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Short-Term Electrical Load Forecasting in Power Systems Using Deep Learning Techniques

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Abstract

The use of big data in deep neural networks has recently surpassed traditional machine learning techniques in many application areas. The main reasons for the use of deep neural networks are the increase in computational power made possible by graphics processing units and tensor processing units, and the new algorithms created by recurrent neural networks and CNNs. In addition to traditional machine learning methods, deep neural networks have applications in anticipating electricity load. Using a real dataset for one-step forecasting, this article compares three deep learning algorithms for short-term power load forecasting: LSTM, GRUs, and CNN. The statistics come from the Turkish city of Zonguldak and include hourly electricity usage loads and temperatures over a period of three years, commencing in 2019 and ending in 2021. The mean absolute percentage error is used to compare the performances of the techniques. Forecasts are made for twelve representative months from each season. The main reason for the significant deviations in the forecasts for January, May, September, and December is the presence of religious and national holidays in these months. This was solved by adding the information obtained from religious and national holidays to the modeling. This is not to say that CNNs are not good at capturing long-term dependencies and modeling sequential data. In all experiments, LSTM, GRUs and encoder-decoder LSTM outperformed simple CNN designs. In the future, these new architectural methods can be applied to long- or short-term electric charge predictions and their results can be compared to LSTM, GRUs and their variations.

Keywords: Short-term forecasting, electricity load, graphical process units, tensor process units

1. INTRODUCTION

One of the key issues that capture the interest of both scholars and electricity supplier companies is the forecasting of electricity load. Electricity load forecasting affects provider companies' operations in operational, tactical, and strategic ways. Overestimating or underestimating loads can result in unstable energy distributions, poor quality supply for distribution systems, excessive resource deployment for the entire supply system, and additional costs like penalty fees and profit losses [1]. Poor forecasting may have long-term negative effects on changes in electricity pricing, competitiveness, and market share of the companies [2]. On the other hand, various forecasting techniques, including statistical, parametric, and non-parametric ones, as well

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as machine learning techniques, have been created and applied to forecasting issues from the perspective of scholars.

Very short-term load forecasting, short-term load forecasting, mid-term load forecasting, and long-term load forecasting are the four categories into which forecasting horizons are divided into forecasting issues [3, 4]. Very short-term load forecasting horizon spans a minute up to half-hour. The short-term load forecasting horizon spans one hour up to one week. Mid-term load forecasting and long-term load forecasting horizons span from one week up to several weeks, and several months to several years, respectively.

In this study, real case data for Zonguldak in Turkey are used to anticipate short-term load. Three years' worth of hourly temperature data and Zonguldak's electricity load consumption are included in the data. One step ahead electricity load forecasting is done by contrasting the data with deep learning techniques like the Gated Recurrent Unit (GRU), Long-Short-Term Memory (LSTM), and Convolutional Neural Network (CNN). Although several traditional machine learning methods are used in the literature for short-term load forecasting, such as in [5-9], deep learning methods are now being used and taking the place of these traditional methods.

In the literature for short-term load forecasting, simple Long-Short-Term Memory (LSTM), and GRUs, as well as simple and encoder-decoder bidirectional LSTM and GRU, are primarily employed techniques as deep learning tools. GCNNs and GRU are utilized in [10-12], while bidirectional LSTM and an attention mechanism are used in [13]. CNN and recurrent neural networks with parallel structures were employed by the authors [14]. In [15], CNN and LSTM are combined, while in [16], GRUs and LSTM are employed to conduct a comparative analysis. In addition to these studies, deep learning approaches may be used with other techniques to improve forecasting, such as empirical mode decomposition, wavelet transform, and Kalman filter. Details on the methodology and applications are provided in the following sections. Conclusions are made, and suggestions for further research are discussed.

The objective of the study is to obtain information about the near future behavior of electric energy consumption in the study region by short-term electrical load forecasting. These forecasts are of great importance in applications such as management of power grids, balancing electricity supply and demand, planning power generation and distribution, integration of renewable energy and efficient and safe operation of power systems. For all these reasons, short-term electrical load forecasting involves the use of different disciplines, data analysis and statistical methods in the electric power sector. These forecasts are beneficial for society and the environment by improving the efficiency of the power sector, ensuring the sustainable use of energy resources, and increasing the security of power systems.

2. LOAD ESTIMATION METHODOLOGY

The selection of the estimation technique to be used is very important in determining the forward load demands. Depending on the nature of the load changes, one method may show advantages or disadvantages over the other. Before choosing a particular method, it is necessary to study the behavior of the load. By choosing the behavior of the load, it can be determined whether it is more accurate to choose an appropriate curve or a stochastic model for the system. Since electrical networks show different characteristics, it is very necessary to examine the structure of the existing system.

Choosing the most suitable method for the examined system is realized by knowing the advantages and disadvantages of different methods. There are basically two estimation methods: extrapolation and correlation analysis. The extrapolation method is an estimation method in which assumptions are made for the future by examining past data and the power values affecting these data [17]. There are many extrapolation methods in which mathematical growth curves are interpreted. Another variation of the extrapolation method is to use the growth averages of the past years for future years.

Correlation is an estimation method performed by associating the condition of the loads with other factors such as weather conditions or economic conditions [18]. In the correlation method, the relationship between weather conditions and the electrical load is digitized. The most important advantage of correlation is that it can evaluate the factors affecting growth according to their importance. The correlation method is also used to determine the cause in case of deviation between the estimated values and the actual values. The economic approach methods used for short, medium, and long-term load estimation, among the estimation methods whose development has accelerated in recent years, are the model structures that are closest to general use. In short-term load forecasting, generally; a similar day approach, various regression models, time series, surface load estimation models Artificial Neural Networks (ANN), and fuzzy logic are used.

Graphical Processing Units (GPUs) are tools of great importance in short-term load forecasting, especially because they have high parallel processing capacity. GPUs are specialized processors optimized for scientific computing and data-intensive operations and are often used to accelerate graphics processing. Electricity consumption data often form large and complex data sets and need to be processed quickly.

For this reason, GPUs are frequently used in short-term load forecasting. Thanks to its parallel processing capability, it significantly reduces processing time by executing repetitive calculations in parallel. It performs large matrix operations, vector operations, transformations, and similar operations quickly. In deep learning studies, it is used to accelerate the training and prediction phases in memory management by minimizing data transfer times. As a result, GPU-based computing approaches contribute to faster and more efficient predictions on large datasets. It also provides advantages such as energy efficiency and time savings.

2.1. Time Series Analysis

From the time series analysis, electricity consumption is estimated using extrapolation techniques. While performing the extrapolation process, the most appropriate function is tried to be obtained by arranging the historical data to reflect the growth trend [19]. Time series are data sets formed by the chronological order of numerical data that occur in certain periods of time-related to a variable. Considering that the data obtained from the past will show similar characteristics in the future, predictions are made on numerical models.

Data on time series are stochastic. The trend of a series can be linear or curvilinear. However, an important feature of the trend is that it is stable in both cases. The factors that affect the trend are called intrinsic factors [20]. Cyclical variations consist of long-term fluctuations around a trend line. While calculating trends, cyclical changes, and seasonal changes with Time series analysis SA, random changes cannot be calculated in any way. Box-Jenkins technique is used as an analysis and estimation method in time series [21]. This technique is based on discrete, linear stochastic processes. In addition, auto-regressive, moving average, auto-regressive-moving average, and combined auto-regressive-moving average estimation models are also used.

2.2. Last User Model Approaches

The econometric model approaches and their combinations are widely used methods for medium and long-term load estimation.

Detailed data such as the identification of the devices used by customers, the width of the houses, the lifetime of the devices, changes in technology, customer habits, and population dynamics are often included in the simulation and statistical models in last-user approaches [22]. Economic factors such as per capita income, working levels, working hours, and electricity prices are added to the econometric models. These models are used in combination with last-user approaches.

2.3. Average Percentage of Increase Estimation Method

In this method, future estimates are made by finding the averages of the annual increase rates in the energy consumed in the past years. It works on the assumption that the average energy increase in the past years will be the same in the future. With this simple method, generally accurate results are obtained. However, different data sources should be evaluated while making future projections of a concept such as energy, which is closely related to every aspect of daily life and economic life, and therefore constantly changing according to time.

2.4. Econometric Methods

Econometric methods combine economic data and statistical techniques for electrical energy demand forecasting. A mathematical function is obtained by establishing a connection between the variables. With this approach, the relationship between energy consumption and economic data is calculated. Regression analysis works by making connections between dependent and independent variables [23]. The demand for electrical energy is not only a function of time but is also affected by economic and social changes, technological developments, innovations in the industry, and environmental conditions. Regression analysis is used to explain the relationship between the mentioned variables and energy demand.

2.5. Regression Analysis

The effect and direction of the independent variables on the dependent variables are indicated by statistical equations. It is decided whether a connection can be established between the two variables by drawing the scatter diagram between the dependent and independent variables. If the connection is established, how the function structure will be determined? The function structure can be in the form of one or more free variables, linear, curvilinear, additive, or non-additive. Graphic drawings are used to determine the functional structure. With regression analysis, different situations that a variable represents with one or more variables are specified as a continuous function. In this way, the existence, direction, form, and standard error of the relationship that is thought to exist between the examined variables are calculated.

3. SUGGESTED SYSTEM MODEL AND APPLICATIONS

This part will provide a brief explanation of data pretreatment and preparation through exams and inspections of the data, along with the methodologies that were used. This section also includes experiment results and analyses.

3.1. Preparing and Processing Data Sets

According to preliminary analyses of the relationship between temperature and load, there is a correlation between temperature and loads of the five-type that is prevalent in electricity load forecasting issues, indicating that temperature will be utilized as a feature in models. Additionally, load pattern is significantly impacted by periodicity. As a result, periodicity is found by inspecting the autocorrelation function plot. The auto correlation function plot indicates that a weekly cycle exists, hence time lag 186 will be used in my studies. Figure 1 and Figure 2 show the temperature-load pattern and the autocorrelation function, respectively.

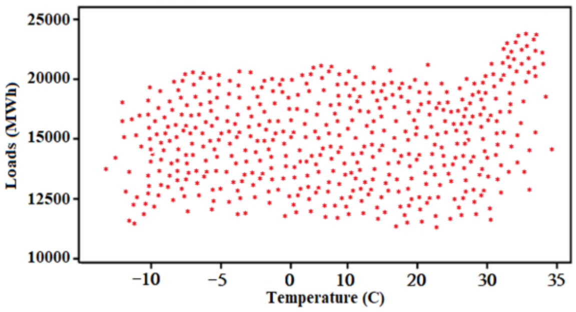

Figure 1 Load temperature correlation

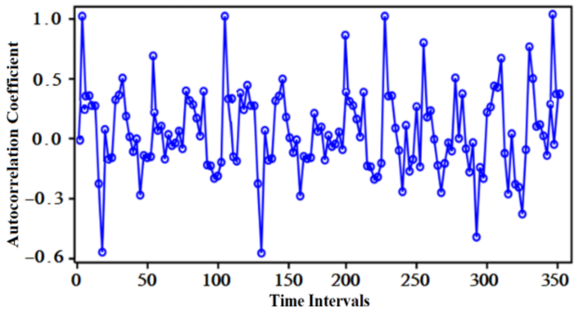

Figure 2 Autocorrelation function plot

In short-term load estimation, the autocorrelation function measures the relationship between previous time intervals. The graph of the function in Figure 2 shows the time intervals on the x-axis and the autocorrelation coefficient on the y-axis. The autocorrelation coefficient on the y-axis measures the relationship between previous time intervals and the current time interval. Dummy variables are employed to represent the effects of these aspects because the dataset also contains information about the seasonal and daily effects on load patterns in addition to the main periodicity. Experimental characteristics are listed in Table 1.

Table 1 Experimental characteristics

Characteristics	***Analysis***
Seasons	4 categorical factors
Days	7 categorical factors
Load	Hourly load values
Temperature	Hourly temperature values

3.2. Application of Deep Learning Techniques

One category of sequential data is time series. In this study, forecasting is carried out using two exceptional recurrent neural network subtypes, GRU, and LSTM, which are deep neural network variants. GRUs and LSTM are good at capturing long-term dependencies in data by applying gating techniques. These approaches' specifications and formulas can be found in [24, 25].

GRUs and LSTM applications are taken into consideration for the challenge because the data displays autoregressive features with weekly regularity. Moreover, one-dimensional CNNs have become popular in modeling sequential data such as speech recognition, text classification, and sentiment classification. This emergence is considered, and a CNN is added to the experiments along with GRUs and LSTM. [26] contains the technical specifications and CNN formulas.

3.3. Application and Tools

In this study, the deep learning methods are applied with some architectural changes. While the CNN is employed with dilations and causal padding as investigated in [26], simple GRUs, LSTM, and encoder-decoder LSTM are also used. After looking at the validation data, the ideal parameters for the experiments are identified. In a CNN, the RMSProp optimizer is employed with values of 0.008 learning rate, 0.96 rho, and 0.001 decay rate. In this technique, different dilation rates are used in successive layers with 150 and 300 filter sizes in subsequent convolutional layers.

The RMSProp optimizer is employed in simple GRUs and LSTM with the following settings: 0.002 learning rate, 0.96 rho, and 0.001 decay rate. Both GRUs and LSTM employ 250, 225, and one filter sizes. Moreover, the RMSProp optimizer is employed in the encoder-decoder LSTM approach with values of 0.0008 learning rate, 0.96 rho, and 0.0006 decay rate. The CNN with a 1200 filter size is initially presented as a previous feature extractor with 1x1 convolution in the encoder component of this LSTM, followed using the 300 and 275 filter sizes in the LSTM. The encoded states are then repeated 15 times using a repeat vector, followed by the usage of successive max-pooling layers within each decoder layer and 225, 200, and 175 filter sizes in the decoding portion.

The top layers of all approaches use dense layers with linear activation functions and rectified linear unit activation functions. All models employ the mean squared error metric as their loss function since it may quadratic penalize weights, is a frequent loss function in regression-type situations, and easily guides a model to local minima during optimization. Mean absolute percentage error, a frequently used performance statistic in time series, is used to compare one model to the others. Mean absolute percentage error and mean squared error formulas are given in equation 1.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - F_i|}{A_i}$$
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2 \tag{1}$$

In equation 1, A_i is the actual value, F_i is the forecast value and n is the total number of observations. Tensors built from experiment inputs have a batch size x time step x feature dimension of (24x168x13), where the batch size is 24, the time step is 168, and the feature is 13 for all models.

The experiments have been performed using the Python 3.4 environment and Keras 2.2.2 with Tensor flow 1.10.0 as the backend. Intel ® CoreTM i7-13700K desktop with 16 CPUs and an NVIDIA GeForce RX6600, 8 GB central process unit has carried out computations. It has taken between 25 and 30 minutes, and the models have been run through 20, 30, and 35 epochs. While examining the validation processes, it has been found that different epochs are suitable for different models and that consequently, a different number of epochs is used with different models.

3.4. Results and Discussions

Three months for each season made up the entire duration of the experiment, which lasted a full year. All test data for each training are for 2021, and 0.18 of the training datasets is split for validation. Mean absolute percentage error comparisons of one-week one-step forward estimates are given in Table 2. As demonstrated in Table 2, all models performed poorly in January compared to other months, notably on Friday, Saturday, and Sunday. This fact might be explained by the fact that it's the first week of the year this week. After the Christmas holiday at the end of December, this week comes. The model that performed the best in January was GRUs, with just minor variations compared to LSTM, and encoder-decoder LSTM. Also, the first day of the year may not have the same electricity consumption as other similar days of the week. These facts, when considered, might be said to have had a negative impact on our autoregressive models. LSTM and encoder-decoder LSTM perform best in March and April, followed by GRUs.

In contrast to the estimates for January, there are little discrepancies between the forecasts for the days. While LSTM and GRUs show the best performance in June, July, and August, they are followed by encoder-decoder LSTM with slight differences. The low differences between the forecasts of the days are also seen in these months.

In September, October, and November, LSTM and encoder-decoder LSTM perform best, followed by GRUs with slight margins. The low differences in the forecasts of the days are seen again in these months. In every trial, the CNN has been clearly outperformed by LSTM, GRUs, and encoder-decoder LSTM in this task. Simple LSTM and GRUs have been seen to perform at least as well as encoder-decoder LSTM in this forecasting test. To compete with LSTM and GRU approaches in these types of tasks, the CNN may pass several architectural modifications.

Table 2 Mean absolute percent error comparison of electricity demand forecast values for each month

	Days	**Methods**			
		Convolutional Neural Network	**Long-Short Term Memory**	**Encoder Decoder Long-Short Term Memory**	**Gated Recurrent Units**
Months	January 02, 2021	0.0139	0.0114	0.0101	0.0103
	January 03, 2021	0.0143	0.0097	0.0087	0.0065
	January 04, 2021	0.0139	0.0081	0.0083	0.0069
	January 05, 2021	0.0127	0.0073	0.0062	0.0187
	January 06, 2021	0.0199	0.0115	0.0148	0.0251
	January 07, 2021	0.0273	0.0286	0.0313	0.0233
	January 08, 2021	0.0301	0.0184	0.0156	0.0109
Months	February 04, 2021	0.0135	0.0127	0.0109	0.0106
	February 05, 2021	0.0139	0.0093	0.0077	0.0084
	February 06, 2021	0.0148	0.0072	0.0070	0.0071
	February 07, 2021	0.0121	0.0069	0.0061	0.0089
	February 08, 2021	0.0184	0.0154	0.0198	0.0137
	February 09, 2021	0.0286	0.0201	0.0217	0.0310
	February 10, 2021	0.0310	0.0179	0.0103	0.0189
Months	March 01, 2021	0.0081	0.0072	0.0094	0.0077
	March 02, 2021	0.0077	0.0105	0.0107	0.0131
	March 03, 2021	0.0107	0.0051	0.0090	0.0304
	March 04, 2021	0.0073	0.0059	0.0109	0.0194
	March 05, 2021	0.0092	0.0071	0.0302	0.0083
	March 06, 2021	0.0144	0.0067	0.0181	0.0096
	March 07, 2021	0.0212	0.0132	0.0103	0.0083
Months	April 05, 2021	0.0084	0.0089	0.0062	0.0076
	April 06, 2021	0.0063	0.0078	0.0060	0.0061
	April 07, 2021	0.0074	0.0043	0.0049	0.0063
	April 08, 2021	0.0091	0.0054	0.0055	0.0078
	April 09, 2021	0.0081	0.0057	0.0372	0.0081
	April 10, 2021	0.0095	0.0069	0.0213	0.0069
	April 11, 2021	0.0102	0.0062	0.0099	0.0093
Months	May 08, 2021	0.0091	0.0055	0.0083	0.0113
	May 09, 2021	0.0121	0.0085	0.0091	0.0118
	May 10, 2021	0.0096	0.0216	0.0107	0.0136
	May 11, 2021	0.0186	0.0162	0.0219	0.0131
	May 12, 2021	0.0104	0.0108	0.0241	0.0094
	May 13, 2021	0.0083	0.0193	0.0164	0.0208
	May 14, 2021	0.0088	0.0138	0.0203	0.0221
Months	June 03, 2021	0.0098	0.0135	0.0095	0.0132
	June 04, 2021	0.0103	0.0101	0.0084	0.0114
	June 05, 2021	0.0094	0.0073	0.0081	0.0097
	June 06, 2021	0.0128	0.0059	0.0066	0.0075
	June 07, 2021	0.0107	0.0064	0.0062	0.0217
	June 08, 2021	0.0088	0.0070	0.0074	0.0312
	June 09, 2021	0.0083	0.0081	0.0093	0.0093
Months	July 05, 2021	0.0098	0.0123	0.0096	0.0057
	July 06, 2021	0.0083	0.0098	0.0082	0.0077
	July 07, 2021	0.0120	0.0066	0.0071	0.0089
	July 08, 2021	0.0149	0.0074	0.0176	0.0096
	July 09, 2021	0.0203	0.0173	0.0098	0.0106
	July 10, 2021	0.0242	0.0139	0.0080	0.0068
	July 11, 2021	0.0093	0.0081	0.0097	0.0172

Table 2 Mean absolute percent error comparison of electricity demand forecast values for each month (Continue)

Days		Methods			
		Convolutional Neural Network	**Long-Short Term Memory**	**Encoder Decoder Long-Short Term Memory**	**Gated Recurrent Units**
Months	August 04, 2021	0.0086	0.0138	0.0094	0.0078
	August 05, 2021	0.0103	0.0101	0.0083	0.0109
	August 06, 2021	0.0099	0.0060	0.0080	0.0203
	August 07, 2021	0.0116	0.0058	0.0062	0.0402
	August 08, 2021	0.0103	0.0064	0.0065	0.0071
	August 09, 2021	0.0091	0.0069	0.0087	0.0216
	August 10, 2021	0.0098	0.0073	0.0076	0.0222
Months	September 02, 2021	0.0117	0.0042	0.0037	0.0203
	September 03, 2021	0.0186	0.0061	0.0053	0.0097
	September 04, 2021	0.0093	0.0054	0.0051	0.0187
	September 05, 2021	0.0204	0.0081	0.0066	0.0194
	September 06, 2021	0.0185	0.0101	0.0094	0.0211
	September 07, 2021	0.0126	0.0077	0.0069	0.0304
	September 08, 2021	0.0198	0.0049	0.0089	0.0176
Months	October 07, 2021	0.0086	0.0054	0.0063	0.0108
	October 08, 2021	0.0091	0.0069	0.0059	0.0102
	October 09, 2021	0.0137	0.0098	0.0083	0.0084
	October 10, 2021	0.0081	0.0059	0.0061	0.0171
	October 11, 2021	0.0088	0.0063	0.0055	0.0128
	October 12, 2021	0.0114	0.0057	0.0067	0.0135
	October 13, 2021	0.0208	0.0102	0.0084	0.0193
Months	November 04, 2021	0.0103	0.0066	0.0055	0.0082
	November 05, 2021	0.0180	0.0051	0.0063	0.0098
	November 06, 2021	0.0091	0.0088	0.0069	0.0149
	November 07, 2021	0.0206	0.0104	0.0091	0.0183
	November 08, 2021	0.0174	0.0093	0.0070	0.0126
	November 09, 2021	0.0139	0.0080	0.0081	0.0205
	November 10, 2021	0.0141	0.0072	0.0103	0.0133
Months	December 09, 2021	0.0162	0.0117	0.0099	0.0142
	December 10, 2021	0.0145	0.0063	0.0078	0.0111
	December 11, 2021	0.0111	0.0098	0.0075	0.0189
	December 12, 2021	0.0176	0.0069	0.0054	0.0077
	December 13, 2021	0.0193	0.0073	0.0063	0.0083
	December 14, 2021	0.0214	0.0059	0.0066	0.0098
	December 15, 2021	0.0283	0.0087	0.0087	0.0094

4. CONCLUSIONS

Forecasts for January, May, September, and December have seen some significant departures from forecasts for other months within the days reviewed. This forecasting issue might be resolved by inspecting these special days along with other religious and national holidays and adding the information that is extracted after the inspections to the models. However, this does not mean that convolutional neural networks are not good at capturing long-term dependencies and modeling sequential data. In all trials, long-short-term memory, gated recurrent units, and encoder-decoder long-short-term memory saliently outperform simple convolutional neural network designs. In the literature, new designs for sequential data modeling using one-dimensional convolutional networks have been proposed.

Future studies may focus on applying these new architectures to issues with electrical load forecasting and comparing the results with long short-term memory, gated recurrent units, and their variations. As an alternative to one-step ahead forecasting, multi-step ahead forecasting, such as next-24-hour recasting with used models and their modifications, may be produced and compared as a new area of research. Finally, combining several signal processing methods, such as empirical mode decomposition, wavelet transform, and Fourier transform, with deep learning algorithms may be another potential research area.

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The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the author.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The author of the paper declares that they comply with the scientific, ethical, and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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