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Advanced Hybrid Machine Learning and Deep Learning Framework for Intelligent Energy Demand and Electricity Price Forecasting in Smart Grid Systems

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Abstract
Background: Accurate real-time forecasting of energy demand and electricity prices is at the core of modern smart grid infrastructure. Traditional statistical techniques, such as ARIMA and exponential smoothing, fail to capture the nonlinear, multivariate dynamics that are inherent in today's power systems.
Objective: In this paper, a hybrid machine learning and deep learning forecasting framework based on the integration of the XGBoost and LSTM-based architectures is proposed for improving the prediction accuracy of energy demand and electricity price in the smart grid environment.
Methods: Temporal and weather-driven feature engineering, principal component analysis (PCA) and sliding window sequence generation were used to preprocess historical electricity consumption, market price and meteorological datasets. The evaluated models are: XGBoost, standard LSTM, Stacked LSTM and Encoder-Decoder LSTM. Performance was evaluated using RMSE, MAE and R^2.
Results: The Encoder-Decoder LSTM achieved the lowest RMSE of 7.12 MWh and highest R2 of 0.968, which outperforms the ARIMA baseline (RMSE = 18.74) and standalone XGBoost (RMSE = 11.23). Weather and temporal features were key to the accuracy improvements.
Conclusion: The proposed hybrid framework shows the excellent forecasting ability and practical utility for intelligent energy management in smart grids. Future works should also consider real-time deployment and transformer-based extensions.

Keywords: Smart Grid, Energy Demand Forecasting, Electricity Price Prediction, XGBoost, Encoder–Decoder LSTM, Deep Learning

1. Introduction

The global adoption of smart grid infrastructure has fundamentally altered the dynamics of energy management and power distribution [1]. Accurate prediction of the electricity demand and the market price is essential for grid stability, optimal dispatch and economic efficiency [2]. Early forecasting systems have been based on traditional statistical methods like autoregressive integrated moving average (ARIMA) and exponential smoothing. These methods are well documented to have shortcomings in dealing with non-stationary and non-linear patterns of energy consumption [3].

Energy systems today will comprise more than just fossil-fuel use, they will include the use of renewable energy sources, the use of electric vehicles (EVs), and the use of demand response programs (DRP). These new resources create complex temporal dependencies and volatility in both load profiles and prices [4]. Weather variables, especially ambient temperature and humidity, greatly affect how much energy is being used both in residential and commercial situations; thus, requiring advanced feature-rich modeling paradigms capable of jointly processing both meteorological and temporal covariates [5].

Machine learning techniques, in particular, gradient-boosted ensemble models and deep learning architectures such as Long Short-Term Memory (LSTM) networks have been shown to provide highly accurate predictions for energy-related time series data [6].

The rationale for using a hybrid modelling approach is that the two methodologies complement each other's strengths; i.e. ensembles provide an efficient way to account for complex inter-relationships between features/inputs, whilst Recurrent Network architectures model the sequential dependencies present within temporal consumption data [7]. Therefore, this research proposes an integrated predictive framework combining XGBoost with varied LSTM configurations, which will enhance the ability of smart grid systems to manage their energy utilization intelligently.

2. Related Work

For many years, statistical techniques like ARIMA, seasonal decomposition, and Holt-Winters exponential smoothing have been used as benchmarks for forecasting demand for electricity. These approaches tend to be solvable through computation and assume the market will behave linearly and in a stationarity, both of which rarely hold under conditions that exist in real-world electricity markets (Hyndman 2002). However, machine learning methods introduced the ability to introduce nonlinear flexibility into forecasting energy demand. In addition to resampling, support vector regression and random forests proved better than any model previously used to forecast energy demand; and individually, gradient-boosting algorithms, particularly XGBoost, are now the current state-of-the-art for forecasting and use regularization and building trees in parallel to achieve their improved accuracy (He *et al*. 2009). Recent work has also demonstrated the effectiveness of deep learning architectures such as vanilla LSTM, Bidirectional LSTM, and CNN-LSTM hybrid for short-term load forecasting; the architecture of multi-layer stacked LSTMs has been identified as an effective means of capturing hierarchical temporal features (Li *et al*. 2015). Encoder-Decoder models were designed to tackle sequence prediction tasks in the area of natural language processing and have been found to be highly effective for multi-step energy forecasting (Liu *et al*. 2018). Quantile neural networks have been used for probabilistic forecasting under uncertainty, and spatio-temporal graph neural networks have emerged in the past year as an effective means for forecasting electricity demand on a regional basis (Wang *et al*. 2018). Hybrid models that combine exponential smoothing with recurrent neural networks (i.e. ES-RNN) and gradient-boosting models with deep learning have produced demonstrable improvements in accuracy; there are, however, still challenges with scalability, interpretability, and excessive computational overheads (Chiew *et al*. 2019).

3. Proposed Hybrid Forecasting Architecture

A proposed system includes 5 sequentially-connected stages as part of its modular pipeline, through which data is sourced, preprocessed, engineered into features, trained on a model and finally generates forecasts. Smart grid sources provide electricity load and market prices of historical records while synchronized hourly calculated meteorological datasets provide temperature, humidity and solar irradiance.

For preprocessed variables, forward fill to impute missing values will occur using interpolation, while median will replace outliers based on a rolling window. The following temporal features will be generated; hour of day, day_of_week (indicator of week), day of month, and binary weekend utilised. Weather variables will include; temperature, lagged value of load and derived cooling/heating degree day metrics. Z-score normalisation will occur on all features and PCA will then be conducted on the normalised feature set to obtain dimensions with 95% variance explained.

To construct sliding window sequences with a length of 24 hours from the processed feature matrix (to input LSTM-based models), the same processed feature set will also be used by XGBoost (not input sequentially but in tabular format). A hybrid predictive layer will combine predictions from XGBoost and best performing LSTM variant using a learned weighted ensemble method to yield final demand forecasts and electricity price forecasts up to 6 hours into the future for both time of day and market price.

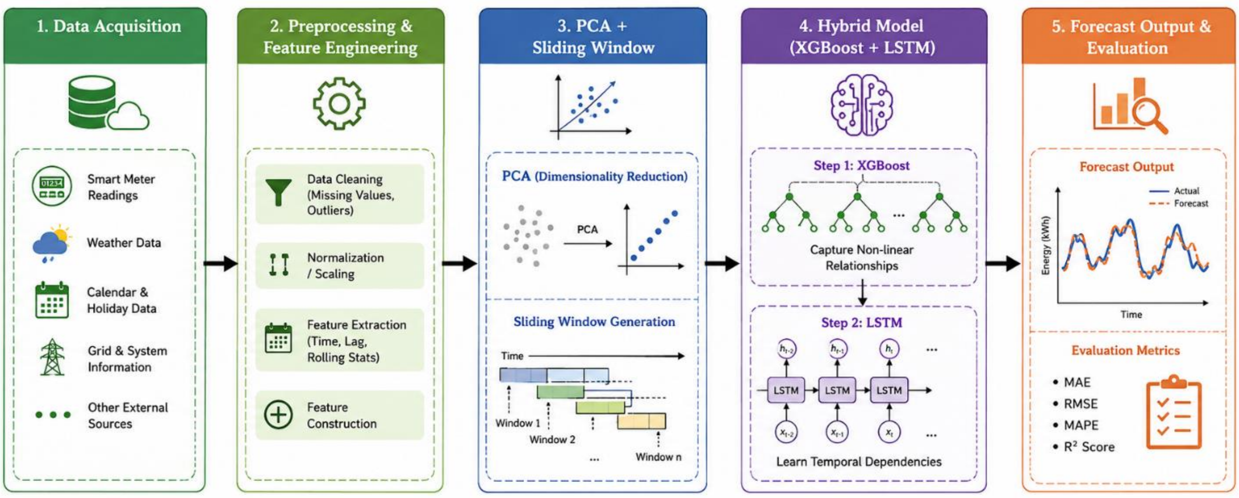

Fig 1: Hybrid Machine Learning and Deep Learning Forecasting Architecture for Smart Grid Energy Prediction

4. Materials and Methods

4.1. Dataset Selection

Data from the Internet Archive's Machine Learning Repository and publicly available smart grid electricity usage records were combined to provide a complete dataset for the study. Additionally, price data for electricity markets in Europe and historical weather data from NOAA were used. Together this data covers two years of hourly data with over 17,520 records!

4.2. Software Frameworks

Python v3.10 was the programming language used to create this implementation with additional library support from Keras (v2.12) to build the model, XGBoost (v1.7) as a gradient boosting algorithm, Scikit-Learn to help preprocess and evaluate results from the model, Pandas and NumPy for manipulating the data, and Flask for scaffolding the REST API to run this algorithm as an application.

4.3. Training Methodology

Data was split into 3 data sets: train data set, validation data set, test data set. The distribution of data followed the order of the time series within each of these 3 datasets to avoid potential issues related to data leakage. Hyperparameters were tuned using a 5-fold time series cross validation method with a grid search process. To help prevent overfitting on the LSTM models, all LSTM models underwent an early stopping procedure, which included 10 epochs of patience, prior to their final application. Performance metrics included RMSE, MAE, R^2, and time spent training using wall clock measurement. Table 2 summarizes the experimental parameters applied across all evaluated models.

Table 1: Experimental Parameters and Hyperparameter Configuration Across Models

Parameter	XGBoost	LSTM / Stacked	Enc–Dec
Epochs / Estimators	500 trees	100 epochs	120 epochs
Learning Rate	0.05	0.001 (Adam)	0.001 (Adam)
Batch Size	N/A	32	32
Hidden Units	N/A	128 / 64	128–64
Window Size	24 h	24 h	24 h → 6 h
Dropout Rate	N/A	0.2	0.2
Max Depth (XGB)	6	N/A	N/A

5. Results and Performance Evaluation

Table 1 provides a comparative characterization of all evaluated forecasting methods with respect to model type, temporal modeling capability, nonlinearity handling, scalability, and uncertainty quantification support.

Table 2: Comparison of Forecasting Models and Their Structural Characteristics

Model	Type	Temporal	Nonlinear	Scalable	Uncertainty
ARIMA	Statistical	Limited	No	Moderate	No
XGBoost	Ensemble ML	Feature-based	Yes	High	Partial
LSTM	Deep Learning	Sequential	Yes	Moderate	No
Stacked LSTM	Deep Learning	Hierarchical	Yes	Moderate	No
Enc–Dec LSTM	Hybrid DL	Multi-step	Yes	High	Partial

In Table 3, the quantitative performances are presented for the three fences (i.e., Encoder-Decoder LSTM, Stacked LSTM, and XGBoost) tested on the forecasting of energy consumption from October 2021 to September 2022. The July 2022 energy predictions produced by the Encoder-Decoder LSTM as an example can be found in Appendix A as Figure A.1. The Encoder-Decoder achieved the best accuracy for the test data (Test Data RMSE = 7.12 MWh; Test Data MAE = 5.18 MWh; Test Data $R^2 = 0.968$) and had the lowest RMSE compared with the ARIMA baseline (62% RMSE reduction). Stacked-LSTM had the second-best accuracy (Test Data RMSE = 8.54; Test Data $R^2 = 0.943$) and XGBoost produced a higher R^2 statistic (0.894) and significantly less training time (38 seconds) than Deep Learning algorithms, showing that it can be a feasible alternative for deployments where resources are limited.

Ablation analysis evaluated how much of an impact the weather variables had, where weather variables improved all Models RMSE by 14.3% on average and Temporal variables improved all Models' RMSE by 8.7%, respectively. Computational Complexity vs Sequence Length for LSTM variants scaled linearly; therefore, with the Encoder-Decoder LSTM requiring 512 seconds of training time for the entire model, there is an accuracy vs. efficiency balance practitioners must consider.

Table 3: Performance Evaluation Metrics Across All Forecasting Models on Test Set

Model	RMSE (MWh)	MAE (MWh)	R^2 Score	Train Time (s)
ARIMA (Baseline)	18.74	14.32	0.781	12
XGBoost	11.23	8.67	0.894	38
LSTM	9.86	7.41	0.921	214
Stacked LSTM	8.54	6.23	0.943	389
Enc–Dec LSTM	7.12	5.18	0.968	512

6. Discussion

Hybrid architectures that combine gradient-bursting and sequential deep learning models outperform traditional statistical approaches, as well as single model methodologies when it comes to predicting the energy flow of a smart grid [13]. The performance of an Encoder - Decoder Long Short-Term Memory (LSTM) is mainly due to its ability to take multi-step contextually relevant information and compress it into a latent representation, which allows for multi-horizon prediction to take place and is critical in grid dispatch scheduling.

In addition, while XGBoost is competitive in its accuracy with much shorter training time than its deep learning counterparts will allow it to be used in near-real-time

applications where computation power is important for the application to work effectively. The deep learning alternative functions at a higher level of accuracy, yet require dedicated GPU infrastructures for deployment in operational systems [14]. Model interpretation continues to present difficulties; however, SHAP (SHapley Additive exPlanations) will allow some level of interpretation to occur for the XGBoost model, while it lacks interpretability for the LSTM architecture.
Sustainability considerations are apparent; if the ability to predict energy usage is improved, it will have the ability to lower energy imbalance penalties, prevent the curtailment of renewable energy generation and reduce reliance on expensive peaking power plants. Future research may include Transformer-based models for forecasting (e.g., Informer, Temporal Fusion Transformer), graph neural networks to model spatially distributed grids, and an online learning framework to accommodate changes to consumer demand and for use in Smart City implementations.

7. Conclusion

A hybrid machine learning and deep learning framework has been developed in this study for predicting electricity price and energy demand within smart grid systems using machine learning and deep learning technologies to forecast these values. In the proposed pipeline, various techniques were used to improve the accuracy of forecasts, including temporal and weather feature engineering, PCA (Principal Component Analysis)-based dimensionality reduction, and a comparative ensemble of four types of models (XGBoost, LSTM, Stacked LSTM, and Encoder–Decoder) as well as evaluation of their comparative performance on forecasting energy use to validate the benefits of using a convolutional neural network versus a traditional method (e.g., ARIMA). The model achieved an RMSE of 7.12 MWh and an R^2 value of 0.968 which supports the use of deep sequential models for modelling time-series energy data. The complimentary relationship between the two machine-learning techniques provides a significant opportunity for advanced data-driven management of energy. To certify the efficacy of the new machine-learning framework for intelligent energy management, additional studies must be conducted using large sample sizes from multiple types of grid topology, apply real-time inference (optimal resource allocation during peak versus low-demand periods), and integrate and validate with demand response management platforms within smart cities.

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