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Gerçek Zamanlı Elektrik Yük Tahmini İçin Bir Derin Öğrenme Yaklaşımı

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ÖZET

Doğru ve gerçek zamanlı elektrik talebi tahmininin artan önemi ışığında, bu araştırma, tahmin doğruluğunu önemli ölçüde artırmak amacıyla bir derin öğrenme modeli sunmaktadır. Doğrusal regresyon gibi geleneksel tahmin yöntemleri, elektrik kullanımıyla ilgili verilerde yer alan karmaşık kalıpları yakalamakta zorlanmaktadır. Standart makine öğrenimi yöntemlerinin, önerilen derin Uzun Kısa Vadeli Bellek (Long Short-Term Memory-LSTM) modeliyle karşılaştırıldığında yetersiz kaldığı görülmüştür. Ortalama Mutlak Hata (MAE) 5.454 ve Ortalama Karesel Hata (MSE) 18.243, derin LSTM modelinin bu sorunun üstesinden gelmedeki yeterliliğini göstermektedir. Doğrusal regresyon ise 47.352 MAE değeri ve 65.606 MSE değeri ile önerilen modelden daha düşük başarı sonucu elde etmiştir. Daha yüksek tahmin hassasiyeti ve güvenilirliği nedeniyle, derin LSTM modeli elektrik talebinin doğru, gerçek zamanlı tahmini için uygun bir seçenektir.

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A Deep Learning Approach to Real-Time Electricity Load Forecasting

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ABSTRACT

In light of the increasing importance of accurate and real-time electrical demand forecasting, this research presents a deep learning model with the goal of dramatically improving predictive accuracy. Conventional methods of forecasting, such as linear regression, have trouble capturing the complex patterns included in data about electricity usage. Standard machine learning methods are shown to be wanting when compared to the suggested deep Long Short-Term Memory (LSTM) model. Mean Absolute Error (MAE) of 5.454 and Mean Squared Error (MSE) of 18.243 demonstrate the deep LSTM model's proficiency in tackling this problem. The linear regression, on the other hand, achieved a MAE of 47.352 and an MSE of 65.606, which is lower than the proposed model. Because of its greater predictive precision and reliability, the deep LSTM model is a viable option for accurate, real-time prediction of electricity demand.

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1. *INTRODUCTION (GİRİŞ)*

The issues related with global warming and the energy resources scarcity are soaring. It therefore calls for strong Energy Management System (EMS) at this moment. Industries are on the look out for improved EMS in order to realize its potential to revolutionize energy monitoring and budgeting. Smart meters represent very sophisticated tools for measuring power consumption at home or office levels. This makes them an extremely strong partner on the way toward efficient and reduced costs when it comes to energy planning [1].

The smart meter's data becomes one of the valued resources that provides a huge pool of data for analytics-based management. Smart microgrid is an integral component in the tapestry of EMS. Examples include interpreting consumption trend, demand forecast, and optimal energy exchange to decipher energy load [2]. Within the realm of load forecasting, varying prediction horizons come to the fore: short term, midterm and longterm forecast . However, decisions concerning prosumers within the smart energy grids will require a short timeline, namely, minutes to days. In addition, medium-term forecasts, weeks to months ahead, are crucial in power systems scheduling [3-4], while long term forecasts, monthly/yearly predictions, support grid maintenance planning.

In essence, load forecasting seeks to predict electricity demand from end-use consumers in advance. This can be done using various methods, out of which machine learning (ML) strategies are becoming increasingly popular for having a more usable approach. To make informed decision making in energy management, accurate forecasts of future energy demands should be provided to enable proper planning and scheduling . Still, load forecasting is also not a walk in the park considering that energy consumption patterns change greatly over time. Dynamism results into concept drifting, which makes traditional ML approaches obsolete [5].

There are numerous reasons why people's energy consumptions behavior could change. These reasons include increasing or decreasing prices for fuel; temporal consideration relating to date or season. As an example, changes in pricing lead to the demand that the customers should react on the cost price increase. However, traditional ML approaches fail and deteriorate due to recognising dynamic nature of energy load demand [6].

Current research focuses on deep learning (DL) based approaches to interval load forecasting using the power of Long-Short Term Memory (LSTM) networks. It should however be noted that LSTM has shown very good results for load forecasting. An adaptive mechanism that grapples with new load consumption patterns due to concept drift in order to improve the efficiency of DL models -the model is updated automatically according to new energy usage patterns that signal changes. Nonetheless, active/passive tracking of concept drift is prone to various problems- particularly defining a magnitude threshold that would ensure overall good predictions [7-8].

This paper offers an interval-load forecast learning model called hybrid LSTM as a solution for these problems. A complete solution encompasses both pass and active drift adaptation. A hybrid LSTM network is developed to be able rapidly learn changing load consumption scenarios having captured the historical consumption patterns. There is a detailed comparison with baseline models in the paper and hence the effectiveness of the proposed hybrid LSTM model. In addition, a trade-off analysis of various adaptation strategies takes into account the predictive performance as well as computation costs that guides appropriate choice of adaptation.

In the subsequent sections, we consider related works in section 2. Section 3 proposes a new hybrid LSTM solution. Section 4 evaluates it experimentally and section 5 concludes the results.

2. *RELATED WORKS* *(İLGİLİ ÇALIŞMALAR)*

Researchers have extensively employed ML algorithms and DL to develop criteria for load-balanced forecasting across a plethora of fields. Using deep learning and the current spatio-temporal correlation in appliance load data, [9] develop a short-term home load forecasting method. Electricity consumption behaviours and their internal spatio-temporal relationship are studied using several time series in the framework. The proposed forecasting method also makes use of a deep neural network and an iterative process. The results demonstrate that both iterative ResBlocks and load data from appliances contribute to better predicting results. The proposed method reduces Root Mean Squared Error by 3.89 percentage points to 20.00 percentage points, Mean Absolute Error by 2.18% to 22.58%, and Mean Absolute Percentage Error by 0.69 percentage points to 32.78 percent. The suggested method is further tested with further trials to examine the effects of incorporating load data from appliances, iterative ResBlocks, and other parameters.

In order to effectively deploy demand response strategies in manufacturing facilities, [10] want to create a system to predict the electrical energy demand of metal cutting machine tools. Based on the findings of the previous research, the effectiveness of LSTM and convolutional neural networks (CNNs) in predicting the electric load of a machine tool for a 100-second time horizon is compared and contrasted. The results show that specifically the combination of CNN and LSTM in a DL strategy delivers accurate and robust time series forecasts with reduced feature preparation work. Different network topologies, such as an attention mechanism for the LSTMs, and other hyperparameter combinations are assessed to see whether they can further enhance the predicting accuracy.

Using a combination of the factored conditional restricted boltzmann machine (FCRBM) and the conditional restricted boltzmann machine (CRBM), [11] provide a rapid and accurate short-term load forecasting system. A rectified linear unit (ReLU) and a sigmoid function are used in training the stacked FCRBM and CRBM. Utilities in the US have offline demand side load statistics that have been put via the suggested framework. Based on predicted demand, power plants may ramp up or down their output, add more generators, or trade energy with nearby grids. Their suggested approach is verified using three performance metrics: the mean absolute percentage error (MAPE), the normalised root mean square error (NRMSE), and the correlation coefficient. When compared to artificial neural networks (ANNs) and CNNs, the results demonstrate the accuracy and robustness of stacked FCRBM and CRBM.

Optimisation of an ANN model is presented by [12] using an embedded multi-population Differential Evolution (DE) micro-Genetic Algorithm (mGA). To begin, a method for optimising and balancing both global and local search—the mGA embedded multi-population DE—is proposed. The projected DE is then used to fine-tune the ANN's training-time weights. Four cutting-edge ML methods are used to compare the entire model's performance against the publicly available Panama electrical load dataset. Compared to the other chosen machine learning methods, the suggested DE based model is shown to have superior prediction accuracy in the evaluation results.

To enhance prediction accuracy, [13] suggested a self-adaptive DL model. Meanwhile, RSPSO is employed to determine the network's optimum architecture, which involves discrete variables (i.e. the amount of neurons in each layer and the quantity of hidden layers) and categorical variables (i.e. activation function in each layer and learning approach). Additionally, the architecture and structure of the dynamic DL model are updated using the moving horizon approach, allowing it to capture the most recent highlighting patterns in the building's electrical load. The electricity consumption of a school building and the local weather profile are used to evaluate the suggested load prediction model. The best model for predicting energy consumption beyond the next horizon is found to be the self-adaptive load prediction model, but this model's prediction performance degrades with increasing horizon length. Prediction accuracy and repeatability are shown by the suggested prediction model's mean squared error, mean absolute error, and coefficient of determination all falling between 4.48 kW and 11.23 kW, 1.28 kW and 2.31 kW, and 97.52% and 98.92%, respectively. Adding Gaussian white noise to meteorological data results in an increase in mean absolute error between 2.08% and 15.33%, showcasing the reliability of the proposed prediction model in dealing with weather forecast uncertainty. Therefore, the suggested accurate, resilient, repeatable and self-adaptive load forecast model can be anchored in practical energy management systems thus facilitate building operation and system control.

The dynamic drift-adaptive Long Short-Term Memory (DA-LSTM) architecture proposed by [14] can enhance the performance of load forecasting models without the need for a drift threshold. They incorporate a number of active and passive adaption mechanisms into the framework. They provide a comprehensive analysis of the proposed framework and apply it to a real-world problem in a cloud context in order to evaluate DA-LSTM in a realistic situation. Each method's efficiency is measured by how well it can make predictions and how much computing time it takes. The experimental findings reveal that, compared to the literature's baseline methodologies, our framework outperforms them across a variety of evaluation metrics.

3. ***MATERIALS AND METHODS*** *(MATERYALLER VE YÖNTEMLER)*

Meticulous design is paramount given its prospective significant impact in real-world applications. The proposed approach harnesses DL techniques for forecasting power consumption. Notably, when regression is performed on the accumulated data, a model predicated on the LSTM algorithm is employed. This data encapsulates various factors influencing energy consumption patterns, such as weekly, monthly, or annual electricity usage.

Upon segregating the data into bifurcated sets, the methodology proceeds in two primary phases: data normalization and inference derivation. The Max-Min normalization technique is utilized to standardize the data, ensuring each constituent datum is normalized prior to the regression phase. The analytical phase is executed using two distinct strategies. Initially, a deep hybrid-based model is proposed, followed by the application of a machine learning linear regression method. Figure 1 delineates the sequential execution of these stages.

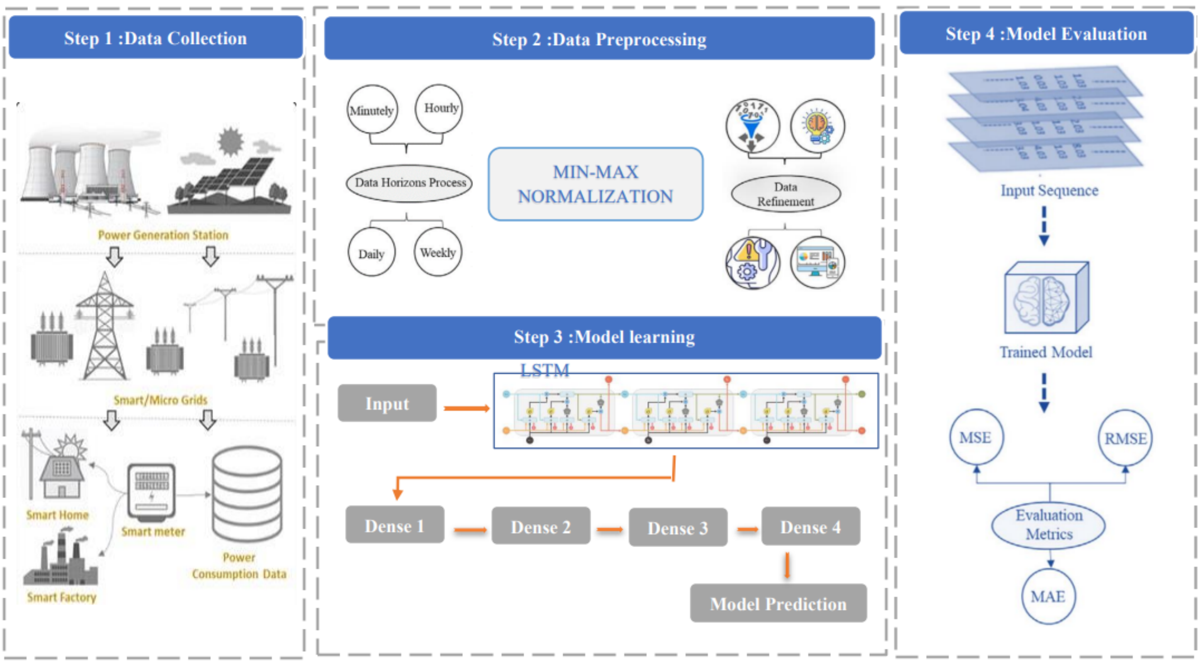

Figure 1. The proposed model

3.1 Dataset *(Veriseti)*

The Short-term Electricity Load Forecasting (Panama) dataset predicts Panamanian post-transmission electricity loads [15]. Weekly load projections are broken down hourly from daily and weekly pre-transmission power generation records in this dataset. Historical electrical load statistics, weekly projections, and calendar features like school sessions and vacations are included in its comprehensiveness. Notably, the information includes temperature, humidity, rainfall, and wind velocity for three major Panamanian cities.

3.2 Pre-processing (Ön İşleme)

For neural networks, pre-processing, especially

Algorithm 2 Linear Regression Computation

procedure LinearRegression(n)
  Read Number of Data (n)
  for $i = 1$ to n **do**
    Read x_i and y_i
  end for
  Initialize:
  $sum\_x = 0$
  $sum\_x2 = 0$
  $sum\_y = 0$
  $sum\_xy = 0$
  for $i = 1$ to n **do**
    $sum\_x = sum\_x + x_i$
    $sum\_x2 = sum\_x2 + x_i^2$
    $sum\_y = sum\_y + y_i$
    $sum\_xy = sum\_xy + x_i \cdot y_i$
  end for
  Compute the slope K and intercept J:
  $K = \frac{n \cdot sum\_xy - sum\_x \cdot sum\_y}{n \cdot sum\_x2 - (sum\_x)^2}$
  $J = \frac{sum\_y - K \cdot sum\_x}{n}$
  Compute the dependent variable:
  $y = J + K \cdot x$
end procedure

normalization, significantly impacts the effectiveness of the training phase. By normalizing raw inputs, the data becomes more conducive to training. Absence of normalization can decelerate the neural network training process, given that normalization's primary role is to ensure uniform scaling of data. A Min-Max normalization process applied to an electricity forecasting dataset [16]. For each feature x in S, the normalization as in Algorithm (1).

It takes as input a vector S consisting of features related to electricity forecasting. The algorithm initializes by determining the minimum X_{min} and maximum X_{max} values within S.

3.3 Linear Regression *(Doğrusal Regresyon)*

Linear regression stands as one of the most prevalent and intuitively comprehensible ML techniques [17], rooted deeply in statistical analysis. Its primary objective is to establish a linear relationship among multiple variables [18]. In the context of this paper, the linear regression methodology is employed to forecast electricity consumption, leveraging the normalized values from the dataset as illstrated in Algorithm (2).

3.4 Hybrid LSTM - Dense Model *(Önerilen Hibrit LSTM – Dense Modeli)*

This research aims to present an innovative model that integrates the capabilities of LSTM with a dense network. The ultimate goal of this fusion is to enhance data regression, with a specific emphasis on electricity forecasting. The proposed network model employs the renowned backpropagation technique. In this method, the weights affiliated with certain network connections undergo consistent adjustments. The primary objective behind this is to minimize the discrepancy between the original output vector, as generated by the designated network, and the anticipated output vector. Through this novel integration of LSTM and dense networks, we aspire to set a new benchmark in the realm of accurate electricity forecasting.

In a model, the output of each neuron in the dense layer is influenced by all of the neurons in the layer below it. Matrix-vector multiplication is performed by the neurons in the dense layer. This is where the row vector from the preceding layers is multiplied by the column vector from the dense layer. The primary rule for multiplying matrices and vectors is that the number of elements in the row vector must match the number of elements in the column vector. Because of this, the output of the dense layer will be an N-dimensional vector.

In general, the proposed hybrid deep model for load forecasting of electricity is made up of five layers as shown in Figure 2, and an optimizer as a final progress.

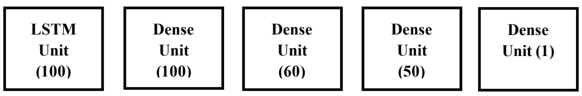

Figure 2. Proposed deep model layer structure

Table 1 outlines the architecture of a specific the proposed deep LSTM regression model, detailing the sequence of layers, the number of parameters for each layer, and the output shape. The model complexity is dictated by the number of parameters, where too many can cause overfitting and too few can result in underfitting.

Table 1. Proposed deep LSTM layers

Layer Type	Parameter	Output shape
LSTM	52400	(non, 100)
Dense	10100	(non, 100)
Dense	6060	(non, 60)
Dense	3050	(non, 50)
Dense	51	(non, 1)

The data's dimensionality at each processing stage is represented by the output shape of each layer. In this model, it begins with an LSTM layer with 52,400 parameters, generating 100 features per sample. Subsequently, a series of Dense layers follow, with varying parameters and output features: the first with 10,100 parameters and 100 features, the next with 6,060 parameters and 60 features, and another with 3,050 parameters and 50 features. The model concludes with a final Dense layer of 51 parameters, yielding a single output per sample, indicating its suitability for regression or binary classification tasks.

3.5 Performance Measurements *(Performans Ölçümleri)*

The performance of the model is evaluated based on specific metrics. The MAE (Mean Absolute Error) and MSE (Mean Squared Error) are two such measures used to assess the proposed model.

1- The Mean Absolute Error (MAE) measures the average discrepancy between two continuous variables [19], X and Y. These variables can represent paired observations of the same phenomenon. Comparisons such as predicted values vs. actual values, posterior time vs. beginning time, or a standard gauge method vs. an alternative measuring approach are examples where Y vs. X might be used. When there are n data points on a scatter plot, each with coordinates (xi, yi), the MAE measures the average vertical distance of each point from the Y=X line. Contrary to the mention, MAE does not stand for the average horizontal distance from the Y=X line; it always denotes vertical distances. The method to compute this distance is presented in Eq. (2) .

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (2)$$

Considering that there are n samples of model errors that are calculated as (ei 5, i = 1, 2 . . . n).

2- The Mean Squared Error (MSE) is the average of the squared differences between predicted and actual values. Because errors are squared before being averaged, the MSE will always yield non-negative values. Values closer to zero indicate better model performance. Graphically, the MSE can be thought of as the second moment of the error distribution. This characteristic allows it to capture both the variance of the estimator (the extent to which estimates differ from one data sample to another) and its bias. The calculation of MSE is detailed in Eq. (3), as described by [20].
Where X_i denote to the original sample data, and Y_i refered to the processed one.
3- Root Mean Squared Error (RMSE)
The RMSE, or root mean squared error [21], is calculated by taking the square root of the MSE. It's another popular metric for estimating the typical size of the mistake, and it uses the same measurement scale as the source data.

$$\text{RMSE} = \sqrt{MSE} \quad (4)$$

These metrics are critical for gauging the model's effectiveness in predicting future electricity demand. Better model performance is indicated by smaller values of MAE, MSE, and RMSE, as this indicates that the projected values are closer to the actual values.

4. RESULTS AND DISCUSSION *(SONUÇLAR VE TARTIŞMA)*

Comparing the best attained result from the deep model within the linear regression algorithm, there is a big difference, and much better regression and prediction performance when utilizing the proposed deep model rather than the machine learning linear algorithm as shown in Table 2.

Table 2. Comparing of two model performance

	MAE	MSE
Linear regression	47.352	65.606
Deep LSTM (Proposed study)	5.454	18.243

Also, Figure 2, and Figure 3, illustrated the MAE, and MSE for the best results of the proposed deep model and linear regression algorithm.

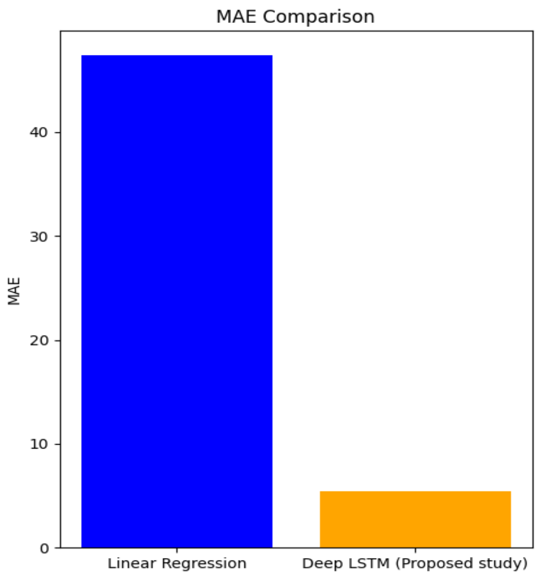

Figure 2. MAE for the proposed deep model and linear regression algorithm.

Visualising model performance shows how much better the proposed Deep LSTM model is than the more traditional Linear Regression method. The enormous gap between the two models is clearly demonstrated by the bar plot when looking at MAE.

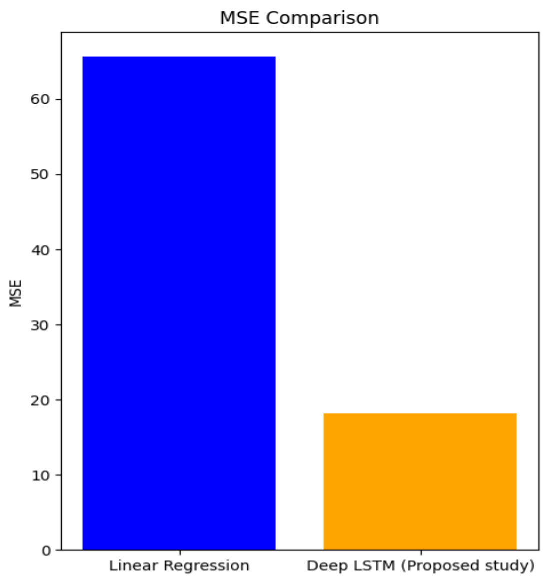

Figure 3. MSE for the proposed deep model and linear regression algorithm.

Linear Regression performs poorly with an enormous MAE of 47.352, however the proposed Deep LSTM model performs impressively better with an MAE of only 5.454. Compared to the more basic linear method of standard regression, the proposed Deep LSTM model's superior performance is clear. This visual representation is a demonstration of the game-changing potential of deep learning for time-series forecasting.

Figure 4 displays the MAE, MSE, and RMSE at three different epochs (100, 200, and 300) for a variety of look-back periods (10, 20, 30, 40, and 50).

As the look-back period lengthens, the MAE, MSE, and RMSE for epoch 100 all tend to decrease. While both MSE and RMSE display variability in epoch 200, MAE increases, especially when considering a look-back of 30.

The MAE maintains its downward trend by epoch 300, and the MSE and RMSE exhibit stable behaviour. The choice of the look-back time effects the model's prediction performance, with a trade-off between short-term accuracy and capturing long-term relationships. These visualisations help assist the selection of an ideal look-back time based on the trade-off between bias and variance in the model.

Interesting insights on the model's generalisation performance can be gleaned from the outcomes of the testing phase as shown in Figure 5. The MAE and RMSE values in epoch 100 are both low, indicating that the model has successfully learned patterns from the training data. However, both MAE and RMSE increase noticeably when we move on to epoch 200. This increase could indicate that the model is having trouble generalising to new data, or that the training approach needs to be tweaked to improve generalisation.

There is no clear pattern by epoch 300. It appears that the MAE is improving while the RMSE is still somewhat volatile. This trend emphasises the need for careful evaluation of model performance throughout numerous epochs, so that overfitting and underfitting can be detected.

These findings highlight the iterative nature of model learning and testing and suggest taking a systemic view when analysing the data. Insightful guidance for improving models for robust real-world applications can be gleaned from the interplay between MAE and RMSE.

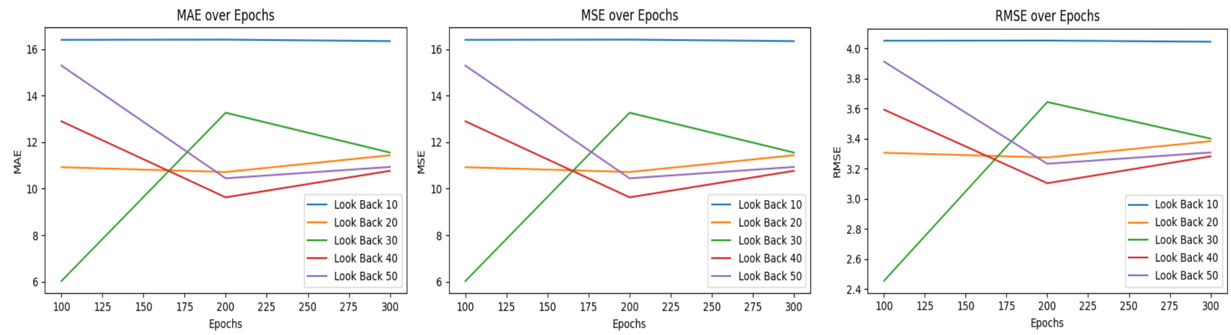

Figure 4 . Results from the training phase.

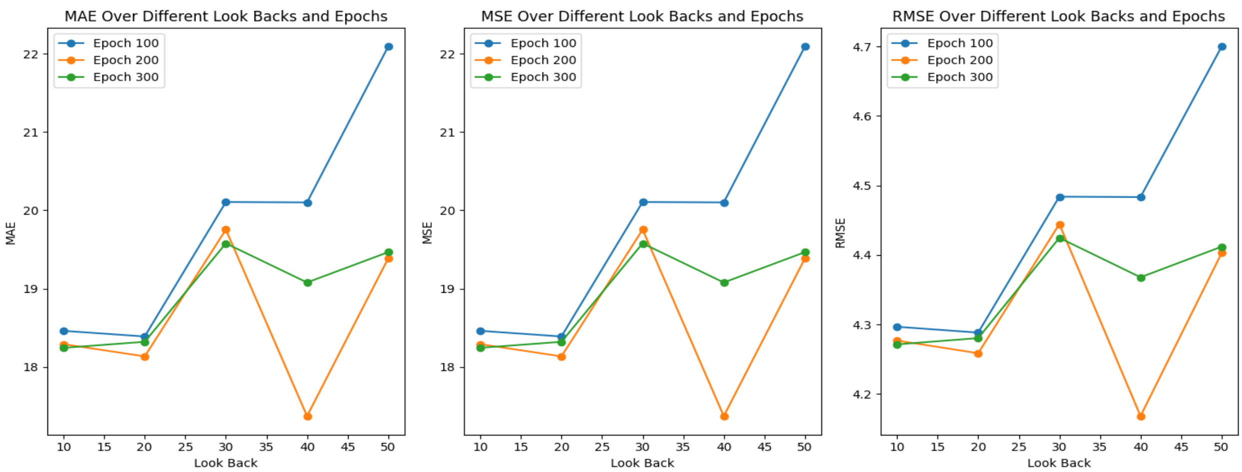

Figure 5 . Results from the testing phase.

5. *CONCLUSION* *(SONUÇ)*

The proposed deep LSTM model provides a clear leap in predictive accuracy. Additionally, the MAEs and MSEs are greatly reduced. Particularly, the deep LSTM model achieves a good MAE of 5.454 and an MSE of 18.243 while the linear regression counterpart is slow with an MAE of 47.352 and an MSE of 65.606. Such a big distinction highlights the ability of the advanced model of providing markedly better and more reliable forecasts, rather than plain linear regressions.

Even though it would be wrong not to recognize the strengths of the deep LSTM model, any study comes with its own limitations. The modelling is quite useful for a short-term power prediction but could have been distorted by the dynamic unpredictable factors. Thirdly, the nature of input data as well their presence affects the model effectiveness. In that order, future research endeavours can focus on addressing these problems in order to improve the reliability and suitability of this deep LSTM model.

Moreover, the study paves way for further research. Further research can be pursued in tuning model hyperparameters, examining additional features for better prediction accuracy, and also applying DL approaches across other forecasting horizons. Further, can contribute to the general discussion of the applicability and limitations of DL models in regression problems.

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