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Predictive Intelligence Technique for Short-Term Load Forecasting in Sustainable Energy Grids

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Abstract: Short-term load forecasting remains pivotal in managing sustainable energy grids, with accuracy directly influencing operational decisions. Conventional forecasting methodologies often falter in adapting to the dynamic complexities inherent in modern energy systems. This paper introduces a predictive intelligence technique rooted in machine learning aimed at enhancing short-term load forecasting accuracy within sustainable energy grids. Leveraging historical data, weather patterns, grid operations, and consumer behavior insights, our study develops a robust predictive model. The model's adaptability to evolving patterns and real-time data integration offers a promising solution to the limitations of existing forecasting methods. Through a comparative analysis and validation against established benchmarks, the proposed technique showcases superior performance, demonstrating its potential for more efficient resource allocation and improved grid management. This research contributes to advancing sustainable energy practices by offering a reliable and adaptive solution for short-term load forecasting, fostering more resilient and responsive energy grid operations.

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1. Introduction

Short-term load forecasting is a critical element of renewable energy grids, which have an impact on decisions regarding allocation and distribution of power. With continuous integration of variable renewable energy sources and the volatility of consumption patterns, short-term load prediction becomes very difficult [1]. Traditional forecasting techniques have historically failed to adapt to changing realities in energy systems. In this regard, one can say that machine learning-based predictive intelligence approaches are still under investigation as possible means to tackle this problem [2].

However, even with all these developments, accurate short term load forecasting has remained an insurmountable challenge. The fluctuation embedded in the renewable sources of energy alongside the intricacy of human power usage habits poses a significant hindrance towards conventional forecast models [3-4]. This causes for further studies aimed at investigating other adaptive more superior predictive intelligence methods that can overcome existing model shortcomings due to fluctuations and complexities associated with this form of data [5-6].

Statistical models and time series analyses have been the most commonly used methods in load forecasting. However, they do not perform well when the modern energy grids become nonlinear and volatile. Moreover, there are limitations in their ability to integrate real-time data or adaptively learn for dynamic load prediction [7]. This research gap necessitates exploration into machine learning's potential for building robust models that can capture intricate variables and evolving trends within sustainable energy systems [8-10].

This paper attempts to fill the existing gaps in short-term load forecasting by employing predictive analytics grounded on machine learning methodologies. Specifically, using historical data, weather patterns, grid operations and consumer behavior insights, this research will aim at developing a predictive model that enhances accuracy of forecasts in sustainable energy grids. Importantly, this study is significant as it may improve operational efficiency as well as enable better resource planning thus leading to sustainable energy practices development.

2. Background and Literature

In this section, the review of literature is carried out in order to understand the methods and developments that have shaped it. Feng and Zhang [10] tried different aggregation strategies for machine learning-based short-term load forecasting. The research compared different approaches' ability to accurately predict energy demand thus revealing optimization techniques for better forecasting models.Rai and De [11] conducted a study that compared classical and machine learning based short-term and mid-term load forecasting mainly in relation with smart grids. Most likely, this study has given a broad idea about different types of forecast methods suitable to smart grid environments. Vantuch et al. [13] analyzed electric load prediction using machine learning (both short-term and long-term). Presumably, the research focused on how machine-learning models can be applied across various time spans demonstrating their adaptability and suitability. Thus Yazici et al [14] investigated deep learning-based short term electricity load forecasting using a real case example? Through this study perhaps we could see some practical implications of adopting deep learning techniques into real world's load forecasting scenarios.

Li et al. [15] proposed a machine-learning method for short-term load forecasting based on fuzzy theory so that it can be used to differentiate between weekdays and weekends. It seems that this study intended to make the use of weekly clustering more accurate by introducing differences in energy consumption patterns into their predictions. Zhang et al. [16] introduced an asynchronous deep reinforcement learning model for hour-ahead electricity demand prediction. There could be an inclusion of different functions, an adaptive early forecasting method, and reward incentive mechanism which may lead to better results in terms of efficiency and accuracy.

Oprea and Bâra [17] used machine learning algorithms for smart metering analysis to forecast the peak loads in residential buildings with smart meters, sensors, and big data solutions. Probably this research demonstrated how these technologies can enhance predictive power in residential settings. Moradzadeh et al. [18] articulated upon deep learning-driven STLF system for sustainable energy management of microgrids. This work was likely aimed at utilizing deep neural networks towards energy optimization in such systems of microgrid operation. Syed et al. [19] suggested the use of a deep learning – based approach for short term load forecasting involving smart grids, as well as clustering and recognition of personal trends.

3. Methodology

This section delineates the comprehensive approach undertaken in our study, aiming to bridge the existing gaps in accuracy and responsiveness.

CatBoost, short for Categorical Boosting, stands as a powerful and efficient gradient boosting framework specifically designed for categorical feature support. Developed by Yandex researchers, it has gained prominence for its ability to handle categorical variables without the need for extensive preprocessing. In the context of our study on short-term load forecasting for energy consumption, CatBoost proves particularly advantageous due to its adaptability to intricate datasets with temporal dependencies and diverse features.

One of CatBoost's distinguishing features lies in its ability to naturally handle categorical features, eliminating the need for manual encoding or transformation. It employs an innovative combination of ordered boosting and categorical boosting, allowing it to efficiently model relationships within the dataset. Additionally, CatBoost incorporates a robust implementation of gradient boosting, providing high predictive accuracy while mitigating the risk of overfitting.

In the context of energy consumption forecasting, temporal dependencies are crucial for accurate predictions. CatBoost excels in capturing these dependencies through its iterative training process. By sequentially building decision trees and correcting errors at each step, CatBoost inherently grasps the temporal nuances within the dataset. This is particularly beneficial when dealing with load forecasting, where past consumption patterns significantly impact future predictions.

CatBoost offers a range of hyperparameters that can be fine-tuned to enhance model performance. Parameters such as the learning rate, depth of trees, and regularization settings play a vital role in adapting the model to the specific characteristics of the energy consumption dataset. Through systematic experimentation and cross-validation, we optimized these parameters to achieve the best possible predictive accuracy for our short-term load forecasting model.

In addition to its predictive power, CatBoost provides insights into feature importance, aiding in the interpretability of the model. This is crucial for understanding the factors influencing energy consumption patterns. By examining feature importance scores, we gain valuable insights into which attributes contribute most significantly to the forecasting accuracy, enabling a more informed analysis of energy consumption dynamics.

4. Experimental Findings and Discussions

In this section, we present the outcomes of our model's interaction with real-world data, shedding light on its predictive capabilities and adaptability to the complexities inherent in modern energy systems.

For our case study, we leverage data from the Turkish Energy Exchange spanning from January 1, 2016, to June 30, 2023. The dataset comprises two key attributes: 'date' and 'consumption_mwh.' The 'date' attribute captures the temporal dimension of the dataset, providing a chronological sequence, while 'consumption_mwh' quantifies the power consumption in megawatt-hours. This case study harnesses the richness of this dataset to evaluate the efficacy of our proposed predictive intelligence technique in the context of short-term load forecasting within the intricate landscape of Turkey's power consumption patterns. In Table 1, we present a comprehensive summary of statistical measures for each feature within the Turkey Load dataset. These summary statistics offer a detailed overview of the dataset's key characteristics, encompassing measures such as mean, standard deviation, minimum, maximum, and quartiles. This exploration provides essential insights into the distribution and variability of the dataset, laying the groundwork for a nuanced understanding of the features under consideration.

Table 1: Summary Statistics of Turkey Load Dataset Features

	count	mean	std	min	25%	50%	75%	max
consumption_mwh	61368	34052.49	5581.143	0	29875.11	33878.18	38058.53	55575.02
rolling_mean_t41	61327	34052.11	5582.215	0	29874.29	33876.9	38059.17	55575.02
rolling_mean_t48	61320	34052.53	5582.382	0	29874.36	33878.04	38059.23	55575.02
rolling_mean_t72	61296	34051.5	5582.619	0	29874.02	33876.42	38057.98	55575.02
rolling_mean_t168	61200	34048.51	5583.271	0	29870.41	33874.17	38050.84	55575.02
rolling_mean_t38	61319	34053.25	4634.667	16810.19	30922.69	33808.13	37053.83	52497.53
rolling_mean_t50	61307	34053.75	4016.824	18350.17	31428.92	34056.96	36638.96	47859.9
rolling_mean_t62	61283	34054.42	3859.145	18968.31	31483.06	34012.11	36489.49	47793.34
rolling_median_t38	61319	34182.88	5085.762	16881.31	30599.48	33904.64	37779.5	52799.49
rolling_median_t50	61307	35207.61	4457.476	17335.35	32441.5	35274.6	38187.34	49156.76
rolling_median_t62	61283	34851.2	4353.427	18281.31	32020.44	34781.51	37806.24	49104.55
rolling_std_t38	61319	2982.374	1288.098	281.7764	1972.649	3022.586	3828.473	9148.479
rolling_std_t50	61307	3873.911	814.4204	1238.547	3277.078	3825.822	4438.058	7328.113
rolling_std_t62	61283	4016.368	686.6626	2051.504	3480.591	3965.734	4497.951	6706.514

Table 2 encapsulates a succinct summary of the experimental settings employed in our study. It outlines key parameters such as the chosen machine learning algorithm, hyperparameter configurations, and any preprocessing techniques applied to the dataset. These details are instrumental in providing transparency and reproducibility, ensuring that our experimental methodology is well-documented and can be easily replicated by fellow researchers.

Table 2: Experimental Settings Summary, Including Machine Learning Algorithm and Hyperparameter Configuration

Description	Value
Session id	7809
Target	consumption_mwh
Target type	Regression
Original data shape	(61200, 22)
Transformed data shape	(59058, 22)
Transformed train set shape	(40698, 22)
Transformed test set shape	(18360, 22)
Numeric features	21
Preprocess	TRUE
Imputation type	simple
Numeric imputation	mean
Categorical imputation	mode
Remove outliers	TRUE
Outliers threshold	0.05
Normalize	TRUE
Normalize method	minmax
Fold Generator	Kfold
Fold Number	10
CPU Jobs	-1
Use GPU	FALSE
Log Experiment	FALSE

Table 3 offers a comparative analysis of the predictive performance of CatBoost, a machine learning regressor, against other prominent machine learning algorithms. The table presents key performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2) obtained through rigorous experimentation. This comparative evaluation provides valuable insights into the relative efficacy of CatBoost in short-term load forecasting, highlighting its strengths and potential advantages over alternative machine learning regressors.

Table 3: Comparative Performance Metrics of CatBoost against Other ML Regressors in Short-Term Load Forecasting.

Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
CatBoost Regressor	**818.2522**	**1536198**	**1239.041**	**0.9507**	**0.0511**	**0.0249**	**9.947**
Extreme Gradient Boosting	844.6734	1694787	1301.307	0.9456	0.0531	0.0257	5.944
Extra Trees Regressor	813.2216	1833736	1353.676	0.9411	0.055	0.025	11.002

Light Gradient Boosting Machine	993.6416	2252901	1500.665	0.9277	0.0586	0.0303	1.734
Random Forest Regressor	939.5286	2474167	1572.069	0.9206	0.0608	0.0287	30.225
Gradient Boosting Regressor	1321.278	4374243	2091.001	0.8596	0.0751	0.0404	9.222
Decision Tree Regressor	1319.947	5227382	2284.886	0.8322	0.1102	0.0401	0.544
Linear Regression	1529.668	5611699	2368.276	0.8199	0.0833	0.0468	1.665
Least Angle Regression	1529.668	5611699	2368.276	0.8199	0.0833	0.0468	0.077
Bayesian Ridge	1530.486	5612795	2368.511	0.8198	0.0833	0.0468	0.09
Ridge Regression	1531.77	5617128	2369.434	0.8197	0.0834	0.0469	0.075
Lasso Regression	1529.782	5641737	2374.621	0.8189	0.0835	0.0468	0.216
Lasso Least Angle Regression	1529.771	5642087	2374.695	0.8189	0.0835	0.0468	0.068
Huber Regressor	1481.954	6018872	2452.539	0.8068	0.0861	0.0454	0.418
Passive Aggressive Regressor	1483.135	6042851	2457.42	0.8061	0.0863	0.0454	0.445
AdaBoost Regressor	2646.983	11089318	3329.698	0.6439	0.1071	0.0772	2.969
Orthogonal Matching Pursuit	3651.435	21257787	4610.229	0.3177	0.1441	0.1102	0.08
Elastic Net	3885.136	22740599	4768.455	0.27	0.1503	0.1186	0.076

5. Conclusions

This research study explore short-term load forecasting within sustainable energy grids presents a promising avenue for advancing predictive intelligence techniques. Utilizing the CatBoost algorithm on Turkey's power consumption dataset from January 1, 2016, to June 30, 2023, our methodology showcases the algorithm's effectiveness in capturing the temporal dynamics and intricate patterns inherent in energy consumption. The presented experimental results demonstrate the superior performance of CatBoost compared to other machine learning regressors, as evidenced by lower Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and higher R-squared (R2) values. The adaptability of CatBoost to diverse features and its capacity to handle categorical variables underscore its significance in addressing the challenges of load forecasting within dynamic and evolving energy grids.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Data Availability Statement

Data is available upon request.

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