AI-based Energy Forecasting for Net Zero Smart Cities

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***Abstract*—The transition toward net-zero smart cities necessitates advanced energy forecasting methodologies to enhance sustainability, optimize energy distribution, and balance supply-demand dynamics. Artificial Intelligence (AI) has emerged as a transformative tool in this domain, leveraging machine learning (ML) and deep learning (DL) techniques to provide highly accurate and adaptive energy predictions. This paper explores AI-driven energy forecasting frameworks, emphasizing the integration of real-time data from IoT-enabled smart grids, weather prediction models, and historical energy consumption patterns. Key AI methodologies, including time-series forecasting models, reinforcement learning strategies, and hybrid AI techniques, are examined for their efficacy in optimizing energy management. Additionally, this study addresses major challenges such as data integrity, model scalability, and cybersecurity risks associated with AI-driven energy systems. Through case studies and comparative analyses, we highlight the tangible benefits of AI in achieving net-zero energy objectives, offering insights into future advancements for sustainable urban development.**

***Index Terms*—AI-based energy forecasting, smart cities, net-zero energy, machine learning, deep learning, renewable energy, energy management**

I. Introduction

The rising global energy demand and the urgency to cut carbon emissions are driving the shift toward net-zero smart cities, where balancing renewable energy production and consumption is crucial. Effective energy forecasting ensures grid stability, optimizes distribution, and minimizes waste. Traditional methods struggle with the complexities of modern energy systems, including fluctuating demand and uncertain renewable generation. AI has revolutionized forecasting by leveraging machine learning (ML) and deep learning (DL) to analyze historical data, weather patterns, and real-time inputs for accurate predictions. This paper explores AI-driven forecasting techniques, their integration with smart grids, and their role in optimizing renewable energy use. Additionally, it examines key challenges such as data integrity, scalability, and cybersecurity, highlighting real-world applications and their impact on sustainable urban development [1].

II. Techniques, Challenges and Solutions

A. AI Techniques for Energy Forecasting

Table I illustrates the AI approaches that are used in energy forecasting [2].

TABLE I
Different Energy Forecasting Methods

Category	Approach	Description
Regression-based	Linear Regression, SVR, Semiparametric	Use historical patterns and smoothing splines to predict energy demand and peak consumption.
Time Series-based	ARMA, ARIMA, SARIMA	Capture temporal dependencies, trends, and seasonal patterns.
Ensemble-based	Bagging, Random Forest, Gradient Boosting Machine, XGBoost	Multiple models combined through aggregation to improve prediction accuracy.
Deep Learning-based	RNN, GRU, LSTM	Neural networks with memory mechanisms to model complex temporal dependencies.
	Attention and Transformer-based Models	Advanced attention mechanisms for enhanced energy forecasting with long-range dependencies.
Hybrid Approaches	CNN-LSTM-Attention, Ensemble + Neural Networks	Combined architectures integrating multiple techniques for enhanced forecasting.

B. Challenges and Solutions

Challenges in AI-based energy forecasting include data quality issues, scalability constraints, and cybersecurity risks. Incomplete or inconsistent datasets can reduce model accuracy, necessitating data augmentation techniques to enhance reliability. Privacy and security concerns arise when collecting real-time energy data, requiring stringent data protection measures. Scalability and real-time processing pose another challenge, as large-scale urban energy systems demand high computational efficiency, which can be addressed through edge computing and cloud-based AI architectures. Additionally, cybersecurity threats, such as data breaches and adversarial attacks, can compromise AI models, making it essential to implement AI-driven anomaly detection and secure model deployment strategies to mitigate risks. Addressing these challenges is critical for ensuring robust, scalable, and secure AI-driven energy forecasting solutions in net-zero smart cities [3].

III. Literature Review

The transition to net-zero smart cities is a growing priority in urban development, driven by increasing global energy demand and the imperative to reduce carbon emissions. Numerous studies have highlighted the limitations of traditional energy forecasting methods when applied to complex energy systems with fluctuating demand and renewable energy generation, leading to increased adoption of AI-based approaches. AI systems will autonomously manage real-time adjustments for many applications such as traffic flow, energy consumption, and public safety. This technological evolution represents a fundamental shift in how cities approach energy management, moving from reactive to proactive strategies that anticipate and respond to energy demands before they manifest.

Machine learning algorithms have been extensively explored for energy forecasting due to their ability to identify patterns in historical data, with various methodologies demonstrating effectiveness across different scenarios. Techniques such as predictive analytics and machine learning play a significant role in forecasting energy demand, predicting renewable generation, and optimizing energy storage utilization. Traditional machine learning approaches include regression models such as linear regression, random forest, and XGBoost, which have proven effective for predicting energy demand based on historical data patterns.

A. Regression-based Approaches

Regression-based methods, such as linear regression and support vector regression, remain foundational due to their interpretability and ease of deployment. [4] developed a methodology for hourly load forecasting aimed at anticipating both regular demand and peak consumption levels. They built a multiple regression model, employed on a rolling, short-term basis (typically hourly to next-day horizons) to generate forecasts. The model is rigorously evaluated on actual system data, demonstrating strong short-run predictive performance in tightly controlled experiments against a wide range of alternative models, thus improving utility operations through more reliable peak detection. [5] proposed a regression-based approach to generate probabilistic forecasts for both the size and timing of peak electricity demand. Their method differed from conventional forecasting by modeling full probability distributions, which helped capture the uncertain timing and size of peaks. They used regression-based models that take both lagged load values and exogenous variables as predictors, which are then combined with statistical techniques to produce predictive distributions rather than single estimates. Their method outperformed conventional deterministic forecasts in accuracy and reliability, providing valuable insights for grid operators and planners who must manage risks associated with extreme demand events. While these methods relied on foundational regression techniques, the work remains influential. Later advancements have built upon this by incorporating probabilistic methods and ensemble regression strategies to further improve performance and uncertainty quantification.

One drawback of classic regression models is that they often fall short when faced with the inherently nonlinear and highly variable behavior of energy systems in urban environments. To overcome these limitations, many more advanced techniques, such as semiparametric approaches, or ensemble-based methods, have been adopted.

There have been reviews on how forecasting in today's competitive power markets has shifted from rigid, fully parametric models to highly flexible, data-driven techniques [6]. This trend towards computationally intensive, semi- or nonparametric methods builds directly on the semiparametric regression method, which mix the interpretability of parametric models with the flexibility of nonparametric techniques. [7] used a semiparametric regression model to estimate how weather affected residential electricity sales. To handle the nonlinear relationship between electricity use and temperature, they extended smoothing spline regression to handle complications such as billing cycle or covariates, and use generalized cross-validation to select the optimal degree of smoothing. Building on top of that, [8] proposed a semiparametric density forecasting methodology for long-term peak electricity demand that forecasted full probability distributions of future peak loads up to 10 years ahead rather than just single point estimations. They combined semi-parametric additive models, which included splines for temperature effects and linear terms for economic/demographic variables, with a double seasonal block bootstrap to generate realistic future temperature paths, while still preserving serial dependence and seasonality. Results have shown that their method achieved high accuracy in reproducing observed demand distributions and provides useful probability-of-exceedance levels for planners.

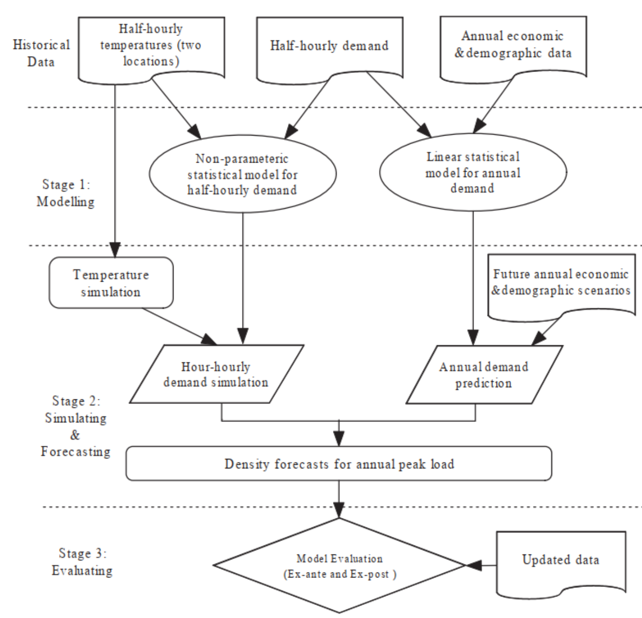

Fig. 1. Diagram of semiparametric density forecasting methodology of [8]

B. Time Series-based Approaches

Time series models have been a core part of energy forecasting due to their ability to explicitly capture temporal dependencies, trends, and seasonality inherent in energy consumption and generation data. Classical models such as Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) have been widely employed for short to medium-term load forecasting. These models offer interpretability and are particularly effective in scenarios where historical patterns dominate future behavior. Despite their limitations in handling nonlinearity and complex feature interactions, time series models continue to serve as strong benchmarks and are often used in hybrid systems with machine learning models.

1) Autoregressive Moving Average (ARMA): ARMA model combines autoregressive (AR) and moving average (MA) components to model stationary time series by capturing both the momentum and shock effects present in past data. It is best suited for short-term forecasts when the data exhibits no trend or seasonality. [9] presented an ARMA mode to forecast short-term solar potential from hourly solar radiation data recorded in Dakar, Senegal. The modeling process involved checking the stationarity of the time series via the augmented Dickey-Fuller test, selecting optimal ARMA parameters using the Akaike Information Criterion, and validating the model with white noise tests on residuals. The best performing model achieved RMSE = 0.629, MAE = 0.528. Similarly, [10] proposed a step-by-step methodology to predict hourly PV solar power output using ARMA models on hourly power data from a solar installation in Australia. Unlike in the previous method, these ARMA models' optimal parameters were selected using Bayesian Information Criterion instead. The best performing model achieved MAE = 39.6 MW and RMSE = 61.0 MW. These results demonstrate that the ARMA model is effective for 24-hour ahead solar radiation prediction and can support photovoltaic energy planning in various regions. Furthermore, ARMA models were also applied to other types of energy forecasting, such as wind power [11].

2) Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA): The ARIMA model extends ARMA by introducing an integration (I) term to account for non-stationarity through differencing, making it suitable for series with trends or changing levels over time. SARIMA further generalizes ARIMA by incorporating seasonal autoregressive and moving average terms, making it effective for datasets with strong periodic patterns such as daily, weekly, or yearly cycles in energy demand. ARIMA and SARIMA have been widely used for electricity load forecasting, especially when external variables are not required. [12] applied the ARIMA method to forecast medium and long-term electrical energy consumption using hourly data aggregated into monthly totals from 2004 to 2018. After testing for stationarity and applying differencing (d = 2), the authors evaluated numerous ARIMA(p,d,q) combinations to find the best model, which achieved the lowest RMSE of 753,983.98 for monthly predictions and an average of 94.7% accuracy. [13] applied the ARIMA model to forecast monthly electricity demand using historical data from an electricity provider in Pennsylvania. The ARIMA model parameters were selected based on analysis of the Partial Autocorrelation Function and Autocorrelation Function, and were trained and tested on decomposed data, yielding a test MAPE of 0.0495. Results have shown that the best ARIMA model's forecasts for the years 2021–2025 showed consistent seasonal patterns, supporting the model's applicability for domestic and commercial energy planning. Later, [14] explored the use of SARIMA models to forecast electricity demand based on time series data from Tetouan, Morocco. The SARIMA model was configured with non-seasonal parameters and seasonal parameters to capture both short and long-term trends. Results have shown that the model accurately predicted near-term electricity consumption patterns, but faced increasing uncertainties for long-term forecasts, leading to wider confidence intervals. These study tells us that ARIMA and SARIMA models are effective for short-term electricity demand forecasting and highlights the need for parameter tuning to enhance long-term prediction reliability.

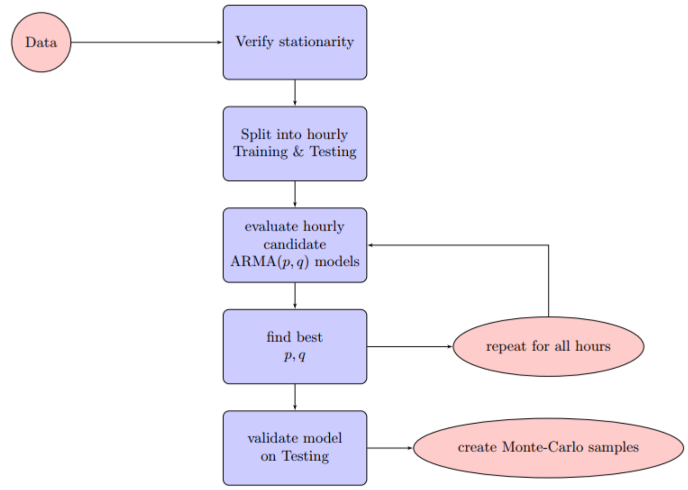

Fig. 2. Diagram of solar forecasting using ARMA model proposed by [10]

C. Ensemble-based Approaches

Following the development of semiparametric and time series methods, ensemble-based methods have emerged as a powerful class for energy forecasting, due to their ability to integrate multiple models and capture complex patterns, enhancing both predictive accuracy and robustness under uncertainty. Ensemble learning combines the predictions of multiple base models to produce a composite forecast that typically outperforms any individual model. These methods are particularly well-suited to energy forecasting, where load patterns, weather influences, and demand variability introduce significant complexity.

1) Bagging: One of the most straightforward ensemble strategies is bagging, or bootstrap aggregation, which trains multiple models on different bootstrapped subsets of data and averages their outputs. Many research applied bagging ensemble learning into multiple different optimization algorithms. [15] applied bagging for day-ahead electricity price forecasting across six major power markets. They compared bagging against the LASSO shrinkage method within a large-scale multivariate model that captures autoregressive, nonlinear, periodic, and weekday effects. Bagging helps improves robustness by resampling the training data, applying model selection via t-statistics in each bootstrap sample, and averaging the forecasts. Intra-day price dependencies were also taken into account using principal component analysis (PCA). Results have shown that their proposed bagging model outperformed LASSO in most settings in terms of forecast accuracy, especially when the predictor set was large and multicollinearity was present, and the best performance was achieved when bagging was combined with PCA augmentation. [16] proposed a machine learning approach for predicting monthly electricity consumption in Saudi Arabia using a K* instance-based learner and a Bagging ensemble approach. The K* model, which uses an entropy-based distance measure, was optimized by tuning its global blend parameter and compared to baseline models such as linear regression, SVM or ANN. The optimized K* alone achieved high accuracy, and incorporating bagging further improved its performance, achieving MAPE = 0.1511, RMSE = 0.0484. The Bagging-K* ensemble outperformed in nearly all error metrics when compared to an ANN trained on the same data, demonstrating better generalization and lower forecast error.

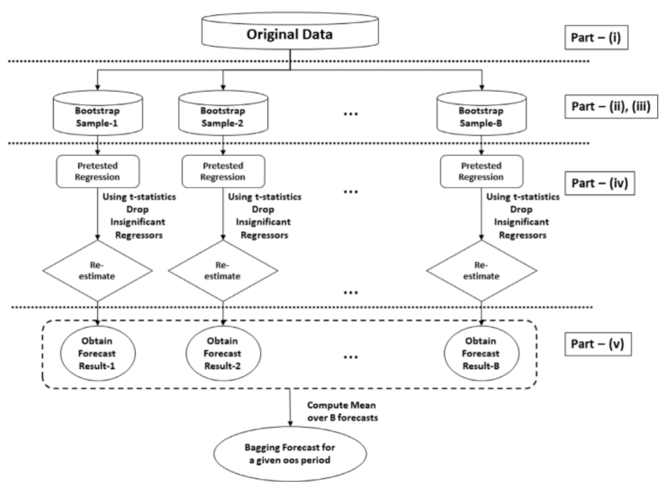

Fig. 3. A schematic representation for bagging forecasting proposed by [15]

2) Random Forest: Random Forest (RF), a widely used bagging method, is also commonly applied in energy forecasting due to their resilience to noise and overfitting. [17] developed and tested RF ensemble models for hourly electricity use prediction in two educational buildings at the University of Florida. The RF's key parameters, such as number of trees, minimum terminal nodes, or mtry, were optimized through cross-validation and they were train on both yearly datasets and semester-specific datasets to explore how seasonal patterns affect accuracy. Results have shown that RF significantly outperformed other methods like Regression Trees and Support Vector Regression, achieving lower test MAPE 7.75% on yearly dataset and 2.81% on monthly dataset. [18] proposed combining PCA with multiple machine learning models, including RFs, to enhance the prediction of building energy consumption. PCA is used as a feature reduction technique to eliminate less influential variables from a 20-feature dataset based on meteorological and operational data, and the remaining features are then used to train and test the predictive models across four distinct climate zones in Iran. Results have shown that PCA significantly reduced execution time while preserving or even improving model accuracy compared to randomly reduced or full-feature datasets. Among the models, RF and Regression Tree performed best, with RF excelling in cities with moderate climates (Tehran and Yazd) and Regression Tree performing better in extreme climates (Tabriz and Bandar Abbas).

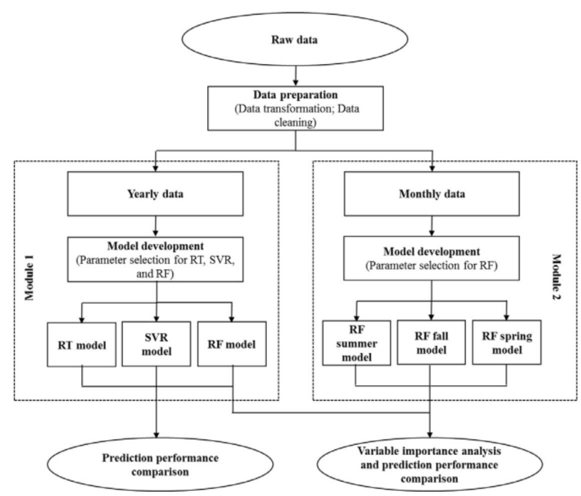

Fig. 4. A schematic representation for Random Forest-based forecasting proposed by [17]

Later, [19] presented a comprehensive evaluation of RF for short-term load forecasting (STLF) across four European countries. In their experiments, seven different pattern types were tested, ranging from week-long sequences to hybrid daily + weekly representations, and the RF models were trained on three different modes: local (only on past days of the same weekday/hour), global (on all historical data), and global extended (global with extra calendar features). Extensive experiments using real-world hourly electricity load data from Poland, Great Britain, France, and Germany demonstrate that the global-extended training mode yielded the most accurate forecasts on 3-week-hourly patterns for Poland, France, Germany, and on the daily + weekly pattern for Great Britain, achieving test MAPEs of 1.05% (PL), 2.36% (GB), 1.67% (FR) and 1.06% (DE), outperforming many classical statistical models and advanced tree ensembles. [20] proposed a novel ensemble RF model for forecasting annual seismic energy, validated globally and applied to the Western Himalayas. In their experiments, the global seismic-energy time series was converted to log-scale and decomposed via Ensemble Empirical Mode Decomposition (EEMD) into a stationary component and a non-stationary combination. Additionally, the raw log-energy and the calendar year were also included as inputs, as intrinsic modes alone struggled to predict endpoint values. Multiple base learners were trained separately on these inputs, and then stacked into a second-level RF of 300 trees to produce the final prediction. This ensemble model significantly outperformed all base learners in both global and regional applications, achieving the lowest test RMSE = 0.236 on Western Himalayas 1964–2023 data and forecasting 2024 seismic energy at approximately $7.2 \times 10^{14} J$, demonstrating its promise for seismic hazard preparedness.

3) Gradient Boosting Machine and XGBoost: Gradient Boosting Machine (GBM) and XGBoost are even more powerful techniques that are adapted to energy forecasting due to their high accuracy, ability to handle nonlinearity, and robustness to overfitting through regularization techniques. Unlike bagging-based models like Random Forests, which build trees in parallel, GBM and XGBoost build trees sequentially, where each new tree corrects the residual errors of the previous ones. [21] proposed a Gradient Boosting Decision Tree model to forecast day-ahead energy consumption for customers of an Italian energy distribution company, aggregated across its seven market zones. They trained LightGBM models monthly with a weighting scheme across surrounding months to emphasize relevant time periods. Results have shown strong performance, with MAPE ranging from 5–15% depending on the region and month. The Gradient Boosting model notably outperforms other baselines, especially during holiday periods when traditional models fail to capture consumption anomalies. [22] compared LightGBM with k-Nearest Neighbors (kNN) for wind energy forecasting using a dataset of weather variables (wind speed, direction, temperature, humidity, pressure, solar radiation) and energy output from a wind farm. While the KNN model's optimal neighborhood size was selected via grid search, LightGBM's hyperparameters were tuned via Bayesian optimization and it achieved superior results (RMSE = 104.1 MW, 93.7% accuracy. This shows that while both methods can forecast wind energy, LightGBM's ability to capture complex, nonlinear relationships leads to significantly better predictive performance.

[23] proposed a comprehensive electricity consumption forecasting approach based on XGBoost to handle diverse user behavior patterns and multiple influencing factors in regional power systems. Users are first grouped into clusters with K-means clustering to capture distinct consumption patterns. For each cluster, the Maximum Information Coefficient is used to identify the most relevant features, which are then used to train separate XGBoost models. Experiments demonstrated that XGBoost outperformed RF in both RMSE (2.09 compared to 2.53) and EVS (0.81 compared to 0.77) metrics. [24] evaluated RF and XGBoost for forecasting electric vehicle (EV) charging energy demand based on historical charging data from the ACN dataset. Feature importance and comparative analysis showed that ensemble tree models outperformed linear and deep models for this regression task, with RF and XGBoost achieve the best accuracy, RMSE (5.9% and 9.0%, respectively) and MAPE (18.8% and 28.8% respectively). This is likely due to ensemble models' ability to handle heterogeneous input patterns and limited feature sets.

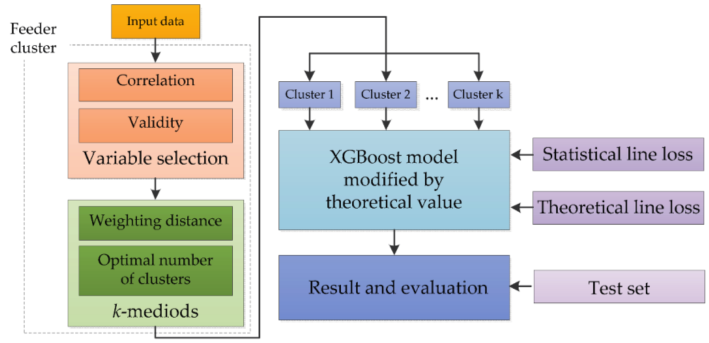

Fig. 5. Simplified flowchart of energy prediction using XGBoost proposed by [23]

D. Deep Learning-based Approaches

Despite the success of traditional and ensemble-based methods, their reliance on manual feature engineering and limited capacity to model complex nonlinear relationships has prompted a shift toward deep learning approaches. Deep Learning models, such as RNNs, GRUs, LSTMs, and Transformers, offer powerful capabilities for capturing long-term temporal dependencies, handling high-dimensional data, and learning complex patterns directly from raw inputs, making them particularly well-suited for energy forecasting in smart cities, where real-time, multivariate, and dynamic data streams are prevalent.

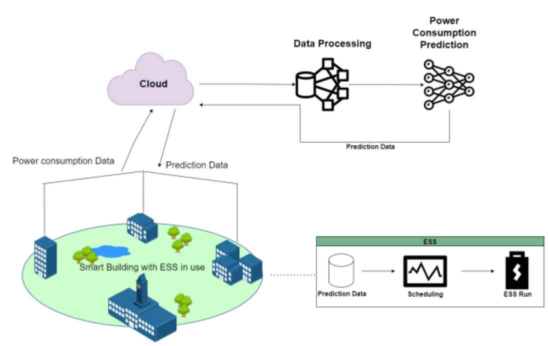

Fig. 6. GRU-based smart building system architecture proposed by [25]

Recurrent Neural Networks (RNNs), along with their more advanced variants such as Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM), are particularly designed for sequential data. These Deep Learning architectures have shown strong performance in modeling temporal dependencies in energy consumption and generation data. [26] presented a RNN–based forecasting algorithm to predict short and medium-term energy consumption and production in Estonia. The proposed model was built with 200 hidden units, trained using the Adam optimizer over 250 epochs, employed a multistep prediction strategy in which each predicted value is fed into the next time step, and was compared with the Estonian National Energy Regulator's forecasting system. It achieved significantly better accuracy, reducing RMSE from 47.3 to 37.0 for production. [25] proposed a GRU-based model to predict hourly power consumption in smart buildings to optimize Energy Storage System (ESS) scheduling. The system architecture integrated cloud-based hourly electricity usage data from 60 buildings, which was preprocessed and input into a GRU model for forecasting future consumption. Its performance was evaluated against an LSTM model. Results have shown that while both models achieved similar accuracy, GRU outperformed LSTM with lower validation loss and better stability across repeated trials. [27] presented a comprehensive comparison of RNN, GRU and LSTM for short-term electricity load forecasting in Palestine. Using real-world SCADA data of over 465,000 minute-level readings with features such as temperature, hour, weekday, and energy consumption, the authors trained and evaluated the three models with hyperparameter tuning. Among the models, the GRU achieved the best performance with R^2 = 0.8732, MAE = 0.03266 and MSE = 0.00215.

E. Hybrid Approaches

Hybrid approaches have also been studied to enhance the forecasting accuracy. [28] developed a novel ensemble forecasting method for monthly natural gas consumption across 18 European countries by combining Maximum Entropy Bootstrap (MEB) resampling (a new variant of Bagging), univariate time series models (such as ETS and ARIMA), and modified regularization techniques (Ridge and LASSO). The MEB method is used to preserve the time dependence structure and better represent uncertainty in nonstationary series. Forecasts are then generated separately for each replica and then combined using modified regularization that assigns weights while retaining the data-generating process. Results show that the combination of MEB resampling and modified ridge aggregation yields the most accurate forecasts across all metrics, outperforming traditional ensembles and machine learning alternatives. [29] proposed a short-term electricity load forecasting method by combining bagging ensemble learning with Stochastic Configuration Networks (SCNs). SCN is a fast-learning neural network that incrementally builds hidden nodes to approximate the target function under inequality constraints. Using bootstrap resampling, multiple SCNs were trained on diverse training subsets, and all their predictions were averaged to form the final forecast. The Bagging-SCNs method outperformed both a single SCN and LSTM neural networks on daily load forecasts for Quanzhou City, China, with MAPE below 1%, much lower than other methods.

Many advanced hybrid methods integrated the use of Attention mechanism and Transformer architecture into their work.

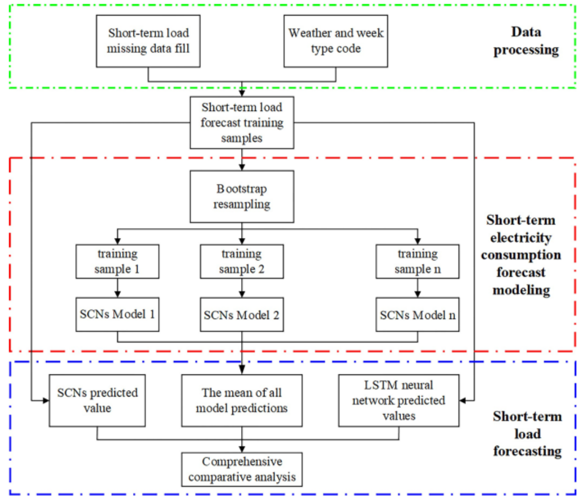

Fig. 7. Hybrid Bagging-SCN architecture diagram proposed by [29]

[30] proposed a model combining GRUs with Attention mechanism for short-term wind power forecasting from the Yalova wind farm in Turkey. The proposed GRU-attention architecture included two GRU layers, followed by an attention layer and two fully connected layers, using ReLU and linear activations respectively, and it outperformed six baseline models across multiple interval horizons, achieving best results for all metrics (RMSE, MAE and R^2). It also had fewer parameters and lower prediction time than other Deep Learning models, demonstrating superior accuracy, computational efficiency, and generalizability for real-time wind power forecasting. [31] proposed a novel hybrid CNN-LSTM model enhanced with an attention mechanism for day-ahead electricity demand forecasting in New South Wales, Australia. The architecture consisted of 20 convolution and pooling layers to extract input features, followed by two stacked LSTM layers integrated with self-attention to focus on specific network features by assigning weights to relevant temporal dependencies, and ending in a dense output layer. It was optimized using grid search, and results have shown that the proposed CNN-LSTM-Attention model outperformed multiple other Deep Learning baseline, achieving the lowest MAE and MAPE = 1.69% for 2020, as well as and strong generalization on 2022–2023 data, offering a promising approach for energy demand prediction, potentially leading to better energy management and cost savings for smart cities.

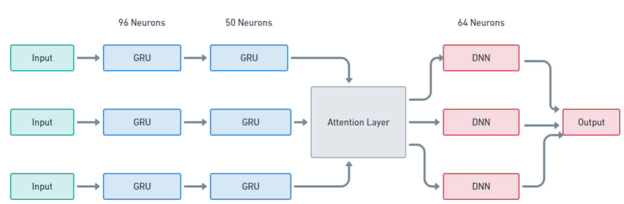

Fig. 8. Hybrid GRU-attention architecture proposed by [30]

IV. Comparison of Existing Models

A comparative analysis of these existing techniques is provided in Table II.

TABLE II
COMPARISON OF ENERGY FORECASTING METHODS

Model	Advantages	Limitations
Regression-based	Easy to interpret and deploy, strong short-term performance with reliable peak detection.	Limited nonlinearity handling, poor performance with highly variable systems.
Time Series-based	Effective for short and medium-term demand forecasting with seasonal patterns.	Complex parameter selection with uncertainty in long-term forecasts.
Ensemble-based	Better robustness and accuracy, handles missing values with built-in regularization.	Reduced interpretability, computationally expensive, need careful hyperparameter tuning.
Deep Learning-based	Automatic feature learning, good for temporal modeling and long-range forecasting, handles complex nonlinear patterns effectively.	Computationally expensive, requires large datasets with many hyperparameters.
Hybrid Approaches	State-of-the-art accuracy, combines strengths of multiple approaches for superior performance.	Very high complexity, even more computationally demanding.

Conclusion

This paper demonstrates the potential of AI in enhancing energy forecasting accuracy, thereby facilitating the transition to net-zero smart cities. Future research will focus on integrating AI with blockchain for decentralized energy management, enhancing model interpretability, and exploring federated learning for privacy-preserving forecasting solutions.

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