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A comparative study of statistical and deep learning models for energy load prediction

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Abstract—The objective of this study is to analyze and compare classical time series and deep learning models for energy load prediction. Energy predictions are important for management and sustainable systems. After analyzing the climacteric factors impact on energy load (a case study in Albania) we considered classical and deep learning models to perform forecasts. We have used hourly and daily time series for a period of three years. In total respectively 26,280 hours and 1095 days. Average temperature is considered as external variable in both statistical and deep learning models. The dynamic evolution of hourly (daily) load is correlated with hourly (daily) average temperature. The performance of the proposed models is analyzed and evaluated based on accuracy measurements (MSE, RMSE, MAPE, AIC, BIC etc.) and graphics results of statistical tests. In-sample and out-of-sample accuracy is evaluated. The models show competitive performance to some recent works in the field of short-and medium-term energy load forecasts. This work may be used by stakeholders to optimize their activities and obtain accurate forecasts of energy system behavior.

Keywords— time series, forecasting, electric energy consumption, deep learning.

I. Introduction

The Mediterranean basin is one of the key points of energy efficiency production and use. Every country's energy consumption is specially affected by its economic and industry development, climatic conditions and its energy production sources. Numerous and diverse sources of energy have undergone significant evolution in the last 30 years. There has been a decline in coal use and a significant increase in natural gas use. Although climate change has affected this region over the last decades again the Mediterranean basin is an area which benefits from a mild climate with mild and warm winters and sunny summers. This climate offers the region a great potential for energy production from renewable energy [1]. Albania is a country in which the energy produced by hydropower plants occupies almost 90% of the energy produced in the country. Given that this energy produced relies on the availability of water in large reservoirs of cascades located mainly in the northern part of the country, or the intensity of the flow of rivers that supply these cascades, precipitation and snowmelt. High summer temperatures and droughts are limiting production by hydropower plants.

What is noticed in recent years in the Mediterranean region and in Albania is also the fact that based on the above factors the utilization rate of hydropower plants has decreased. This decline has been followed by an increase in interest in solar energy which is mainly influenced by surface solar radiation whose variations depend mainly on the atmospheric composition (aerosols, water vapor) and clouds [2], [3].

An increase in solar radiation has been observed in Europe [4] and especially for the Mediterranean basin these solar sources are seen with special interest as one of the areas with medium to high solar radiation on the continent [5]. Exactly at the beginning of winter in 2021, the region was involved in an energy crisis and not only. Experts emphasize the importance of a safe and sufficient energy, especially when the energy sources are not numerous and diverse. In this context, they suggest the addition of new and clean energy sources, in the same time they highlight to focus on the importance of optimal management of existing resources. Climate change associated with drought can reduce power generation and result in less electricity produced by the hydro power plants. Significant changes in production and consumption have been observed which have influenced government policies to provide optimal and long-term solutions. Many European countries are part of the energy crisis and have already had wide-ranging impacts on their economy and environment.

There is a lot of work done regarding prediction in different areas. In their work [6] have presented most of the challenges the prediction field has faced with during 25 years of forecasting. More than one decade ago they pointed out the necessity of computational ability for the high complexity amount of data to become the power of prediction in many areas. The relationship between energy consumption and economic growth was analyzed in a considerable number of countries in Europe by [7]. They indicate that attention is required to the relation between the efficiency use of resources and climate change in consequence the global warming. Researchers are provided with a systematic literature review of a considerable number of articles on energy demand modeling. Reference [8] reviewed and offered a classification of different techniques used in energy demand. There is also a lot of work done especially in machine learning (ML) techniques which rely on historic data and are extensively used to short-term forecasting [9]. Classical statistical techniques on energy prediction are often used as a benchmark for many techniques but in many cases depending on the nature of the data used and exogenous variables these techniques perform comparable with engineering-based models or ML models [2], [3].

Given the high ability of deep learning techniques to deal with the change of power generation and load there are many neural network structures which have been utilized to obtain short term load predictions [10]. The study undertaken by [11] presents a forecasting model for hourly load consumption considering external variables unitizing convolutional neural networks (CNNs) to extract the features of variables used. They also show in their study their ability to deal with short-term and long-term memories. ANNs (Artificial Neural Networks) are used by [12] for Greek interconnected power system. They point out that the accuracy of the ANNs' prediction depends on the quality and availability of the training data. An analysis of the accuracy of ML and statistical techniques for Albanian energy sector is done by [2]. In their work they consider the energy production by hydropower's which is the main source of production in the country. They came in the conclusion that neural networks have handle with seasonal patterns of monthly energy produced by HPP and provide accurate forecasts in short-term. Reference [13] proposed a short-term load forecasting method for hourly data using long short-term memory (LSTM) algorithm as an algorithm which have shown to deal with regularity of historical data. They use encoded external factors to predict the load in the next half an hour and showed accurate results.

In their work [14] present forecasting methodology for daily electricity demand using weather ensemble predictions. They show that weather ensemble predictions can improve the accuracy of electricity demand forecasts. When forecasting energy demand, it's often a good practice to use temperature as an exogenous variable. Reference [3] present a methodology of ensemble models to predict energy production by hydropower relying in exogenous variables such as temperature, precipitation, water inflow. The show accurate results of combining statistical and machine learning models for monthly data.

Depending on many factors when dealing with energy data studies have shown that in special circumstances such as: geographical position, climate conditions , variables taken into considerations, seasonality patterns and frequency of data there are not consensus on the "best" model used in the energy situations. Going through the results of [15], they show the efficiency of STL decomposition (Seasonal-Trend decomposition using LOESS) when used as a pre-processing step in statistical models. Another study which shows the efficiency of statistical time series models is the one proposed by [16] which is a simple procedure combining time series models dealing with multi seasonality. In reference [17] the authors offer a new approach for forecasting time series with complex seasonal.

Although there is plenty of material, research and competitions about recommended models for forecasting in different fields [18] there is still discussion of the conditions under which different methods perform best.

A. Data

In our study we use hourly time series of energy load for a period of three years (2016-2018) in total there are 26,280 hours and 1095 days. Together with energy load we have considered also the average temperature (hourly and daily).

In this material we have used the terms described below:

Hour: The time of day for which the variables are expressed. The time is expressed as an integer with values ranging from 0 to 23

Load: The aggregated energy load (consumption) observed each hour (measured in Mwh).

Temperature: The hourly average value (in Celsius) of the temperature of the day.

When dealing with hourly time series data there are a few models that one can try. Since hourly time series contain multiple seasonal patterns (daily, weekly, and yearly); in your case it contains all these seasonality's because it contains 3 years of hourly data. Many time series exhibit complex seasonal patterns.

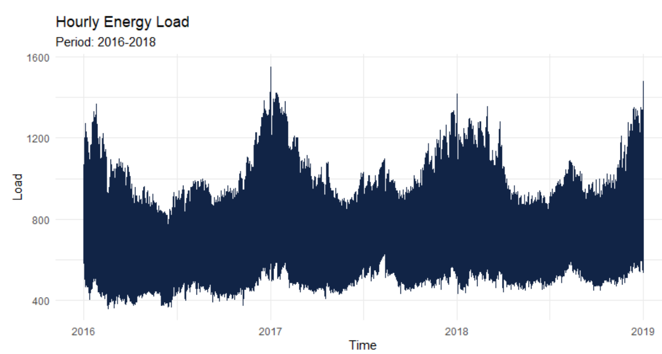

Fig. 1 Hourly energy load (unit MWh)

In Fig. 1 is shown the hourly energy load for a period of three years. What is clearly observed is the fact that the time series has multi seasonality patterns. After an accurate investigation of each year we observe a high load at the beginning of the year which corresponds to the winter season and accompanied by a noticeable decrease during the spring season. Further an upward trend for the period of summer which in the Mediterranean climate is accompanied by high temperatures, and with a marked decline during the autumn. Patterns are distinct from year to year due to the extreme temperatures and weather situations during the winter months mainly in the entire Mediterranean region and especially in Albania for that year. This behavior can be observed in Fig.2, Fig.3 and Fig.4.

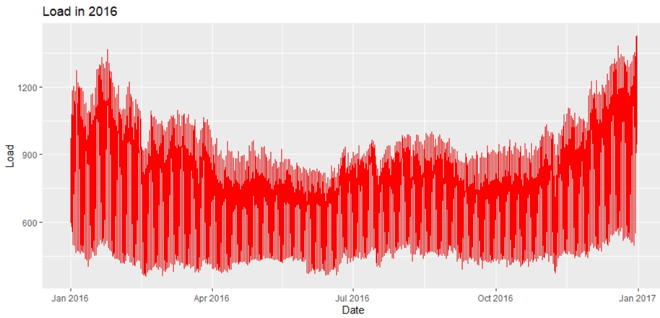

Fig. 2 Hourly energy load (2016)

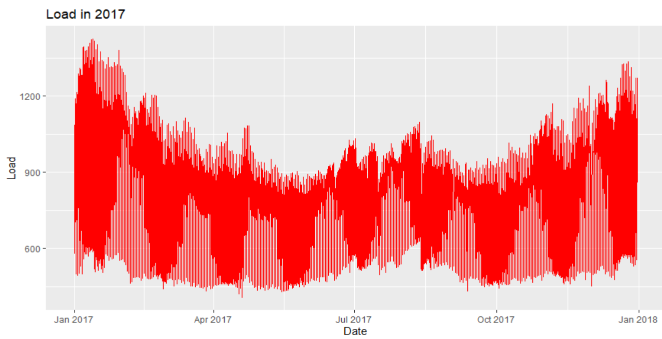

Fig. 3 Hourly energy load (2017)

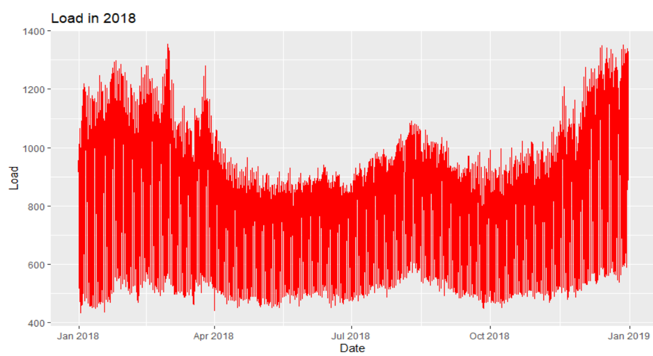

Fig. 4 Hourly energy load (2018)

The hourly average temperature (measured in Celsius degree) for the period under consideration is shown in Fig.5. The Mediterranean climate would certainly not be absent in the seasonal behavior of the average temperature. High temperatures are observed during the summer months (up to 42 degrees Celsius) and low temperatures during the winter months (up to -7 degrees Celsius).

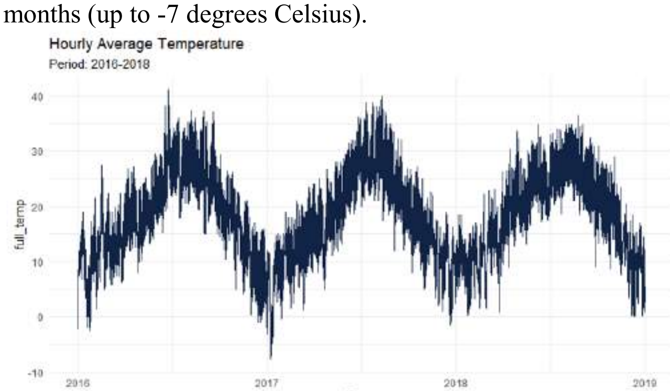

Fig. 5 Hourly average temperature (Celsius degree)

These extreme values are especially noticeable during 2016, and there is a decrease in values for both high and low temperatures for 2017 and further for 2018 which is also confirmed by world indicators related to climate change and global warming. Fig.6 shows the different levels of daytime peak energy demand by month. The situation is displayed for three years in separate and we may notice a flattened pattern from May to September and a clear three peaks for other months. The lower peak in energy demand is observed from midnight to 5am and then a rapid increase of the demand from 5am to 8am, then a steady situation which culminates with the evening hour 8pm and then a decrease again to the lowest levels of the day. Especially for January and December the morning "jump" load is more distinctive and very fast in levels from 20000 Mwh to 35000 Mwh. It is also observed a slightly increase of energy load levels from 2016 to 2018.

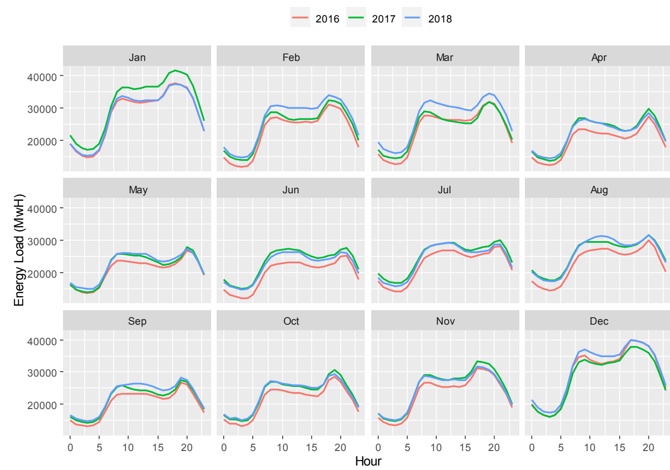

Fig. 6 Twenty-four-hour load by month (MWh)

The twenty-four-hour load helps us to investigate the levels of daytime and peak loads which depends also on the solar penetration conditions and variations.

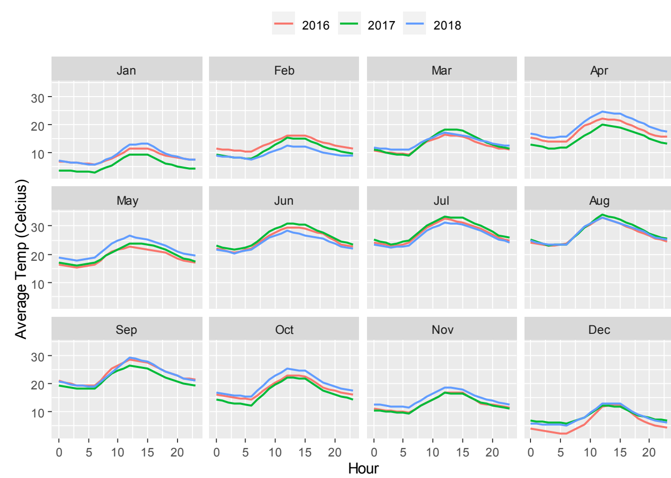

Fig. 7 Twenty-four-hour load by month (MWh)

The Mediterranean climate of Albania show a correlation of energy demand and average temperature. This can be easily observed also by 24 hour evolution of these variables faced by month as shown in Fig.6 and Fig.7. In both variables we observe presence of seasonality and one high peak for the average temperature which obviously is reached in midday and high average temperature levels for the summer and low levels for winter. No noticeable differences of levels from 2016 to 2018.

A correlation analysis of energy load and climacteric factors such as temperature is important. Pearson correlation coefficient is a measure of linear correlation between two sets of data. It is defined as: $\rho_{XY} = \dfrac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y}$ and takes values from -1 to 1. A value close to -1 or 1 indicates a significant (negative or positive) relationship between X and Y.

This correlation analysis between load and temperature is illustrated graphically in Fig.8. The interesting part which is observed is the fact that aggregated energy load displays a significant correlation with the average temperature (by hour) when observed by month. We notice a significant positive correlation between these two variables especially for the summer season (it varies from 0.64 up to 0.72).Another pattern we clearly observe is the density plot which corresponds to daily and night hours of the day. These findings may be used to focus on the research of seasonal power load prediction in order to satisfy and optimize power supply and demand. In this study we have not taken into consideration the seasonal modeling by hour or month which can be further studied.

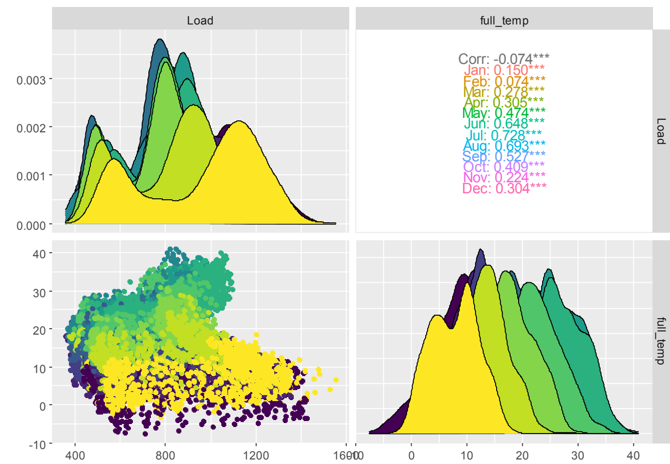

Fig. 8 Density plot and correlation of energy load (consumption) and average temperature by month

Fig.9 shows the correlation of energy load (consumption) and average temperature faced by year and also colored by month. It is clear that the same behavior is observed for each year taken into observation. What makes different the spread are the registered values of the average hourly temperature which clearly display a compression in the amplitude for the last year 2018. The scatterplot of hourly energy load and average temperature shows two clusters which correspond to daily and night hours. The behavior is almost the same apart the shift of the daily cluster above the night cluster. This shift corresponds also to the higher differences in temperature which suggest the need of electricity due to heating or cooling in respect also to the month or season.

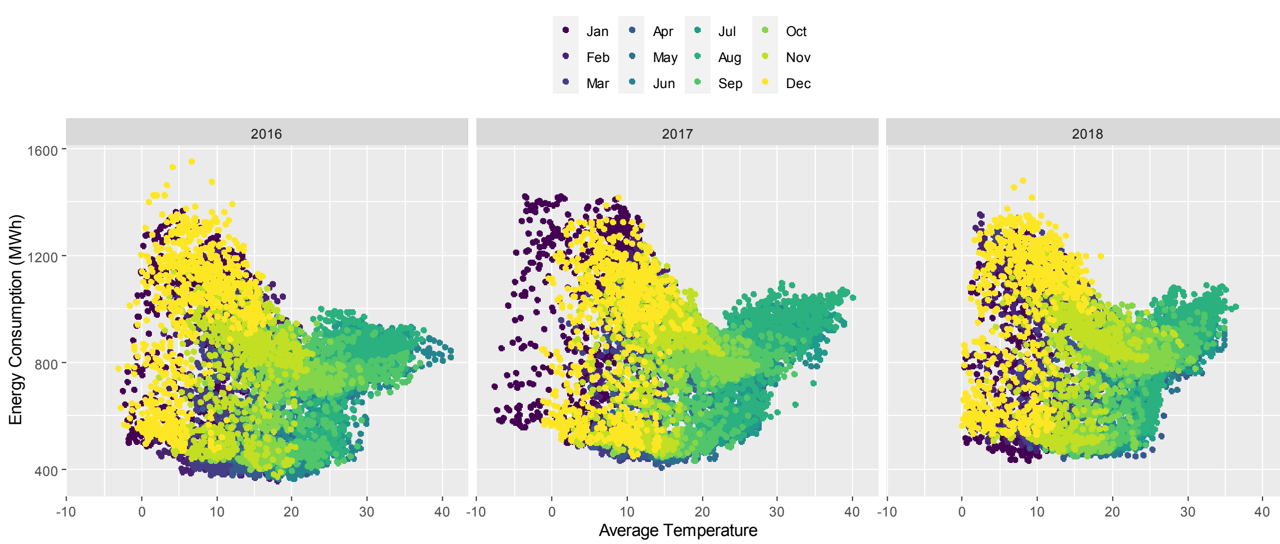

Fig. 9 Correlation of energy consumption and average temperature faced by year (hourly observations)

II. Methodology

A. Data preprocessing

The data was organized in training and testing dataset respectively (80% and 20%). The testing dataset was used for validation which corresponds to the forecast horizon. Some machine learning methods face difficulties when dealing with missing observations, but this was not our case. The daily energy load was the aggregated load of 24 hours and the average temperature was the average calculated for 24 hour of that corresponding day. Given the complexity of the data and the luck of other external variables which can handle and better explain multi seasonal patterns of energy load we switched to daily aggregated time series of energy load and daily average temperature. Based on the above analysis of the data and the literature review we have proposed some of the models which can deal with the multi seasonality pattern of the energy load and which can handle exogenous variables. In our case we have tried the average daily temperature as external variable in some of our models.

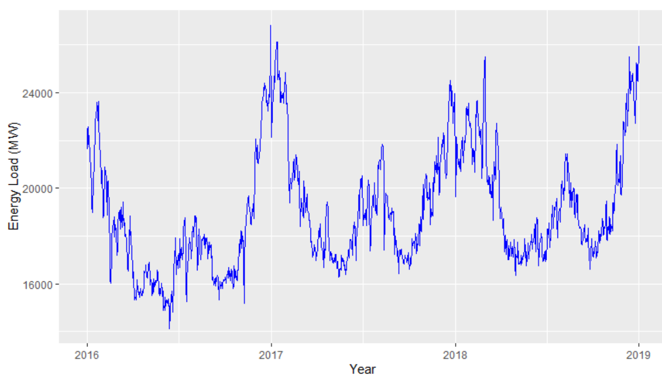

Fig. 10 Daily energy load ((aggregated energy load MW/day))

B. Statistical Techniques

First we focused our attention on statistical forecasting models such as: Naïve, moving average, ARIMA, Exponential Smoothing and Seasonal Naïve. In many situations is shown that STL is a successful try on decomposing the time series into their seasonal, trend, and remainder components. After that STL can be used for modeling purposes. In this study we have used the Hyndman-Khaldakar algorithm for performing STL and ARIMA models [19], [20], [21]. In reference of [23] the STL decomposition shows good performance when used in statistical methods and time series with monthly seasonalities but was not performing well in machine learning methods. The choice of the best algorithm depends on the nature of the data and the frequency as well. In precence of seasonality patterns and trend ARIMA and exponential smoothing methods are the ones which can perform good in prediction. In their work [20] present a complete modeling framewrok for time series exponential smoothing models.

The autoregressive integrated moving average (ARIMA(p,d,q)) processes are a combination of autoregressive (AR(p), where *p*-the degree of autoregressive model) and moving average (MA(q), where *q*- degree of moving average model) processes and *d* is the degree of differences [22]. For implementation of ARIMA models in R we have used *forecast* package in R which combines unit root tests, minimization of the AICc and MLE to obtain the ARIMA parameters and coefficient estimates [21]. There are many models which use STL (Seasonal and Trend decomposition using Loess- a method for estimating nonlinear relationships.) to understand seasonal data and fit appropriate models [24].

C. Deep Learning Techniques

Machine learning techniques and deep learning are attracting more and more attention from researchers of many fields. Especially in the forecasting field these methods have passed through many competitions such as the M Competitions [25], [26], [27]. Artificial neural networks are forecasting methods that are based on simple mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors. There are many studies of using deep learning methods in energy prediction and reviewed by [28]. In their study [29] present a neural network approach for short-term energy load prediction paying attention to seasons and using temperature as an external variable. They achieved reliable results for hour ahead load prediction. In reference to the work presented by [30] they agreed on the weakness of NNs when dealing with seasonality. Many researches suggest removing seasonality before modeling, to achieve better predictions. Testing were made by [31] on this topic and they showed that for clear seasonality patterns RNNs are adequate but when this is not the case then a deseasonalisation technique should be used.

In this study we have considered Recurrent Neural Nets (RNNs). The scheme of how this network performs is shown in Fig.11.

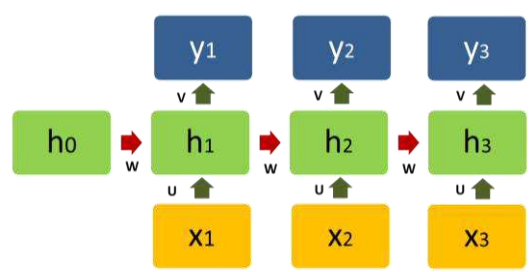

Fig.11 RNN Architecture

Here, *x*'s in yellow are *predictor variables*, *h*'s in green are *hidden layers*, and *y*'s in blue are *predicted values*.

Recurrent Neural Nets are essentially a bunch of neural nets stacked on top of each other. The output of the model at h*1* feeds into the next model at *h2* as shown. The goal of the learning process is to find the best weight matrices *U*, *V* and *W* that give the best prediction of *y^(t)*, starting from the input *x(t)*, of the real value *y(t)*.

Neural Network AutoRegression (NNAR) models are developed on the principle of using lagged observations as inputs to a neural network. They are feed-forward networks with one hidden layer. These models perform good with seasonal data, where it adds as input the last observed values from the same season. In general the model NNAR(*p, k*) uses *p* lagged inputs and *k* nodes in the single hidden layer. Seasonal *NNAR*(*p, P, k*): with *k*-neurons in the hidden layer. and input $(y_{t-1,} y_{t-2}, \ldots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-Pm})$. NNAR(p, P, 0)$_m$ model is equivalent to an *ARIMA(p, 0, 0)(P,0,0)*$_m$ model but without stationarity restrictions. More generally, an *NNAR(p,P,k)m* model has inputs : $(y_{t-1,} y_{t-2}, \ldots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-Pm})$ and k neurons in the hidden layer. If the values of p and P are not specified, they are selected automatically [21]. For *seasonal time series*, the default values of P is *1* and p is chosen from the optimal linear model fitted to the data after seasonally adjusted. If k is not specified then it is set to $k=(p+P+1)/2$ (which is rounded to the nearest integer).

D. Evaluation metrics

The performance of the models presented in this study were evaluated in terms of a number of metrics. The selection of the most accurate model is made by analyzing and comparing error measurements and information criteria for in-sample and out-of-sample data. As well as extending personal judgment to the advantages offered by each model based in the nature of the data. The metrics used to assess and compare the various methods are :

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{X}_t - X_t| \text{ Maximum Absolute Error}$$

$$ME = \frac{1}{n}\sum_{i=1}^{n} (\hat{X}_t - X_t) \text{ Mean Error}$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n} \frac{|\hat{X}_t - X_t|}{|X_t|}\right) \cdot 100\% \text{ Mean Absolute Percentage Error}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{X}_t - X_t)^2} \text{ Root Mean Square Error}$$

$$MASE = \frac{MAE}{MAE_{in-sample,naive}} \text{ Mean Absolute Scaled Error}$$

In many research studies there are many arguments of using different accuracy measurements of the model. This depends of course on the nature of the data and their complexity. In reference of [32] MASE offers a straightforward indication on the relative model performance compared with the naïve benchmark. It is a scale-independent measure where a value less than one indicates that the performance of the model is better than the naïve benchmark on average. And a value greater than one indicates the opposite. What is important is the fact that this critical value should not conclude the performance of the model but further analysis are suggested.

III. Analysis of Result

This section provides a comprehensive analysis of the results obtained from the modeling process. Results in terms of all error metrics used to evaluate the performance of the models are shown in Table 1. The abbreviations used to denote the "top model" selected from the work done in this study are respectively: '*Snaive*'- seasonal naïve method, '*STL+ARIMA*'- STL decomposition with ARIMA errors, '*Hybrid*'- ensemble model with combination of statistical and deep learning models , '*NNAR*'- Neural network with autoregression, '*NNAR-Xreg'*- neural network with autoregression and average temperature as external variable.

In Table 1, the best model based on the error is indicated in boldface respectively for training and testing dataset. Analyzing the values of error metrics for each model we observe that for the training dataset STL+ARIMA seem to perform better than seasonal naïve. On other hand, NNAR with daily average temperature as regressor seem to perform better than NNAR without regressors. The difference between NNAR and NNAR-Xreg is not significant. In this situation we may suggest adding other exogenous variables (such as humidity) to explain daily energy load. Overall for training dataset the neural network with average temperature as external variable is significantly better compared to other statistical models.

The MASE value for all proposed models is lower than 1 which suggest that all the models perform better than the naïve benchmark on average. The situation changes apparently for the testing data where we have approximately seven months of observations (20% of the three years taken into consideration). Investigating the lowest value of error measurements in this part STL+ARIMA shows significantly better performance compared to the other models. MASE is higher than 1 but close to this value. Comparing the MASE value of STL+ARIMA for the training data and testing data we may gain confidence that this model outperforms the other models. Again between NNAR and NNAR with exogenous variable the first has a slightly difference in error values.

For a better understanding and comparison of the error metrics for training and testing data we plotted the performance displayed in Fig. 12.

TABLE I.
MODEL PERFORMANCE ERROR METRICS FOR TRAINING AND TESTING DATASET

	Train						Test					
Model	**ME**	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**	**ME**	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**
Snaive	1134	2105	1671	5.67	8.28	1.00	-6255	6255	6255	-35.36	35	3.74
STL+ARIMA	6.98	401	298	0.00	1.57	0.18	**-260**	**3185**	**2405**	**-2.58**	**12**	**1.44**
Hybrid	277	646	501	1.36	2.49	0.30	-17959	18008	17959	-2561	2561	10.74
NNAR	1.16	201	138	-0.02	0.70	0.08	-18048	18132	18048	-2577	2577	10.80
NNAR-Xreg	**0.93**	**160**	**115**	**-0.01**	**0.60**	**0.07**	-18529	18620	18529	-2645	2645	11.09

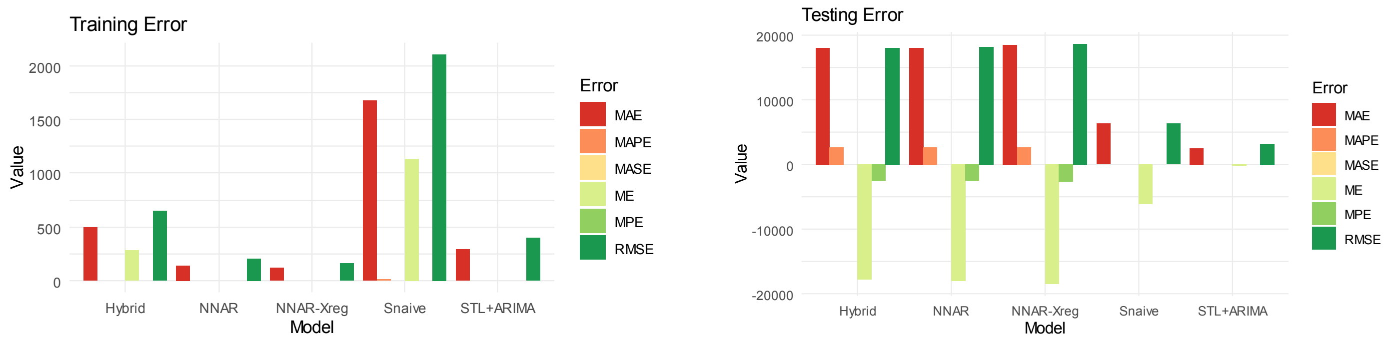

Fig. 12 Model performance error metrics for training and testing dataset

In the left side of Fig.12 are displayed the metrics for the training data and right the metrics for testing data. It is clear that the NNAR with external variable outperformed the traditional univariate methods in training dataset and it is comparative to the hybrid model. The hybrid model was obtained as a combination with equal weights of four models: *nnetar, stlm, tbats* and *snaive* [33].

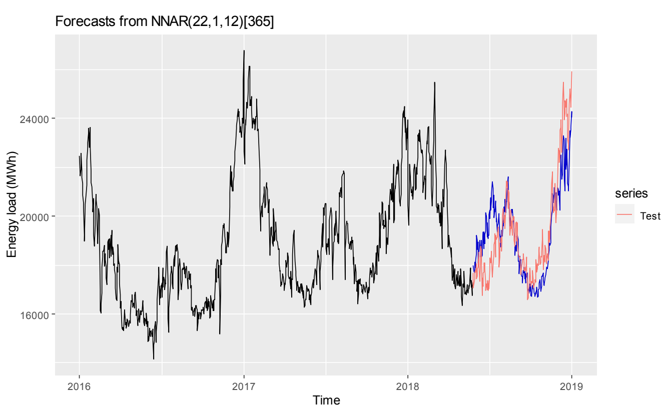

Fig. 13 Energy load forecast from NNAR with daily average temperature as regressor (aggregated energy load MW/day)

In Fig. 13 is displayed the daily energy load prediction obtained from a neural network model where daily average temperature is used as an external variable.

As we mentioned above these models perform good with seasonal data, where the last observed values from the same season are added as input. For energy load the model has $k=12$ neurons in the hidden layer and use $(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-Pm})$ observations as input where $p=22, P=1$ and $m=365$ daily seasonality.

Fig. 14 shows the energy load point forecast and confidence intervals (80% and 95%) from STL+ARIMA model.

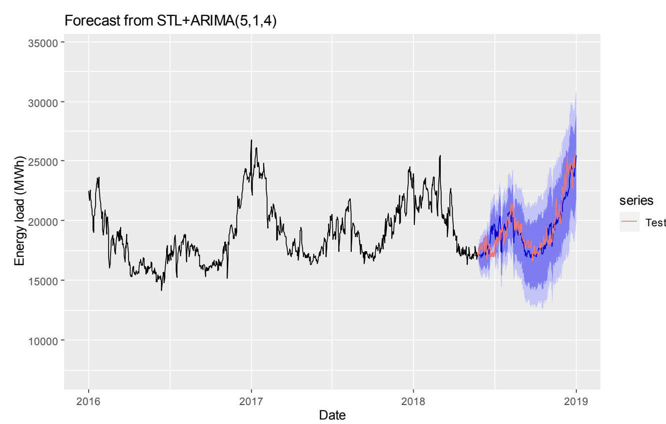

Fig. 14 Energy load forecast from STL+ARIMA model with no-regressor (aggregated energy load MW/day)

IV. Conclusions

Energy supply and demand plays an important role in the economy of a country and the region. Predictions are important for energy management and sustainable systems. The motivation for this study was to address some of the key issues with related to the ability of predicting energy load using statistical and deep learning models. The work presented here can be used as a reference from researchers and practitioners working in the energy field and especially in the

Balkan region.

We showed that due to the high complexity of the hourly data and multiple seasonalities it was easy as a start of our analysis to work with daily data. We performed many statistical and machine learning models which are capable of handling seasonality in time series. In our work we took into consideration a decomposition method which would give better performance of the modeling process. The models were evaluated on error metrics and comparative view of in sample and out of sample dataset. NNAR architecture was able to outperform the statistical techniques for in sample data in terms of all error metrics used at the performance evaluation phase but STL decomposition with ARIMA error was the best model when evaluated to the testing data. The proposed models can be used as a short term or medium term prediction models for energy load. Other exogenous variables can give a better effect to the models.

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