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Research Article

Intelligent Forecasting of Electric Energy Demand with Artificial Neural Networks

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ABSTRACT

Energy demand forecasting is critically important for the effective planning and management of energy production and distribution. Accurate demand forecasts in the energy sector can help reduce costs and enhance the reliability of energy supply. In this study, data-driven methods are employed to predict future energy demand. Multidimensional datasets, including historical consumption data, weather conditions, economic indicators, and demographic information are utilized in the forecasting process. To select the most appropriate model and improve prediction accuracy, various time series modeling techniques and artificial neural network algorithms are tested. The results demonstrate that the RNN-based deep learning model outperforms other methods, such as LSTM and CNN, in terms of forecasting accuracy. Particularly during periods of high variability, such as seasonal transitions, RNN models provide predictions that are more reliable by reducing the Mean Absolute Percentage Error (MAPE) to 9%. This study contributes to the literature by offering a comparative analysis of different forecasting approaches using real-world data. Furthermore, it presents a repeatable and adaptable forecasting framework for energy suppliers and decision-makers, delivering tangible benefits in resource planning and mitigating operational risks.

Introduction

In recent years, the rapid development of machine learning and deep learning techniques has offered a new perspective on energy demand forecasting. These techniques can potentially obtain more accurate and reliable predictions through their data analysis and modeling capabilities. A deep learning model called a recurrent neural network (RNN) stands out for its ability to capture dependencies and dynamics in time series data.

The objective of this study is to evaluate the effectiveness and accuracy of the RNN model in energy demand forecasting, comparing it with traditional forecasting methods. Additionally, by examining the impact of different parameters on the model's performance, the optimal configuration will be determined, providing a useful tool for energy demand management.

Energy demand forecasting is a valuable tool in energy management decision-making. Accurate forecasts contribute to ensuring energy supply security, reducing production costs, and optimizing resource use. However, factors such as seasonal fluctuations in demand, economic variations, and sudden weather changes make demand forecasting challenging.

Traditional methods for energy demand forecasting can become inadequate over time and fail to capture the complex dynamics of energy demand patterns. Traditional forecasting methods often rely on simple statistical models and may not fully capture the dynamics and dependencies in complex time series data. Therefore, their prediction accuracy and precision can diminish over time. Additionally, they may be limited in dealing with the variability and uncertainty in energy demand forecasting.

In this study, three different methods were compared to predict energy demand accurately. Each technique is evaluated based on its ability to capture distinct characteristics of the energy demand series. This study aims to determine the most suitable forecasting method in the energy sector by analyzing the strengths and weaknesses of different modeling approaches.

Energy demand forecasting is a fundamental element that supports strategic planning across all processes, from energy production to distribution. Accurate energy demand forecasting is crucial for planning production capacity, optimizing resource utilization, and managing costs effectively. Today, energy demand exhibits a complex structure influenced by numerous factors such as population growth, economic development, seasonal changes, and climatic conditions [1].

Therefore, advanced modeling techniques that can learn from historical data and predict future possibilities are essential for accurate forecasts. Energy demand forecasting studies not only help to reduce uncertainties in the energy sector but also play a critical role in enhancing energy supply security and achieving sustainable development goals. This study aims to compare various methods to improve the accuracy of energy demand forecasts, contributing to better planning and management processes in the energy sector.

Machine learning and deep learning techniques offer a new perspective in energy demand forecasting through their data analysis and modeling capabilities [2]. Particularly, deep learning models like the recurrent neural network (RNN) model excel at capturing complexity and dependencies in time series data. Therefore, the effectiveness and accuracy of the RNN model in energy demand forecasting are evaluated and compared with traditional methods.

Our method allows us to make more precise and accurate predictions. Our method enables us to make energy demand forecasts more accurately. This helps energy companies and planners better understand future demands. Based on this information, energy companies can develop better strategies and improve decision-making processes.

In this context, the recurrent neural network (RNN) model has emerged as an effective method for energy demand forecasting. RNN is a deep learning algorithm that can capture complex relationships and trends in time series data. This model is trained using historical energy consumption data to predict future demand. The memory cells in RNN enable the preservation of long-term connections, allowing for meaningful evaluation of past data. This enables the model to forecast future demand changes more accurately. Due to its ability to make stronger predictions compared to other traditional methods, the RNN model has become a popular choice in the energy sector [3].

Energy demand forecasting is an analysis and modeling process conducted to predict future energy needs. These predictions are important for various sectors, such as energy producers, distribution companies, and energy-consuming industries. Energy demand forecasting utilizes statistical and machine learning techniques to estimate future energy demand using historical data. During this process, several factors, such as weather conditions, economic factors, seasonal variations, and demographic data, are taken into consideration [4]. Accurate energy demand forecasting helps in effectively managing energy resources and optimizing energy planning and production strategies. It also enables efficient resource utilization and cost reduction and stabilizes the energy supply. Energy demand forecasting is a process that requires data science and statistical analysis skills. Proper data collection, data cleaning, model selection, and validation processes enhance the reliability of these forecasts.

Literature Review

Artificial neural networks, particularly recurrent neural networks (RNN) and long short-term memory (LSTM) networks, are increasingly popular in energy demand forecasting due to their high accuracy in working with time series data. This literature review summarizes relevant studies, findings, and methods related to using RNN and LSTM models for energy demand forecasting.

Artificial Neural Networks (ANNs) provide effective results in energy demand forecasting and can integrate multiple influencing factors, such as weather conditions, socioeconomic data, and seasonal effects, into the model. Unlike traditional statistical methods, ANN-based methods can learn complex, nonlinear relationships, making them advantageous in energy demand forecasting [5].

Notably, RNN and LSTM models excel in predicting future demand based on historical data. Their main strength lies in capturing sequential dependencies within energy demand data and learning long-term relationships.

A. Energy Demand Forecasting with RNN Models

RNNs possess a recurrent structure that allows them to retain information from previous time steps, making them advantageous for energy demand forecasting, as demand typically exhibits sequential dependencies over time [6].

RNN-based forecasting models yield stable results, particularly in short-term demand predictions. However, classical RNN models can encounter issues like "gradient vanishing," which can limit the model's performance in learning long-term dependencies. Consequently, for long-term forecasting, advanced RNN models, such as LSTMs, are preferred.

Applications of RNN in Energy Demand are as follows:

- Short-term energy demand forecasting: RNN models are effective for hourly or daily energy demand predictions.
- Seasonal analysis: RNN can analyze seasonal energy demand data to predict future demand trends [7].

B. Energy Demand Forecasting with LSTM Models

LSTM networks, a variant of RNN, are particularly effective in modeling long-term dependencies, which are essential in energy demand forecasting. They excel in capturing trends, seasonal variations, and sudden fluctuations within energy demand data, learning more complex dependencies than RNNs.

The success of LSTM networks lies in their "cell state" structure, which allows them to store information and forget unnecessary data, optimizing the model. This feature makes LSTMs highly accurate and capable of long-term learning in energy demand forecasting [8].

Applications of LSTM in Energy Demand

- Long-term forecasting: LSTM models provide high performance in long-term forecasts, such as monthly or yearly energy demand predictions.

• Factor-based forecasting: LSTMs are highly effective at integrating multiple variables, such as weather data and economic indicators that influence energy demand.

C. Similar Studies in Energy Estimation

In his thesis study conducted at Bilecik Şeyh Edebali University, Özkay (2021) utilized hourly wind speed data from the Bilecik Meteorology Directorate [9]. A dataset of hourly measurements collected over 10 years was employed 67% of the data was reserved for training, while 33% was allocated for testing. A 3-layer LSTM model was used for prediction, and two types of LSTM were compared. The implementation of prediction models was carried out using Python software. While this study shares similarities with his thesis in terms of using the LSTM algorithm and Python software, it distinguishes itself by presenting other learning algorithms and utilizing different location data as input.

Görgel and Kavlak (2020) utilized a 1-year dataset from a wind farm in the Urla district of Izmir province, Türkiye. The dataset consists of wind power values measured at 10-minute intervals between 01.05.2017 and 31.05.2018. Three hundred instances were used for training, while the remainder was allocated for testing. Like this study, neural networks, LSTM, and GRU algorithms are employed in the prediction model. In the LSTM model, three hidden layers are used, and the process is repeated five times with 100 iterations each. Error rates were determined using the MAE absolute error method. This study differs from their research in its use of different location data as input [10].

Ceylan and Demirören have used regression and artificial neural network (ANN) methods for short-term load forecasting in the Gölbaşı region. In their study, they used maximum and minimum temperature values and days as input variables for the ANN model and power consumption values as the output [11].

Zhang and Wang (2019) applied recurrent neural networks (RNNs) for short-term energy demand forecasting in China. Their study demonstrated that RNN-based models significantly outperformed traditional methods like ARIMA and support vector machines (SVM). The authors highlighted the effectiveness of RNNs in capturing the complex time-dependent patterns in energy consumption data. Their results showed that RNNs could provide more accurate forecasts, especially during periods of peak energy demand, making them a promising tool for short-term energy prediction tasks. The research concluded that RNNs are highly suitable for modeling energy consumption data due to their ability to learn from sequential data without losing information over time [12].

Liu and Xu (2018) explored the integration of weather data with RNNs for short-term energy demand forecasting in urban areas. The study demonstrated that including external weather variables, such as temperature and humidity, improved the forecasting accuracy of the RNN model. The authors showed that energy consumption is closely tied to weather patterns, and by adjusting for these external factors, RNNs were able to produce more reliable predictions. This study underscored the potential of RNNs to handle not only the historical energy consumption data but also incorporate external factors that influence demand, which significantly enhanced the model's performance compared to traditional approaches [13].

In their 2020 study, Jebara and Ghorbel developed a hybrid model combining RNN and Long Short-Term Memory (LSTM) networks for energy demand forecasting. Their hybrid approach was found to be superior to both standalone RNN and LSTM models, as it was able to capture both short-term fluctuations and long-term trends in energy consumption. This study highlighted the strengths of combining the capabilities of both models, where RNN is effective in handling shorter sequences, and LSTM excels at capturing long-term dependencies. By combining these models, the authors were able to improve forecasting accuracy and provide more precise predictions of energy consumption [14].

Kim and Song (2016) compared RNNs with traditional time-series models, such as ARIMA and exponential smoothing, in the context of energy demand forecasting. Their study found that RNNs significantly outperformed traditional methods, especially in capturing non-linear trends and seasonality in energy consumption. The authors concluded that RNNs were more suitable for handling complex relationships in energy data and performed better in forecasting energy demand during peak periods. This comparison demonstrated that RNNs are a powerful tool for energy forecasting, offering greater flexibility and accuracy in modeling time-series data. [15].

Farahat used Artificial Neural Network (ANN) and Bayesian Model (BM) methods for long-term load forecasting in Egypt's industrial city. In the forecasting models, he employed year, temperature, and past load values as input variables and reused past load values as the output. The application aimed to predict the annual peak load and total load over a 24-month period. He stated that the error values obtained from the testing process were at reasonable levels. Using the model, five-year interval forecasts made up to the year 2020 [16].

Short-term hourly demand forecasting was performed in Turkey in a study conducted by Toker and Korkmaz in 2011. Electricity consumption data from 2008-2009 for Turkey and meteorological data for Istanbul were used. The monthly seasonality in the consumption data is separated using the spectrum analysis method. Two different forecasts made hourly day-ahead and one-week-ahead predictions. For the day-ahead forecast, the MAPE value was found to be %2 for the last five months of 2009, while for the one-week-ahead forecast, the MAPE value was found to be %4 [17].

In the thesis study at Osmaniye Korkut Ata University in 2023, a dataset consisting of measurement data from the Gökçedağ Wind Energy Plant located in the Bahçe district of Osmaniye province was utilized. Conducting data analysis, he divided the dataset into eight different data groups. Subsequently, he attempted to predict the power output of the wind turbine using Artificial Neural Networks

(ANN). Comparing the results, he determined the accuracy of the predictions using methods such as R-squared, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The study stands out for using a dataset from a different location and not employing different models such as LSTM or GRU.

D. Methods Used

RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory) are models commonly used in time series analysis, including for predicting future values.

RNN is a type of neural network that is designed to process sequential data, such as time series data. Unlike traditional neural networks, RNN has a feedback loop that allows information to pass from previous steps to the current step. This enables the network to have a memory of past information while processing new inputs. RNNs are widely used in natural language processing, speech recognition, and, of course, time series analysis.

LSTM is a type of RNN that is specifically designed to overcome the "vanishing gradient" problem, which occurs when traditional RNNs have difficulty retaining long-term dependencies in the data. LSTM introduces a special memory cell that can retain information over extended periods. This allows the model to remember important patterns and relationships in the time series data, even when the time intervals between relevant events are large.

When applied to time series analysis, RNN and LSTM models are trained using historical data. The models learn from past patterns and relationships in the data and then use that knowledge to predict future values. These models can capture complex patterns and dependencies in the data, making them effective in capturing the temporal dynamics of time series.

To analyze the research topic, RNN and LSTM models can be used to predict future energy demand. By training the models with historical energy consumption data, they can learn the patterns and trends in the data and make accurate predictions for future demand. These models can take into account factors such as seasonality, trends, and other relevant variables to provide reliable forecasts.

Overall, RNN and LSTM models are powerful tools in time series analysis, particularly for predicting future values. They successfully applied in various domains, including finance, weather forecasting, and energy demand prediction.

Advantages of Artificial Intelligence in Energy Demand Forecasting

Artificial intelligence (AI) offers significant advantages in energy demand forecasting, including more accurate predictions, increased efficiency, and better decision-making in energy management. Here are some of the key advantages AI provides in energy demand forecasting

A. Increased Accuracy and Precision

AI, particularly through deep learning and machine learning models (such as RNN, LSTM, and CNN), can achieve high accuracy and precision in energy demand forecasting. Compared to traditional methods, AI models can analyze large datasets, recognize complex patterns, and make more precise predictions based on historical data.

B. Effective Performance with Time-Series Data

AI excels in handling time-series data, which is crucial in energy demand forecasting as energy consumption typically varies over time. AI models, such as RNNs, can accurately forecast energy demand by capturing complex temporal dependencies in the data, accounting for seasonal variations, daily differences, and factors like weekdays and weekends, leading to more reliable results.

C. Handling Big Data

The data used in energy demand forecasting is often large and complex, involving sensor data, weather conditions, energy production data, and user behavior. AI can process and analyze big data efficiently, making it capable of handling more data and complexity than traditional models. This allows AI models to extract valuable insights from diverse and voluminous data sources.

D. Adaptability

AI models have the ability to adapt to evolving and changing conditions in energy demand forecasting. For instance, energy demand can change based on factors such as temperature variations, holidays, and economic changes. AI algorithms can adjust to new data over time, improving prediction accuracy as new patterns emerge, making them well-suited for dynamic environments.

E. Real-Time Forecasting and Optimization

AI enables real-time energy demand forecasting, which is crucial for energy managers to monitor and manage energy consumption efficiently. AI models can provide continuous and accurate predictions based on real-time input data, facilitating better decision-making. Additionally, AI-based models can optimize energy systems, improving efficiency and reducing costs.

F. Integration of Multiple Factors

AI can integrate and account for multiple factors and variables simultaneously when forecasting energy demand. For example, weather data, historical energy consumption, economic indicators, and user behavior can be combined to make more comprehensive and accurate predictions. By considering these factors together, AI models provide a more complete view of energy demand.

G. Anomaly and Error Detection

AI can detect anomalies and errors in energy demand forecasts. This is especially beneficial for identifying discrepancies or system faults early on, allowing energy distributors to adjust their predictions and operations. By detecting these issues early, AI contributes to more reliable and accurate decision-making in energy distribution.

H. Cost Savings and Efficiency

The use of AI models leads to more effective and efficient solutions in energy distribution and consumption management, which can result in cost savings. Accurate energy demand forecasts allow for optimal production and distribution capacity, reducing unnecessary energy generation and transportation costs.

İ. Deep Analysis with Complex Models

AI can perform deep analysis through the use of complex models, which allows for a more detailed understanding of energy consumption patterns. Specifically, deep learning techniques can create sophisticated models that provide deeper insights into energy demand trends and fluctuations.

J. Decision Support Systems

AI helps energy managers make data-driven decisions, facilitating the development of more effective decision support systems. AI-powered forecasts assist in creating better planning, production, and distribution strategies, ultimately optimizing energy demand management.

Artificial intelligence offers significant advantages in energy demand forecasting by providing high accuracy, efficiency, and flexibility. The use of AI helps us better understand the dynamics of energy consumption, utilize resources more efficiently, and develop more sustainable energy solutions in the long term.

Data Analysis Methods

This study focuses on the implementation of several artificial neural network models, such as RNN, LSTM, and CNN, for energy demand prediction. Firstly, an accurate and up-to-date dataset was collected, and data preprocessing steps were performed. Subsequently, artificial neural network models were trained and optimized for energy demand predictions. The performance of the trained models was evaluated, and the results were presented. Depending on the scope and objectives of the research, further details and analysis are conducted [18].

Firstly, data collection was conducted to gather accurate and up-to-date data for energy demand prediction. The dataset should include factors that influence energy consumption and have sufficient historical data. Collaboration with energy providers, government institutions, or other sources may be necessary to obtain data on electricity consumption, weather conditions, seasonality, holidays, and other potential variables [19].

Secondly, data preprocessing is necessary to prepare the collected dataset for analysis. This step involves handling missing data, detecting and correcting outliers, and normalizing the data. Additionally, it is important to partition the dataset into training, validation, and test sets.

Thirdly, the RNN model is implemented on the dataset to train and predict energy demand. Determining the architecture of the model, tuning hyperactive parameters, and conducting the training process are essential in this step. Evaluation of the model's performance using criteria and metrics is also important.

Next, optimization of the model and error analysis were performed. Trying out different optimization techniques to improve the model's performance is necessary during the training process. Error analysis, where the model's predictions are compared with actual values, helps identify weaknesses of the model and enables improvements.

The results were evaluated by assessing the performance of the trained RNN model in predicting energy demand. Comparisons with actual data and other existing prediction methods were made to determine the success of the models.

A. Data Collection

Collect historical data on energy consumption for each store location over a specific period. Obtain weather data, including temperature, humidity, and precipitation, for the corresponding period. Additionally, gather data on store-specific factors such as operating hours, holidays, and promotions.

Clean the collected data by handling missing values, outliers, and inconsistencies. Normalize the data to bring them to a consistent scale. Split the dataset into training, validation, and test sets.

The data used in the study is the total amount of energy entering the region on an hourly basis from 2015-01-01 to 2023-10-17 in the Dicle Elektrik Dağıtım region. The Dicle Elektrik Dağıtım region includes the provinces of Şanlıurfa, Diyarbakır, Şırnak, Mardin, Batman, and Siirt. The total energy entering the Dicle Elektrik Dağıtım system is composed of several different data sources.

Out[6]:

Date	Tuketim(Mwh)	haftanin_gunu	gunler	ceyreklik	ay	yil	yilin_gunleri	ayin_gunleri	mevsim	yilin_haftalari
2015-01-01	57262.16	3	Thursday	1	1	2015	1	1	Kis	1
2015-01-02	56512.42	4	Friday	1	1	2015	2	2	Kis	1
2015-01-03	57612.95	5	Saturday	1	1	2015	3	3	Kis	1
2015-01-04	57431.43	6	Sunday	1	1	2015	4	4	Kis	1
2015-01-05	58533.53	0	Monday	1	1	2015	5	5	Kis	2
...	...	...	...	...	...	...	...	...	...	...
2023-10-13	41506.00	4	Friday	4	10	2023	286	13	Sonbahar	41
2023-10-14	40376.00	5	Saturday	4	10	2023	287	14	Sonbahar	41
2023-10-15	40676.00	6	Sunday	4	10	2023	288	15	Sonbahar	41
2023-10-16	37726.00	0	Monday	4	10	2023	289	16	Sonbahar	42
2023-10-17	37154.00	1	Tuesday	4	10	2023	290	17	Sonbahar	42

Figure 1. Data import table

The data was obtained from the DEDAS Energy Markets unit. During the observation period at the beginning of the pandemic in 2020, there was a dramatic decrease in the months of March, April, and May. Therefore, a correction coefficient was used to adjust the seasonal patterns of the data during these months. According to the observations, this correction of approximately 5% helped adjust the regular seasonal patterns.

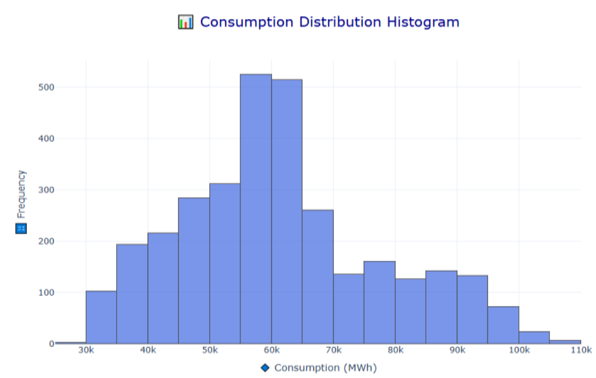

Figure 2. Demand (MWh) histogram

As seen in the histogram table of our data, it shows a normal distribution between 30k and 100k MWh. When examining the histogram graph for consumption quantities between 2015 and 2023 years, it was observed to follow a normal distribution. The data is concentrated between 55K and 65K, rarely exceeding 100K, and the lowest value is observed to be 30K.

In addition, weather data was extracted with Python from "open-meteo," an open-source site, and added to our main data.

B. Data Processing

Python programming language used for data preprocessing. Python was preferred due to its flexible structure, extensive library support, and continuous development as an open-source language. Data processing refers to the operations performed to make datasets suitable for analysis or use. These operations can include cleaning, transforming, merging, scaling, or feature extraction.

The hourly energy consumption data is converted into a daily-based system. Subsequently, variables such as weather, temperature, seasons, and wind conditions are calculated.

Date	Tuketim(Mwh)	haftanin_gunu	gunler	ceyreklik	ay	yil	yilin_gunleri	ayin_gunleri	mevsim	yilin_haftalari
2015-01-01	57262.16	3	Thursday	1	1	2015	1	1	Kis	1
2015-01-02	56512.42	4	Friday	1	1	2015	2	2	Kis	1
2015-01-03	57612.95	5	Saturday	1	1	2015	3	3	Kis	1
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...	...	...	...	...	...	...	...	...	...	...
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2023-10-17	37154.00	1	Tuesday	4	10	2023	290	17	Sonbahar	42

Figure 3. Transposing daily data

Energy consumption is analyzed by categorizing it into specific periods of the year. In daily energy consumption data, seasonal, monthly, daily, and weekly patterns are also identified.

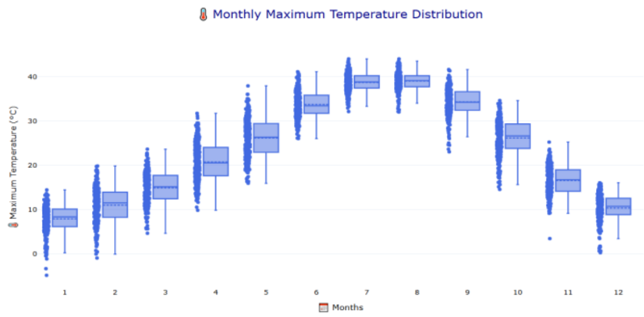

Figure 4. Historical features

In this graph, the temperature variation by month is examined. As seen in the graph, temperatures in the region increase during the summer months, exceeding 40 degrees. Some additional features to use in time series forecasting are generated. Features such as day of the week, season, days of the year, etc., were added to the data model [20].

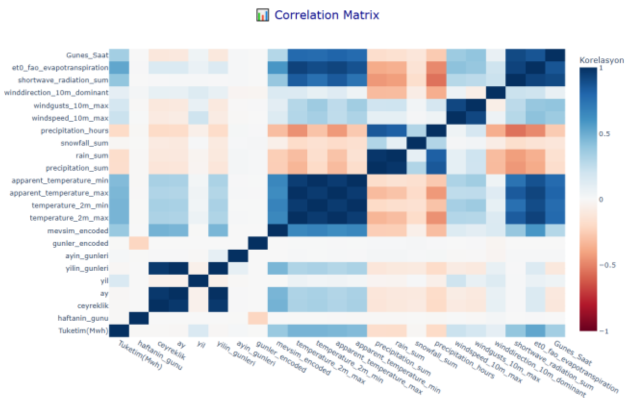

Figure 5. Weather data (Daily, 2015-2023)

In this graph, the correlation between the data examined. Accordingly, it is seen which variable the Consumption variable is related to. Additionally, the correlation between other variables was also identified [21].

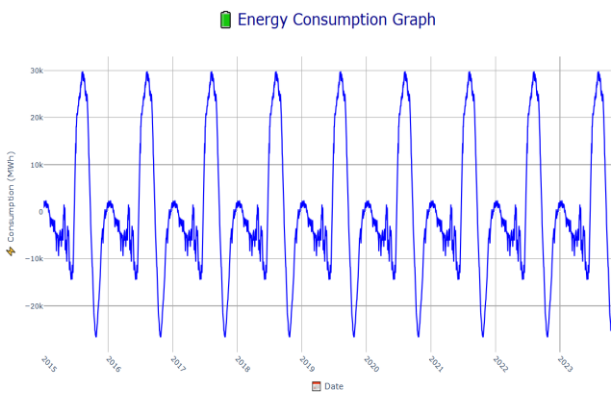

Figure 6. Variation of consumption data by year and month

In this graph, the correlation between the data examined. Accordingly, it is seen which variable the Consumption variable is related to. Additionally, the correlation between other variables was also identified. Above, the correlation between model features was observed. According to this, the values with the highest correlation with Consumption are the hourly data. The next most important correlated features observed are evaporation, perceived temperature, season, and year variables. Variables with low correlation related to precipitation amount and conditions.

Additionally, the graph also depicts the correlation between variables. Naturally, there is close to a 99% correlation among hourly consumption. However, the correlation between precipitation and wind variables was observed to be low.

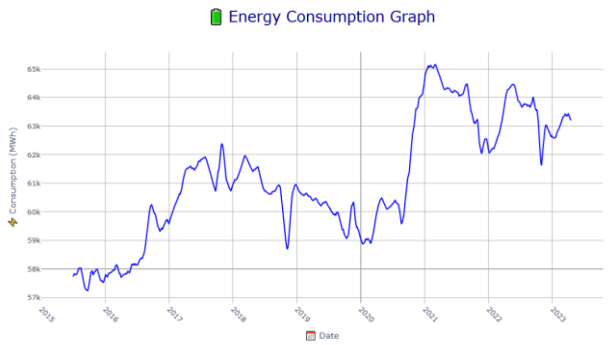

Figure 7. Trend chart

The other component is the trend. In this graph, the trend of the data has been isolated. Accordingly, it said that there has been an increasing trend over the years. What is crucial here is that the residual values are low because residuals contain values that cannot be modeled for the data. These values represent consumptions that occur unexpectedly, such as significant outages in a distribution area, disrupting the normal seasonality values. These values are reflected in the data as residuals.

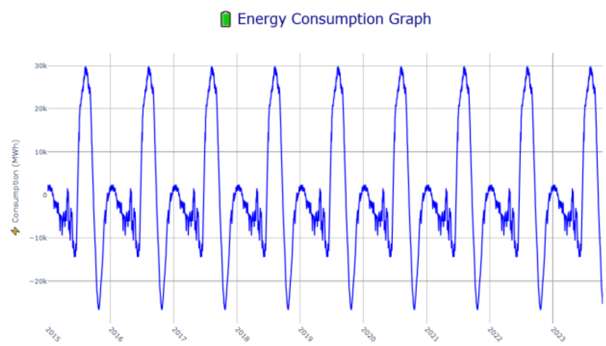

Figure 8. The consumption graph by season

When seasonal values were examined, it was observed that values up to 30 K were explained during periods of high consumption. Another component is the trend and the values remaining after the seasonality is removed from the data. These values show random increases and decreases. They consist of other factors affecting consumption.

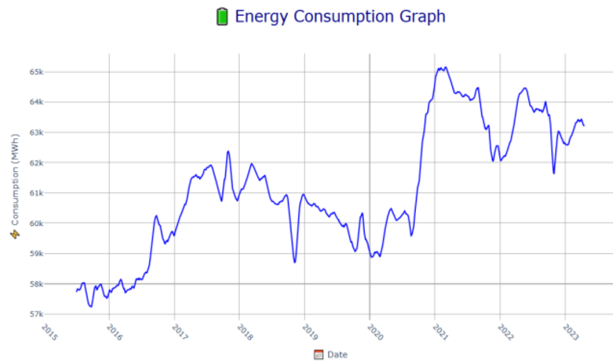

Figure 9. The consumption graph by years

An upward trend shift was observed in the trend data after the year 2021. This increase indicates the emergence of additional consumption points in the region.

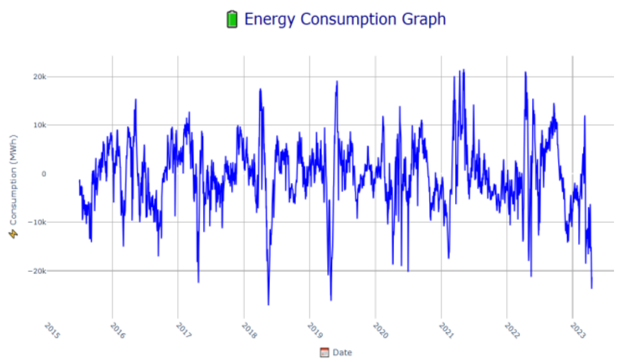

Figure 10. The consumption graph by trend

The fact that errors do not exhibit a trend in the graph and are randomly distributed around zero indicates that the component analysis of the model was correctly performed. Additionally, the residual values are important in showing unexplained consumption increases. According to the graph, unexplained consumption was observed in the range of +20 K to -20 K.

Model Selection

The model will be determined by testing several types of artificial neural networks. Model selection is based on the data structure, data quantity, and data complexity [22]. In this study, model selection will involve testing multiple models, and the model with the highest score after testing is chosen.

Making forward-looking predictions based on past values is quite challenging in terms of the complex relationships between inputs. In the study, predictions are made based on past values of energy consumption, which is difficult to predict accurately and foresee within certain limits. It is directly influenced by many other meteorological variables, such as wind direction, pressure, humidity, and light. For energy consumption prediction, machine-learning methods such as simple RNN, LSTM, and CNN Simple RNN models were used, and the performance of these models was analyzed to examine their usability for energy consumption forecasting.

A. Simple RNN Model

Simple RNN (Recurrent Neural Network) is a model belonging to the family of recurrent neural networks (RNNs) and is particularly used in time series analysis, natural language processing, and other sequential data problems. Simple RNN has a cell structure and is known for its ability to use past information in making future predictions [23].

RNN is a type of artificial neural network that processes sequential data. Unlike traditional networks, it not only considers the current input but also relates it to past inputs, allowing the network to carry information across time.

RNN stores past information to be used in the next step, but it struggles to learn long-term dependencies, especially in time series data, where long-term dependencies are crucial.

Training Process:

- Forward Pass: RNNs learn the time dependencies of the data by taking the previous output of the data set as input at each step. This helps them understand long-term dependencies in sequences.
- Backpropagation Through Time (BPTT): The training process in RNNs is done using a method called "Backpropagation Through Time." This process involves comparing the network's output to calculate the error, and the error is propagated backward through time (at each time step).
- Vanishing Gradient Problem: In RNNs, as the number of time steps increases, problems such as vanishing gradients (where the gradients become very small) or exploding gradients (where the gradients become excessively large) can occur. To overcome these issues, advanced models like LSTM or GRU are preferred.

Simple RNN uses a loop to combine past information with current inputs to make future predictions. This structure represents the model's ability to understand temporal dependencies. The cell structure of a Simple RNN produces an output at each step by using the inputs received at that step and the output from the previous step.

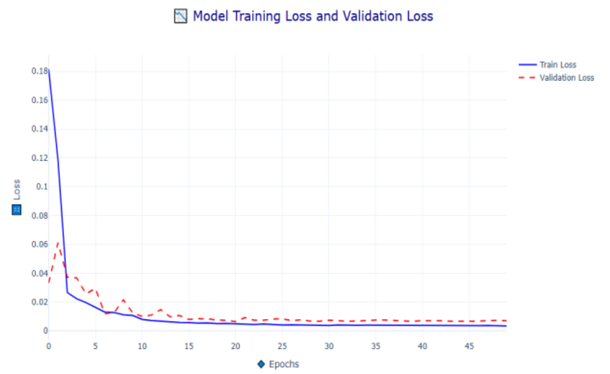

Figure 11. Validation loss and train loss for RNN

Validation performed for the model by examining the Loss values of the training and test data is shown in Figure 11. The train and test errors should be similar and show a decrease toward zero together.

Table 1. Performance scores of the simple RNN model

Metric Name	Value
MAPE	9.6008%
RMSE	7785.1538
R^2	0.8253

Figure 12 denotes the plots of the values predicted by the model alongside the actual values. It should be noted that the horizontal axis in Figure 12 denotes the time in terms of days, which is also true for Figure 15 and Figure 18. The dataset was made more manageable for prediction by normalized and appropriately framed modeled. Different numbers of epochs are applied during the implementation of each model in the prediction application. The Simple RNN model provided the most suitable result for 50 epochs. When higher epochs, such as 60 and 90, were applied, it was observed that there was not much change in the prediction values, but the runtime of the program significantly increased on the other hand, when fewer epochs, such as 10, 15 were applied, it was observed that deviations from the prediction increased.

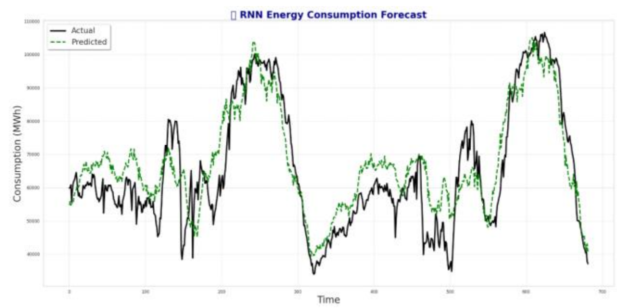

Figure 12. The comparative analysis of demands (actual versus predicted) obtained by RNN

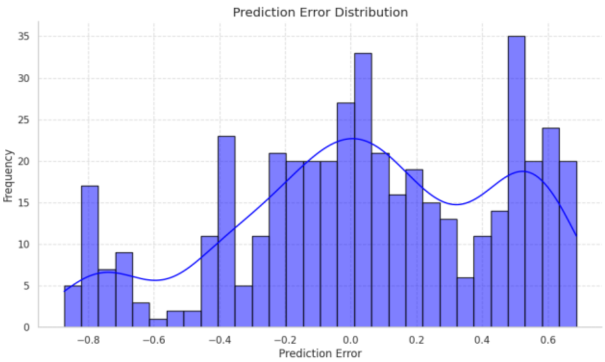

Figure 13. Histogram of the RNN time series forecast error distribution

This histogram shows the distribution of prediction errors from the model. The X-axis represents the magnitude of the prediction errors, while the Y-axis represents the frequency of those errors. The histogram bars indicate the range in which the model most frequently makes errors, while the KDE (Kernel Density Estimation) curve reveals the overall shape of the error distribution.

If the error distribution is symmetric and centered, it suggests that the model is making balanced predictions. However, if the errors tend to shift in one direction, it may indicate the presence of a systematic bias. This graph is an important visualization tool for analyzing the model's accuracy and identifying potential sources of error.

B. LSTM Model

In the traditional Recurrent Neural Network (RNN) method, the contribution of information decreases over time, making it challenging to learn from previous time steps in longer sequences. Consequently, the problem of gradient loss arises. When the gradient approaches zero, learning can slow down or even stop. This issue particularly occurs when it is necessary to evaluate information from many steps back to understand the input. To solve the vanishing gradient problem and facilitate learning complex patterns, the Long Short-Term Memory (LSTM) method is used. The LSTM method is a type of RNN commonly used for processing and predicting data sequences [24].

LSTM is a type of RNN designed to address the challenges RNN faces in learning long-term dependencies. LSTM incorporates mechanisms for forgetting, remembering, and updating information using a cell state.

Training Process:

- Special Structure: LSTMs are an improved version of RNNs. LSTM cells use "cell state" and "gates" to enhance the ability to learn long-term dependencies in time series data. This makes them much more successful, especially in learning long-term dependencies.
- Forget Gates and Memory: LSTMs work with forget gates, input gates, and output gates that control the flow of information. This allows unnecessary information to be forgotten and important information to be retained for a longer period.
- Backpropagation: LSTMs, like RNNs, use BPTT, but due to their structure, they operate in a more stable and efficient manner.

LSTM uses these gates to retain important information for longer periods and forget irrelevant information, making it more capable of learning long-term dependencies compared to traditional RNNs.

LSTMs have a unique design consisting of a memory cell and three gates: "Input, Forget, and Output." The memory cell allows the network to store information for extended periods, while the gates control the flow of information into, out of, and within the cell. The advantage of using these components is their ability to selectively remember and forget information, enabling them to maintain "long-term memory [25].

Figure 14. Validation and train loss obtained by the LSTM model

In Figure 14, validation is performed for the model by examining the Loss values of the training and test data. The train and test errors should be similar and show a decrease toward zero together. Figure 15 denotes the plot of the values predicted by the model alongside the actual values.

Table 2. Performance scores of the LSTM model

Metric Name	Value
MAPE	10.0414%
RMSE	8418.2729
R^2	0.7958

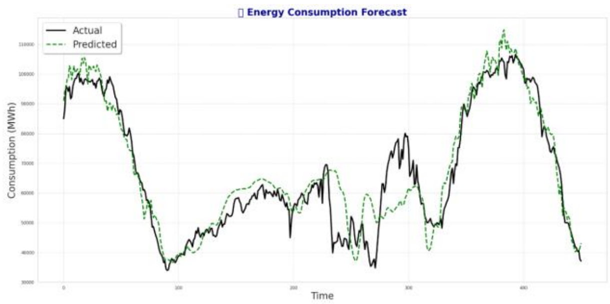

Figure 15. The comparative analysis of demands (actual versus predicted) obtained by LSTM

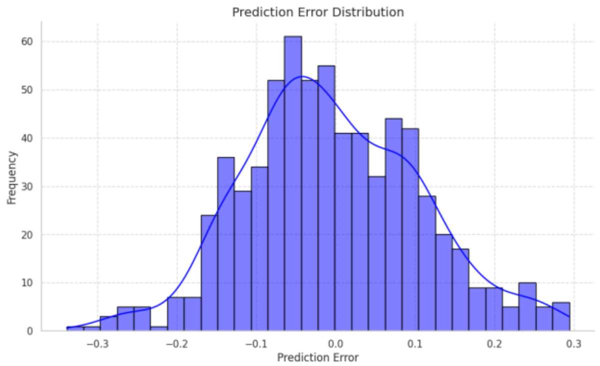

Figure 16. Histogram of the LSTM time series forecast error distribution

C. CNN Model

The CNN (Convolutional Neural Network) model is an effective forecasting tool for data with structural features such as time series data. This model can capture relationships in time series and compute long-term dependencies using convolutional networks (CNN). For a forecasting problem based on continuous and dynamic variables, such as energy consumption prediction, the CNN model is an effective choice. This model can process inputs from several different data sources (e.g., weather, seasons, and consumption data) and is used in determining energy demand [26].

Training Process:

- Filters and Feature Extraction: While CNNs are commonly used in image data, they are also suitable for time series data. CNNs work with convolutional layers that automatically extract features from the data. These features are used to help the model make better predictions.
- Max Pooling and Stride: During convolutional operations, techniques like "stride" and "max pooling" are used to reduce the data dimensions. This process speeds up the training and allows the model to learn more general features.
- Deeper Architectures: Deep CNNs learn the data at more complex levels and provide better generalization capabilities.

Figure. 17. Validation and train loss obtained by CNN model

Table 3. Performance scores of the CNN model

Metric Name	Value
MAPE	12.5120 %
RMSE	99.0515
R^2	0.7616

Figure 18 illustrates the representation of the values predicted by the model alongside the actual values.

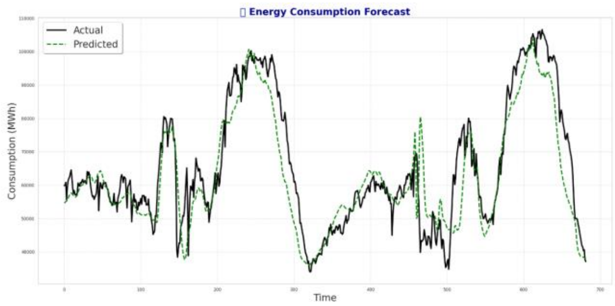

Figure 18. The comparative analysis of demands (actual versus predicted) obtained by CNN

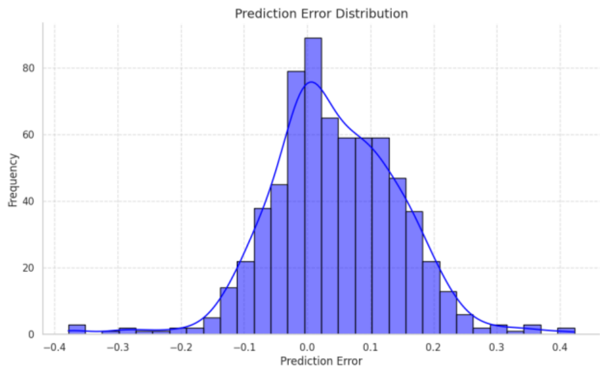

Figure 19. Histogram of the CNN time series forecast error distribution

D. Factors Affecting Performance

Data Attributes:

- Feature Selection: Properly chosen features can improve model accuracy. For example, including seasonal patterns or external factors can enhance time series prediction.
- Data Preprocessing: Proper scaling and handling of missing values are crucial. Inadequate or incorrect data preprocessing can negatively impact the model's performance.

Model Parameters:

- Hyperparameters: Learning rate, the number of layers, the number of neurons in each layer, and activation functions all directly affect the model's performance.
- Weight Initialization: The initialization of weights can either speed up or slow down the learning process.

Time Series Characteristics:

- Seasonality and Trends**:** If the time series data has seasonal fluctuations or long-term trends, the model needs to be configured to capture these features effectively.
- **Noise:** Noise in the data can affect the model's accuracy. Noisy data can cause overfitting if not handled properly.

Dataset Size and Time Steps:

- Amount of Data: The model needs to be trained with a sufficient amount of data. Training with too little data can lead to overfitting or underfitting.
- Time Steps: Focusing on shorter or longer time intervals may impact the model's performance.

Training Process:

- Overfitting and Underfitting: Overfitting or underfitting can significantly affect the accuracy of time series predictions. Regularization techniques like L2 regularization or dropout can help address these issues.

Model Depth and Complexity:

- Number of Layers: Deeper networks can learn more complex relationships, but they can also lead to higher computational costs and overfitting.
- Hidden Layers: More hidden layers allow the model to capture more complex features, but this can also increase training time.

E. RNN, LSTM, and CNN Comparison

The use of each model depends on the problem and the dataset. If your data contains long-term dependencies, LSTM may be the best solution. RNNs offer simple and fast solutions but are limited to complex datasets. CNNs, on the other hand, are particularly powerful when working with visual data and extracting local dependencies in time series data.

RNN and LSTM models can be used to predict future energy demand by training them with historical energy consumption data. These models can learn patterns and trends in the data and provide reliable forecasts by considering factors such as seasonality, trends, and other relevant variables. In time series analysis, RNN and LSTM models are particularly powerful tools for predicting future values.

They have been successfully applied in various fields, including finance, weather forecasting, and energy demand prediction.

Criterion	RNN (Recurrent Neural Network)	LSTM (Long Short-Term Memory)	CNN (Convolutional Neural Network)
Model Type	Recurrent neural network (for sequence data)	Advanced RNN (for learning long-term dependencies)	Convolutional neural network (primarily for image and time-series data)
Training Process	- Gradient propagation through time (BPTT)	- Gradient propagation through time with forget, input, and output gates (BPTT)	- Feature extraction with convolutional layers
Long-Term Dependencies	Weak (Vanishing Gradient Problem)	Strong (Learns long-term dependencies with cell states and gates)	Limited (Good for short-term dependencies in time-series data)
Hyperparameter Optimization	- Learning rate	- Learning rate	- Number of filters
	- Number of cells	- Number of cells	- Kernel size
	- Time steps	- Dropout	- Learning rate
		- Batch size	- Batch size
Error Analysis	- Difference between training and test error (Overfitting)	- Difference between training and test error (Overfitting)	- Difference between training and test error (Overfitting)
	- Vanishing Gradient	- Vanishing/Exploding Gradient	- Extracts features at different levels
Advantages	- Simple and fast to train	- Excellent at learning long-term dependencies	- Highly effective for image and time-series data
	- Suitable for sequence data	- Manages gradient problems better	- Extracts local features efficiently
Limitations	- Struggles to learn long-term dependencies	- More complex structure and computationally intensive	- Struggles to capture long-term dependencies in time-series data
	- Vanishing gradient problem	- Longer training times	
Recommended Use Cases	- Simple time series predictions	- Learning long-term dependencies in time-series prediction	- Image data analysis
	- Sentiment analysis	- Natural language processing	- Time-series data for convolutional feature extraction

Figure 20. Comparison of RNN, LSTM, and CNN architectures

Results

Three different deep neural network models, namely CNN, RNN, and LSTM, were developed for the prediction of active energy consumption. These models, particularly the recurrent neural network-based architectures, are trained under the same conditions to enable a fair comparison of their performance. The findings were evaluated based on key performance metrics such as RMSE, MAPE, and R^2 [27-31].

Among these architectures, it was observed that the CNN model exhibited lower performance compared to the other neural networks. The performance of the CNN model fell below expectations; however, it is believed that its performance was enhanced through various updates. The results presented in Table 1 indicate that the performances of the architectures are close to each other, with the best performance achieved by the simple RNN model. The performance measures obtained for RNN are as follows: MAPE: 9.60%, RMSE: 7785, 15 and R^2: 0.825. These measures are considered satisfactory since the mean absolute percentage error is below 10% and the coefficient of determination (R^2) value is above 0.5.

Table 4. Performance measures of the models

Model	MAPE	RMSE	R^2
Simple RNN	9.60%	7785.15	0.82
LSTM	10.04%	8418.27	0.79
CNN	12.51%	9095.15	0.76

Table 5. Summary of the architecture and the parameters used in the models

Parameters	RNN	LSTM	CNN
Number of hidden layers	3	2	1
Number of units in a hidden layer	60,40,32	64,32	64
Batch size	10	20	9
Epochs	50	100	50
Learning rate	0.001	0.001	0.001
Optimizer	RMSProp	RMSProp	RMSProp

The regression graphs of actual data versus. Predicted data for the three artificial neural network models are given in Figure 12, Figure 15, and Figure 18, which are summarized in the previous section. When the predicted data is compared with the actual data in these figures, it is observed that all three models produced satisfactory results. To detect that the model performs better, prediction and actual data are graphically represented, where it is observed that the data points are quite close. Thus, it said that the predicted values approximate the actual values.

Conclusion

In this article, the application of Python and machine learning techniques in the field of energy consumption prediction is modeled using the dataset of energy consumption in the DEDAŞ region. Data analysis methods and data mining applications are employed to prepare the dataset for the model. For the implementation of the prediction model and time series analysis, machine learning methods such as Simple RNN, LSTM, and CNN are used. The best performance results were obtained by the simple RNN model. This prediction study in the energy sector demonstrates the feasibility of more predictable, more sustainable, and efficient energy production. When the model is set up and run, it is observed that after 50 epochs, the loss values for the model approach are zero. As seen, even 10 epochs are sufficient for this model.

In the modeling phase, machine-learning models such as simple RNN, LSTM, and CNN are applied. Through data analysis, missing and incorrect (nonsensical) values in the dataset are filled with average values to ensure more accurate predictions, making the data more orderly. In the analysis of outliers, many column values were found to have values far outside the range of meaningful values, negatively affecting the results. These values are adjusted to appropriate boundary values. While using machine-learning methods, those suitable and applicable to this study were identified.

When the model stages (epochs) were applied with 50 stages in the Simple RNN model, 19 stages in the LSTM model, and six stages in the CNN model, the most efficient results were obtained. By maintaining the same model framework and only applying different models of Simple RNN, LSTM, and CNN, the results were observed. It noted that there were changes in the number of parameters when different models were applied.

Energy demand forecasting is a process of analyzing and modeling to predict future energy requirements. These forecasts are crucial for sectors like energy producers, distribution companies, and industries that consume energy. The forecasting process uses statistical and machine learning methods to estimate future energy needs based on historical data. Various factors, including weather conditions, economic influences, seasonal fluctuations, and demographic information, are considered in this analysis. Accurate forecasting helps in managing energy resources effectively, optimizing planning and production strategies, and improving the efficiency of resource utilization. It also leads to cost savings and ensures a stable energy supply. Energy demand forecasting requires expertise in data science and statistical analysis. Proper data collection, cleaning, model selection, and validation are essential for ensuring the reliability of these predictions.

This study focuses on using artificial neural network-based models for energy demand forecasting. Energy demand prediction is crucial for energy companies and consumers, as accurate forecasts play a significant role in resource planning and energy efficiency. In this study, the simple RNN model is employed to predict future demands by utilizing historical energy consumption data. The results obtained demonstrate the effectiveness of the RNN model in energy demand forecasting.

This study provides a valuable contribution to the planning and decision-making processes in the energy sector. Additionally, it enables more accurate predictions of future energy demand, thereby offering benefits in terms of energy efficiency and resource management.

Ethics Committee Approval and Conflict of Interest Statement

Ethics committee approval is not required for the prepared article. There is no conflict of interest with any person or institution in the prepared article.

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