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FORECASTING PEAK LOAD ON THE POWER GRID

In the modern world, precise forecasting of peak electricity consumption stands as a pivotal pillar in the efficient management of power grids. The paramount importance of this task necessitates a comprehensive examination of various forecasting methodologies, leveraging hourly electricity consumption data and a diverse array of predictive models.

This article is dedicated to a thorough analysis of distinct peak load forecasting methods, elucidating the research methodology encompassing data preprocessing, model selection, and parameter optimization. The models under scrutiny encompass a spectrum of techniques, including ARIMA, SARIMA, LSTM, GRU, and Random Forest. To gauge their performance, a suite of evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), R-squared, and Receiver Operating Characteristic Area Under the Curve (ROC AUC) were employed.

The findings of this investigation underscore the nuanced strengths and limitations inherent to each forecasting model when tasked with predicting peak electricity consumption. Notably, certain approaches exhibit superior accuracy in short-term forecasting scenarios, while others excel in long-term predictions. The selection of the optimal forecasting method becomes contingent upon the specific conditions, constraints, and objectives of the study at hand.

The LSTM and GRU models, representing deep learning neural networks, manifest their prowess in addressing the intricate dynamics of electricity consumption data. Their capacity to discern intricate patterns, nonlinearities, and long-term dependencies positions them as formidable contenders in the domain of long-term peak consumption forecasting.

The Random Forest model emerges as a versatile choice, adept at accommodating the multifaceted characteristics of electricity consumption data. Its ability to autonomously identify complex dependencies, nonlinear relationships, and seasonal patterns while considering external factors amplifies its utility across a broad spectrum of forecasting scenarios.

This comprehensive work is of great importance for the practical study of various methods of forecasting peak electricity consumption. The results obtained from this analysis have significant implications for improving power grid management strategies, ultimately contributing to microgrid stability and resilience.

Keywords: forecasting, peak consumption, electricity, clean energy, Random Forest, neural networks.

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ПРОГНОЗУВАННЯ ПІКОВОГО НАВАНТАЖЕННЯ НА ЕЛЕКТРИЧНІ МЕРЕЖІ

У сучасному світі точний прогноз пікового споживання електроенергії використовується як одне з ключових значень для ефективного управління електромережами. Вирішення цієї задачі вимагає ретельного розгляду різних методів прогнозування, використовуючи годинні дані споживання електроенергії та різні моделі прогнозування.

Ця стаття присвячена аналізу різних методів прогнозування пікового навантаження, використовуючи дослідницьку методологію, що включає обробку даних, вибір моделі та оптимізацію параметрів. Моделі, що розглядаються, охоплюють широкий спектр методів прогнозування, включаючи ARIMA, SARIMA, LSTM, GRU та Random Forest. Для оцінки їх ефективності було використано низку метрик оцінки, таких як середня абсолютна помилка (MAE), коренева середня квадратична помилка (RMSE), середня абсолютна відсоткова помилка (MAPE), R-квадрат та площа під кривою характеристики отримувача (ROC AUC).

Результати цього дослідження підкреслюють сильні та слабкі сторони кожної моделі прогнозування споживання електроенергії. Зокрема, деякі підходи проявляють себе з більшою точністю в короткострокових сценаріях прогнозування пікового споживання електроенергії, тоді як інші відзначаються в довгострокових прогнозах. Вибір оптимального методу прогнозування стає залежним від конкретних умов, обмежень та цілей конкретного дослідження.

Моделі LSTM та GRU, що представляють собою нейронні мережі глибокого навчання, проявляють свою ефективність в розгляді складних динамік даних щодо споживання електроенергії. Їх здатність розпізнавати патерни, нелінійності та довгострокові залежності робить їх потужними конкурентами в області довгострокового прогнозування піку споживання.

Модель Random Forest виявилась універсальною, здатною адаптуватися до багатогранних характеристик даних споживання електроенергії. Її здатність автономно визначати складні залежності, нелінійні відносини та сезонні патерни, враховуючи зовнішні фактори підвищує її корисність в широкому спектрі сценаріїв прогнозування.

Ця робота має значення для практичного вивчення різних методів прогнозування піку споживання електроенергії. Результати, отримані з цього аналізу, мають значні значення для вдосконалення стратегій управління електромережами, що в кінцевому рахунку сприяє стабільності та стійкості енергетичної мікромережі.

Ключові слова: прогнозування, пікове споживання, електроенергія, чиста енергетика, Random Forest, нейронні мережі.

Introduction

Forecasting peak electricity consumption is of great importance for effective planning and management of the energy microgrid. This allows early detection of periods of high consumption and adaptation of resources to ensure the best response to changes in demand.

Planning and management of the energy microgrid involves using resources in an efficient way, minimizing costs and ensuring the stability of energy supply. Overtime forecasting helps determine the need for backup resources during peak load periods, helping to maintain network resilience and avoid supply failures.

Peak electricity consumption is one of the key characteristics of the energy system, which reflects the maximum load on the electrical network during a certain period of time. This characteristic is critically important for proper planning and management of power supply, energy security, and efficiency of the power system [1].

With the introduction of smart meters and the development of collective data technologies, more objective and detailed data on electricity consumption became available [2]. These data can be used to develop predictive models that provide accurate forecasts of peak consumption [3]. Forecasting peak consumption is of great importance to energy companies, allowing them to effectively plan electricity production, avoid congestion and ensure reliable and stable electricity supply.

This article is devoted to a comprehensive exploration of diverse techniques and strategies employed in predicting peak electricity consumption. It encompasses both conventional statistical methods and contemporary advancements rooted in machine learning and deep learning. The primary aim of this study is to scrutinize and identify effective methodologies for forecasting peak consumption, further facilitating a comprehensive comparison of their respective performance and accuracy.

Furthermore, an ensemble of models was taken into account, encompassing Random Forest, a technique that amalgamates multiple models to enhance prediction accuracy [4]. Moreover, specific libraries tailored for time series analysis were employed, such as Neural Prophet, leveraging neural networks for predictive purposes.

Subsequent sections delve into an in-depth exploration of the employed methods, their performance assessment, and a comparative analysis. The objective is to advance the cause of efficient and stable electricity provision by means of predictive examination of peak electricity consumption.

The study delves into the prediction of peak electricity consumption by analyzing a time series dataset spanning four years, which includes hourly electricity consumption figures. The primary objective is to forecast upcoming peak consumption values based on historical data, employing a range of forecasting methods. This endeavor aims to enhance the efficiency and reliability of power system operations.

Related works

The forecasting of peak electricity consumption has gained importance in recent years due to its importance for the management of energy processes and the stability of the power grid. Time series forecasting, including the energy sector, uses a variety of methods. These methods can be classified into three categories: statistical methods, machine learning methods, and deep learning methods [4]. Among the statistical methods considered are ARIMA, SARIMA and ETS, which are based on the analysis of trends and seasonality. Machine learning techniques include Random Forest, Gradient Boosting, SVM, and k-NN, which are used to detect complex dependencies in data [5]. Deep learning techniques such as LSTM, GRU, and 1D CNN are able to interact with sequential data and capture long-term dependencies [3]. This section delves into a survey of research that has investigated different methodologies for peak load forecasting.

The article [6] considers a wide range of methods and approaches to load forecasting in energy systems using smart networks. The authors review the literature on load forecasting and highlight the main trends and challenges related to this area. The article examines various methods, including statistical approaches, machine learning methods, and artificial neural networks, their advantages and disadvantages. In addition, the authors of the paper analyze important factors affecting load forecasting, such as weather, seasonality, geographic and social aspects. They also consider the implementation of smart grid technologies in the load forecasting process and emphasize the importance of accurate forecasting to ensure grid efficiency and reliability.

In the work [7], a data-driven approach for load forecasting in smart grids is proposed. The approach combines statistical and machine learning methods to predict load demand. The authors employ techniques like autoregressive integrated moving average (ARIMA), exponential smoothing, support vector machines (SVM), and artificial neural networks (ANN) to enhance load prediction accuracy.

Another study is presented in [8], introduces a novel load forecasting method for smart grids. This method relies on deep learning using long-short-term memory (LSTM) to simulate dynamic load changes. The authors demonstrate significant improvements in prediction accuracy compared to traditional methods.

The research [9] presents a load forecasting technique for smart grids based on cloud computing and LSTM neural networks. This approach offers enhanced prediction accuracy, scalability for large grids, and adaptability to varying conditions.

Moreover, the article [4] delves into the application of Kalman and filtered Monte Carlo methods for load forecasting. By analyzing unlinked time series models, the authors forecast peak and total electricity demand. Utilizing data containing peak demand and electricity production information, they observe consumption trends, identify outliers, and establish inter-day relationships.

These articles collectively contribute to the field of load forecasting for smart grids, introducing advanced methods to improve accuracy, flexibility, and efficiency in predicting electricity demand.

The obtained results indicate the convergence of the Monte Carlo and Gibbs methods Sampling when estimating model parameters, in particular covariances. The authors analyze changes in covariances between different components of the model and indicate correlations between different days of electricity consumption. They also emphasize the dynamics of autocorrelation, which indicates a relationship between days and electricity demand.

Methodology

To achieve the goal of forecasting peak electricity consumption, the following methodology is proposed:

- Data Preparation and Research:
  - Collect historical electricity consumption data, including hourly values, for four years.
  - Conduct data analysis to understand distribution, trends, seasonality, and possible anomalies in the data set.
  - Preprocess the data by addressing issues with missing values, outliers, and feature normalization.
- Selection and Engineering Features:
  - Identify relevant attributes that may affect peak power consumption, such as 'month', 'day_of_week', 'day_length' and 'night'.
  - Create additional features that can reflect patterns or variations in energy consumption.
- Selection of Models:
  - Use a variety of predictive models, both traditional and machine learning-based, to account for different aspects of the time series.
  - Selected models include ARIMA, SARIMA, LSTM, GRU, NARX and ensemble models such as Random Forest and Gradient Boosting.
- Model Training and Evaluation:
  - Divide the data set into training and test sets. For time series, it is important to apply chronological separation to simulate real-world conditions.
  - Train each selected model on the training set and tune the hyper parameters as needed.
  - Evaluate the performance of models on the test set using appropriate evaluation metrics such as MAE, RMSE, and MAPE.
- Detection and Treatment of Emissions:
  - Apply anomaly detection techniques to identify unusual patterns or outliers in data that may affect forecasting accuracy.
  - Resolve detected anomalies through data imputation or by considering their impact during the modeling process.
- Ensemble Approaches:
  - Explore ensemble methods to combine predictions from multiple models to improve the accuracy and reliability of peak energy demand forecasting.
  - Evaluate the performance of ensemble models using metrics such as F1-Score, Precision-Recall, and ROC-AUC.
- Visualization and Interpretation:
  - Use visualization libraries such as Matplotlib to create visual representations of forecasting results, comparing predicted values with actual consumption.
  - Analyze patterns and insights from visualizations to make informed decisions.

The proposed methodology aims to use a combination of traditional time series forecasting models, machine learning algorithms and ensemble methods to achieve accurate and reliable forecasting of peak energy consumption.

To effectively forecast peak electricity consumption, a dataset with hourly electricity consumption metrics and consistent weather-related features is essential. The dataset should ideally be free of gaps or missing values to ensure accurate predictions. These hourly measurements provide the necessary granularity to capture fluctuations in electricity demand, while the weather-related attributes contribute to understanding external factors that influence consumption patterns.

Choosing an appropriate model for forecasting peak electricity consumption is a key task in research, as the effectiveness and accuracy of predictions depends on its correctness. In this section, an in-depth examination of diverse methods and models utilized for peak performance prediction will be conducted. This analysis will encompass their merits, drawbacks, and domains of applicability.

ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) [5] are popular time series forecasting methods. They are based on a combination of autoregressive (AR), moving average (MA) and integrated (I) models. SARIMA includes a seasonal component to ARIMA.

The ARIMA model uses three parameters [13]: p, d, q, where:

- p is the degree of autoregression (the number of previous observations to be included in the model).
- d is the order of differentiation (how many times it is necessary to take the difference between consecutive observations to make the series stationary).

– q is the degree of the moving average (the number of previous forecasting errors to be included in the model).

The ARIMA model can be represented by the formula:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad (1)$$

where: Y_t is the value of the time series at time *t*,
c is a constant component,
ϕ_i – autoregression coefficients,
ϕ_{t-i} is the value of the time series at previous time points,
θ_i – moving average coefficients,
ε_t is the prediction error at time *t*.

The SARIMA model includes an additional seasonal component [13], which allows simulating seasonal changes in the time series. For this, the SARIMA model has three more parameters: *P*, *D*, *Q*, and *s*, where:

– P is the degree of seasonal autoregression,
– D is the order of seasonal differentiation,
– Q is the degree of the seasonal moving average,
– s is the period of seasonality (the number of observations per seasonal cycle).

The SARIMA model can be represented by the formula:

$$\begin{aligned} Y_t &= c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \\ &+ \Phi_1 Y_{t-s} + \Phi_2 Y_{t-2s} + \cdots + \Phi_p Y_{t-Ps} + \Theta_1 \varepsilon_{t-s} + \Theta_2 \varepsilon_{t-2s} + \cdots + \Theta_Q \varepsilon_{t-Qs} + \varepsilon_t, \end{aligned} \quad (2)$$

where: Φ_i – coefficients of seasonal autoregression ,
Y_{t-s} is the value of the time series with observations separated by s (seasonal lag),
Θ_i – seasonal moving average coefficients,
ε_{t-s} is the prediction error at the moment of time $t-s$.

Both of these models help to analyze and forecast time series taking into account autocorrelation, seasonality and changes in the time series.

After exploring autoregressive models for forecasting peak electricity consumption, let's turn our attention to the use of more complex and powerful neural network architectures, in particular LSTM, which allow us to better avoid the limitations of traditional approaches and obtain more accurate and realistic forecasts.

LSTM model (Long Short-Term Memory) is a subtype of recurrent neural networks designed to process and model data sequences such as time series [11]. One of the key advantages of LSTM is its ability to efficiently deal with long-term dependencies in data. LSTM includes special mechanisms for storing, retrieving, and updating information from previous time steps. The basic idea is to use an internal state that can store information for a long period of time, and use gates to adjust the internal state and output the information to the outer layer.

The LSTM structure includes the following components [14]:

– Forget Gate:

The building gate, responsible for deciding which information from the previous state should be forgotten, is characterized by the formula (3) used to construct these gates.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right), \quad (3)$$

where:
f_t is the building gate vector at step *t*,
W_f – matrix of weights,
h_{t-1} is the vector of the hidden state in the previous step,
x_t is the input vector at step *t*,
b_f - displacement,
σ – activation function (sigmoid).

– Input Gate:

The update gate, which determines the incorporation of new information into the internal state, is defined by the formula (4) for the update gate.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad (4)$$

where:
i_t is the update gate vector at step *t*,

W_i– matrix of weights,
$h_{t-1}$is the vector of the hidden state in the previous step,
$x_t$is the input vector at step *t*,
b_i- displacement.
– New Cell State:
The formula for the new internal state is:

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \quad (5)$$

where:
$\tilde{C}_t$is the new internal state at step *t*,
W_C– matrix of weights,
$h_{t-1}$is the vector of the hidden state in the previous step,
$x_t$is the input vector at step *t*,
b_C- displacement,
$tanh$– activation function (hyperbolic tangent).
– Output Gate:
The output gate, responsible for selecting the output from the internal state, is defined by the formula (6) for the output gate.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \quad (6)$$

where:
$o_t$is the output gate vector at step *t*,
W_o– matrix of weights,
$h_{t-1}$is the vector of the hidden state in the previous step,
$x_t$is the input vector at step *t*,
b_o- displacement.
– Hidden State:
The formula for calculating the new hidden state at step t is:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t,$$
$$h_t = o_t \cdot \tanh(C_t), \quad (7)$$

where:
$C_t$is the new internal state at step *t*,
$f_t$is the building gate vector at step *t*,
$C_{t-1}$is the internal state at the previous step *t*,
$i_t$is the update gate vector at step *t*,
$\tilde{C}_t$,is the new internal state at step *t*,
$o_t$is the output gate vector at step *t*,
$h_t$is the new hidden state at step *t*.

LSTM can be applied to predict peak load by learning from historical data and using the acquired knowledge to predict future values. Its ability to model long-term dependencies and account for a variety of input parameters makes it a powerful tool for time series analysis and forecasting.

After a detailed consideration of LSTM, it is worth turning to another important type of recurrent neural networks - Gated Recurrent Unit (GRU). Following this, the Nonlinear Auto Regressive model with exogenous inputs (NARX) [13] will be discussed, offering efficient modeling and forecasting of time series while accounting for external influences.

Gated Recurrent Unit (GRU) is an improved version of LSTM that has fewer parameters and may be less prone to overtraining on small datasets [15]. The GRU also uses gates to control the flow of information. It has two gates: the update gate (update gate) and priority gate (reset gate). An update gate decides what information should be transferred to a future state, while a preference gate helps decide what information should be forgotten from a previous state.

Evaluating the performance of forecasting models is a critical step in the process of developing forecasting algorithms, which helps determine how well the model fits real data and how accurately it can predict future values.

For the evaluation of forecasting models, an initial step involves partitioning the accessible data into distinct training and test subsets. Within this framework, the training set assumes the role of facilitating model training, essentially fine-tuning its parameters in accordance with the input data. Conversely, the test set is integral in gauging the predictive precision of the model when applied to novel data instances that remain unfamiliar to the model.

Various metrics are employed to evaluate the precision and effectiveness of a model's forecasting performance, with the selection of appropriate metrics contingent upon the specific characteristics of the forecasting task at hand [16]. These evaluation metrics serve as essential tools for quantifying the level of agreement between the predicted outcomes and the actual observations, thereby shedding light on the model's capability to capture underlying patterns, trends, and fluctuations within the data [13]. For instance, popular metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are commonly utilized to measure the extent of deviation between predicted values and observed data.

The selection of evaluation metrics may vary depending on whether the task involves point forecasts, interval forecasts, probabilistic forecasts, or the assessment of accuracy across multiple time horizons. These metrics play a pivotal role in enabling researchers and practitioners to comprehensively gauge the quality of forecasting results, allowing for informed decisions, model comparisons, and the identification of potential areas for refinement in the predictive models under investigation. Graphs can be effectively employed to visually represent the outcomes of estimation, encompassing elements like comparative plots showcasing forecasted versus actual values, as well as graphical representations of error distributions. These visual aids play a pivotal role in conveying the extent of alignment or divergence between projected and observed data points. In the selection process of an optimal model for a particular peak load forecasting endeavor, meticulous consideration should be given to identifying the paramount metric that aligns with the primary objectives of the task.

Experiments

This section provides a comprehensive overview of the conducted experiments to assess various forecasting techniques on the dataset for peak electricity consumption. The dataset encompasses hourly records of electricity usage from a two-story building situated in Houston, Texas, USA. The temporal span of the data spans from June 01, 2016 to August 2020.

The dataset contains a variety of parameters, including electricity consumption in kWh, as well as notes indicating the type of day (working, weekend, quarantine due to COVID, holiday). In addition, the dataset contains information about weather conditions, including temperature, humidity, pressure, etc.

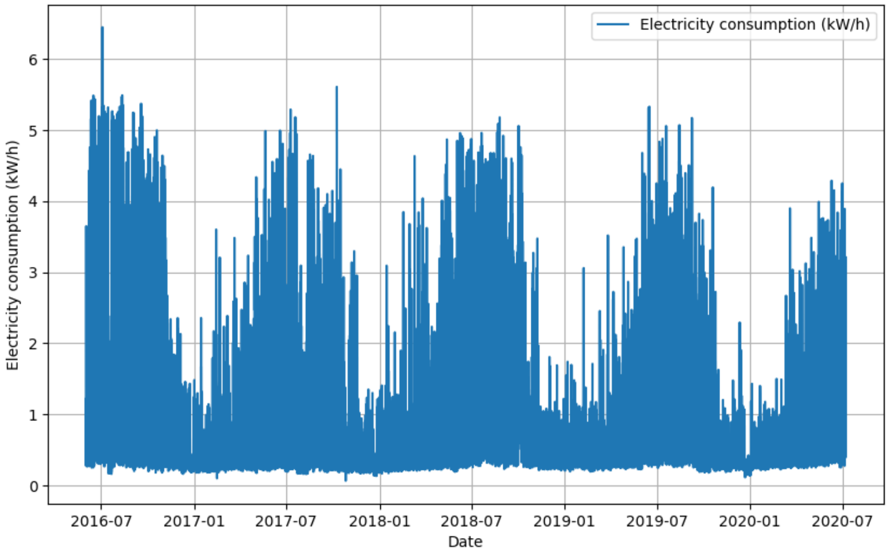

Fig. 1. Electricity consumption data set

The next stage was data processing. It included removing possible anomalies and missing values, normalizing the data and grouping it according to some parameters, such as days of the week, time intervals, etc. In addition, work was carried out to combine data on electricity consumption and weather conditions to create a connection between these factors. According to research, the peak consumption of electricity in a private house is usually observed in the evening period from 17:00 to 21:00. During this time, households actively use electrical appliances for cooking, lighting, working with electronics, as well as for the comfortable use of air conditioners and other appliances.

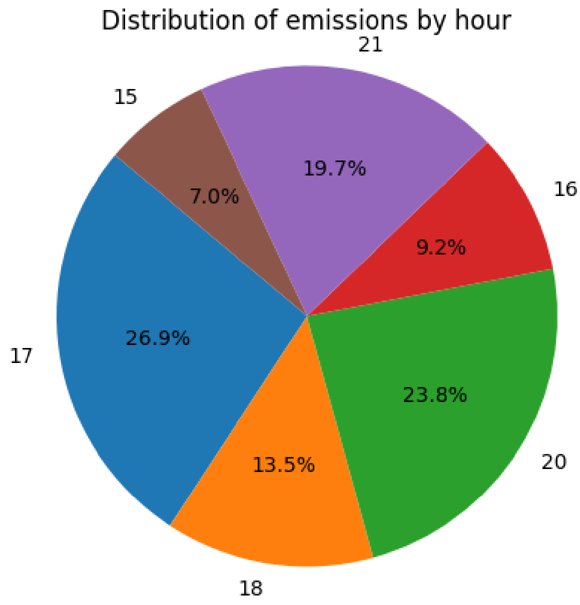

Fig. 2. The largest amount of peak value of electricity consumption

For this purpose, a range of forecasting techniques was employed, encompassing both traditional models like ARIMA and SARIMA, and more advanced approaches like LSTM and GRU.During the experiments, the dataset was split into training and test subsets. Each selected prediction model was trained on the training data, and model-specific techniques were employed to optimize and fine-tune hyperparameters. The accuracy and performance of each model were subsequently evaluated using the test data.

The initial approach involved utilizing a SARIMAX statistical analysis model. This type of model is well-suited for analyzing and predicting time series data, incorporating autoregressive, moving average, and external exogenous variables. Peak electricity consumption can be related to various factors such as weather, time of day, working hours, etc. For this code uses exogenous parameters such as 'length_of_day', ' Hour ', ' day_of_week ' which may affect power consumption. These metrics add additional context for analyzing and predicting peak values.

The model parameters (p, d, q, P, D, Q, s) are adjusted taking into account the properties of the time series and the specifics of peak consumption. Parameter selection involved trying different combinations and testing their performance on the training data using criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion). Using ACF, PACF plots, and trying different parameter values helped to find the best combination for a particular time series.

SARIMAX model parameters are the following: p: Autoregressive order (AR) – 0; d: Degree of difference – 1, q: The order of the moving average (MA) - 1, P: Order of seasonal autoregression (Seasonal AR) – 1, D: The degree of seasonal difference - 0, Q: The order of the seasonal moving average - 0, s: Seasonality period - 24 (one day)

The final metrics (MAE, RMSE, MAPE) provide quantitative insight into the accuracy of model predictions. This helps to determine how effective the model is in predicting peak electricity consumption in different time frames (Table 1).

Table 1

Estimates of the accuracy of the SARIMAX model using the best parameters

Accuracy score/ prediction interval	Week	Month	Year
MAE	0.859	1.185	7.36
RMSE	1.001	1.47	8.58
MAPE	136.37	85.5	102.2

A graph is plotted comparing the actual data and the predicted values for the week using the SARIMAX model. The red points on the graph indicate the maximum predicted values that meet the given condition. A shadow range is also used for confidence intervals around predicted values (see Fig. 3).

Random Forest model was chosen next. This model is an ensemble of decisions based on decision trees, which allows to predict the peak load of electricity consumption. The data set was divided into training and test parts, where the training part contains 80% of the total amount of data. Next, important features (parameters) are selected for the model, such as 'month', 'day_of_week', 'length_of_day', 'Night ', ' Winter ' and ' Hour ', which are used to predict the peak load.

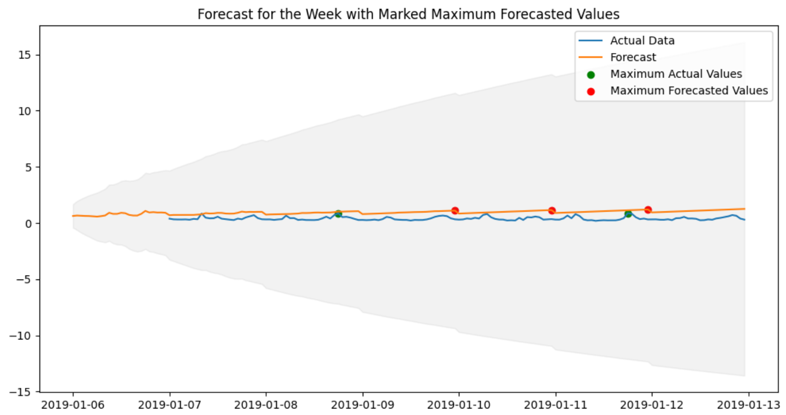

Fig. 3. Indicators of forecasting peak loads using the SARIMAX model

With the help of the trained model, peak load forecasting was carried out at different time horizons: week, month and year. The predicted values were compared with real data (Table 2).

Table 2

Accuracy estimates of the Random Forest model

Accuracy score/prediction interval	Week	Month	Year
MAE	0.802	0.835	0.48
RMSE	1.13	1.151	0.766
MAPE	93.87	58.59	50.75

A graph is plotted comparing the actual data and the predicted values for the week using the Random Forest model (see Fig. 4).

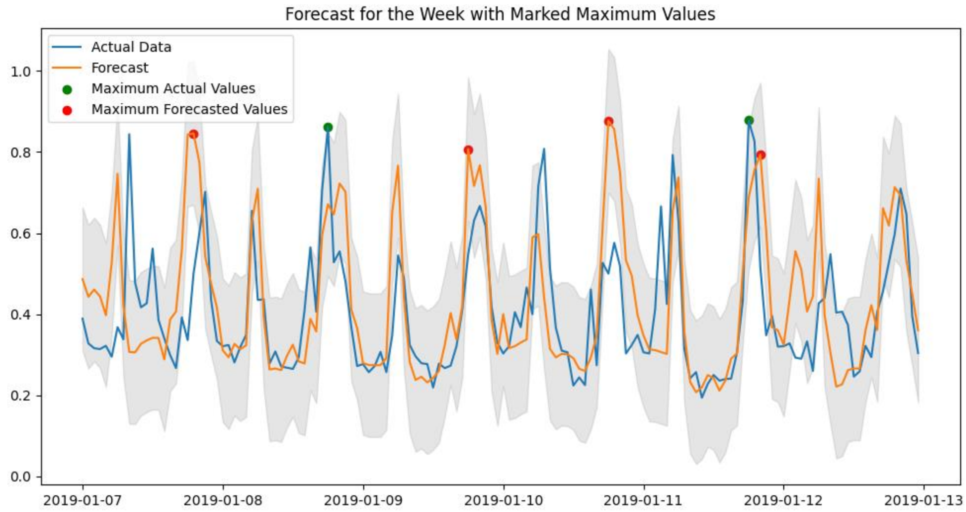

Fig. 4. Indicators of forecasting peak loads using the Random Forest model

Consider the results of the LSTM model. Input data included information on electricity consumption (' Value (kWh)') and various factors that may affect it, such as month, day of the week, length of day, time of day, etc. To improve model performance, the data were normalized to a range of 0 to 1.

After dividing the data into training and test sets, where the latter was selected for testing, an LSTM model was built. It had one LSTM layer with 50 neurons that helped detect dependencies in time series. The model training process took five epochs, and each epoch used packets of size 168.

After the training was completed, a prediction was made on the test data set. The resulting predicted values were transformed back to the original measurement scale. The predicted values were compared with the real data (Table 3).

Table 3

LSTM model accuracy estimates

Accuracy score/prediction interval	Week	Month	Year
MAE	0.10	0.13	0.29
RMSE	0.13	0.17	0.53
MAPE	25.1	30,12	31.52

When displaying the graphs, the graph displayed the observed values and the predicted data of electricity consumption per week using the LSTM model (see Fig. 5).

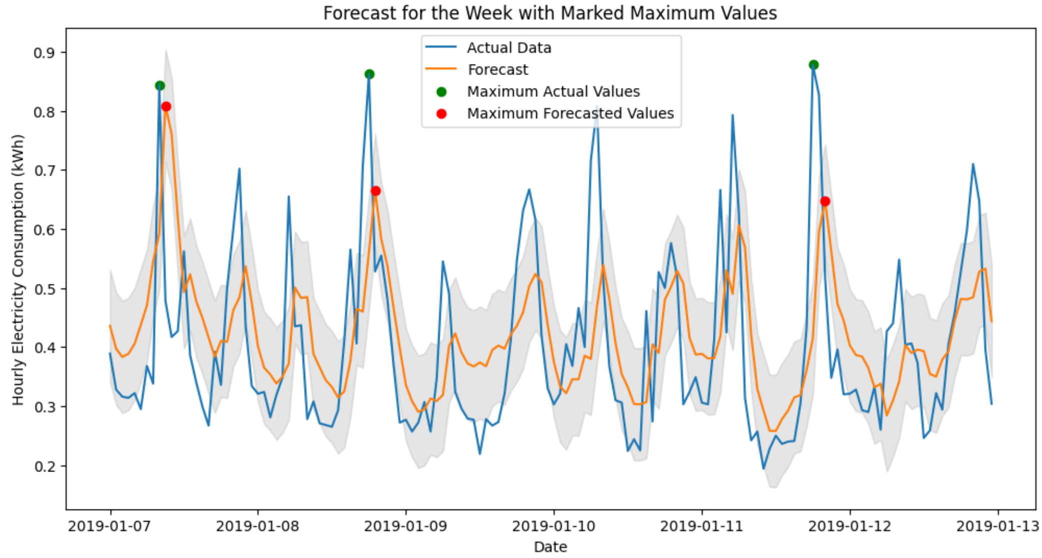

Fig. 5. Prediction of peak load indices using models LSTM

Deep recurrent neural networks (RNNs) include a variety of architectures such as LSTM and GRU (Gated Recurrent Unit), which are designed to process sequential data. These two architectures have some differences in the way they work, which makes them effective for different tasks.

Parameters of the GRU model are the following: the number of neurons in GRU layer –50; Activation function – default (of course sigmoid and tanh for GRU gates); Optimizer – Adam; Loss function – Mean Squared Error (MSE); Number of learning epochs – 20; Pack size – 168 (manually selected number); Length of incoming sequence – 24 hours.

The GRU uses two internal blocks - an update block and a transfer block. The update block specifies how much information will be updated, while the carry block specifies how much information will be passed to the next step. This allows the GRU to control the information flow in a simpler way.

Predicted values, as in other models, were compared with real data (Table 4).

Table 4

Estimates of the accuracy of the GRU model

Accuracy score/prediction interval	Week	Month	Year
MAE	0.12	0.18	0.30
RMSE	0.15	0.22	0.54
MAPE	32.94	45.50	36.07

A graph is drawn showing the observed values and predicted data of electricity consumption per week using the GRU model (see Fig. 6).

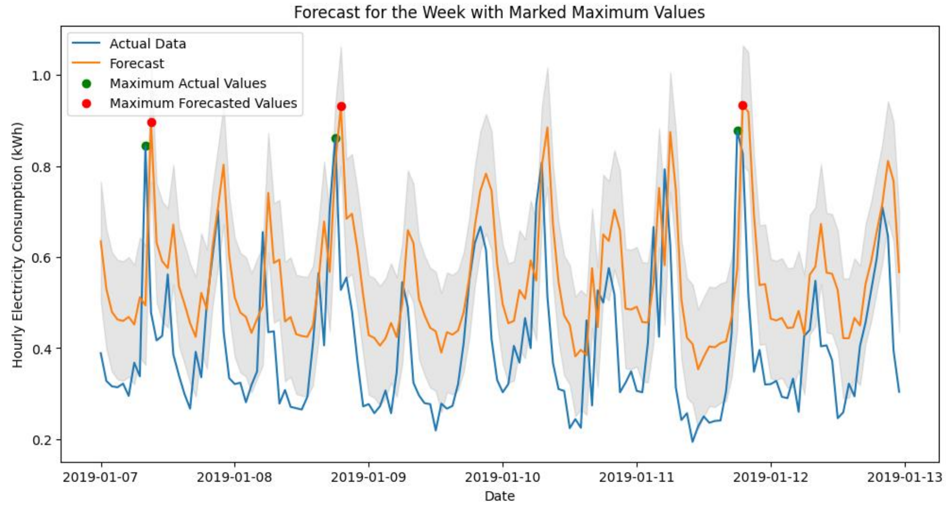

Fig. 6. Prediction of peak load indices using models GRU

As a result of the study, a consolidated (table 5) was compiled, encompassing the predictions of peak electricity consumption generated by all the employed models. Notably, among the models examined, LSTM and GRU exhibited the highest accuracy in predicting peak load, with a discrepancy margin of just one hour.

Table 5

Actual and forecasted time of peak electricity consumption indicators

Actual	LSTM	GRU	Random Forest	SARIMAX
2019-01-07 08:00:00	2019-01-07 09:00:00	2019-01-07 09:00:00	2019-01-07 19:00:00	2019-01-09 23:00:00
2019-01-08 18:00:00	2019-01-08 19:00:00	2019-01-08 19:00:00	2019-01-09 18:00:00	2019-01-10 23:00:00
2019-01-11 18:00:00	2019-01-11 20:00:00	2019-01-11 19:00:00	2019-01-11 20:00:00	2019-01-11 23:00:00

Conclusions

In this study the different forecasting methodologies, including SARIMAX, Random Forest, LSTM, and Gated Recurrent Unit, which collectively demonstrated efficacy in forecasting peak electricity consumption, were studied. Each model exhibited distinct strengths and limitations that warrant careful consideration in selecting an optimal approach.

Starting with the SARIMAX model, its suitability for long-term peak electricity consumption forecasting proved limited due to its inability to effectively capture the intricate dynamics and transformations inherent in energy systems, particularly over extended forecast horizons.

The Random Forest model showcased its versatility by efficiently accommodating the complex dynamics of electricity data. This model autonomously identified dependencies, nonlinearities, and seasonality within input data while considering external factors influencing consumption.

Deep neural models, namely LSTM and GRU, emerged as formidable tools for managing trends, seasonality, and non-linearities within electricity consumption time series. Of particular significance is the remarkable performance of LSTM and GRU in accurately forecasting long-term peak values.

The SARIMAX model serves as a viable tool for predicting general trends and standard changes in electricity consumption but lacks optimal performance for long-term peak value forecasting. Random Forest, LSTM, and GRU models demonstrated their prowess in addressing complex data variations and offering accurate peak electricity consumption forecasts.

As the result, using the LSTM model the highest forecasting accuracy across all time intervals was achieved. With M.A.E values of 0.10 kW/h for weekdays, 0.13 kW/hr for weekends, and 0.29 kW/h for holidays, the LSTM model showcased its robust performance. Additionally, both the LSTM and GRU models exhibited the capacity to identify all peak electricity consumption instances within a few hours, thus solidifying their role in the task of assessing the state of energy microgrids. The developed models will serve as integral components in the ongoing evaluation of energy microgrid conditions, contributing to the enhancement of energy distribution system assessment and management.

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