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D2 INFORMATION SYSTEMS, TELECOMUNICATIONS AND CYBERSECURITY

D2 PS1 - IT/OT Solutions to improve the Efficiency and Resilience of Electric Power Systems

State-of-the-Art Algorithms for short-term residential Load forecasting for Smart Grids

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SUMMARY

In recent years, the electricity sector has received significant scientific attention due to global regulatory efforts promoting sustainability and decarbonisation. DSOs transmission and distribution system operators are being asked to respond to the most crucial challenge in their history, namely the energy transition of the power system. Sustainable development and technological advancements, especially in artificial intelligence and machine learning, are key in transforming conventional power networks into smart grids. A critical aspect of this transformation is to accurately predict electricity consumption for residential users. Smart electricity metering technologies in smart grids collect extensive consumption data, enabling energy consumption forecasting. This forecasting is crucial to managing electricity demand and to help utilities in load planning. The aim of this paper is to draw useful conclusions on the behaviour of residential consumers and the level of precision that can be achieved when predicting their demand, a fact that significantly improves the operation of Smart Grids and their interaction with the electricity markets. The assets and consumers of the distribution grid could participate in the electricity markets providing additional flexibility services. In this paper, an extensive study on residential load forecasting is presented, which concerns on small residential consumers, who are established on the Greek island of Skiathos. For this purpose, state-of-the-art algorithms are investigated with the aim of short-term forecasting of their electricity energy consumption. The dataset used contains data in hourly resolution from the aggregation of 15 individual low-voltage consumers. More specifically, five different models are created to draw safe comparative conclusions. Initially, a multilayer perceptron model (MLP) is constructed, which consists of a series of fully densely connected layers. Then, a convolutional neural network model is created, followed by a single dense layer (CNN-Dense).

Additionally, to further investigate the problem, a Long-Short-Term Memory (LSTM) model and a Temporal Convolutional Network (TCN) are implemented, which are exclusive models for time series problems. For further investigation, an ensemble model is implemented, which combines CNN and LSTM predictions. For the best performance of the models, the Bayesian Optimization technique is deployed, in order to use iterative processes through which the best hyperparameters of the models will be determined. Finally, a Naïve model is implemented, which is used as benchmark model, to compare the predictions of the five Deep Leaning algorithms with a statistical model. This paper has been divided into the following parts: First, a brief literature review is presented with the aim of highlighting similar scientific studies that have been developed. Subsequently, the operation of the five models is briefly described. Then, an Exploratory Data Analysis (EDA) is carried out, to investigate all the main features of the demand time-series, such as its seasonality among different months of the year and the peak and nonpeak values. Then, the forecasting errors are introduced with a comparative analysis. Severalerror metrics are used to compare the accuracy of the models' predictions with the actual values. Finally, the conclusions drawn from this study are discussed, as well as proposals for future studies resulting from the work carried out.

KEYWORDS

Energy - Residential Load Consumption - Electricity Forecasting - Long Short-Term Memory - Multilayer Perceptron - Convolutional Neural Network - Ensemble Model - Naïve model

1. Introduction

The energy sector presents rapid growth and transformative changes that attract the attention of researchers and investors. New investments require the deployment of new equipment with a main concern of forming rules which protect the environment and address the greenhouse effect. These developments underscore the increasing importance of the sector and establish essential conditions for its oversight [1].

Simultaneously, the ongoing conflict in Northern Europe spreads a worldwide level energy crisis. Increased operational costs have led large industrial units and businesses to halt their operations, due to this geopolitical condition. Uncertainties and energy-related risks have escalated because of the increased global electricity demand [2].

The short-term prediction of household electricity consumption seems as a key factor for the uninterrupted operation of modern electrical networks [3]. The forecasting of the short-term trends in the electricity consumption of residential consumers acts a significant role in ensuring the effective operation of modern power grids. Accurate recognition of short-term patterns of electricity consumption leads to preventive resource management, optimising grid performance, and increased reliability [4].

In terms of buildings power usage prediction, different practices were applied to overcome the difficulties due to its high energy consumption, nonlinearity of data, and dynamic occupant behaviour [5]. On one hand, statistical methods are used, as Awerkin et al. [6] propose a hybrid model which consists of statistical parametric methods of Fourier analysis and stochastic differential equations. The paper findings conclude that this model is more suitable for short-term predictions in small time intervals rather than for a long-term forecasting horizon. On the other hand, in recent power prediction works, experts utilise machine learning (ML) and deep learning (DL) algorithms. Dinesh et al. [7] present a new method for forecasting energy consumption in a house based on non-intrusive load monitoring (NILM), and affinity-aggregation spectral clustering is introduced, with the idea of extending it to forecast consumption in a larger number of houses, such as a microgrid. Furthermore, Biswas et al. [8] developed Artificial Neural Network models based on the Levenberg-Marquardt and OWO-Newton algorithms, which produce show promising prediction results using data from TxAIRE Research houses. Kim and Cho [9] processed data an apartment with a resolution of one minute with a sliding window technique to develop a 60-minute time frame and set the next 60 minutes as a prediction. The multi-variable time series is converted to a two-dimensional array to feed a hybrid forecasting model (Convolutional Neural – Long-Short Term Memory Networks). Furthermore, Ullah et al. [10] examine the use of an intelligent hybrid approach that incorporates a convolutional neural network (CNN) with a multilayer bidirectional long-short-term memory (M-BDLSTM) method to effectively learn the sequence pattern of the predicted data.

The main contribution of this paper lies in the direct application of deep learning models to the final demand curve, which is an important aspect in economic or market contexts. The specificity of this application is underscored by using a limited sample of consumers, deliberately avoiding assumptions and data smoothing. Despite these constraints, the research claims that not only is the proposed task feasible, but can be applied and implemented effectively under real-world operational conditions, such as its integration into the systems developed by the transmission system operator (TSO) and distribution system operator (DSO). From the DSO perspective, the provision of local flexibility services, such as congestion management and voltage control, is a pivotal role challenge, and from the TSO point of view, these small consumers will be enabled through IoT devices to participate in a secure manner directly into the balancing market, for adjusting the frequency of the grid. This emphasis on practicality suggests a focus on the applicability and robustness of the DL models in addressing real-world scenarios, offering insight into the potential implications of the findings for broader contexts beyond the limited data of the study.

This paper is organised as follows: Section 2 discusses the data collection process and the forecasting models used. Section 3 shows the results of the short-term residential power prediction, and Section 4 concludes this work.

2. Methodology

2.1 Data

The data set of this study refers to the power consumption of 15 residential consumers. These properties are located on Skiathos Island in Greece. Skiathos Island is a famous tourist destination during the summer period, so the consumer load curve presents increased usage. Due to the privacy of client data, we studied the aggregated value of the 15 residences, as presented in Figure 1. The investigation period is 1-8-2020 to 30-06-2023. Data were provided to the researchers of the current study by the Hellenic Electricity Distribution Network Operator [11].

In addition, the weather conditions of the island are recovered from the meteorological station of the Skiathos airport. The International Civil Aviation Organisation (ICAO) code for this airport is LGSK. In general, the airport meteorological station publishes twice-in-hour reports, named METAR [12], [13], on the weather conditions that occur on the runway. These reports include the elements temperature, humidity, wind speed, and direction, among others, which are also the elements that were used for this work.

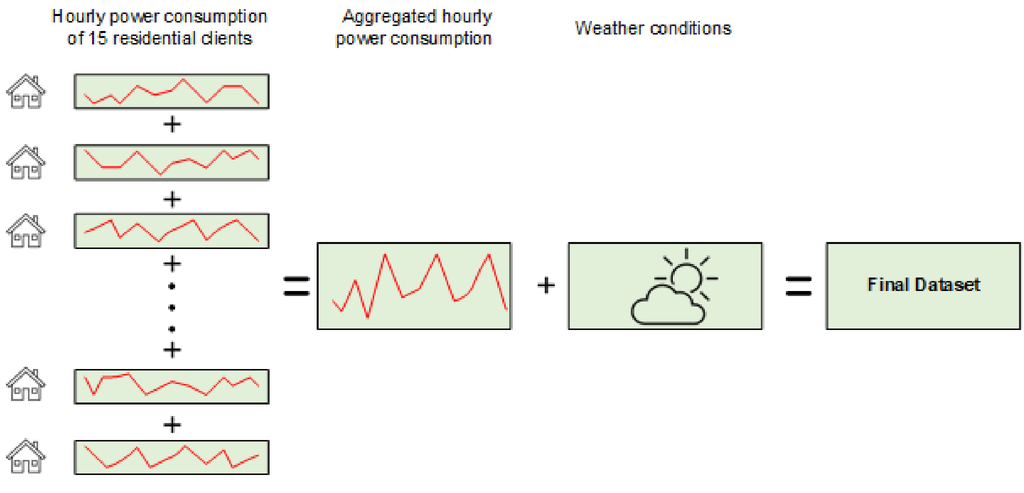


Figure 1 - Creation of the dataset

2.2 Models

In this section, the DL models created, as well as the benchmark Naive model, are analysed. About the Multilayer Perceptron (MLP) model, it is a basic Neural Network with layers of interconnected nodes, used for tasks like predicting trends and timeseries forecasting. Convolutional Neural Network (CNN) is a DL model with specialization in images, detecting features like edges, and suitable for problems such as image classification. Long-Short-Term Memory (LSTM) is a DL model used for sequences like time-series and language, helping to understand context over time. The Temporal Convolutional Network (TCN) model is similar to CNN, but more suitable for sequential data, like timeseries. A Weighted Average Ensemble model combines LSTM and CNN forecasts, giving a weighted predictive model. Finally, Naive model is a statistical algorithm that takes into account historical average values. More particularly, all the models are described below.

2.2.1 Multi-Layer Perceptron

A Deep Learning Feed-forward Neural Network known as the Multilayer Perceptron (MLP) [14] consists of fully connected hidden layers, along with one input and one output layer, as is depicted in

Figure *2*. The training process for MLP models, which aims to predict future data, involves several steps. Initially, the MLP uses a Forward Propagation Process during the training period, where data is propagated from the input to the output layer to calculate its parameters. The algorithm then calculates the loss function, which represents the difference between the actual and predicted values. Finally, using backpropagation, the gradient of the loss function is calculated until its minimum value is found. In this way the model got its final form.

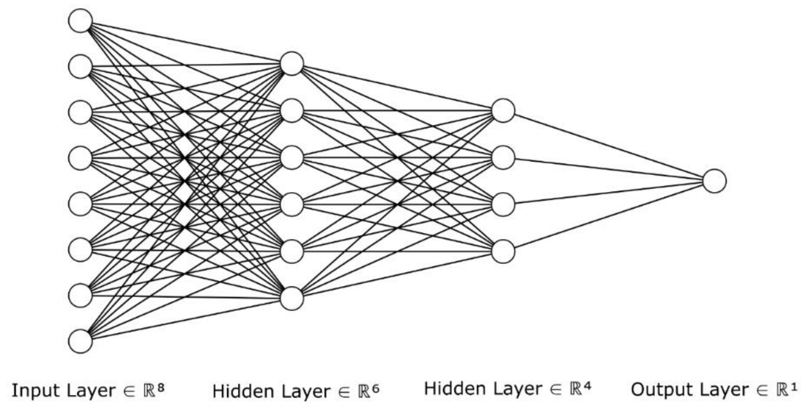


Figure 2 - Multilayer Perceptron Architecture

2.2.2 Convolutional Neural Networks

A Convolutional Neural Networks (CNN) [15] model is structured as a sequence of layers, and each neuron within the CNN does a vector operation, specifically a dot product, on received inputs. The three primary types which consist of the fundamental architecture of a CNN are the Convolutional, the Pooling, and the Fully Connected Layers. Every layer takes a 3D vector as input and transforms it into a 3D vector through a differentiable function. The core operating principles of these three layers are elucidated at the following paragraph and illustrated in Figure 3.

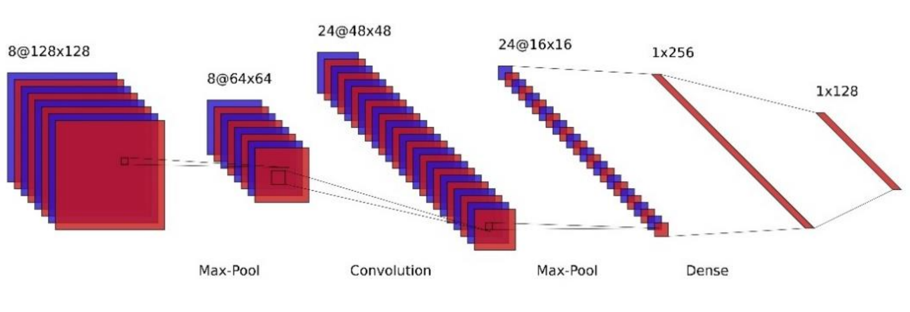


Figure 3 - Convolutional Neural Network Architecture

The Convolutional Layer is foundational in CNNs, handling a significant portion of computational tasks by performing essential convolutional operations. The Pooling Layer aims to reduce spatial dimensions, minimizing computational load and overfitting by subsampling and summarizing information from previous layers. Lastly, the Fully Connected Layer establishes complete connections between neurons, enabling comprehensive information exchange and facilitating the learning process in neural networks.

2.2.3 Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) [16] models belong to a specialized category of Recurrent Neural Networks (RNNs) designed to tackle the challenge of vanishing or exploding gradients often encountered by traditional RNNs when dealing with long-term dependencies in time series data. Figure 4 shows the basic structure of an LSTM. As it seems, the horizontal black line at the top is the cell state, which is responsible for the model to learn and adapt to long dependencies.

The working strategy of this model is analysed below:

- Forget Gate (f_t): Determines what information from the cell state should be deleted or saved.
- Input Gate (i_t): Updates the cell state. Initially, a sigmoid layer determines the values that will be updated. After, a $tanh$ layer creates a vector with the values that can be added to the cell

state.

- Cell State (c_t): Multiplies the old state C_{t-1} by f_t and then adds $i_t * \tilde{C_t}$.
- Output Gate (o_t): Determines the output of the model using a sigmoid and a $tanh$ function.

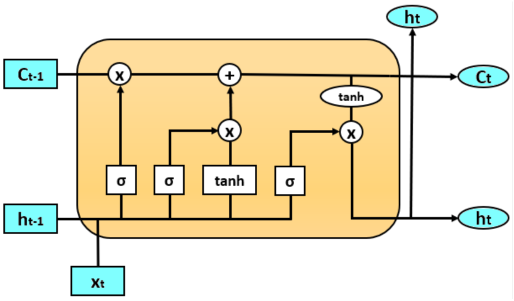


Figure 4 - LSTM Module

2.2.4 Temporal Convolutional Network

Temporal Convolutional Networks (TCNs) [17] are deep learning models that are used in time series forecasting tasks. They use one-dimensional convolutional layers, with dilated convolutions, in order to efficiently capture short and long-term dependencies. Their structure offers advantages such as the effective modelling of temporal patterns in time series forecasting problems.

2.2.5 Weighted Average Ensemble Model

The Weighted Average Ensemble model [17], which appears in Figure 5, combines a LSTM and CNN model and belongs to the family of ensemble learning algorithms. In this algorithm, each model is trained separately on the dataset, learning unique patterns, and creating representations. The weighted average mechanism combines the forecasts of the two algorithms using multiplicative weights to each output. The final forecast is the average prediction of the above two models.

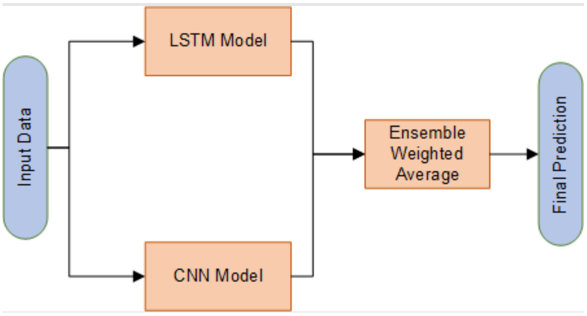


Figure 5 - Weighted Average Ensemble Model

2.2.6 Naïve model

It is a statistical model, which for each forecast hour, considers the average value of the same hour one week ago and the same hour two weeks ago. The premise of this method is that the time series under study presents specific patterns, such as seasonality between the month, the week and the day. This approach can be used as a benchmark model for comparison in time series forecasting tasks.

2.3 Software environment

This paper's trials were conducted in Python language, version 3.10, leveraging the Open-Source software library Tensorflow 2.14.0 and the high-level API Keras 2.15.0, for training and testing the deep learning algorithms. Additionally, Pandas 2.1.0 and Numpy 1.26.0 libraries for data analysis. Furthermore, the Seaborn and Matplotlib libraries were used for visualisation purposes of the exploratory analysis and prediction results. The trials were carried out on Google Colab Pro platform, which utilizes GPU NVIDIA (Version 460.32.03), RAM: 25.45 GB, disk space: 166.77 GB, and CUDA (Version 11.2).

2.4 Prediction evaluation

For this study the following three most common error prediction metrics in regression analysis are used.

Mean Absolute Error (MAE): This metric estimates the average of the absolute differences between the forecasted and true values. MAE is calculated as:

$$MAE = \frac{\sum |y - \hat{y}|}{n}$$

Root Mean Squared Error (RMSE): This metric calculates the square root of the average of the squared differences between the predicted and true values. RMSE is calculated as:

$$RMSE = \sqrt{\frac{\sum (y - \hat{y})^2}{n}}$$

Mean Absolute Percentage Error (MAPE): This metric computes the average of the absolute percentage differences between the predicted and actual values. MAPE is calculated as:

$$MAPE = \frac{\sum \frac{|y - \hat{y}|}{y}}{n} * 100$$

where y is the actual value, $\hat{y}$ is the predicted value, and n is the number of observations.

3. Data Analysis and Results

In this section, the analysis of the studied data is initially presented, followed by a focus on the fundamental architectures and hyperparameters of each model. Finally, a detailed presentation of the prediction results of each algorithm is provided.

3.1 Exploratory Data Analysis

Concerning the variation in consumption data, the boxplots in Figure 6 illustrate the average consumption per day of the month (a), per day of the week (b), and per month (c). It is observed that the months with the highest consumption are July and August, a phenomenon that is logical due to the increased temperatures during the summer period. Notably, during the day, the average hourly consumption follows a consistent trend, as does the average consumption during the midday hours per week. These variations are indicative of the non-uniform fluctuation exhibited by the data and the absence of specific patterns.

Figure 7 presents the correlation between the variables of weather characteristics and the electricity consumption. None of the variables exhibit a high correlation, a fact that led us to utilize univariate prediction methods.

3.2 Feature Engineering

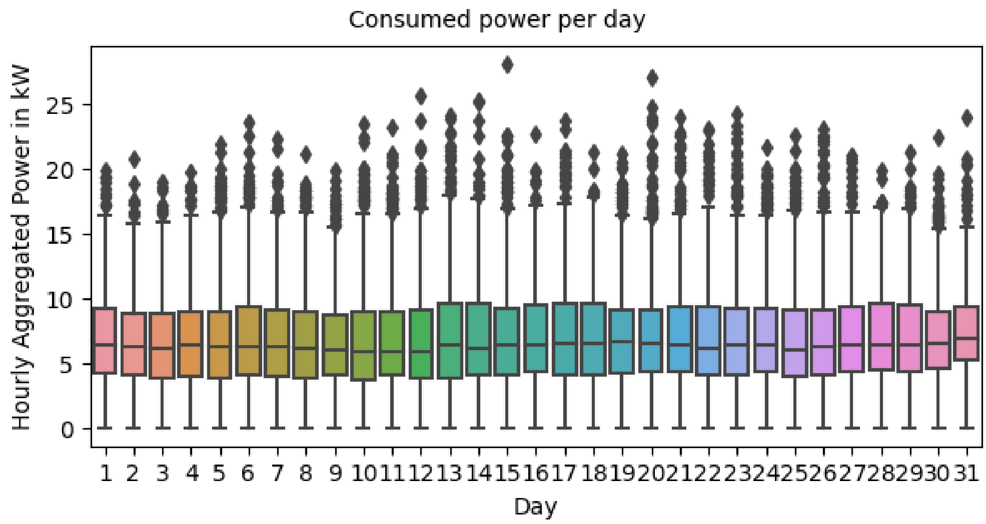
With the aim of create appropriate features for the optimal training of models, the *One-Hot Encoding technique* is employed. This is a scientific approach which transforms categorical data into numerical vectors and converts numerical information into cyclical patterns through trigonometric transformation. This method converted weekdays, hours, and months into sine and cosine representations. Specifically, the features created as follows:

- Hourly Consumption: The historical 24 hours of values for 1 every predicted hour.
- Sin and Cos of the day: Sin and cosine representation for the day.
- Sin and Cos of the hour: Sin and cosine representation for the hour.
- Sin and Cos of the month: Sin and cosine representation for the month.
- Weekend: Dummy variable where 0 represents working days and 1 weekend.

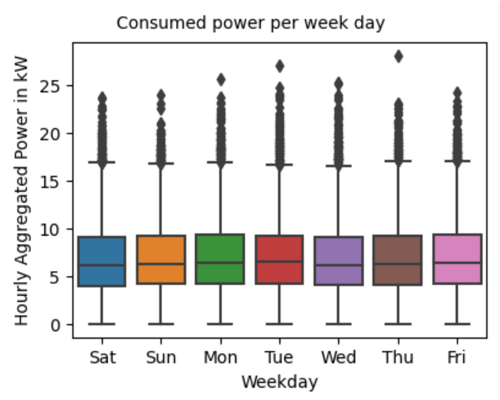
3.3 Deep Learning Architectures

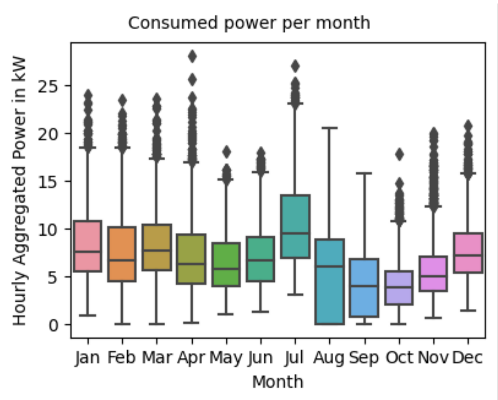
The hyperparameters for all models were determined through the application of the *Bayesian Hyperparameter Optimization Algorithm*. For every algorithm, *Adam Optimizer* was chosen, due to its adaptive learning rate, efficient handling of sparse gradients, fast convergence, and robustness to noisy data. The specific details of the final hyperparameters are outlined as follows:

- *MLP Model:* Batch size = 64, Learning rate = 0.0010128, Neurons for the Dense Layer.
- *CNN-1D Model*: Filters = 64, Learning rate = 0.0010, Kernel_size = 3, MaxPooling1D (pool_size = 2), Neurons of Dense Layer = 16, ReLU activation function for CNN and Dense Layer.
- *LSTM Model*: Batch size = 128, Learning rate = 0.0010, Units of lstm network = 48, ReLU activation function.
- *TCN Model*: Batch size = 128, Learning rate = 0.0010, Filters = 256, Dilations = [1, 2, 4, 8, 16, 32].
- *Weighted Average Ensemble Model*: Batch size = 128, Learning rate = 0.0010, Filters = 64, Kernel_size = 3, 48 units for the LSTM Module, MaxPooling1D with pool_size = 2, Contribution of LSTM: W^{lstm} = 0.5, Contribution of CNN: W^{cnn} = 0.5.



(a)





(b) (c)

Figure 6 – Daily (a), weekly (b), and monthly (c) consumption

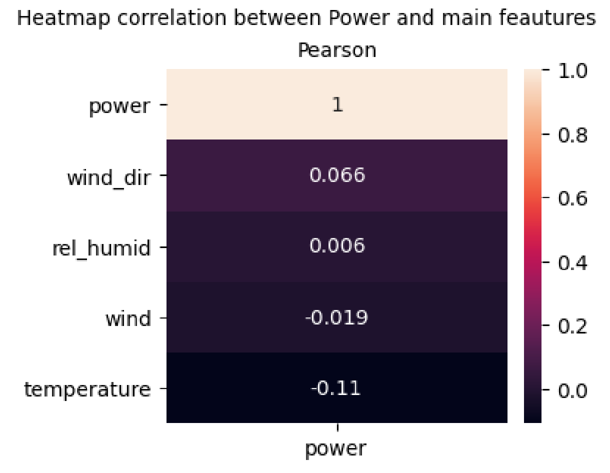


Figure 7 - Correlation Heatmap

3.4 Results

Data used in this work were divided in training and testing sets. As testing set the last six month of the initial dataset was selected. The previously mentioned models were trained, and the values of the relevant metrics used to evaluate the performance of each algorithm are presented in

Table I.

It is observed that all Deep Learning models consistently outperform the benchmark statistical model used. According to MAE, the best performing model is the Ensemble, with values of 1.580kW. Additionally, the three individual models, CNN, LSTM and MLP, exhibit very close prediction accuracy values, with MAE scores of 1.606kW, 1.586kW, and 1.624kW, respectively. The poorest prediction model is Naïve (Benchmark), achieving MAE, RMSE, and MAPE values of 2.608kW, 3.344kW, and 28.50%, respectively. This fact implies the superiority of DL and ML models over statistical model, as the latter are unable to capture the non-linear variations in time series and the abrupt changes in instantaneous values.

For better representation of the results, Figure 8 illustrates the predicted values in comparison to the actual values for a one-week period for every evaluation month. It becomes evident that the fluctuation of actual hourly consumptions does not follow a specific pattern, it presents multiple seasonality between the duration of the day, and it also exhibits volatility, a factor that complicates the operation and prediction of the models further.

Table I - Error Metrics

Model	MAE (kW)	RMSE (kW)	MAPE (%)
CNN	1.606	2.114	16.25
LSTM	1.586	**2.084**	16.38
MLP	1.624	2.092	17.55
TCN	1.691	2.192	17.67
Ensemble	**1.580**	2.109	**15.62**
Benchmark	2.608	3.344	28.50

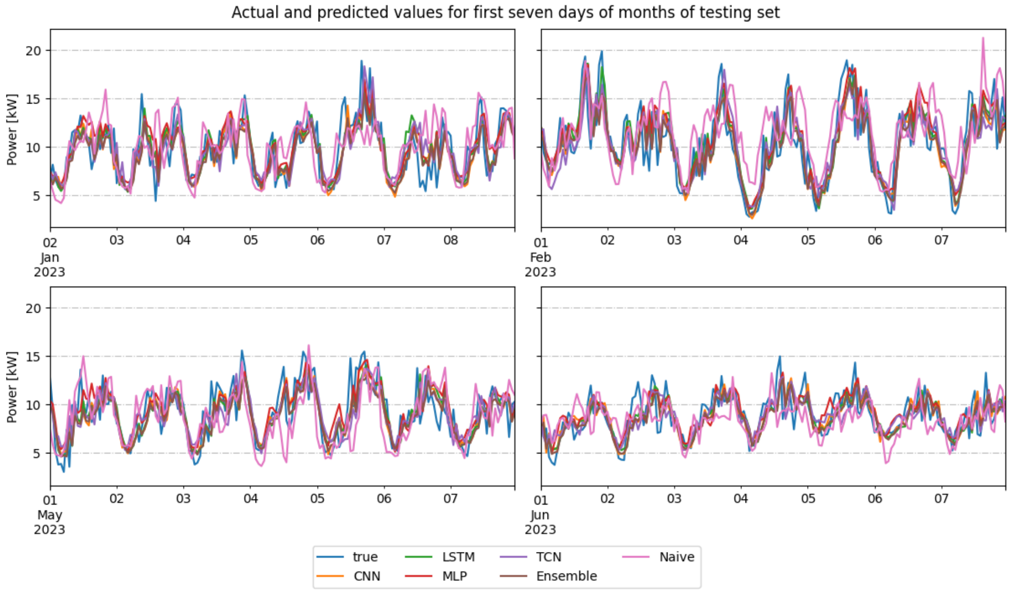


Figure 8 – Actual and Forecasting Results

4. Conclusion and Future Study

In this work, an extensive attempt is made to forecast the consumption of household consumers from Skiathos Island. For this reason, hourly data from 15 households are used. The problem is that having only a few households makes it hard to create a reliable prediction model. Also, the amount of electricity used by homes changes based on the time of the month, week, and day. This happens because people's electricity usage follows a stochastic attitude sometimes. More generally, as the sample size of consumers increases, the final load curve exhibits more stable patterns, which helps the models perform with greater predictive accuracy.

The research findings demonstrate that deep learning models surpass statistical models, like the naive model employed, in accurately capturing the consumer behaviour curve. Another significant conclusion is that, for a limited consumer sample, weather phenomena, including temperature, humidity, and wind speed, do not significantly impact the hourly variation in consumption. This assertion is supported by the low correlation observed among these specific variables in our research.

Looking ahead to future research ideas based on this study, a key focus is on creating Artificial Intelligence models tailored for predicting how consumers behave. The close connection between what people do in their homes and how much electricity they use is an important area that needs in-depth exploration. The strong link noticed between household activities and electricity consumption highlights the potential success of Machine and Deep Learning models in predicting and understanding how consumers use energy.

Moreover, there's a significant area gaining a lot of interest worldwide in research circles, and that's Demand Side Management (DSM) and Demand Response (DR) programs [18], [19]. These efforts, aimed at improving how we use energy and making the power grid more reliable, offer another area for thorough exploration. Companies, like DSOs, in various European countries are actively involved in these initiatives to achieve intelligent energy conservation. Consequently, the amalgamation of the algorithms meticulously developed within this research paper holds promise as a crucial determinant for the successful implementation and functioning of such advanced programs. The potential ramifications of incorporating these algorithms extend beyond theoretical considerations, suggesting a practical application in the operationalisation of sophisticated energy management initiatives.

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