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Comparison of Robust Machine Learning and Deep Learning Models for Midterm Electrical Load Forecasting

Fatma Yaprakdal[1*], Fatih Bal[2]

[1*] Kirklareli University, Electrical and Electronics Engineering Department, Kirklareli, Turkey. (e-mail: fatmayaprakdal@klu.edu.tr).
[2] Kirklareli University, Software Engineering Department, Kirklareli, Turkey. (e-mail: fatihbal@klu.edu.tr).

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Corresponding author:
Fatma Yaprakdal

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ABSTRACT

Electrical load forecasting (ELF) is gaining importance especially due to the severe impact of climate change on electrical energy usage and dynamically evolving smart grid technologies in the last decades. In this regard, medium-term load forecasting, a crucial need for power system planning (generation optimization and outages plan) and operation control, has become prominent in particular. Machine learning and deep learning-based techniques are currently trending approaches in electrical load estimation due to their capability to model complex non-linearity, feature abstraction and high accuracy, especially in the smart power systems environment. In this study, several load forecasting models based on machine learning methods which comprise linear regression (LR), decision tree (DT), random forest (RF), gradient boosting, adaBoost, and deep learning techniques such as recurrent neural network (RNN) and long short-term memory (LSTM) are studied for medium-term electrical load demand forecasting at an aggregated level. Performance metric results of these analyzes are presented in detail. State-of-the-art feature selection models are examined on the dataset and their effects on these forecasting methods are evaluated. Numerical results show that forecasting performance can be significantly improved. These results are validated by the results of other studies on the subject and found to be superior.

1. INTRODUCTION

The increase in the integration of renewable energy sources in power grids and the intermittent nature of these sources has increased the need for better resolution and accuracy of electrical load forecasting, while creating new problems. In addition, inadequacies in regional energy storage have made ELF extremely essential. Establishing the balance between energy production and consumption is a great necessity in today's modern power system operation, management and planning. Thus ELF plays an important role at this point [1].

In terms of time horizons, ELF methods can generally be split into three forecasting classes as short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). Although different forecasting horizons are defined in the literature for these categories; STLF, MTLF, and LTLF can last for a few minutes or hours to a week, a week to one year, and a few years up to decades, respectively. Each of these categories takes advantage of several forecasting methods to satisfy the certain objectives of application areas in power systems. In particular, the application areas of MTLF are of great importance as they are vital in power system operation, control and planning at any level such as generation, transmission, and distribution. A proper MTLF is required for getting a better generation and maintenance scheduling, planning programs in unit commitment, demand-side management, hydro thermal coordination, control of the system with many distributed energy resources, economic supply of different fuels, and more power system applications [2, 3].
According to the input data set, the load forecasting is divided into two levels as aggregated level (AL) and individual level (IL). While the dataset used for the forecast at AL contains aggregated datasets belonging to a certain group of end-users like system-level and feeder-level, a dataset of a specific building such as a residential building or commercial building is used for forecasting at IL.

On the other hand, there are various explicit factors such as weather-related factors, electric energy prices, days of the week, public holidays, economic indicators, and the population of a country or a region that affect the aggregated electrical energy consumption [4]. The effects of weather variables on the electricity consumption forecast are equally addressed in STLF, while in MTLF these variables affect this forecast to a certain extent. In terms of explicit factors affecting the electrical load consumption in [5], it is recommended that MTLF be divided into two classes as the conditional modeling approach and the autonomous approach. Factors affecting the electrical energy consumption addressed in the conditional modeling approach are historical electrical energy consumption and weather data, socio-economic indexes and sustained energy policies. In addition to the electrical energy consumption forecast, weather and socio-economic situation forecasts are also taken into account in this approach. The parameters considered in the autonomous approach are only historical electrical energy consumption and weather data that involves values such as temperature, humidity, and wind speed. This approach is much more suitable for regions with strong economies and especially for forecasting periods of one year or less [5].

ELF methods are examined in two groups as parametric and non-parametric methods. Parametric methods are created on the basis of analytical models and non-parametric methods are created on the basis of artificial intelligence techniques. Among the non-parametric methods, especially machine learning (ML) and deep learning (DL) techniques are preferred more for ELF with the increase in their development rates in the past few years, as they can model the complicated and non-linear relationships between load and external factors [6].

In ELF algorithms, feature selection is extremely important because the sizes of input data are getting bigger with digitalization while the prediction models are complex as well. Feature selection can significantly improve the forecasting model performance by reducing the uncertainty of overfitting, improving the algorithm to a certain extent, and preventing irrelevant features used in training from increasing the system cost and runtime.

In recent decades, most existing works on ELF have focused on ML- and DL-based models due to their remarkable performance in the area. However, most of these studies are on STLF methods. There are a limited number of research studies in the literature regarding MTLF methods \cite{Han19}. Because of the reason that short-term forecasting can be done by fitting a model to a dataset computationally or statistically and then extending a graph, curve, or range of values by making inferences about unknown values from trends in the known data while medium-term forecasting is a completely different and complicated problem than short-term forecasting [7,8].

This paper presents a comparative analysis implementing state-of-the-art machine learning and deep learning methods on MTLF at AL. A great number of robust and most-practiced ELF models as of the date are performed: LR [9–12], DT [13], RF [14–16], gradient boosting [17, 18], AdaBoost [19–22] as the representatives of ML methods; RNN [23] and LSTM [24–29] as the representatives of DL models. The ELF results by all these methods have been achieved as daily forecasting steps for monthly forecasting intervals. In addition, feature selection as a technique that improves the overall performance of the system significantly has been realized based on the autonomous approach to the worked forecasting algorithms by using Pearson, random forest, chi-square, and light gradient boosting machine (Light-GBM) models; different from other existing forecasting methods.

This study is prepared as follows. Section 2 and Section 3 give detailed information on the materials and forecasting methods used, respectively. Section 4 shares experimental results by specifying them with different measurement techniques. These results are validated by related literature studies in Section 5. Finally, Section 6 presents a conclusion related to the overall study covering a few challenging points in MTLF and future aspects.

2. MATERIALS

2.1. Dataset

The electrical load consumption data is obtained as open-source from Czech Transmission System Operator (CEPS) for this study [30].

Electrical load data for the Prague region between January 1, 2015 and February 20, 2021 are used. The considered feature name for electrical load is LOAD-MW and distribution of the aggregated electrical load in TW (terawatt) can be seen in Figure 1. The weather information data belonging to the electrical load is taken from Nasa Power Data Access Viewer [31].Temperature (T2M), dew/frost Point (T2MDEW), wet bulb temperature (T2MWET), and relative humidity is taken for 2 meters. Wind speed (WS10M) and wind direction (WD10M) are taken for 10 meters. Wind speed (WS50M) and wind direction (WD50M) are taken for 50 meters. In addition, all-sky insolation incident on horizontal surface (CLRSKY-SFC-SW-DWN) precipitation (PRECTOT) and surface pressure (PS) are taken for prediction. The unit values and their short names for all features are shown in Table I.

TABLE I

THE UNIT VALUES AND SHORT NAMES FOR FEATURE NAME

#	Feature Name	Short Name	Unit
1	Electrical load	LOAD_MW	TW
2	All sky insolation incident on horizontal surface	CLRSKY_SFC _SW_DWN	kW/hr
3	Temperature at 2 meters	T2M	°C
4	Dew/Frost point at 2 meters	T2MDEW	°C
5	Wet bulb temperature at 2 meters	T2MWET	°C
6	Relative humidity	R2HM	%
7	Precipitation	PRECTOT	mm
8	Surface pressure	PS	kPa
9	Wind speed at 10 meters	WS10M	m/s
10	Wind direction at 10 meters	WD10M	Degrees
11	Wind speed at 50 meters	WS50M	m/s
12	Wind direction at 50 meters	WD50M	Degrees

2.2. Dataset Input Selection and Preparation

Feature selection evaluates the features piece by piece to determine how the features in the dataset are effective on the results. Feature selection methods are employed to reduce the number of relevant features.

Pearson feature selection is a correlation number which stays in the range -1 and 1. It indicates the degree that two variables are linearly related. As it gets closer to zero, a weaker correlation is meant to be found.

Chi-square feature selection aims to test the independence of two events. When the features are independent, the observed count becomes more similar to the expected count. As the chi-square value gets higher, the feature can be inferred to be more dependent on the response thus it can be selected.

In RF feature selection, each tree calculates the importance of a feature by increasing the pureness of the leaves. The higher the increment in leaves purity the higher the importance of the feature.

Light-GBM feature selection utilizes tree-based learning. Light-GBM grows tree vertically while in parallel growing horizontally; ending up growing the tree leaf-wise and level-wise concurrently. The features selected after performing feature selection methods in this study are shown in Table II.

TABLE II
SELECTED FEATURES OF FEATURE SELECTION METHODS.
(TRUE: SELECTED, FALSE: NOT SELECTED)

Feature	Pearson	Chi-Square	Light GBM	Random Forest
LOAD_MW	Predict	Predict	Predict	Predict
CLRSKY_SFC_SW_DWN	True	True	True	True
T2M	True	True	True	True
T2MDEW	True	True	True	True
T2MWET	True	True	True	True
R2HM	True	False	True	True
PRECTOT	True	False	True	True
PS	True	True	True	True
WS10M	True	True	True	True
WD10M	False	False	False	False
WS50M	True	True	True	True
WD50M	False	False	False	False

3. METHODS

3.1. Linear regression

LR aims to find the best fit straight line or hyperplane for training samples. In this regard, a relationship between the dependent variable and one or more independent variables is provided using the best fit straight line, in other words the regression line.

3.2. Decision tree

DT aims to divide a dataset with many samples into smaller sets by finding a set of decision rules. Simple decision-making steps are learnt from the data for this purpose.

3.3. Random Forest

RF combines the predictions of many decision trees, aiming to end up a single result. It can simply handle classification and regression problems. RF is not heavily dependent on hyper-parameter estimation.

3.4. Adaptive boosting algorithms (AdaBoost)

In this model, learning is initialized by training a weak learner. In the next training, more priority is given to the incorrectly learned training data in the first step. Prioritized data are retrained by increasing their weight. It is continued by training the weak learner output to be the input to the other learner. At the end, the results are fused to form the final decision.

3.4.1 Gradient boosting algorithms

Gradient boosting is available both for regression and classification problems. A combination of weak predictive models typically creates a model of decision trees. The purpose of gradient boosting is to define and minimize a loss function.

3.4. Recurrent Neural Networks

RNN helps extracting information from sequences of time-series data. RNN allows previous outputs to be used as inputs while having hidden states. RNN architecture utilized in this work is described in the [32].

3.4. Long Short-Term Memory

LSTM is an improvement of RNN, originated from the problem of short-term memory. LSTM has feedback connections in addition to feed-forward connections. LSTM networks are well suited for making predictions based on time series data. A common LSTM unit composes of a cell, an input, output, and forget gates. The cell remembers values in variable-length time intervals and these three gates aims to regulate the information flow into and out of the cell. LSTM unit facilitated in this work is described in the [32].

4. EXPERIMENTAL RESULTS

4.1. Metrics

In this part of the study, the regression metrics used are mentioned. Mean squared error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) metrics are frequently practiced regression metrics in the related field in the literature. To more clearly compare the performance of our test results with the concerned studies, performance evaluations of test results are carried out with these metrics. MSE depicts the mean of the squared differences between predicted and expected values in a dataset.

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left|(A_j - F_j)^2\right|. \quad (1)$$

where Aj is the actual value, Fj is the forecast value and n is the total number of test samples. MAE and MAPE are defined similarly in what follows

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|A_j - F_j\right|. \quad (2)$$

4.2. Results

The results related to the prediction of electrical load are shown in Table III, IV, V. According to all these tables it seen that in the application without feature selection, the model that gives the best results is the LSTM model with the MAPE value which is evaluated as 8.66%. Among the models made by applying Pearson, RF and Light-GBM feature selection techniques, the model that gives the best result according to the MAPE value is the LSTM model with 2.02%. Based on chi-square feature selection results, LSTM gives the best result in the MAPE metric evaluation, with the value of 2.12%. Graphical comparisons of the actual and predicted electrical load values for the best performing models are illustrated in Figure 1.

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TABLE III

THE RESULTS OF THE REGRESSION MODEL PERFORMED ON DATA WITHOUT USING FEATURE SELECTION.

Model	MAE (%)	MSE (%)	MAPE (%)
Random Forest	1,38	3,30	10,93
Decision Tree	3,17	4,30	11,09
Linear Regression	6,32	8,01	14,78
Ada Boosting	6,42	0,67	13,45
Gradient Boosting	6,11	0,60	13,36
RNN	1,23	2,61	12,18
***LSTM**	2,04	0,22	8,67

TABLE IV

THE RESULTS OF REGRESSION MODELS PERFORMED ON DATA USING PEARSON, RF AND LIGHT-GBM FEATURE SELECTION.

Model	MAE (%)	MSE (%)	MAPE (%)
Random Forest	3,05	5,50	9,37
Decision Tree	4,23	5,89	10,90
Linear Regression	5,88	7,93	13,61
Ada Boosting	6,88	0,77	13,98
Gradient Boosting	5,97	0,58	13,07
***LSTM**	4,93	0,37	2,02
RNN	1,96	0,07	2,52

TABLE V

THE RESULTS OF REGRESSION MODELS PERFORMED ON DATA USING CHI-SQUARE FEATURE SELECTION.

Model	MAE (%)	MSE (%)	MAPE (%)
Random Forest	3,05	5,45	10,37
Decision Tree	4,23	5,90	10,90
Linear Regression	6,24	7,93	13,61
Ada Boosting	6,26	0,63	13,30
Gradient Boosting	6,04	0,59	13,23
***LSTM**	1,61	0,04	2,12
RNN	2,57	0,11	9,58

5. BENCHMARKING STUDY

At a glance to the comparison Table IV, the result of our research is superior in terms of the accuracy of forecasting, and on par with [17]. However, [17] has longer period of data compared to our data and just 12 points have been forecasted while we forecast 100 points considering point forecasting. It is clearly seen from the table that other studies have estimated much less points compared to ours, with a maximum of 24-point forecasting. Our study nevertheless seems to be more successful in MTLF, as the accuracy of the prediction decreases while the prediction interval is getting larger. From here it can be easily inferred that; Pearson, RF and Light GBM feature selection methods are of great importance in increasing the accuracy of the estimations made with ML and especially deep neural network (DNN) models. Proposed study uses Czech Republic (2015-2021) as the dataset. Historical power load and meteorological data are used as input features. Pearson, RF and Light-GBM are used for feature selection. LSTM is considered as the best forecasting model. [1] studies a small region in Ontario, Canada over 10 years. Input features are historical power load and meteorological data. Non-linear auto-regressive exogenous (NARX) and RNN-LSTM are utilized as forecasting models.

[17] studies United States (1987-2009) as the data. As for the features; historical power load, natural gas load, natural gas price, average retail price of electricity, electric power sector natural gas consumption and CO2 emissions are facilitated. Quantile regression and kernel density estimation are utilized as models. [33] studies Seoul, South Korea over 14 months. Input features are historical power load and air temperature. A hybrid model based on dynamic and fuzzy time series is facilitated. [34] covers 35 European countries until 2014. Features in use are historical power load and meteorological data. Exponential smoothing is used for feature selection. Residual dilated LSTM is utilized as the forecasting model. [35] studies 25 districts in Seoul between 2005 and 2018. Considered features are calendar, population and meteorological data. Feature selection is applied with Pearson correlation coefficient. DNN is utilized via transfer learning.

TABLE VI

COMPARISON WITH THE RELATIVE LITERATURE STUDIES.

Works	Forecasting steps	Forecasting intervals	MAPE (%)
Proposed	Daily	~3,5 months	2,12
[1]	Hourly	12 months	4-10
[17]	Monthly	12 months	2,12
[33]	Monthly	4 months	~3
[34]	Monthly	12 months	4,46
[35]	Monthly	24 months	6,46

6. CONCLUSION

Machine learning models including deep learning have been successful and performing better than traditional time series and regression techniques. However, non-linear energy consumption patterns are in need to be better modelled while obtaining high accuracy and prediction performances for the medium-term monthly forecasting [25]. In this study, the electricity load estimation of the Prague region of the Czech Republic for the years 2015-2021 has been carried out. In order to better observe the results of the methods used, initially, all the features of the data are used without applying any feature selection process. Then, feature selection techniques are applied and the results are evaluated. Among all the ML and DL-based ELF methods studied, the LSTM approach gives the best results both with feature selection and without feature selection study. While the MAPE value difference between the results obtained with this approach and the results obtained with other approaches is at least 3% without applying feature selection, it is around 9% when feature selection is applied. Such an improvement is of great importance for ELF. Moreover, when the results of the applications performed with three different methods are examined, it is seen that the results of the deep learning methods are close to each other when the Pearson, RF, Light-GBM feature selection is applied. In this context, it has been concluded that these feature selection methods are more effective in terms of comparison of the methods discussed and the accuracy of the results obtained.

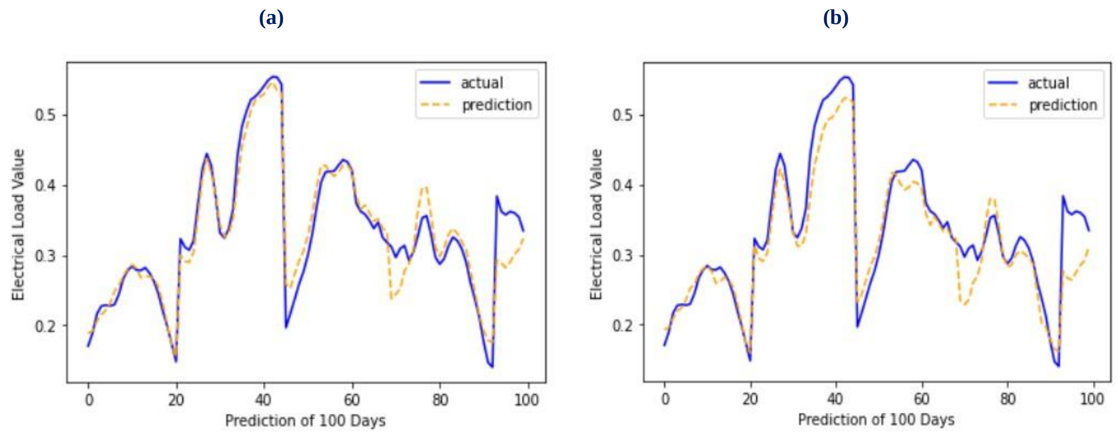

Figure 1. (a) LSTM with Pearson, RF and Light-GBM feature selection, **(b)** LSTM with chi-square feature selection.

For future studies, the facilitated forecasting methods will also be analyzed for the LTLF which is of great importance especially in the expansion planning of real-world power systems [36]. Since LTLF shows similar structures to MTLF in terms of algorithms and features, the applications of the same feature selection methods will be carried out for LTLF, and improvement studies will be made on it. In addition to these estimation methods and feature selection techniques that have been studied on aggregated load data, all the proposed techniques will be studied for individual loads, and the impacts of these methods and development techniques on all load types will be evaluated.

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BIOGRAPHIES

Fatma Yaprakdal obtained her BSc degree in electrical engineering from Yildiz Technical University (YTU) in 2004. She received the MSc. diploma in Energy Science and Technology Department from the Istanbul Technical University in 2012, and PhD degrees in Electrical Engineering from the Yildiz Technical University in 2021. Her research interests are electrical power systems, microgrids, energy forecasting and machine learning. In 2010, she has started her academic career as a research assistant in Yalova University. In 2021 she joined the Faculty of Engineering, Kirklareli University as a assistant professor, where she is presently working at the same position.

Fatih Bal obtained his BSc degree in software engineering from Istanbul Maltepe University in 2014. He received the MSc. diploma in Computer Engineering from Beykent University in 2017. He is still doing his PhD education in Duzce University. His research interests are Deep Learning, Machine Learning, Computer Vision, Data Science. In 2016 he has started his academic career as a research assistant in Maltepe University. After 2 years experience there, in 2018 he joined Kirklareli University as a lecturer, where he is presently a lecturer.