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Energy Consumption Forecasting in Smart Cities Using Machine Learning

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Abstract

Accurate forecasting of electricity consumption is a foundational requirement for smart cities, enabling grid stability, demand response, energy efficiency initiatives, and long-term infrastructure planning. Over the past decade, significant advances in data availability from smart meters and Internet of Things (IoT) devices, combined with progress in machine learning (ML) and deep learning (DL), have transformed the landscape of urban energy forecasting. This paper presents a comprehensive survey of energy consumption forecasting techniques applied in smart city contexts. We systematically review classical statistical approaches, machine learning models, deep learning architectures, hybrid techniques, and emerging transformer-based methods. The survey also examines commonly used datasets, feature engineering practices, evaluation metrics, uncertainty quantification techniques, and deployment considerations such as privacy, explainability, and federated learning. By synthesizing recent literature, this paper highlights strengths, limitations, and open research challenges, and provides guidance for researchers and practitioners in selecting appropriate forecasting models for different smart city scenarios.

1. Introduction

The concept of smart cities integrates digital technologies, sensing infrastructures, and intelligent decision-making to enhance urban sustainability and quality of life. Energy systems are a core component of this vision, as cities account for a major share of global electricity consumption and greenhouse gas emissions. Accurate forecasting of electricity demand at building, district, and city levels supports critical applications such as real-time grid operation, renewable energy integration, demand-side management, and long-term capacity planning.

Electricity load forecasting is traditionally categorized into short-term (minutes to days), medium-term (weeks to months), and long-term (months to years) horizons, each serving different operational and planning objectives. While classical statistical techniques dominated early research, the proliferation of smart meters and high-resolution sensor data has enabled the adoption of machine learning and deep learning methods capable of modelling complex, non-linear consumption patterns.

The rapid growth of forecasting approaches has resulted in a fragmented body of literature, making it difficult for researchers and practitioners to assess which models are most suitable for specific smart city contexts. This survey aims to consolidate and structure existing knowledge, focusing on methodological trends, comparative insights, and practical considerations beyond raw predictive accuracy.

The main contributions of this survey are:

* A structured review of classical, machine learning, deep learning, hybrid, and transformer-based energy forecasting models

* A synthesis of commonly used datasets, features, and evaluation metrics in smart city studies

* A discussion of uncertainty estimation, privacy preservation, and deployment challenges

* Identification of open research directions for future smart city energy forecasting systems

2. Taxonomy of Energy Forecasting Approaches

Energy consumption forecasting methods in smart cities can be broadly classified into five categories: classical statistical models, machine learning models, deep learning models, hybrid approaches, and transformer-based architectures. Figure-based taxonomies are often used in the literature to illustrate this progression from linear to highly non-linear and data-driven models.

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3. Classical Statistical Methods

Classical time-series forecasting methods form the foundation of energy demand prediction research. Widely used techniques include Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Exponential Smoothing (ETS).

Strengths

* Strong interpretability

* Well-suited for stationary and seasonal data

* Low computational requirements

Limitations

* Limited ability to model non-linear relationships

* Performance degrades with complex exogenous factors

* Scalability challenges for large, multivariate datasets

Despite these limitations, statistical models remain important as baseline methods and are still applied in short-term forecasting scenarios with stable consumption patterns.

4. Machine Learning-Based Methods

Machine learning approaches gained popularity as smart city datasets began incorporating exogenous variables such as weather, calendar effects, and occupancy indicators. Commonly used algorithms include linear regression variants, support vector regression, random forests, and gradient boosting methods such as XGBoost, LightGBM, and CatBoost.

Strengths

* Effective handling of heterogeneous and feature-rich data

* Strong performance with proper feature engineering

* Relatively good interpretability compared to deep models

Limitations

* Dependence on manual feature engineering

* Limited capacity to model long-term temporal dependencies without windowing strategies

Gradient boosting models, in particular, are frequently reported as strong baselines in smart city forecasting benchmarks.

5. Deep Learning Approaches

Deep learning models automatically learn temporal and spatial representations from raw data, reducing the reliance on handcrafted features.

5.1 Recurrent Neural Networks and LSTM

Long Short-Term Memory (LSTM) networks are the most widely adopted deep learning models for energy forecasting. Variants include stacked LSTMs, bidirectional LSTMs, and attention-augmented architectures.

***Advantages:-**

* Ability to capture temporal dependencies

* Suitable for high-resolution smart meter data

***Challenges:-**

* Training instability and hyperparameter sensitivity

* Limited parallelization

5.2 Convolutional Neural Networks

CNNs are often combined with LSTMs to capture local temporal patterns or spatial correlations across buildings and districts.

6. Hybrid Forecasting Models

Hybrid models combine complementary techniques to exploit their respective strengths. A common strategy integrates LSTM networks for baseline sequential modeling with tree-based models to predict residuals or peak demand.

Benefits of Hybrid Models

* Improved peak-load prediction

* Better robustness to irregular consumption patterns

* Enhanced accuracy across multiple horizons

Hybrid approaches are particularly effective in smart city environments influenced by events, behavioral changes, and extreme weather conditions.

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7. Transformer-Based Time-Series Models

Inspired by advances in natural language processing, transformer architectures use self-attention mechanisms to model long-range dependencies. Time-series-specific adaptations such as Informer, Autoformer, and hybrid transformer models have recently been applied to energy forecasting.

Advantages

* Superior modeling of long-term dependencies

* High parallelization efficiency

Limitations

* High computational cost

* Data-intensive training requirements

Current literature suggests that transformers are especially promising for multivariate and long-horizon forecasting tasks in smart cities.

8. Data Sources and Feature Engineering

8.1 Common Data Sources

* Smart meter energy consumption data

* Weather and climate variables

* Calendar and socio-economic indicators

* Grid-level and distributed energy resource data

8.2 Preprocessing Practices

* Time alignment and resampling

* Missing value imputation

* Normalization and scaling

* Lagged and rolling statistical features

9.Evaluation Metrics and Uncertainty Estimation

Forecasting performance is commonly evaluated using MAE, RMSE, and MAPE, with peak-oriented metrics gaining attention for grid reliability. Recent studies emphasize probabilistic forecasting, employing techniques such as quantile regression, ensembling, and Monte Carlo dropout to estimate uncertainty.

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10. Deployment, Privacy, and Explainability

Smart city energy forecasting systems must operate under strict privacy and reliability constraints. Federated learning and edge computing are increasingly explored to minimize data sharing. Explainability techniques, including SHAP and attention visualization, help improve trust and adoption by grid operators and policymakers.

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11. Open Challenges and Future Research Directions

Key challenges identified in the literature include:

* Data heterogeneity and quality issues

* Distribution shifts due to renewable integration and electric vehicles

* Scalability of deep models for city-wide deployment

* Balancing accuracy, interpretability, and privacy

Future research is expected to focus on adaptive, uncertainty-aware, and privacy-preserving forecasting systems tailored to evolving smart city infrastructures.

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12. Conclusion

This survey reviewed the evolution of energy consumption forecasting methods in smart cities, from classical statistical techniques to advanced deep learning and transformer-based models. No single approach is universally optimal; model selection depends on forecasting horizon, data availability, and operational constraints. By consolidating current knowledge and identifying research gaps, this survey aims to support the development of robust and sustainable energy forecasting solutions for future smart cities.

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