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Long Term Load Forecasting based Fuzzy Logic cases of Albania

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Abstract— Load forecasting is very important for power system planning, its operation and control. It has vital importance in electric industry. There are many applications of load forecasting which includes energy purchasing and generation, load switching, contract evaluation, and infrastructure development. It is very important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. It is helpful for peak demand levels and energy consumption patterns. It is also very helpful for an electric utility to make important decisions in power system. Forecasting means estimation of active load at various load buses ahead of an actual load occurrence. A good forecasting model has to capture some important features like economy, climate, weather, human activities, interactions etc. Planning and operational application of load forecasting requires certain lead time known as forecasting intervals. Depending upon the time interval it is divided in to three categories i.e. Long term load forecasting, medium term load forecasting, short term load forecasting. A good forecaster takes in to account the various demographic factors which will affect the future load e.g. population, temperature, humidity etc. In case of long term load forecasting, population will affect the most, the other two factors will have more importance in short term load forecasting. For load forecasting different methodologies are adopted. The various methodologies are Artificial Neural Network (ANN), Support Vector Machine (SVM), Fuzzy Logic Models and Genetic algorithm.

This paper is devoted to study long term load forecasting of two stations. For this research work, load data for last 10 years.

Keywords—Fuzzy Logic, Load Forecasting, Long Term, energy Consumption.

I. INTRODUCTION

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

Fuzzy set theory and fuzzy logic was first introduced by Zadeh (1965) which provides a general method for handling uncertainty and vagueness in information available in linguistic terms. Song and Chissom (1993) used the fuzzy set theory given by Zadeh to develop models for fuzzy time series forecasting and considered the problem of forecasting enrollments on the time series data of University of Alabama.

A. Fuzzy Systems:

Fuzzy systems are like expert systems in relaying upon certain rules. These rules here allows fuzzy input. Natural way of behavior of human being are almost fuzzy in all its aspects. Fuzzy systems can solve problems which are difficult for expert systems. It allows the possibility of representation of imprecise human knowledge. Fuzzy systems are based on fuzzy logic which will be discussed in details later on in this paper.

Just as there is a strong relationship between Boolean logic and the concept of a subset, there is a similar strong relationship between fuzzy logic and fuzzy subset theory. In practice, the terms "membership function" and "fuzzy subset" get used interchangeably. Let's talk about people and "tallness". In this case the set S (the universe of discourse) is the set of people. Let's define a fuzzy subset TALL, which will answer the question "To what degree is person x tall?" Zadeh describes TALL as a LINGUISTICVARIABLE, which represents our cognitive category of "tallness". To each person in the Universe of discourse, we have to assign a degree of membership in the fuzzy subset TALL. The easiest way to do this is with a membership function based on the person's height.

B. Fuzzy Logic in Power System Operation and Planning:

There is an increasing number of publications on the application of fuzzy logic in the field of power engineering. This shows the potential of this field in getting better performance of power systems with this logic. There are problems in power systems that contain conflicting objectives. In power systems operation, economy and security, maximum load supply and minimum generating cost are conflicting objectives. The combination of these objectives by weighing coefficients is the traditional approach to solve this problem. Fuzzy theory offers better compromise and obtain solutions which cannot be found by weighing methods. The benefits of fuzzy set theory over traditional methods are as follows:

- It provides alternatives for the many attributes of objective selected.
- It resolves conflicting objectives by designing weights appropriate to a selected objective.
- It provides capability for handling ambiguity expressed in diagnostic process which involves symptoms and causes.
- It develops process control as fuzzy relation between information about the condition of the process to be controlled.
- It develops intelligent robots that employ sensors for path or position determination.
- It improves human reliability models in cases where many people perform multiple tasks.

The areas where fuzzy logic can be used in power Systems cover all the aspects of the power system:

Definition (Proposition) as in our ordinary informal language, "sentence-ce" is used in the logic. Especially, a sentence having only "true (1)" or "false (0)" as its truth value is called "proposition".

Definition (Logic variable) as we know now, a proposition has its value (True or false). If we represent a proposition as a variable, the variable can have the value true or false. This type of variable is called as a "PROPOSITION VARIABLE" OR "LOGIC VARIABLE".

We can combine prepositional variables by using "connectives". The basic connectives are negation, conjunction, disjunction, and implication.

- Negation

Let's assume that prepositional variable P represents the following sentence.

P: 2 is rational.

In this case, the true value of P is true.

P = true

But its negation is false and represents as follows.

P = false

- Conjunction

If a and b are prepositional variables, their conjunction is represented as follows and is interpreted as "a AND b", a ^ b

- Disjunction

The disjunction of two propositions a and b is represented as follows a˅b

The disjunction is interpreted as "a OR b". But it has two different meanings: "exclusive OR" and "inclusive OR". The exclusive OR is used in which two events could not happen simultaneously.

Are you awake or asleep?

The inclusive OR is used when two events can occur simultaneously.

Are you wearing a shirt or sweater?

- Implication

The proposition "if a, then b." is represented as follows a →b

Definition (Fuzzy logic) Then the fuzzy logic is a logic represented by the fuzzy expression (formula) which satisfies the followings.

- Truth values, 0 and 1, and variable x ([0, 1], i = 1, 2, n) are fuzzy expressions.
- If f is a fuzzy expression, ~f is also a fuzzy expression.
- If f and g are fuzzy expressions, f ^ g and f expressions, f ˅g are also fuzzy expressions.

Representation of Fuzzy Rule

When we consider fuzzy rules, the general form is given in the following.

If x is A, then y is B.

The fuzzy rule may include fuzzy predicates in the antecedent and consequent, and it can be rewritten as in the form.

If A(x), then B(y)

This rule can be represented by a relation R(x, y).

R(x, y): If A(x), then B(y)

or

R(x, y): A(x) →B(y)

If there are a rule and facts involving fuzzy sets, we can execute two types of reasoning.

(1) Generalized modus ponens (GMP)

Fact: x is A" : R(x)

Rule: If x is A then y is B : R(x, y)

Result: y is B : R(y) = R(x).R(x, y)

(2) Generalized modus tollens (GMT)

Fact: y is B' : R(y)
Rule: If x is A then y is B : R(x, y)
Result: x is A : R(x) = R(y). R(x, y)

In the above reasoning, we see that the facts (A and B) are not exactly same with the antecedents (A and B) in the rules; the results may be also different from the consequents. Therefore, we call this kind of inference as "fuzzy (approximate) reasoning or inference".
In general, when we execute the fuzzy (approximate) reasoning, we apply the "compositional rule of inference". The operation used in the reasoning is denoted by the notation "", and thus the result is represented by the output of the composition when we use the GMP.

R(y) = R(x).R(x, y)

The need for electric load forecasting is increasing as power system planning attempts to decrease its dependence on chance and becomes realistic in dealing with its environment. This section presents the application of a fuzzy regression technique to long-term
annual peak-load forecasting. The proposed technique takes into account the uncertainties in the nature of the peak load. Different factors are taken into account on modeling the peak load. These factors include the gross domestic product (GDP), population (POP), Weather (HDD&CDD).

II. Methodology

C. *Method of data collection*

The data are collected from:

Energy distribution operator for the historical for historical energy consumption data, from the weather forecast institute for temperatures, and the data on GDP from the statistics institute in Albania.

The block diagram of Fuzzy interface shows how to forest the future load.

D. *Fuzzy interface*

The fuzzy interface can be actualized using the block diagram of fig 1.

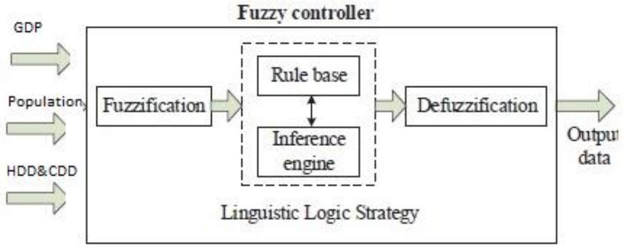


Fig 1. Fuzzy Interface

The inputs parameters are fed to the fuzzifier and the output of fuzzifier and fuzzy rule base enter into the Fuzzy interface engine which is the heart of the system as it processes input data and gives out the forecasted load.

E. Assigning of membership function

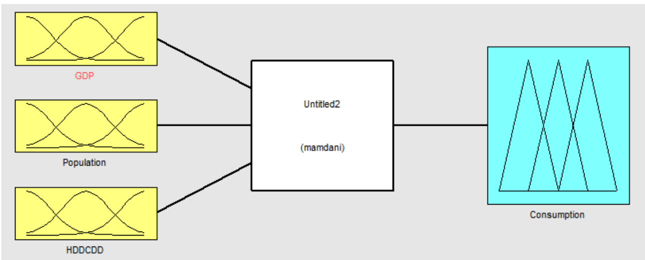


Fig 2. Fuzzy Interface System

Membership function (MF) is a curve that defines how to each point in the input space is mapped to a membership value between 0 and 1. The fuzzy logic machine accepts fuzzified linguistic fuzzy variables for the inputs. Each linguistic variable belongs to a set of values and is represented by a triangular membership function in the range [0, 1], which corresponds to the degree to which the input belongs to the linguistic class.

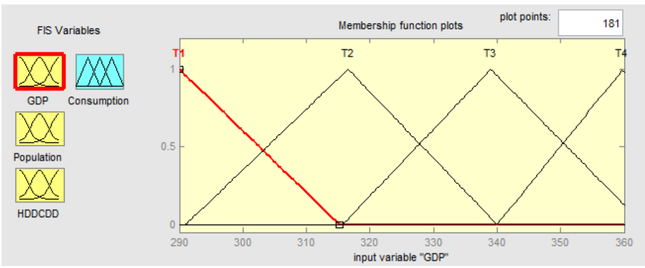


Fig 3. Membership function

A. *Fuzzy rule base*

This aspect is the most important of the whole work. The forecast output will depend of these 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. The views of our rules is Figure 4

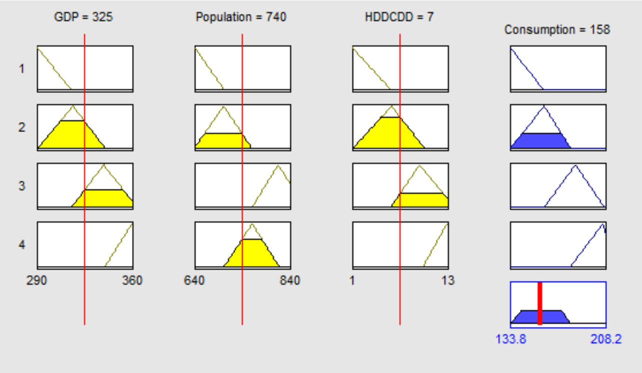


Fig 4: The Fuzzy rules

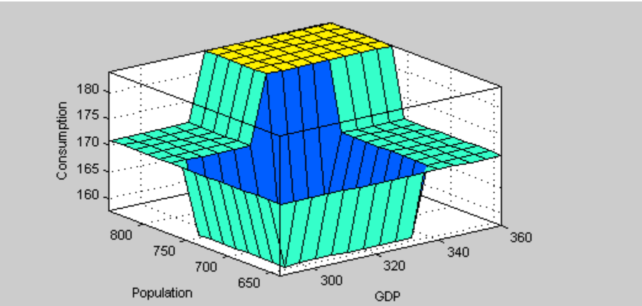
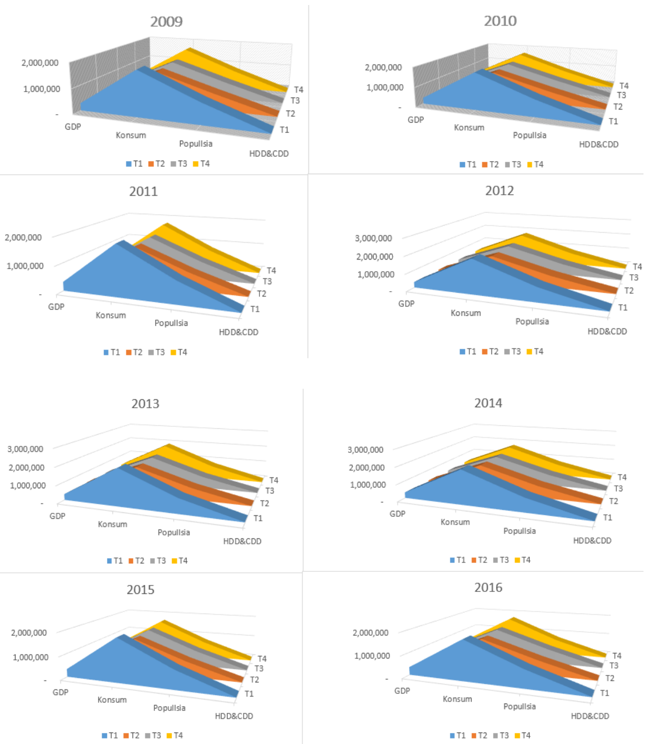


Fig 5: The Fuzzy surface

In the graphs below we can see the projection of energy consumption, GDP, population as well as HDD and CDD divided into 3-month semesters for 2009-2016 years



III. Discussion and Results

Our intention is to predict the yearly electricity consumption with an error as small, so to be as close to real values as we predict we propose to share our time series in three months semesters T1: Jan-Mar, T2: Apr-Jun, T3: Jul-Sep, T4: Oct-Dec.

Absolute percentage error (APE):

$$APE = \frac{Actual\ Consumption - Forecasted\ Consumption}{Actual\ Consumption} x100$$

					10^2		
Year	Period	GDP	Population	HDD&CDD	ACT LOAD	FRC LOAD	Deviation
2009	T1	295	833	12.0	1,803	1,710	-5%
	T2	301	652	6.3	1,338	1,380	3%
	T3	300	672	4.5	1,390	1,350	-3%
	T4	299	779	6.4	1,663	1,710	3%
2010	T1	306	838	11.7	1,841	1,710	-7%
	T2	309	656	7.3	1,372	1,380	1%
	T3	311	671	3.5	1,408	1,480	5%
	T4	312	755	6.2	1,622	1,580	-3%
2011	T1	323	813	11.0	1,846	1,840	0%
	T2	306	646	6.7	1,417	1,480	4%
	T3	319	675	8.0	1,482	1,580	7%
	T4	324	773	5.3	1,739	1,710	-2%
2012	T1	321	833	10.7	2,016	1,840	-9%
	T2	320	655	10.2	1,516	1,580	4%
	T3	325	669	6.1	1,551	1,580	2%
	T4	324	746	5.3	1,768	1,710	-3%
2013	T1	325	826	10.3	2,083	2,040	-2%
	T2	328	648	6.5	1,560	1,580	1%
	T3	318	660	5.2	1,606	1,580	-2%
	T4	330	764	6.4	1,897	1,840	-3%
2014	T1	329	820	9.3	2,011	1,840	-9%
	T2	329	684	9.2	1,621	1,580	-3%
	T3	333	670	1.2	1,579	1,580	0%
	T4	335	722	6.0	1,724	1,710	-1%
2015	T1	337	813	12.1	1,873	1,840	-2%
	T2	339	659	4.6	1,452	1,580	9%
	T3	344	688	9.7	1,524	1,580	4%
	T4	343	732	5.6	1,645	1,710	4%
2016	T1	347	806	8.9	1,805	1,840	2%
	T2	350	660	4.0	1,411	1,480	5%
	T3	355	686	7.5	1,475	1,480	0%
	T4	354	735	6.5	1,709	1,710	0%

Fig6. Table of results

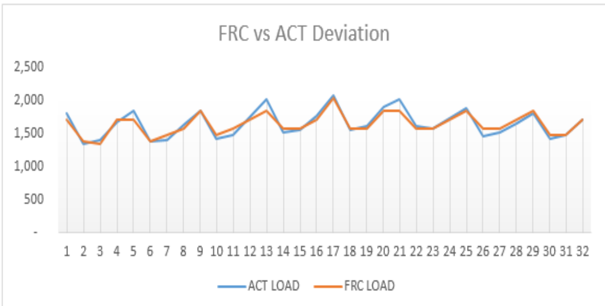


Fig7. Forecast and Actual data for energy consumption

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