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EVALUATION OF LOAD FORECAST MODEL PERFORMANCE IN CROATIAN DSO

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SUMMARY

During the revitalization of the Remote Control Systems of four Distribution System Operators in Croatia: Elektra Zagreb, Elektroslavonija Osijek, Elektroprimorje Rijeka and Elektrodalmacija Split, the load forecasting subsystems were implemented as an integral part of the DMS system.

Accurate electricity load forecasting presents an important challenge in managing supply and demand of electricity since it cannot be stored and has to be consumed immediately. Electricity consumption forecasting has an important role in the scheduling, capacity and operational planning of the distribution power system. Load forecasting of certain parts or the whole distribution network helps to improve distribution network planning, operation and control which also increases the safety level of the entire distribution system.

Although many forecasting methods were developed, none can be generalized for all load patterns. Accurate results of electricity load models are essential to make important decisions in planning and controlling so it is important to keep models as accurate as possible regarding input variables such as historical loads and meteorological data. This article gives a description of the implemented load forecasting subsystems using an artificial neural network with a feedforward multilayer perceptron and backpropagation as a learning strategy. The emphasis is on the simple and systematic use of input and output data as well as on forecasting scenarios of specific measured points where hourly forecasted results for a week ahead are presented and compared for Croatian Distribution Centers.

KEYWORDS

Short-Term Load Forecasting, Artificial Neural Networks, Load Forecast Model, Parameters Tuning

1. INTRODUCTION

The power sector was traditionally based on vertically integrated utilities including generation, transmission, distribution and retail. Due to remarkable changes in the electric power industry in recent years, the new structural organization is mainly based on liberalized electricity markets that promote competition. The utilization of renewable energy sources in electrical power production, mainly photovoltaic panels, wind turbines and biomass, has rapidly grown in past decades. Current and future power systems with intensive use of distributed renewable generation and the liberalization of the electricity market increase power systems complexity and bring huge challenges to the power industry. Power system planning, control and operation require an adequate use of existing resources to increase system efficiency. Power unit activities' planning has become a more complex process as companies have to take care of various variables of a technical and social character but still produce electrical energy with minimum costs, provide power quality, safety of the power system, etc. Electricity load forecasting is considered one of the critical factors for economical operation of a power system. Accurate load forecasting holds a great saving potential for electric utility corporations. Load forecasting helps an electric utility in making important decisions regarding the purchase of electric energy, dispatching generation units, load switching, security analysis, maintenance scheduling and infrastructure development.

The increase of power system complexity has led to enhanced use of computational intelligence methods because of their quality results in solving diverse power system optimization problems. Load forecasting highly depends on the selection of a mathematical model and on the quality of the input variables. The load forecasting technique used in this article is Artificial Neural Network (ANN). Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain.

Load forecasting involves the accurate prediction of the electricity load in time scales compatible with operational requirements. Depending on the planning horizon, load forecasting can be divided into three categories: short-term forecasts, medium-term forecasts and long-term forecasts. Short-term forecasts usually span from one hour to one week and are commonly referred as hourly load forecasts. They play an important role in the day-to-day utility operations such as unit commitment, economic dispatch and load management. Medium-term forecasts are necessary for scheduling unit maintenance and energy trading. They usually span from a few weeks to a few months. Long-term electricity forecasts are required to be valid from 5 to 25 years. They are important because of their direct influence on production, transmission and distribution capacities planning [1].

During the revitalization of the Remote Control Systems of the four biggest Distribution System Operators in Croatia: Elektra Zagreb, Elektroslavonija Osijek, Elektroprimorje Rijeka and Elektrodalmacija Split, the load forecasting subsystems were implemented as an integral part of the DMS system (*Distribution Management System)*. The total consumption of the Distribution areas is different depending on the size of Distribution, population and type of customers. Elektra Zagreb covers an area of 2,550 km^2 and is the smallest in size of the four mentioned Distributions but with more than 550 000 customers and peak consumption in 2014 of 665,25 MW it is the biggest Distribution in the country. On the other hand, Elektroslavonija Osijek covers an area of 4,152 km^2 but has around 150 000 customers and peak consumption in 2014 of 163 MW [2]. This paper presents the survey of a neural-network-based short term load profile prediction for Distribution areas. The neural network inputs are load data and meteorological data, while the neural network output is load at a particular moment. Neural network training and verification are performed on load data recorded at each Distribution center and on meteorological data obtained from the Meteorological and Hydrological Service of Croatia, from September 2014 to December 2017. Several models have been surveyed to identify the load pattern and predict the future load.

2. LOAD FORECASTING SYSTEM

2.1. Load forecasting calculation algorithm

The implemented load forecasting system is based on Artificial Neural Networks (ANN). Artificial Neural Networks are computational models inspired by the human brain that are capable of machine learning, pattern recognition and data fitting. They are based on sophisticated mathematical techniques for identification and studies of connecting links (linear and non-linear) between observed variables. By structure, artificial neural networks can be divided into two groups, static (feed-forward) and dynamic (feed-back). Unlike dynamic ones, static neuron models do not contain dynamic elements and their output depends entirely on current values of input signals and model parameters.

A neural network consists of multiple neurons organized in layers - the input and output layer, and also of a number of hidden layers in between, where each hidden layer can contain an arbitrary number of neurons. In this paper, we deal with a static neural network with MultiLayer Perceptron, the so called MLP, with a single hidden layer. Figure 1 shows a static MLP neural network with an input layer with two inputs, two hidden layers with three neurons in each hidden layer and with an output layer with two outputs [3].

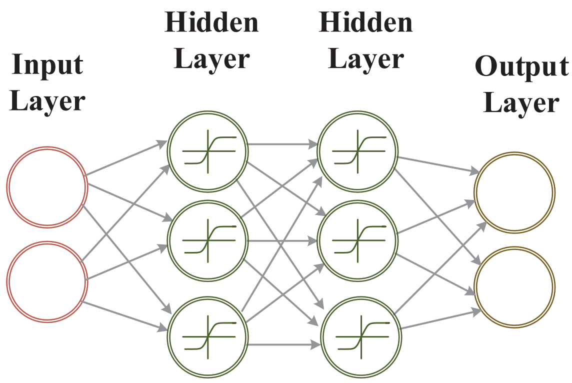

Figure 1 Static MLP Neural Network

Neural networks are tuned to carry out a required mapping of inputs to the outputs using training algorithms. The most commonly used training algorithm for static networks is *error backpropagation*. The learning method can be divided into two categories, unsupervised learning and supervised learning. The *Error backpropagation* method is a supervised learning model where the error between the expected output and the calculated output is computed and minimized by adjusting the weights between two connection layers starting backwards from the output layer to the input layer [4]. In this paper, a backpropagation algorithm uses the learning concept and the historical relationship between the load and temperature for a given period, day type and hour of the day.

2.2. Factors affecting electricity load forecasting

The purpose of neural network learning is to find the model with a load pattern as reliable as possible. A lot of factors are considered to have an impact on load forecasting, but the most important ones are the following [1]:

- **Time factor** – electricity consumption varies as cyclic time dependency on an hour of day basis, day of week basis and time of year basis. The specific load patterns can be presented on characteristic curves of consumptions that present activities during a certain period in time. The load curve changes during the time period depending on the type of customers. The characteristic consumption curve for areas populated mainly with households and business areas has different forms for weekdays (two peaks in a day) and weekends while the consumption curve for industrial areas has more similar form during time periods.

- **Weather conditions** – the most important weather variables affecting electricity consumption are:
  - Temperature – A huge correlation between electricity consumption and temperature exists during the whole year. As temperatures rise during summer, the increased usage of cooling appliances also increases load consumption. As temperatures fall in the winter season, the more usage of heating appliances also increases load consumption.
  - Humidity - Humidity affects short term load forecasting since it increases the feeling of the severity of the temperature in summer and during rainy seasons. Thus, load consumption increases during a humid summer day.
  - Wind speed
  - Cloud cover
- **Economic factor** – In general, electricity consumption enlarges with population growth, industry development, increase of Gross Domestic Product, reduction of electricity costs, etc.
- **Customer factor** – The characteristic curve of consumption depends on customer classes. Most electric utilities serve different types of customers as residential consumer, commercial consumer and industrial consumer.

2.3. Remote control system configuration

Hardware configuration for the Remote Control Systems installed in the dispatching centers Elektra Zagreb, Elektroslavonija Osijek, Elektroprimorje Rijeka and Elektrodalmacija Split is shown in Figure 2. The configuration of the SCADA/DMS system is based on a server/client model, on a distributed model of hardware and software equipment including a process database.

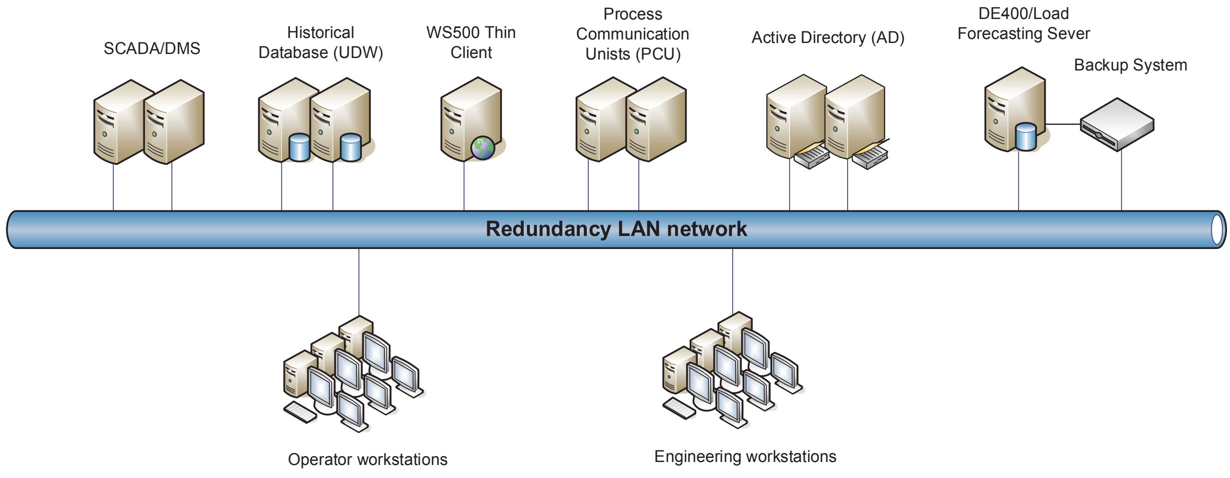

Figure 2 SCADA/DMS Hardware Configuration

Load forecasting system software functions are implemented on the Oracle database on the Load Forecasting Server. The load forecasting system is installed on an individual HYPER-V virtual server on the DE Server (*Data Engineering*), the server for the maintenance and data engineering of the entire SCADA System. The load forecasting system can be accessed remotely by connecting to the Load Forecast Server.

2.4. *Load forecasting system implementation*

The data required for the load forecasting process is automatically transferred from the Historical Database called UDW (*Utility Data Warehouse*) in a defined file format to predefined directories on the Load Forecasting Servers. After the load forecasting process, the file with the forecasted data is automatically sent to the predefined location on the Load Forecasting Server, after which the data is transferred to the SCADA server.

Automatic data exchange between the Load Forecasting Server and SCADA and UDW Servers is done by using the DCI functionality (*Data Communication Interface*) which ensures the transfer of correctly structured data from the Historical Database to the Load Forecasting Server using a FTP protocol (*File Transfer Protocol)* and vice versa, the forecasting process results transfer on the SCADA Server and their insertion in the Historical Database.

In this way all data is available to the operators though the SCADA HMI.

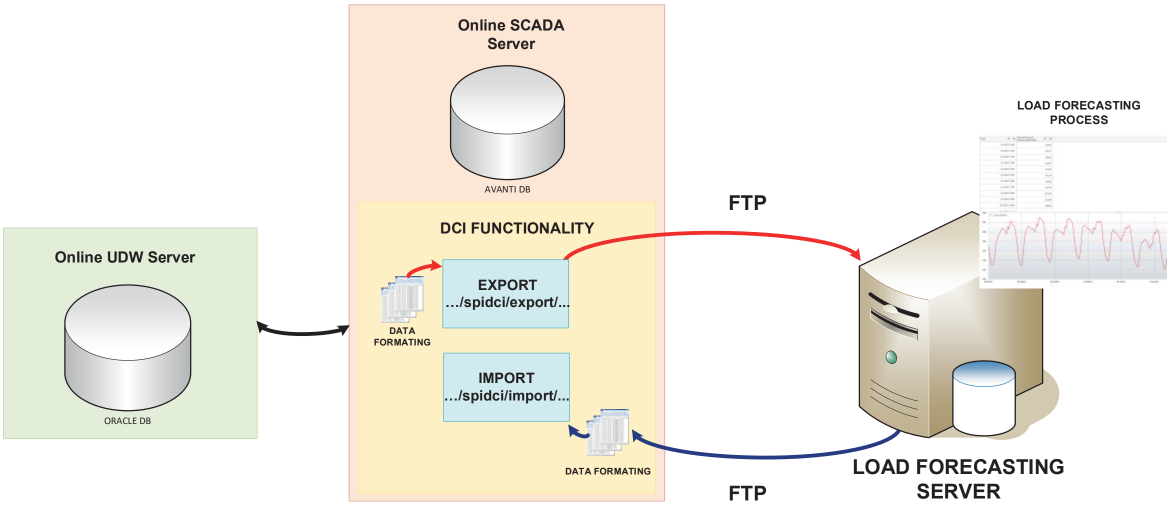

Figure 3 Functional Data Exchange Scheme

2.5. *Load forecasting results control*

The accuracy of output values can be verified with a large number of measures [5]. In this article, MAPE, MAE and RMSD measures are used to verify the neural network performances.

MAPE (*Mean Absolute Percentage Error)* expresses accuracy as percentage and is defined by the formula:

$$M = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|, \tag{1}$$

Where A_t is the *Actual value* and F_t is the *Forecast value*. The difference between A_t and F_t is divided by the *Actual value* A_t. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points *n*.

RMSD (*Root Mean Square Deviation*) is defined as square root of the average square differences between values predicted by a model or an estimator and the values actually observed. It is calculated by:

$$RMSD = \sqrt{\frac{\sum_{t=1}^{T} (F_t - A_t)^2}{n}}, \tag{2}$$

Where F_t is *Forecasted value* and A_t is *Actual value*. It is computed in *t* moment for *T* different predictions.

MAE (*Mean Absolute Error)* is a measure of average difference between two variables. It is given by:

$$MAE = \frac{\sum_{i=1}^{n}|A_i - F_i|}{n}, \quad (3)$$

Where F_t is *Forecasted value*, A_t is *Actual value* and *n* is number of fitted points.

3. MODEL RESULTS EVALUATION

3.1. Load forecasting model configuration

Each of the four biggest Croatian Distribution Operators has its own Load Forecasting System with several models defined. Each Distribution Operator predicts the total consumption of its distribution area as well as the loads of smaller parts such as forecasting consumption of certain cities or islands. In this article, four models with forecasting of the total consumption of Distributions Elektra Zagreb, Elektroslavonija Osijek, Elektroprimorje Rijeka and Elektrodalmacija Split are studied.

The models are configured to make calculations with meteorological data from the Meteorological and Hydrological Service of Croatia. The data files with future data (seven days ahead) and past data (last 24 hours) are sent to the Load Forecasting Systems once a day at a specified time. Meteorological data for the observed models includes past and future hourly temperatures for Zagreb, Osijek, Rijeka and Split – the centers of distribution areas. In accordance with the available meteorological data for seven days ahead, the load forecasting outputs are values for the same period.

The importing files have a predefined form with the possible time period of the input variable: 15 minutes, 30 minutes, an hour, a day, etc. Input variables used in this article, both meteorological and load variables, are hourly values. To prevent overfitting, load data sets are divided into training and verification data sets. In all observed models, the period from September 2014 until June 2016 is used for neural network training, while the period from July 2016 until the end of 2016 is used for neural network verification.

The days with deviation from usual consumption are also specified in all models. They include all national holidays and significant days such as sport events, cultural events, etc.

Additional parameters related to the complexity of the neural network and the duration of model learning are: Number of Training Passes and Number of Hidden Nodes. Number of Training Passes is the number of passes through the training data for each of the cycles of training. For Back Propagation, the total number of iterations through the data is this number times 50 training cycles. Number of Hidden Layer Nodes is the number of layer nodes in the second layer in which the input data is processed. Increasing the number of nodes in the hidden layer may result in better training and thus better forecast results but it also increases the complexity of the neural network and therefore increases the time required to train the network. These parameters can be changed as many time as necessary to improve output values therefor the parameters are different for all four models. According to some recommendations, number of Hidden Neurons to start model training should be 10 [6].

After getting an output variable, models can be re-trained and corrected as many times as necessary by having the user change the input variables in order to get better output values.

3.2. Comparison of models' Error Statistic

The four models with different input data but same training and verification time period are defined. It is possible to draw a conclusion by checking the models Error Statistic (Table 1) that described forecasting models are reliable (MAPE < 5%). Elektra Zagreb model has the smallest MAPE measure 4.46%, while the Elektroslavonija Osijek model has the smallest

RMSD measure (7) and MAE measure (5). Different MAPE measures indicate that some models could be better, i.e. should be re-trained. MAPE measure for Elektrodalmacija Split model is 5.31% which indicates model re-training in order to get more accurate results.

Models' errors depend on changing input data. Just a little modification of input data such as time period, makes the output data, thus error statistic, different. The operators in each Distribution maintain their own models to have output values as accurate as possible. The accurate output variables are the result of adjusting model's parameters and keeping input data correct.

Table 1 Comparison of four models' Error Statistic

DISTRIBUTION	MAPE	RMSD	MAE
Elektra Zagreb	**4.46%**	**15**	**10**
Elektroslavonija Osijek	**4.91%**	**7**	**5**
Elektrodalmacija Split	**5.31%**	**20**	**15**
Elektroprimorje Rijeka	**4.97 %**	**13**	**10**

3.3. A month result preview

The forecasting values depend on accuracy of the defined model. The less model errors, the output forecast values are more similar to actual ones. As it was concluded from the model error statistic, the output values are reliable. The following figures present the comparison graphs of Actual and Forecast Values in January 2017 for four defined models for four Croatian Distributions. The load forecast graphs follow the load actual graphs in all figures. Due to winter and cold meteorological conditions the consumption in January is higher than in other parts of the year. The biggest residuals between Actual and Forecast Values are when Actual Value differs significantly from the value of the day before or the value from the same day a week ago.

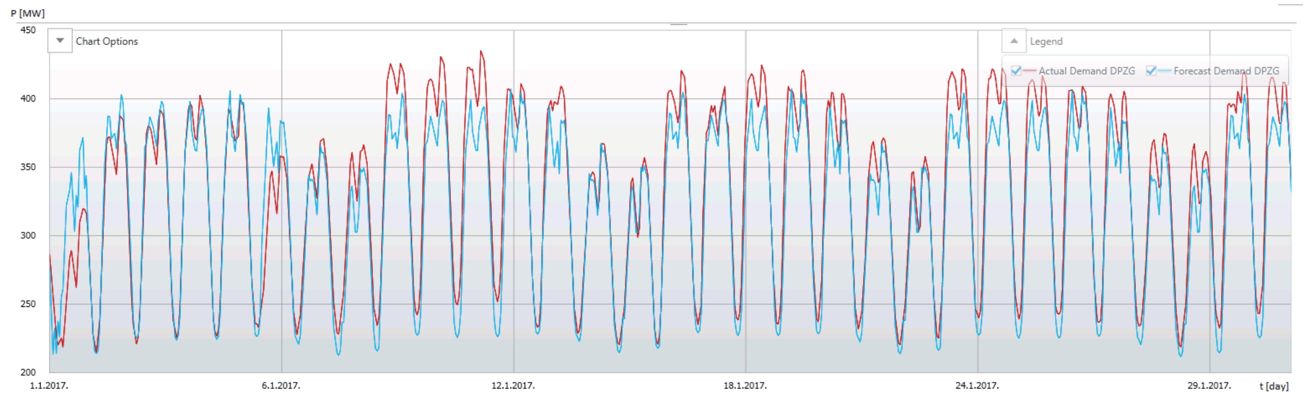

Figure 4 Comparison graph of Actual and Forecast Load Values for Elektra Zagreb Distribution in January 2017

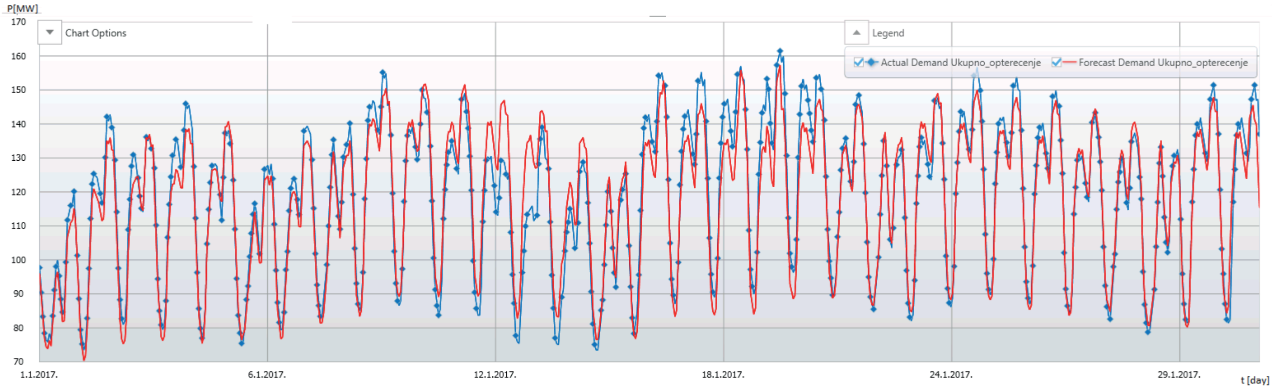

Figure 5 Comparison graph of Actual and Forecast Load Values for Elektroslavonija Osijek Distribution in January 2017

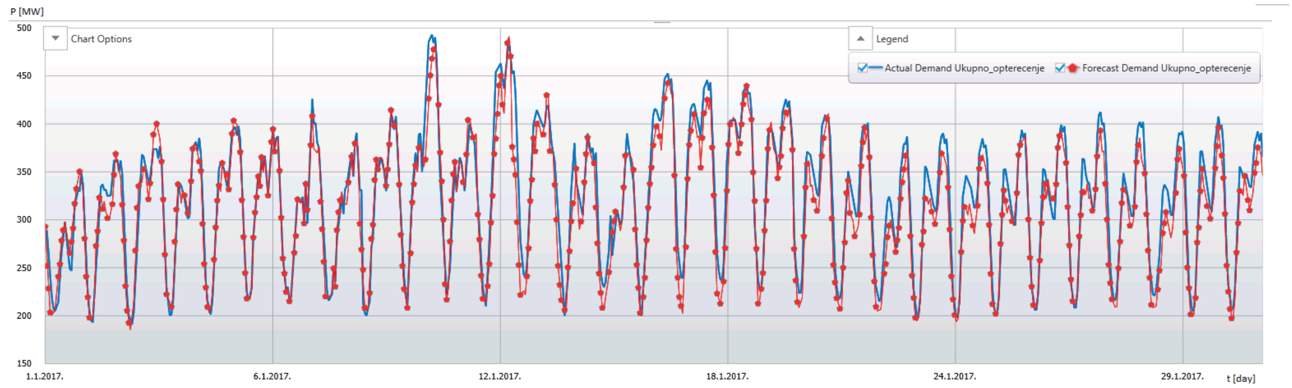

Figure 6 Comparison graph of Actual and Forecast Load Values for Elektrodalmacija Split Distribution in January 2017

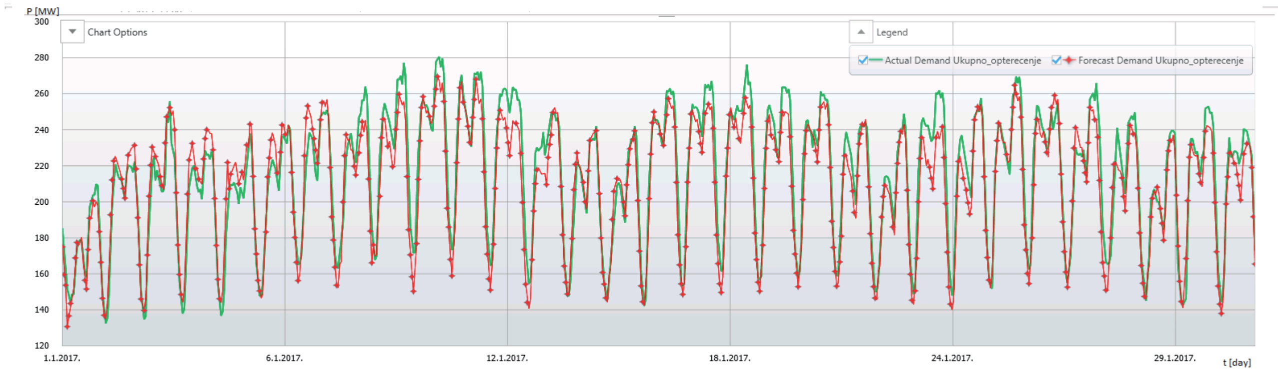

Figure 7 Comparison graph of Actual and Forecast Load Values for Elektroprimorje Rijeka Distribution in January 2017

3.4. Updated model for Elektroslavonija Osijek Distribution

The models have to be maintained regularly and input data has to be updated on a regular basis in order to keep output values accurate. Due to changes in each Distribution regarding population, economic and customers' factors, models have to be re-trained after a certain amount of time.

The Elektroslavonija Osijek Distribution is specific because of the significant increase of renewable energy sources installed in the network. The renewable sources contain biomass and photovoltaic panels. The total installed power in biomass and biogas sources is 30 MW where the number of biogas units is 13 and number of biomass units is 3. The number of installed photovoltaic panels is 393 and the total installed power is 25 MW. These changes, as well as other social and economic changes, bring huge challenges to operators in order to plan the supply and demand of electricity consumption.

The consumption of Elektroslavonija Osijek is predicted for the period from August 15th until August 31st 2017 with two models, with the existing one (model used in the previous case with input data until December 31st 2016) and a new model that contains updated input data until July 31st 2017. Figure 8 shows comparison of Actual Value (light blue) and two Forecast Values (from two models). The model with updated input values (dark blue graph) has more accurate output values for August 2017 than the model with the input data until December 31st (yellow graph).

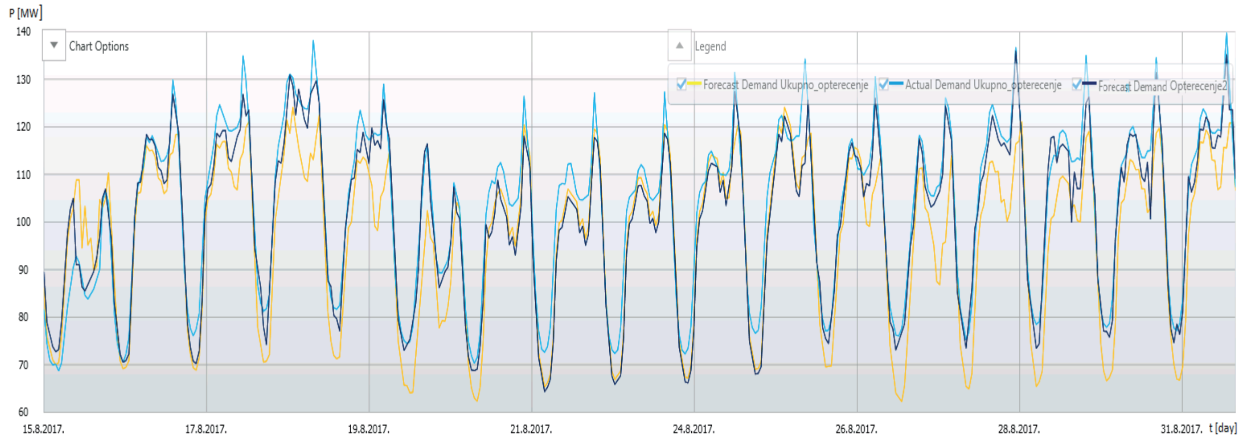

Figure 8 Comparison graph of Actual and Forecast Load Values from two models for Elektroslavonija Osijek Distribution for part of August 2017

4. CONCLUSION

The article describes the principles of the load forecasting systems implemented within four Distribution System Operators in Croatia: Elektra Zagreb, Elektroslavonija Osijek, Elektroprimorje Rijeka and Elektrodalmacija Split. Four neural network models for short-term prediction of active electrical energy consumption are observed. Neural network inputs are the total consumption of observed Distributions and the meteorological data for the period from September 2014 until December 2016. It is shown that trained neural networks have a very good performance and are reliable in predicting future consumption. Residuals between actual and forecast values are alleviated by neural network tuning with which the neural network is able to adapt to nonlinearities. By MAPE measure, forecasting model for Elektra Zagreb is the most accurate of four observed models. In order to improve model, results it is important to improve the quality of input variables and optimize the complexity of the model. To keep forecasting model correct after certain period of time, it is necessary to update input variables, regularly maintain and re-train the model.

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