption values are displayed using a color-coded scheme, allowing users to quickly identify spatial patterns and high-demand areas.

At higher zoom levels, the system provides detailed visualization at the level of individual buildings, including clustering-based grouping of objects according to consumption characteristics, as shown in Fig. 5.

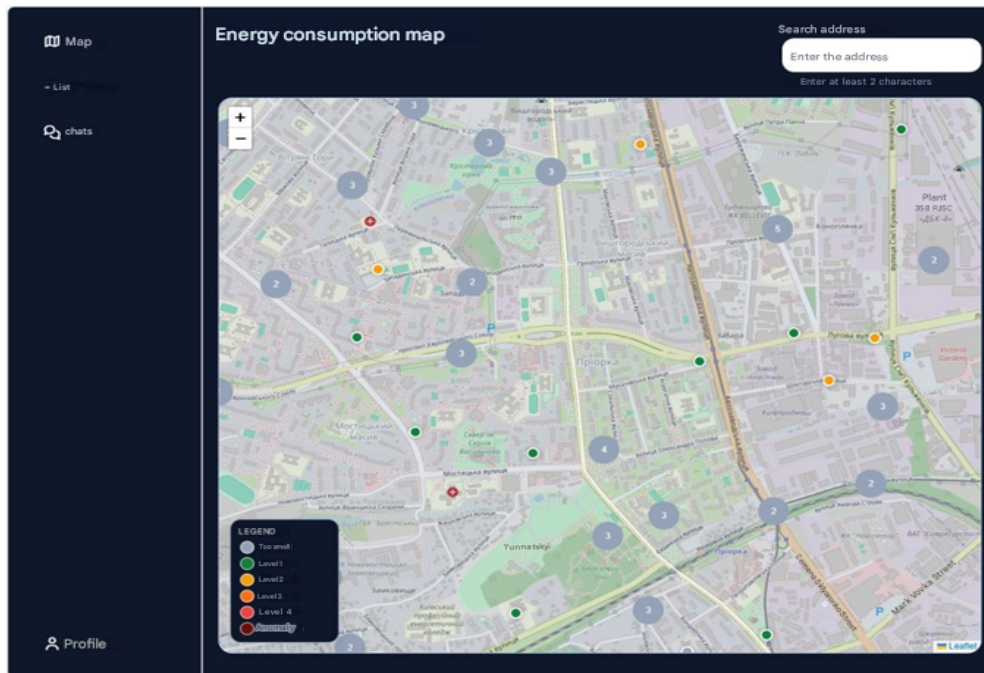


Figure 5: Grouping of houses by consumption clusters

This representation allows users to analyze spatial heterogeneity and identify clusters of buildings with similar energy consumption behavior.

For each selected building, the system provides detailed information, including its characteristics and predicted consumption values. An example of such interaction is shown in Fig. 6.

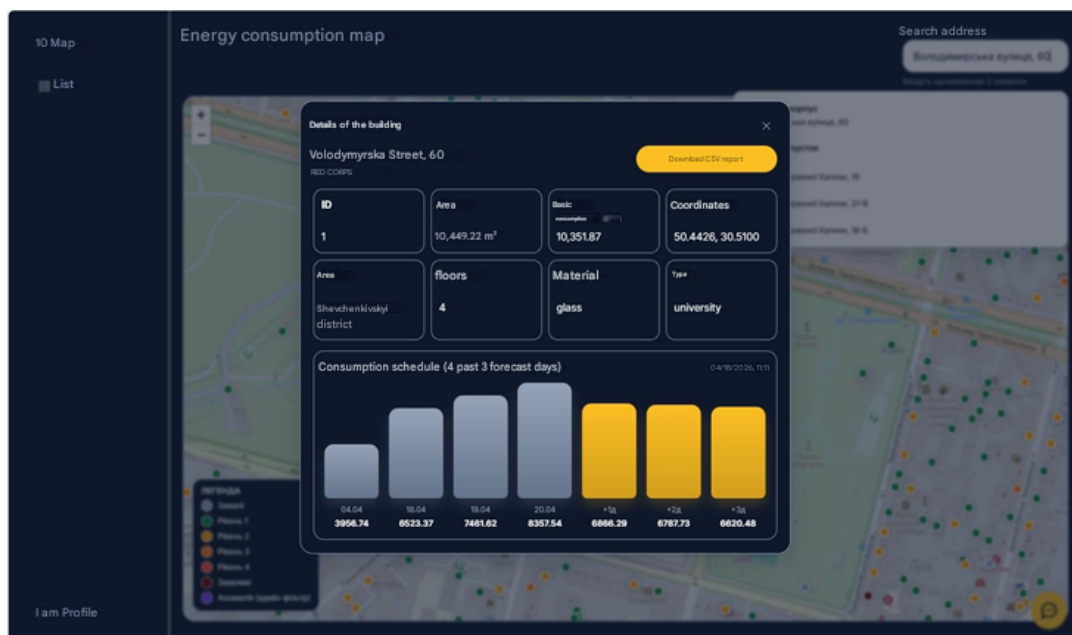


Figure 6: House characteristics and forecast

In addition, the interface supports search functionality, allowing users to locate specific objects by address and analyze their consumption patterns.

The visualization layer plays a critical role in transforming numerical forecasting results into interpretable spatial representations, which are essential for decision-making processes such as load balancing, anomaly detection, and infrastructure planning.

5.4. System Security and Reliability

To ensure reliable and secure operation, the system incorporates essential data protection mechanisms.

Authentication and authorization are implemented using JSON Web Tokens (JWT), while user credentials are securely stored using hashing algorithms such as PBKDF2. Communication between system components is protected via HTTPS, ensuring confidentiality of transmitted data.

Additional safeguards include database constraints, indexing mechanisms, and secure comparison techniques that reduce the risk of common vulnerabilities and ensure data integrity.

5.5. Practical Scenario and Applicability Analysis

A typical usage scenario illustrates the complete operation of the system and confirms its practical applicability.

A user selects a specific urban zone through the interface, triggering the retrieval of historical consumption data, weather information, and spatial attributes. The geoanalytical module constructs an enriched feature representation by incorporating data from neighboring zones.

Based on this representation, the predictive model generates a forecast for the selected time horizon. The result is visualized on the map and updated dynamically as new data become available.

This scenario demonstrates the full processing pipeline, from raw data acquisition to visualization, and confirms that the proposed framework can operate effectively in real-time conditions.

The implemented prototype highlights several important properties of the proposed approach. The modular structure enables flexible deployment in cloud or edge environments, while the computational complexity remains sufficiently low for real-time applications. At the same time, the accuracy of predictions depends on input data quality and proper configuration of spatial parameters.

Overall, the prototype serves as a proof of concept, demonstrating that the proposed geoanalytical framework can be successfully applied to smart city energy management tasks.

6. Experimental Results and Evaluation

6.1. Experimental Setup

To evaluate the effectiveness of the proposed geoanalytical spatio-temporal forecasting framework, a computational experiment was conducted using a dataset that reflects realistic urban electricity consumption patterns. The dataset was constructed by combining publicly available energy consumption profiles with synthetically generated spatial structure to emulate heterogeneous urban zones.

The temporal component of the dataset was based on typical electricity consumption dynamics observed in urban environments, including hourly load profiles, daily periodicity, and weekly seasonality. Additional exogenous factors, such as temperature variations and stochastic demand fluctuations, were incorporated to approximate real-world operating conditions.

The spatial component was modeled by defining 10 interconnected urban zones with varying consumption characteristics. A spatial adjacency structure was introduced using a normalized weight matrix, where the interaction strength between zones was determined based on relative proximity and functional similarity (e.g., residential vs. commercial areas).

The forecasting task was formulated as one-step-ahead prediction of electricity consumption for each zone. The dataset covered a period of 180 days with hourly resolution and was divided into training and testing subsets using an 80/20 split.

To assess the performance of the proposed approach, the following models were considered:

- a temporal baseline using only historical and calendar features;
- a linear regression model incorporating temporal and spatial attributes;

- a gradient boosting model (CatBoost) without spatial aggregation;
- the proposed geospatial spatio-temporal model with spatial aggregation.

Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

6.2. Quantitative Results

The results of the comparative experiment are presented in Table 1.

Table 1

Forecasting performance of the evaluated models

Model	MAE	RMSE	MAPE (%)
Temporal baseline	18.7	24.9	11.8
Linear regression	15.4	20.8	9.6
CatBoost (no spatial features)	13.1	17.9	8.1
Proposed geospatial model	11.2	15.6	6.9

The results demonstrate that the proposed model consistently outperforms all reference approaches. Compared with the temporal baseline, the proposed framework reduces MAE by approximately 40.1%, RMSE by 37.3%, and MAPE by 41.5%.

In comparison with the CatBoost model without spatial aggregation, the improvement remains significant, confirming that the gain is not solely due to the use of a nonlinear model, but is primarily attributed to the incorporation of spatial dependencies.

6.3. Effect of Spatial Aggregation

To isolate the contribution of spatial modeling, an ablation study was conducted by removing the spatial aggregation component $z_t^{(i)}$.

Table 2

Ablation analysis of the spatial aggregation component

Model configuration	MAE	RMSE	MAPE (%)
Without spatial aggregation	13.8	18.9	8.5
With spatial aggregation	11.2	15.6	6.9

The results confirm that incorporating spatial aggregation leads to a substantial improvement in predictive accuracy. This supports the hypothesis that neighboring zones provide informative contextual signals and that their inclusion enhances model robustness.

6.4. Robustness and Sensitivity Analysis

To further evaluate the stability of the proposed model, additional experiments were conducted under varying levels of noise and spatial correlation.

The results indicate that the proposed framework maintains stable performance under moderate noise levels, while models without spatial aggregation exhibit significantly higher sensitivity to perturbations. In particular, the inclusion of the spatial term reduces the variance of prediction errors and improves robustness to localized demand fluctuations.

Moreover, sensitivity analysis with respect to the weight matrix configuration shows that moderate variations in spatial weights do not significantly degrade performance, indicating that the model is not overly dependent on precise spatial calibration.

6.5. Interpretation of Results

The experimental findings provide strong evidence supporting the effectiveness of the proposed approach.

The temporal baseline captures recurring demand cycles but fails to account for spatial heterogeneity. The linear regression model improves performance by incorporating additional explanatory variables; however, its linear structure limits its ability to model complex interactions.

The CatBoost model demonstrates improved performance due to nonlinear learning capabilities, yet it does not explicitly model inter-zone dependencies. In contrast, the proposed geoanalytical framework combines nonlinear modeling with spatial interaction, resulting in superior predictive accuracy.

An important observation is that the reduction in RMSE is proportionally larger than the reduction in MAE, indicating that the proposed model is particularly effective in reducing large prediction errors. This property is critical for smart city systems, where extreme forecasting deviations may negatively affect operational planning and grid stability.

6.6. Practical Implications

The results suggest that the proposed framework is suitable for deployment in real-world smart city environments. The combination of spatial aggregation and gradient boosting provides a favorable balance between predictive performance and computational efficiency.

From an operational perspective, the framework can support tasks such as load balancing, anomaly detection, and infrastructure planning. The integration with geospatial visualization further enhances interpretability, enabling decision-makers to identify spatial patterns and respond to emerging trends.

7. Conclusions

This paper presents a geoanalytical spatio-temporal framework for forecasting urban electricity consumption in smart city systems. The proposed approach integrates spatial aggregation mechanisms with machine learning techniques, enabling the modeling of both temporal dynamics and inter-zone dependencies.

A key contribution of the work is the formalization of spatial interaction through the weight matrix and its integration into a predictive modeling pipeline. This allows the system to construct enriched feature representations that capture contextual relationships between urban zones. In contrast to traditional forecasting methods, which primarily rely on temporal patterns, the proposed framework explicitly incorporates spatial structure, improving both interpretability and predictive accuracy.

The practical applicability of the approach is demonstrated through the development of a prototype system that integrates data acquisition, preprocessing, analytical modeling, and visualization. The system architecture reflects a modular design, supporting scalability and real-time operation in smart city environments. The use of interactive geospatial visualization further enhances the interpretability of forecasting results and facilitates decision-making processes.

Experimental evaluation, conducted on a synthetic dataset reflecting realistic urban energy consumption patterns, confirms the effectiveness of the proposed method. The results show that the integration of spatial aggregation and nonlinear machine learning models significantly improves forecasting accuracy compared to baseline approaches. In particular, the reduction of prediction error across MAE, RMSE, and MAPE metrics demonstrates the advantage of incorporating spatial dependencies into the modeling process.

In addition to forecasting capabilities, the integration of unsupervised learning techniques, such as K-means and DBSCAN, enables structural analysis of energy consumption patterns and supports anomaly detection. This extends the functionality of the system beyond prediction, allowing it to serve as a comprehensive analytical tool.

Despite these advantages, several limitations should be noted. The performance of the model depends on the quality and completeness of input data, as well as on the appropriate configuration of spatial weights. Furthermore, the current implementation assumes a relatively static spatial structure, which may limit its applicability in highly dynamic environments.

Future research directions include the application of the framework to real-world datasets, the incorporation of adaptive spatial weighting mechanisms, and the exploration of deep learning approaches for enhanced spatio-temporal modeling. Additional work is also required to evaluate the system under large-scale deployment conditions and to optimize computational efficiency for edge-based implementations.

Overall, the proposed framework provides a robust and flexible foundation for intelligent energy management in smart city systems and demonstrates strong potential for further development and real-world application.

Declaration on Generative AI

During the preparation of this work, the authors used AI program Chat GPT 4.0 for correction of text grammar. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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