Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025

ENERGY CONSUMPTION FORECASTING WORK ON PREDICTING ENERGY FUTURE USAGE

[1] A. Srinivasarao,[2] J. Mounika,[3] Sd Shehanaz Begum,[4] Ch Naveen Kumar, [5] P Ramakrishna Reddy

[1]Associate Professor, Department of CSE- AI

[2,3,4,5] UG Scholar, Department of CSE- AI
Chalapathi Institute of Technology, Guntur, Andhra Pradesh, India-522016

ABSTRACT

Energy consumption forecasting is a crucial aspect of energy management, enabling efficient resource allocation, grid stability, and cost reduction. Accurate forecasting models help policymakers, utility companies, and industries optimize energy generation and distribution while integrating renewable energy sources [2]. Various methods, including statistical techniques (ARIMA, exponential smoothing), machine learning approaches (neural networks, decision trees, support vector machines), and hybrid models, are employed to improve prediction accuracy. The increasing availability of big data and advanced computational tools has further enhanced forecasting capabilities. This paper explores different forecasting techniques, their applications, challenges such as data quality and uncertainty, and future trends in energy consumption prediction. Key points in an energy consumption forecasting abstract. To predict future energy consumption based on historical data and relevant variables [1]. Grid operations, demand response programs, renewable energy integration, energy market forecasting. Statistical models (e.g., ARIMA), machine learning techniques (e.g., neural networks, support vector machines), and deep learning approaches (e.g., LSTMs).Historical energy consumption, weather data, socioeconomic factors, appliance usage patterns. Dealing with non-linearity, seasonality, and unpredictable events.

This study investigates the application of a Long Short-Term Memory (LSTM) recurrent neural network for short-term residential electricity consumption forecasting. By leveraging historical consumption data and weather variables as input, the model aims to accurately predict hourly energy demand, enabling better grid management and potential cost savings through demand response initiatives.

***Keywords**: Energy management, enabling efficient resource allocation, Long Short-Term Memory, grid management, and Grid operations.*

1. INTRODUCTION

Energy consumption forecasting refers to the practice of predicting future energy usage levels, typically by analyzing historical consumption data alongside external factors like weather conditions and economic indicators, to enable efficient energy management, planning, and grid optimization by predicting future demand and supply imbalances across different time scales - from short-term hourly predictions to long-term seasonal forecasts; essentially, it's about anticipating how much energy will be needed in the future to ensure a stable power system. Energy consumption forecasting plays a vital role in ensuring the efficient operation of power systems, optimizing energy distribution, and supporting sustainable energy policies [21]. With the growing demand for electricity, integrating renewable energy sources, and the need to reduce carbon emissions, accurate forecasting has become more critical than ever. Forecasting energy consumption helps governments, utility providers, and industries in demand-side management, infrastructure planning, and cost reduction. It also aids in

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025

balancing supply and demand, preventing power shortages or excess generation [22]. Various forecasting methods, ranging from traditional statistical techniques like autoregressive integrated moving average (ARIMA) and exponential smoothing to advanced machine learning models such as artificial neural networks (ANNs) and deep learning, have been developed to improve prediction accuracy [11]. Despite advancements, energy consumption forecasting faces several challenges, including data variability, external influencing factors (such as weather, economic conditions, and consumer behaviour), and the integration of decentralized energy sources [10]. Addressing these challenges requires robust models capable of handling uncertainty and large datasets. This paper explores different energy consumption forecasting techniques, their applications, challenges, and future directions to enhance prediction accuracy and support the transition to more sustainable and intelligent energy systems.

2. EXISTING SYSTEM

Energy consumption forecasting is essential for efficient energy management, cost reduction, and sustainable energy use. Existing systems for energy consumption forecasting can be categorized based on their methodologies and technologies [2]. These include Traditional Statistical Methods These methods rely on historical data and statistical techniques to predict energy consumption. Examples include Time Series Models Autoregressive Integrated Moving Average (ARIMA) – Uses past consumption data to make future predictions [4]. Exponential Smoothing (ETS) – Gives more weight to recent observations. Regression Analysis is linear or multiple regression models that correlate energy consumption with influencing factors like temperature, time of day, and industrial activity. Machine Learning & AI-Based Methods improve forecasting accuracy by identifying complex patterns in large datasets. Examples include Artificial Neural Networks (ANNs) Mimic human brain functions to detect non-linear relationships in energy data. Support Vector Machines (SVMs) Used for regression and classification based forecasting [6]. Random Forest & Gradient Boosting Ensemble methods that enhance predictive accuracy. Deep Learning (LSTM, CNNs) Used for long-term time series forecasting, especially in smart grid applications. Renewable Energy & Load Forecasting Systems Solar & Wind Forecasting Models Use weather data and AI models to predict energy generation and consumption. Demand Response Forecasting Predicts energy demand and adjusts supply dynamically. Smart Grid & IoT-Based Forecasting Systems use real-time data collected from smart meters and IoT devices to improve energy forecasting. Examples include Smart Meter Data Analytics Uses AI models to predict consumption at the household or industrial level [8]. Edge Computing & Cloud-Based Forecasting Enables real-time predictions using decentralized computing.

3. PROPOSED SYSTEM

Data Collection & Pre-processing Smart meters, IoT sensors, historical usage data, weather data, economic indicators, and social behaviour patterns. Pre-processing consist of handling missing values, normalization & scaling, feature engineering (e.g., temperature impact, seasonal variations) [12]. And Forecasting Models are Traditional Models Time Series Models: ARIMA, SARIMA, Regression Models, Linear Regression, Multiple Regression. Machine Learning Models are Random Forest, Gradient Boosting (XGBoost, LightGBM), Support Vector Machines (SVM). Deep Learning Models are Long Short-Term Memory (LSTM), Transformer-based models, Convolutional Neural Networks (CNN) for spatial patterns. Model Training & Evaluation Training the models using historical data Performance metrics Mean Absolute Error (MAE),Root Mean Square Error (RMSE), R-squared (R^2)
Deployment & Real-Time Monitoring are using Cloud-based or edge computing for real-time predictions, API integration for smart grid systems, Dashboard for visualization (Power BI, Tableau). Optimization & Feedback Loop Adaptive learning for model updates, Demand response strategies for energy efficiency [23].

Key components of a proposed energy consumption forecasting system: Data Acquisition Layer are Smart meters to collect real-time energy consumption data. Building management systems to capture environmental data like temperature, humidity. Weather data from external sources and Occupancy sensors to monitor building usage [19]. Data Preprocessing Layer is Data cleaning to handle missing values and outliers. Feature engineering to create relevant variables like time of day, day of week, seasonality indicators [14]. Data scaling to normalize values for optimal model training.

4. SYSTEM DESIGN

4.1.Developing an energy consumption forecasting system typically involves: data collection and pre-processing, choosing a suitable forecasting model (often utilizing machine learning techniques like neural networks or statistical methods), model training, evaluation, and deployment to predict future energy consumption based on historical data and relevant external factors like weather conditions or economic trends; the key is to select the most appropriate model based on the specific data and forecasting horizon required [18]. Requirement Analysis Phase Identify Stakeholders Energy providers, industries, smart grid operators, residential users. Define Objectives Short-term & long-term energy forecasting. Optimize energy consumption, Reduce operational costs, Improve demand-supply balance, Collect Requirements.

Functional: Data collection, preprocessing, forecasting, visualization.

Non-Functional: Accuracy, scalability, security, real-time processing.

System Design Phase Architecture Design Three-Tier Architecture: Data Layer – Smart meters, IoT devices, weather data, energy logs. Processing Layer – Machine learning models, AI-driven forecasting [19]. Presentation Layer – Dashboards, reports, APIs for smart grids. Deployment Options: Cloud-based, Edge computing, Hybrid model. Module Breakdown , Data Collection & Storage Ingest real-time & historical data. Preprocessing: Cleaning, normalizing, feature engineering. Forecasting Engine: AI/ML models (ARIMA, LSTM, Transformer). Visualization & Reporting: Graphs, reports, predictive alerts. Data Collection & Preprocessing Phase Sources of Data: Smart meters, weather APIs, IoT sensors, industry reports [15]. Data Cleaning: Handling missing values, noise removal. Feature Engineering: Adding seasonality, time-based trends, and temperature effects. Model Development & Training Phase Choosing Models: Time Series Models: ARIMA, SARIMA for pattern-based forecasting. Machine Learning: XGBoost, Random Forest for high-accuracy predictions. Deep Learning: LSTM, Transformers for long-term forecasting. Training Process: Splitting dataset (Train/Test), Hyper parameter tuning for optimization, Performance evaluation using MAE, RMSE, R^2 score.

4.2. System Implementation Phase Deployment Options: Cloud (AWS, Azure, GCP) Large-scale scalability. Edge Computing Real-time decision-making on IoT devices. Hybrid Model Combination of both for optimal performance [10]. Database & API Development: Storing processed data & predictions. Exposing APIs for integration with smart grids & user applications. Testing & Validation Phase Unit Testing: Checking individual components (data processing, ML models, visualization). Integration Testing: Ensuring seamless interaction between modules. Performance Testing: Evaluating system speed, scalability under heavy loads. User Acceptance Testing (UAT): Getting feedback from stakeholders before full deployment 19]. Deployment & Monitoring Phase Final Deployment: Cloud, Edge, or On-Premise setup. API integrations for energy management systems. Live Data Monitoring:

Detecting anomalies & recalibrating models. Automated alerts for unusual energy spikes. Maintenance & Continuous Improvement Phase [12].

Adaptive Learning: Periodic model retraining with new data. User Feedback Integration: Refining system features based on user needs. Security Enhancements: Ensuring compliance with energy regulations & cyber security protocols. Software Development of Energy Consumption Forecasting System [11]. The software development of an energy consumption forecasting system involves creating an efficient, scalable, and user-friendly system that uses historical data, real-time inputs, and machine learning models to predict future energy consumption [18]. The system is designed to provide insights for energy providers, consumers, and smart grid operators.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025

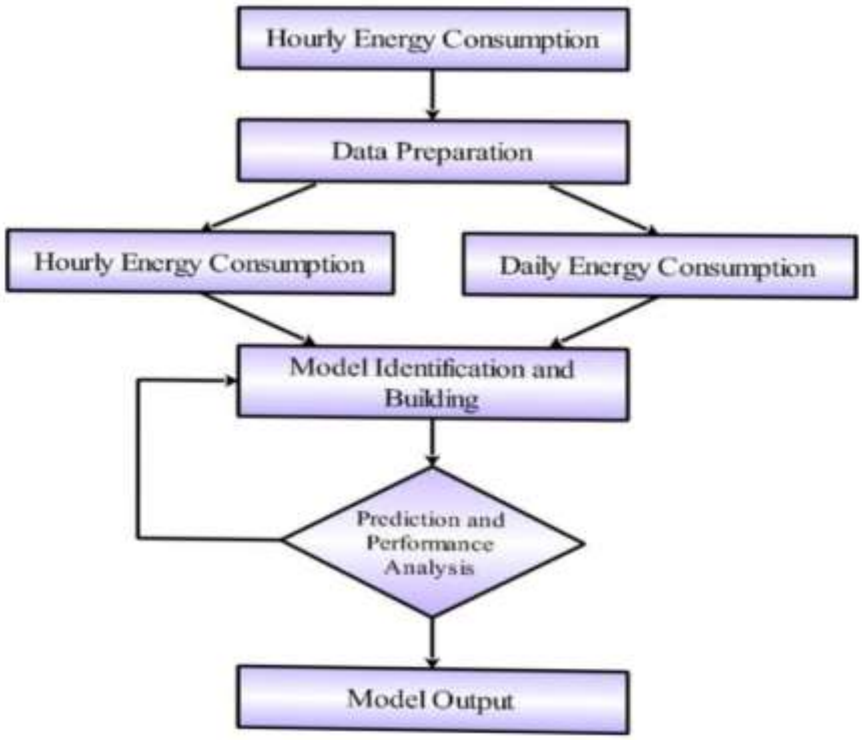

Fig1: System Design

5. CONCLUSION

Energy consumption forecasting is a critical discipline that combines advanced data analytics, statistical methods, and machine learning techniques to predict future energy needs. The theoretical framework underpinning this field offers several key insights. Energy consumption forecasting exemplifies the integration of disciplines such as statistics, computer science, and domain-specific energy knowledge. This interdisciplinary approach enables more accurate and nuanced predictions by accounting for various influencing factors like weather, economic activity, and consumer behaviour.

A variety of models—ranging from traditional time series methods (e.g., ARIMA) to modern machine learning techniques (e.g., LSTM networks)—are employed to capture the dynamics of energy use. Each method brings its own strengths and limitations, and often a hybrid or ensemble approach is adopted to improve forecast reliability. The success of any forecasting system hinges on the quality of input data. Theoretical frameworks emphasize rigorous data preprocessing, including cleaning, normalization, and the handling of missing or anomalous data points, as essential steps in ensuring the robustness of forecasts.

The design and testing of forecasting systems especially when implemented via APIs or integrated into broader energy management platforms must focus on both functional correctness and seamless integration. Functional testing confirms that each component meets its specifications, while integration testing ensures that disparate modules, such as data ingestion, processing workflows, and prediction engines, work together cohesively. Given the inherent uncertainties in predicting future events, effective energy forecasting systems incorporate mechanisms for error handling and uncertainty quantification. The theoretical models often include confidence intervals or probabilistic forecasts that provide stakeholders with a range of expected outcomes, facilitating better decision-making under uncertainty. As energy systems evolve and new data sources become available (e.g., from smart grids or IoT sensors), forecasting models must adapt. The theory supports continuous model evaluation and retraining to maintain accuracy over time, ensuring that forecasting tools remain relevant and scalable in rapidly changing environments. Ultimately, energy consumption forecasting plays a pivotal role in energy management, helping utilities, governments, and businesses optimize resource allocation, plan for future infrastructure needs, and implement energy-saving initiatives. The theoretical advances in forecasting contribute directly to operational efficiency, economic savings, and sustainable energy practices. In Summary the theoretical foundation of energy consumption forecasting is robust, grounded in a deep understanding of data-driven predictive analytics and system integration. By emphasizing interdisciplinary methods, rigorous data management, and comprehensive testing strategies, this field continues to evolve, promising enhanced accuracy and operational efficiency in managing energy resources. As the energy landscape transforms with emerging technologies and shifting consumption patterns, these theoretical principles will remain essential in guiding the development of next-generation forecasting systems.

REFERENCE

[1]"Deep Learning for Customer Retention in Subscription-Based Services": https://www.sciencedirect.com/science/article/pii/S095741742100587X.

[2] "Predicting Customer Churn with Machine Learning – A Systematic Review": https://arxiv.org/abs/2001.01537,

[3] Kalyankumar Dasari, Mohmad Ahmed Ali, NB Shankara, K Deepthi Reddy, M Bhavsingh, K Samunnisa, "A Novel IoT-Driven Model for Real-Time Urban Wildlife Health and Safety Monitoring in Smart Cities" 2024 8th International Conference on I-SMAC, Pages 122-129.

[4] S Deepajothi, Kalyankumar Dasari, N Krishnaveni, R Juliana, Neeraj Shrivastava, Kireet Muppavaram, "Predicting Software Energy Consumption Using Time Series-Based Recurrent Neural Network with Natural Language Processing on Stack Overflow Data", 2024 Asian Conference on Communication and Networks (ASIANComNet), Pages:1-6, Publisher: IEEE.

[5] Dr.D.Kalyankumar, Muhammad Shaguftha, Putti Venkata Sujinth, Mudraboyina Naga Praveen Kumar, Namburi Karthikeya, "Implementing a Chatbot with End-To-End Encryption for Secure and Private Conversations", IJMTST, Vol: 10, Issue: 02, Pages:130-136, 2024.

[6] Kommineni, K. K., Pilli, R. B., Tejaswi, K., & Siva, P. V. (2023). Attention-based Bayesian inferential imagery captioning maker. Materials Today: Proceedings.

[7] Kalyan Kumar Dasari, K Dr , "Mobile Agent Applications in Intrusion Detection System (IDS)'-JASC, Vol: 4 Issue : 5, Pages: 97-103, 2017.

[8] V.Monica, D. Kalyan Kumar, "BACKGROUND SUBTRACTION BY USING DECOLOR ALGORITHM", IJATCSE, Vol. 3 , No.1, Pages : 273 – 277 (2014).

[9] Netflix Prize Dataset (User behavior and ratings): https://www.netflixprize.com

[10] Kaggle : Customer Churn Prediction Datasets: https://www.kaggle.com/datasets

[11] Kalyan Kumar Dasari & Dr, K Venkatesh Sharma, "A Study on Network Security through a Mobile Agent Based Intrusion Detection Framework", JASRAE, vol : 11, Pages: 209-214, 2016.

[12] Dr.D.Kalyankumar, Saranam Kavyasri, Mandadi Mohan Manikanta, Pandrangi Veera Sekhara Rao, GanugapantaVenkata Pavan Reddy, "Build a Tool for Digital Forensics to Analyze and Recover Information from Compromised Systems", IJMTST, Vol: 10, Issue: 02, Pages:173-180, 2024.

[13] Dr.D.Kalyankumar, Kota Nanisai Krishna, Gorantla Nagarjuna, PuvvadaVenkata Naga Sai Jagadesh Kumar, Modepalli Yeswanth Chowdary, "Email Phishing Simulations Serve as a Valuable Tool in Fostering a Culture of Cyber security Awareness", IJMTST, Vol: 10, Issue: 02, Pages:151-157, 2024.

[14] Dr.D.Kalyankumar, Panyam Bhanu Latha, Y. Manikanta Kalyan, Kancheti Deepu Prabhunadh, Siddi Pavan Kumar, "A Proactive Defense Mechanism against Cyber Threats Using Next-Generation Intrusion Detection System", IJMTST, Vol: 10, Issue: 02, Pages:110-116, 2024.

[15] Kommineni, K.K., Prasad, A. Enhancing Data Security and Privacy in SDN-Enabled MANETs Through Improved Data Aggregation Protection and Secrecy. Wireless Pers Commun (2024). https://doi.org/10.1007/s11277-024-11635-w

[16] Kumar, K. K., Kumar, S. G. B., Rao, S. G. R., & Sydulu, S. S. J. (2017, November). Safe and high secured ranked keyword searchover an outsourced cloud data. In 2017 International Conference on Inventive Computing and Informatics (ICICI) (pp. 20-25). IEEE.

[17] Dr.K.Sujatha, Dr.Kalyankumar Dasari , S. N. V. J. Devi Kosuru , Nagireddi Surya Kala , Dr. Maithili K , Dr.N.Krishnaveni, " Anomaly Detection In Next-Gen Iot:Giant Trevally Optimized Lightweight Fortified Attentional Convolutional Network," Journal of Theoretical and Applied Information Technology, 15th January 2025. Vol.103. No.1,pages:22-39.

[18] Kalyankumar Dasari*, Dr. K. Venkatesh Sharma, "Analyzing the Role of Mobile Agent in Intrusion Detection System", JASRAE, vol :15, Pages: 566-573,2018.

[19] Kalyan Kumar Dasari&amp, M Prabhakar, "Professionally Resolve the Password Security knowledge in the Contexts of Technology", IJCCIT, Vol:3, Issue:1, 2015.

[20] Kommineni, K. K. ., & Prasad, A. . (2023). A Review on Privacy and Security Improvement Mechanisms in MANETs. International Journal of Intelligent Systems and Applications in Engineering, 12(2), 90–99. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/4224

[21] S Neelima, Kalyankumar Dasari, A Lakshmanarao, Peluru Janardhana Rao, Madhan Kumar Jetty, "An Efficient Deep Learning framework with CNN and RBM for Native Speech to Text Translation", 2024 3rd International Conference for Advancement in Technology (ICONAT), Pages: 1-6,Publisher :IEEE.

[22] A Lakshmanarao, P Bhagya Madhuri, Kalyankumar Dasari, Kakumanu Ashok Babu, Shaik Ruhi Sulthana, "An Efficient Android Malware Detection Model using Convnets and Resnet Models", 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Pages :1-6, Publisher :IEEE.

[23] Churn Prediction in Subscription- Based Busi ness es Using Machine Learning", https://www.science "Customer direct.com/science/article/pii/S18770509193155.