Forecasting Next-Day the Electricity Demand Based On Fuzzy Logic Method Case for Albania

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Abstract—Forecasting of electricity load demand is key task for the effective operation and planning of power system. Electrical load forecasting is the process of prediction future electrical load demand on the basis of given historical load information. This chapter overviews the applications of fuzzy logic in power system in Albania. Adoption of the Model Market for the Electricity, is one of the important steps towards consolidation and sustainable development of the Electricity Market in Albania. Forecasting of electricity load demand is key task for the effective operation and planning. Time, historical and forecasting value of the temperature, previous day load are used as the independent for the forecasting next-day consumption. The load data are influenced by the variances in day types, namely the normal working day, the weekend and holidays as each of these day type has different load behavior. Following we propose the solution methodology using fuzzy logic for short-term load forecasting and implemented. That minimize the error we propose to share geographical map climate according to the regions. The algorithm calculate rule base using madman implication for each regions. Total forecasting consumption is sum of load forecasting for each regions. Mat Lab SIMULINK software is used, the result are very good.

Keywords—Fuzzy Logic, Forecasting, Electricity Demand, Short - Term Demand, Temperature

I. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. One of the most important works of an electric power utility is to correctly predict load requirements. Adoption of the Model Market for the Electricity, is one of the important steps towards consolidation and sustainable development of the Electricity Market in Albania [1]. Participants main of market are:

- TSO (Transmission System Operator) an independent company that performs the function on the operation of the transmission network from the physical point of view and operation of the system in term of dispatching.
- WPS (Wholesale Public Supplier) who is responsibility to provide a sufficient supply for retail public supplier.
- DSO (Distribution System Operator) has a duty to provide all the available supplies in order to ensure the supply of tariff customers load while avoiding the limitation of the situation unpredictable.

Thus, based on market model, Distribution System Operator (DSO) is obliged to send in TSO and WPS the program of energy consumption for the next day in 24 hours, in order to achieve timely provide, and take measures for the continued supply Electricity. Energy consumption forecast should be as accurate as respecting the limit allowed for the application of the penalties for the imbalances bigger than 0% in the absolute value.

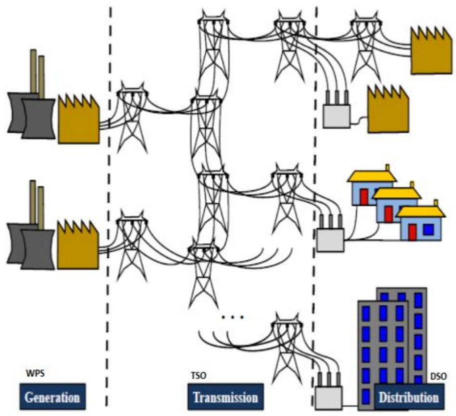

Fig1. A representation of the existing power distribution system architecture in Albania.

Electricity-supply planning requires efficient management of existing power systems and optimization of the decisions concerning additional capacity. Demand prediction is an important aspect in the development of any model for electricity planning. Short-term load forecasts are required for the control and scheduling of power systems. The focus varies from minutes to several hours ahead. The predictions are required as inputs to scheduling algorithms for the generation and transmission of electricity. The load forecasts help in determining which devices to operate in a given period, so as to minimize costs and secure demand even when local failures may occur in the system. In the short run, the load is mainly influenced by meteorological conditions, seasonal effects (daily and weekly cycles, calendar holidays) and special events. Weather related variation is certainly critical in predicting electricity demand for lead times beyond a day ahead (Chow and Leung, 1996; Taylor and Buizza, 2003). Time scales and benefits in the energy sector predictions are needed on different time scales. These time scales can be divided into three groups:

- Short term forecasts cover periods from some hours up to 7-10 days
- Medium range predictions deal with time lags of a few weeks up to a couple of years
- Long term forecasts go beyond one year

Type of forecast short term forecasts cover periods of a few hours up to about 7-10 days. In the energy sector such forecasts are usually based on meteorological data (temperature, humidity, wind speed, cloud coverage,), on characteristic diurnal and weekly cycles, public holidays, school holidays, and the current (today/now) energy consumption. In principle, however, many other factors may be relevant. Examples for such factors are socio-economic indices or big cultural and sport events. Short term forecasts are designed to predict as precisely as possible individual events, i.e. the actual energy demand/consumption on a rather fine time pattern and to forecast unusual energy demands due to special weather patterns or other unusual events. Benefits short term forecasts have become the principal tool for scheduled energy interchange.

As an example we give a brief outline of the system established in Albania. To obtain an optimized net schedule every electricity producer, electricity distributor or network operator has to announce its demand of energy. Each day before 12:00 am OSHEE needs to send WPS and TSO schedule of the electricity demand for the following day. The network management is based on those announcements. The differences between the actual needs and the announced needs is then assessed later on. This energy exchange is used to trade balance energy on a day to day basis. Again short term forecast systems are the principal tools for every market player to optimize their trading strategies and to minimize the need of purchasing relatively expensive balance energy. In many countries contracts between electricity producers and distributors or network operators still take into account the peak load (power) measured over one year. Energy distributors usually have to pay a fee which is proportional to the height of the peak. In order to get more favorable contracts, network operators therefore try to cut those peaks. Again, short term predictions are the main instrument for this sort of energy management.

For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes. The medium- and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors.

The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors. An electric load prediction survey published in [2] indicated that of the 22 research reports considered, 13 made use of temperature only, 3 made use of temperature and humidity, 3 utilized additional weather parameters, and 3 used only load parameters.

II. OVERVIEW OF LOAD FORECASTING METHODS

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting. They may be classified into two categories (Rafal, 2006) statistical and artificial intelligence.

A. Statistical Methods

The statistical techniques are attractive and allowing scientist to understand the system behavior under study. The drawback of this methods is their limit ability to model the nonlinearity of load consumption.

B. Similar-day Method

This approach is based on searching historical data for days within one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days (Yu-Jun He *et al*, 2005).

C. Regression methods

Regression is the one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class. The regression method tries to determine the current value using a mathematical combination of previous loads variable (Ruzic et al, 2003), Charytoniuk et al, 1998). Engle et al. [3] Presented several regression models for the next day peak forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather. References [4], [5], [6], [3] describe other applications of regression models to loads forecasting.

D. Multiple regression

Multiple regression analysis for load forecasting uses the technique of weighted least-squares estimation. Based on this analysis, the statistical relationship between total load and weather conditions as well as the day type influences can be calculated. The regression coefficients are computed by an equally or exponentially weighted least-squares estimation using the defined amount of historical data. Mbamal u and El-Hawary (1993) used the following load model for applying this analysis:

$$Y_t = v_t a_t + \varepsilon_t,$$

Where

t sampling time,
Y_t measured system total load,
v_t vector of adapted variables such as time, Temperature, light intensity, wind speed, Humidity, day type (workday, weekend), etc.
a_t transposed vector of regression coefficients, and
ε_t Model error at time t.

In most cases, linear dependency gives the best results. Moghram and Rahman (1989) evaluated this model and compared it with other models for a 24-h load forecast. Barakat et al. (1990) used the regression model to fit data and check seasonal variations. The model developed by Papalexopulos and Hesterberg (1990) produces an initial daily peak forecast and then uses this initial peak forecast to produce initial hourly forecasts. In the next step, it uses the maximum of the initial hourly forecast, the most recent initial peak forecast error, and exponentially smoothed errors as variables in a regression model to produce an adjusted peak forecast.

E. Exponential smoothing

Exponential smoothing is one of the classical methods used for load forecasting. The approach is first to model the load based on previous data, then to use this model to predict the future load. In exponential smoothing models used by Moghram and Rahman (1989), the load at time t, y (t), is modelled using a fitting function and is expressed in the form:

$$y(t) = \beta(t)^T f(t) + \varepsilon(t)$$

Where

$f(t)$ Fitting function vector of the process,
$\beta(t)$ Coefficient vector,
$\varepsilon(t)$ White noise, and
T transpose operate

The winter's method is one of several exponential smoothing methods that can analyses seasonal time series directly. This method is based on three smoothing constants for stationary, trend and seasonality. Results of the analysis by Barakat et al. (1990) showed that the unique pattern of energy and demand pertaining to fast-growing areas was di cult to analyses and predict by direct application of the winter's method. El-Keib et al. (1995) presented a hybrid approach in which exponential smoothing was augmented with power spectrum analysis and adaptive autoregressive modelling. A new trend removal technique by Infield and Hill (1998) was based on optimal smoothing. This technique has been shown to compare favorably with conventional methods of load forecasting.

F. Time series

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such a structure. Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. Some of the time series models used for load forecasting

G. Autoregressive (AR) model

If the load is assumed to be a linear combination of previous loads, then the autoregressive (AR) model can be used to model the load profile, which is given by Liu et al. (1996) as:

$$\hat{L}_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k-1} + w_k$$

Where $\hat{L}_k$ the predicted load at time k (min) is, w_k is a

Random load disturbance, $\alpha_i, i = 1,...., m$ are unknown coefficients, and equation is the AR model of order *m.*

H. *Autoregressive moving-average (ARMA) model*

In particular, ARMA (autoregressive moving average), In the ARMA model the current value of the time series $y(t)$ is expressed linearly in terms of its values at previous periods $[y(t-1), y(t-2),...]$ and in terms of previous values of a white noise $[a(t), a(t-1),...]$. For an ARMA of order (p, q), the model is written as:

$$y(t) = \phi_1 y(t-1) + ... + \phi_p y(t-p) + a(t) - \theta_1 a(t-1) - ... - \theta_q a(t-q).$$

The parameter identification for a general ARMA model can be done by a recursive scheme, or using a maximum likelihood approach, which is basically a non-linear regression algorithm. Barakat et al. (1992) presented a new time-temperature methodology for load forecasting. In this method, the original time series of monthly peak demands are decomposed into deterministic and stochastic load components, the latter determined by an ARMA model.

Fan and McDonald (1994) used the WRLS (Weighted Recursive Least- Squares) algorithm to update the parameters of their adaptive ARMA model. Chen et al. (1995) used an adaptive ARMA model for load forecasting, in which the available forecast errors are used to update the model.

I. *Autoregressive integrated moving-average (ARIMA) model:*

ARIMA (autoregressive integrated moving average), If the process is non-stationary, then transformation of the series to the stationary form has to be done first. This transformation can be performed by the differencing process. By introducing the ∇ operator, the series $\nabla_{y(t)} = (1-B)y(t)$

For a series that needs to be differenced times and has orders p and q for the AR and MA components, i.e. ARIMA (p, d, q), the model is written as:

$$\phi(B)\nabla^d y(t) = \theta(B)a(t).$$

The procedure proposed by Elrazaz and Mazi (1989) used the trend component to forecast the growth in the system load, the weather parameters to forecast the weather sensitive load component, and the ARIMA model to produce the non-weather cyclic component of the weekly peak load. Barakat et al. (1990) used a seasonal ARIMA model on historical data to predict the load with seasonal variations. Juberias et al. (1999) developed a real time load forecasting ARIMA model that includes the meteorological incudes as an explanatory variable.

J. *ARMAX Model based on genetic algorithms*

ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods. Yang et al. (1996) described the system load model in the following ARMAX form:

$$A(q)y(t) = B(q)u(t) + C(q)e(t),$$

Where

$y(t)$ Load at time t,
$u(t)$ Exogenous temperature input at time t,
$e(t)$ White noise at time t, and
q^{-1} Back-shift operator

and A(q), B(q), and C(q) are parameters of the autoregressive (AR) exogenous (X), and moving average (MA) parts, respectively.

ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non- stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models. Fan and McDonald [7] and Cho et al. [8] Describe implementations of ARIMAX models for load forecasting. Yang et al. [9] Used evolutionary programming (EP) approach to identify the ARMAX model parameters for one day to one week ahead hourly load demand forecast. Evolutionary programming [10] is a method for simulating evolution and constitutes a stochastic optimization algorithm. Yang and Huang [11] proposed a fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasts.

K. *Artificial intelligence based methods:*

An artificial neural network is mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks.

L. *Neural networks:*

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 (see [12]). Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting.

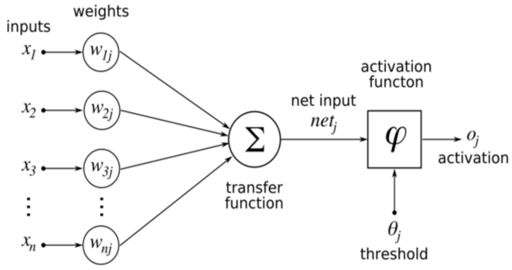

Fig 2: Artificial neural Network

The outputs of an artificial neural network are some linear or non-linear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feed-back paths are sometimes used. In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or unidirectional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally.

The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, un- der supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a preoperational “training session”. Artificial neural networks with un-supervised learning do not require pre-operational training. Bakirtzis et al. [13] Developed an ANN based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer. Feed forward ANN and back propagation algorithm was used for training. Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days. Also Papalexopoulos et al. [14] Developed and implemented a multi-layered feed forward ANN for short-term system load forecasting.

It has been proved that FNN can be used as a universal function approximate [15]. A function defined on a compact set in C [a, b] or LP [a, b] can be approximated arbitrarily well by an FNN with one hidden layer [16]. In many time-series predictions, the time-series model is always based on nonlinear autoregressive (NAR) models [17] which are

$$x_t = h(x_{t-1}, x_{t-2}, \dots, x_{t-p}) + e_t$$

Hence, the neural optimal predictor is given by

$$\hat{x}_{t+1} = \sigma\left(\sum_{i=0}^{H} W_i^1 \sigma\left(\sum_{j=0}^{24} W_{ij}^0 x_{t-j} + \sum_{k=1}^{m} W_{ik}^0 w_k^t\right)\right)$$

Where 0 < I < 24 and the function o is a smooth bounded monotonic function, tang (0.5x). The vector w_t, of m components contains the available weather information at time t. The parameters W_{ij}^0, W_{ik}^0 and W_i^l are the neural network weights.

M. Fuzzy logic

Fuzzy logic is a generalization of Boolean logic; it allows deduction of output system from fuzzy imprecise inputs. However, model based on fuzzy logic are robust in forecasting because there are no need to mathematical formulation between system inputs and outputs Kim *et al,* 2000*).* (Mastorocostas *et al*, 1999), (Chow *et al*, 1997). Electrical load forecasting using fuzzy logic controller can use several factors as inputs like temperature and time. A defuzzification process is used to produce the desired output after processing logic inputs. In forecasting electricity demand with many uncertainties, fuzzy logic would be the most appropriate approach. The basic concept of fuzzy set theory was first introduced by Zadeh in 1965 (Zadeh, 1965). Fuzzy set theory can considered as a generalization of the classical set theory. In classical set theory, an element of the universe either belongs to or does not belong to the set. Thus, the degree of association of an element crisp. In the fuzzy set theory, the association of an element can be continuously varying. Mathematically, a fuzzy set is a mapping from the universe of discourse to the closed interval {0, 1}. The membership function is usually designed by taking into consideration the requirement and constraints of the problem. Fuzzy logic implements human experiences and preferences via membership functions and fuzzy rules. Due to the use of variables, the system can be made understandable to a non-expert operator. In this way, fuzzy logic can be used as a general methodology to incorporate knowledge, heuristics, or theory into controllers and decision makers. Some advantage of fuzzy set theory over conventional methods are as follows (Momoh et al, 1998; Bansal, 2003);

- It based on ordinary language and conceptually easy to understand
- It resolves conflicting objectives by designing weights appropriate to the selected objectives
- It is tolerant of imprecise data and provides capability for handling ambiguity expressed in diagnostic processes, which involve system and causes
- It develops process control as a fuzzy relation between information about the conditions of the process to be controlled

III. Presentation of the Problem

Regarding the above, it is necessary to forecast Electricity consumption for day ahead n+1 for the next 24 hours.

$$APE = \frac{|Actual\ load - Forecasted\ load\ |}{Actual\ load} x100$$

IV. Proposed Methodology

The proposed methodology is to share geographical map climate according to the generations in order to have a good correlation of both series you will use, the series of temperature and energy load, the amount of consumption provided by all cities that belong to a generation climate will constitute the total consumption throughout the country. The purpose of this proposal is to increase the accuracy in predicting the total, based on the fact that different cities have different correlation of energy consumption and temperatures.

V. Implementation

For the implementation of our proposed methodology we have received data on electricity consumption for 24 hours from 5th January 2015 to 8th November 2015, for 13 regions Tirane, Durresi, Shkoder, Elbasan, Fier, Kukes, Lac, Burrel, Korce, Berat, Vlore, Sarande, Gjirokaster and data for temperature at the same regions. Referring to the history of data for energy consumption, we see that the same day of the week have similar consumption, so the weekend or holidays energy consumption is another trend.

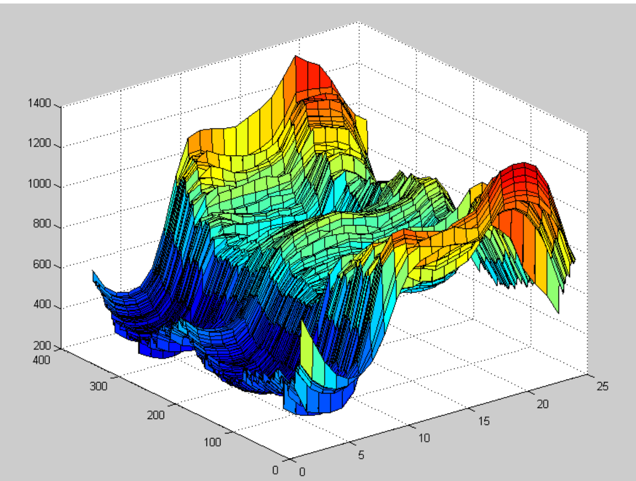

Fig 3: load consumption within a year 2015 in 24 hours

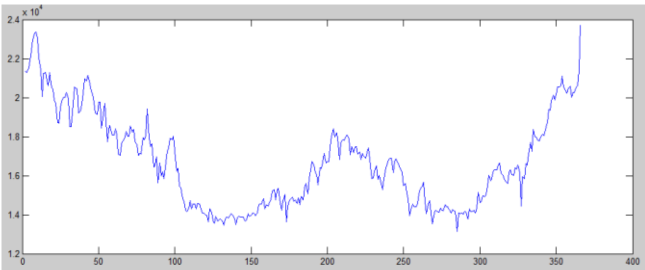

Fig 4: load consumption within a year 2015

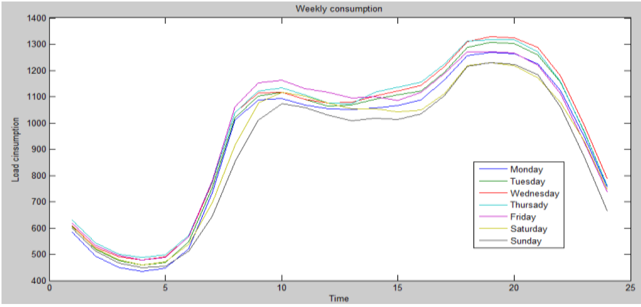

Fig 5: load consumption by day of week in 24 hours

The fluctuation pattern of electricity demand can be as follows: The graph begins with a load demand from 12:30 am until 12:00 midnight. The load demand is rather low from 12:30 am and begins to increase from 8am until 12:00pm. Most school, factory, office department and any building start activities at 8:00 am and some factory and private office department start operate on 9:00 am while the shopping complexes start operating at 10:00 am. Hence the pattern increases obviously during that time period. Human activities break for lunch between 12:00 pm until 5:00 pm and most office department will be closed after 5:00 pm. As result, the fluctuation was decrease after 5:00pm. The load somehow increase again after 5:00pm and this is due to some factory starting the second shift, night shift for their workers. Many shop for the day, hence the load decreases after 9:30pm.

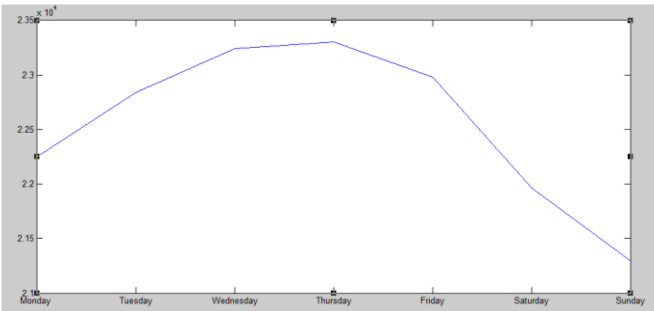

Fig 6: load consumption by day of week (05-11 January 2015)

In general, the weekend electricity load demand was lower than weekday because of weekday is working day. Most of department factory, university and schools are operating on weekly. Sunday load was lowest load because most all building was closed and any actives such as machines, air conditioner and lamp were not used at the time.

As we can see from figure 1 and 2 the load consumption on weekend is different from workdays. For a good prediction of load series, building of a model must take into account variations in monthly and seasonal as well as the various factors, affecting the load, such as weather fluctuations. However, the power consumed during one week in winter cold due to increasing use the electric heaters differs from the power consumed during one week in summer warm which also increases due to the use of air conditioning

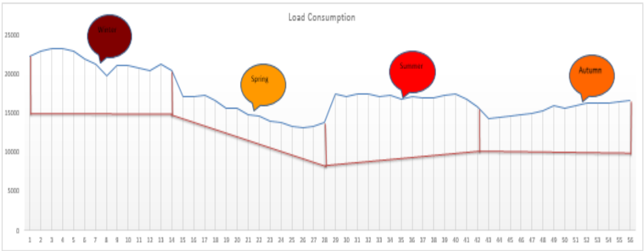

Fig 7: comparison of weekly sketch over the year

For different seasons, we can observe that maximum load consumption occurs in winter and summer, spring and autumn are similar and the load consumption is lower.

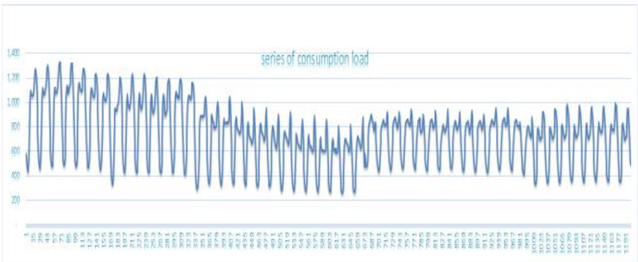

Fig 8: load consumption in 24 hours (05-18 Jan)-(06-19 Apr) - (03-16 Aug) - (26-08 Nov) 2015

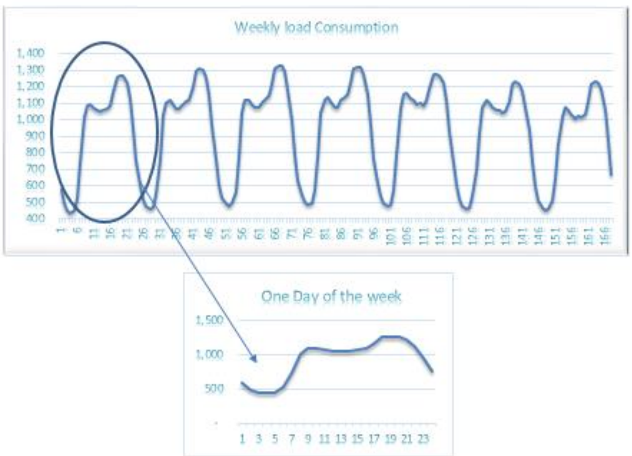

Fig 9: load consumption in 24 hours (05-11 January 2015)

Figure 9 presents the load curve for one week in January. It's found that the daily consumption usually begins with low values early in the morning continuing increase in peak hours, the maximum consumption is about from 06:00 am to 10:00 pm and the load consumption decreases significantly towards the end of the day.

VI. STRATEGY OF FUZZY TECHNIQUES BASED SHORT TERM LOAD FORECASTING

Now as we can see above will use data as input to our model

Database development:

Load data in MW

- Actual values for weeks 5^{th}-18^{th} January 2015, 6^{th}-19^{th} April 2015, 3^{th} -16^{th} Aug 2015, 26^{th} October – 08^{th} November 2015 by days of the week for 24 hours
- Actual values for weeks 05^{th}-18^{th} January 2015, 06^{th} -19^{th} April 2015, 03^{th} -16^{th} Aug 2015, 26^{th} October – 8^{th} November 2015 by days of the week for 24 hours (for calculation deviation)

Temperature data (°C)

- Actual values for weeks 05^{th}-11^{th} January 2015, 06^{th} -12^{th} April 2015, 03^{th} -09^{th} Aug 2015, 26^{th} October – 01^{th} November 2015 by days of the week for 24 hours
- Forecast values for weeks 12^{th}-18^{th} January 2015, 13^{th}-19^{th} April 2015, 10^{th} -16^{th} Aug 2015, 02^{th} -08^{th} November 2015 by days of the week for 24 hours

Input 1: Time 1-24
Input 2: Pervious TMP (temperatures data for the same day of last week)
Input 3: Pervious LOAD (load data for the same day of last week)
Input 4: Forecast TMP (temperatures data for the day to be forecast)
Output: Forecast LOAD (load data forecast)

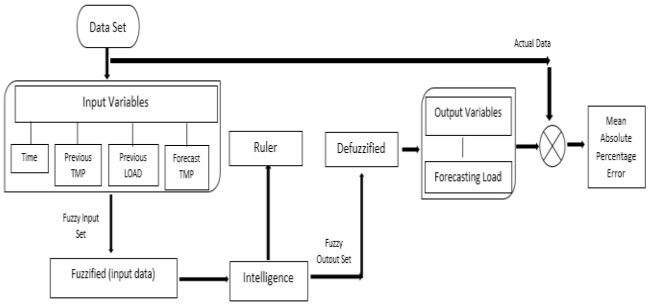

Figure 10: Flowchart of Forecasting Process

The structure of proposed Fuzzy logic based forecasting system is shown Figure 10.

VII. MODEL DEVELOPMENT

There are two factors that we use to forecast next day electricity load which are temperature and load. Temperature is important because demand of load is depending on temperature of the day. The data for the temperature are obtained from the MeteoAlb institute of meteorology in Albania and the electricity load consumption is provide from DSO, Distribution System Operator

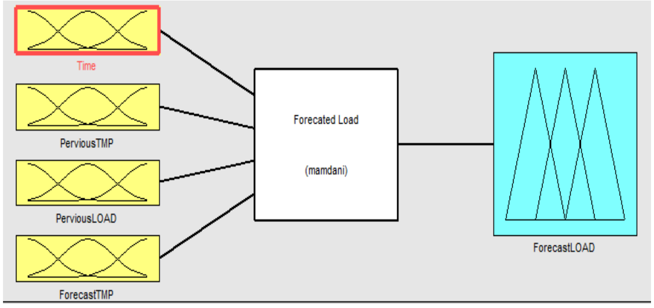

Figure 11: Fuzzy rule mechanism

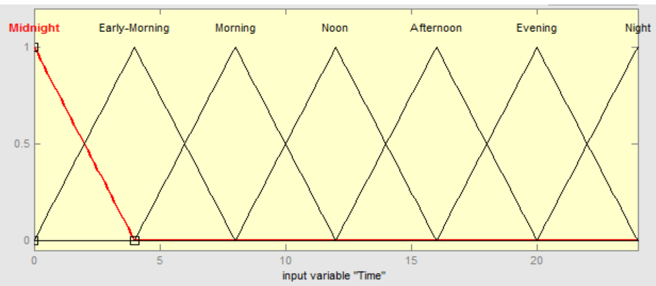

Fig11: Fuzzy membership function input plot

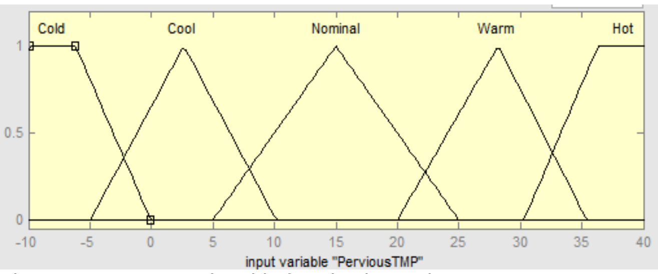

Figure 12: Fuzzy membership function input plot

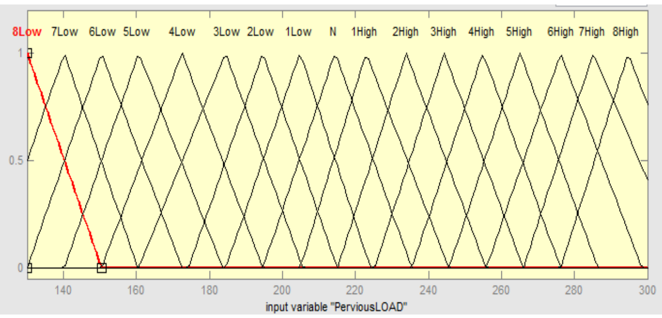

Figure 13: Fuzzy membership function input plot

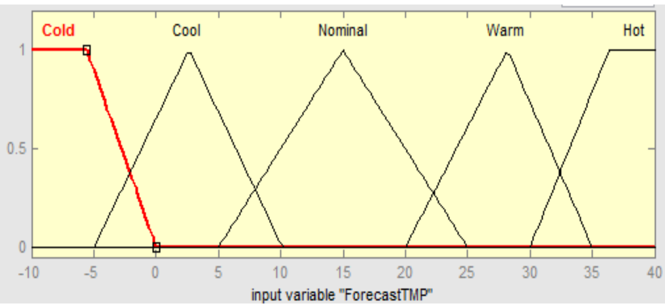

Figure 14: Fuzzy membership function input plot

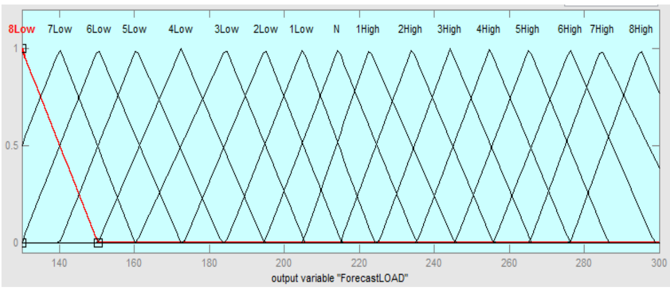

Fig 15: Fuzzy membership function output plot

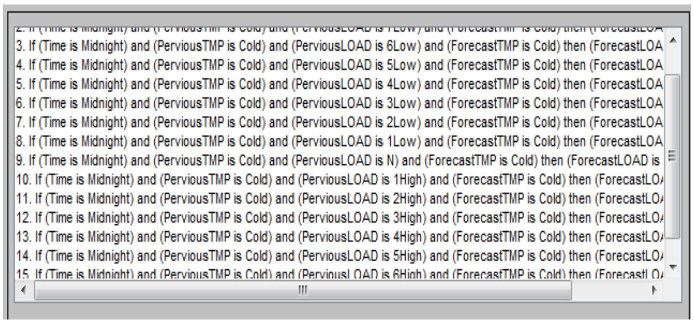
3. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 6Low) and (ForecastTMP is Cold) then (ForecastLOA
4. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 5Low) and (ForecastTMP is Cold) then (ForecastLOA
5. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 4Low) and (ForecastTMP is Cold) then (ForecastLOA
6. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 3Low) and (ForecastTMP is Cold) then (ForecastLOA
7. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 2Low) and (ForecastTMP is Cold) then (ForecastLOA
8. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 1Low) and (ForecastTMP is Cold) then (ForecastLOA
9. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is N) and (ForecastTMP is Cold) then (ForecastLOAD is
10. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 1High) and (ForecastTMP is Cold) then (ForecastLO
11. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 2High) and (ForecastTMP is Cold) then (ForecastLO
12. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 3High) and (ForecastTMP is Cold) then (ForecastLO
13. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 4High) and (ForecastTMP is Cold) then (ForecastLO
14. If (Time is Midnight) and (PerviousTMP is Cold) and (PerviousLOAD is 5High) and (ForecastTMP is Cold) then (ForecastLO

Fig16: The Fuzzy rules

The IF-THEN rules are employed to make a more accurate inference for the variations of forecast error from the linear load model. Part of Fuzzy Rule Base is the most important of the fuzzy system. The heuristic knowledge of the forecasted is stored in terms of "IF-THEN" rules. It send information to fuzzy interface system, which evaluates the gained information to get the load forecasted output

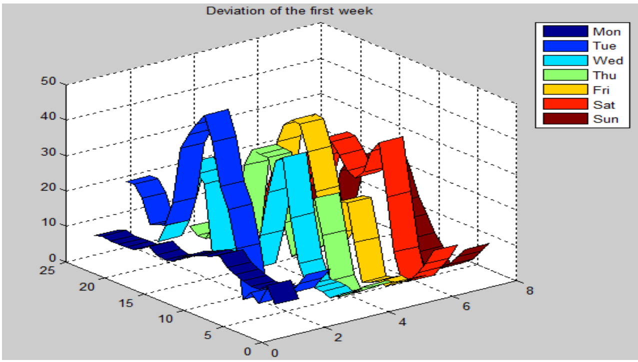

Figure 17: The result for deviations for the first week

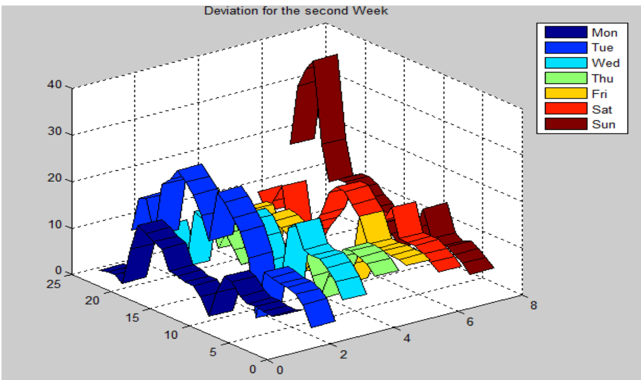

Figure 18: The result for deviations for the second week

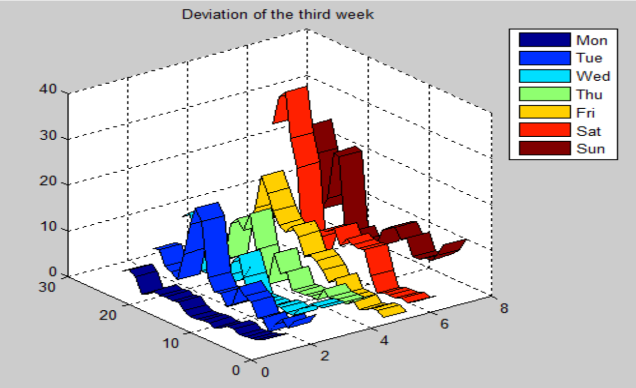

Figure 19: The result for deviations for the third week

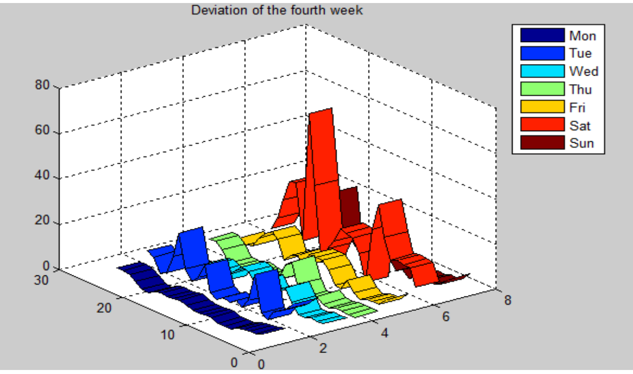

Figure 20: The result for deviations for the fourth week

VIII. CONCLUSION

In this paper we propose a methodology for a short term load forecasting electricity consumption for Albania. Our intention is to predict the next-day electricity consumption with a much smaller error because only that way can we will monitor the situation, to minimize the cost and to secure a good service to electricity, as we can see above we anticipated energy consumption using fuzzy logic, analyzing and consumer trends, the months of the year and days of the week.

We built a model in the Mat lab for each of the 13 regions using time series of temperature and energy consumption and making forecasts for each of these regions. The amount of consumption load for each regions represents total consumption throughout the country so $FRC_{load}(i) = \sum FRC_{load(i,j)}$ where, i=1-24 hours and j=1-13 regions.

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