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Forecasting of a hydropower plant energy production with Fuzzy logic Case for Albania

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Abstract—Forecasting of energy production for such small power plants is an essential tool for ensuring ongoing power supply for user demand, planning of reserve power supply and transaction between power plants. Applying several techniques to the datasets we have tried to determine the best method to build a one-step-ahead prediction model. Also we have been aiming to estimate the impact of different attributes on the forecasting process. This paper mainly deals with the design of forecasting model for Hydro power generation using Fuzzy time series. The fuzzy time series has recently received an increasing attention because of its capability of dealing with vague and incomplete data. There have been a variety of models developed either to improve forecasting accuracy or reduce computation overhead. This technique has been applied to forecast various fields and have been shown to forecast better than other models. Hence, in this paper fuzzy time series forecasting technique has been applied on hydro power generation data set. An algorithm is designed and based on the numerical calculations and graphical representations it reveals that Hydro Power generation can be forecasted by using Fuzzy Time Series.

Keywords—Fuzzy Logic, Forecasting, HydroPower, time series, energy prediction.

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.

Energy is considered to be a key point in sustainable economic development and a necessity of a modern life. Sustainable development demands a sustainable supply of energy resources. Renewable energy sources, such as sunlight, wind, geothermal heat, hydropower, etc., are generally related to a sustainable ones considering relatively long-term periods of time. For example, for large-scale conventional hydroelectric stations (dams) which have water reservoirs electricity production can be flexible since stations turbine systems can be adjusted to adapt to changing energy demand. Energy production of a small and micro hydropower plants depends on the weather conditions like precipitation and temperature. As a result, the energy production of such systems fluctuates and need to be forecasted.

In the last decade, fuzzy time series have received more attention to deal with the vagueness and incompleteness inherent in time series data. Different types of models have been developed either to improve forecasting accuracy or reduce computation overhead. However, the issues of controlling uncertainty in forecasting, effectively partitioning intervals, and

Consistently achieving forecasting accuracy with different interval lengths have been rarely investigated.

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.

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:

C. Fuzzy Time Series

In view of making the exposition self-contained, the various definitions and properties of fuzzy time series forecasting found in are summarized and reproduced as:

Definition 1. A fuzzy set is a class of objects with a Continuum of grade of membership. Let U be the Universe of discourse with $U = \{u_1, u_2, u_3, ...u_n\}$ where u_i are possible linguistic values of *U*, then a fuzzy set of linguistic variables A_i of *U* is defined by

$$A_i = \mu_{Ai}(u_1)/u_1 + \mu_{Ai}(u_2)/u_2 + \mu_{Ai}(u_3)/u_3 + ... + \mu_{Ai}(u_n)/u_n$$

Here μ_{Ai} is the membership function of the fuzzy set A_i, such that $\mu_{Ai} : U = [0,1]$.

If u_j is the member of A_i, then $\mu_{Ai}(u_j)$ is the degree of belonging of u_j to A_i.

Definition 2. Let $Y(t)(t = ...,0,1,2,3,...)$, is a subset of R, be the universe of discourse on which fuzzy sets $f_i(t)(i = 1,2,3...)$ are defined and $F(t)$ is collection of f_i, then $F(t)$ is defined as fuzzy time series on $Y(t)$.

Definition 3. Suppose $F(t)$ is caused only by $F(t-1)$ and is denoted by $F(t-1) \to F(t)$; then there is a fuzzy relationship between $F(t)$ and $F(t-1)$ and can be expressed as the fuzzy relational equation:

$$F(t) = F(t-1) \circ R(t, t-1)$$

here " $\circ$ " is max-min composition operator. The relation R is called first –order model of $F(t)$. Further, if fuzzy relation R (t, t-1) of $F(t)$ is independent of time t, that is to say for different time t_1 and t_2, $R(t_1, t_1 - 1) = R(t_2, t_2 - 1)$ and $F(t)$ is called a time invariant fuzzy time series.

Definition 4. If $F(t)$ is caused by more fuzzy sets $F(t-n), F(t-n+1), ...F(t-1)$, the fuzzy relationship is represented by

$$A_{i1}, A_{i2}....A_{in} \to A_j$$

here $F(t-n) = A_{i1}, F(t-n+1) = A_{i2}, ..., F(t-1) = A_{in}$

This relationship is called n^{th} order fuzzy time series model.

Definition 4. Suppose $F(t)$ is caused by an $F(t-1), F(t-2), ...andF(t-m)(m > 0)$ simultaneously and relations are time variant. The $F(t)$ is said to be time variant fuzzy time series and relation can be expressed as the fuzzy relation equation:

$$F(t) = F(t-1) \circ R^w(t, t-1)$$

Here $w > 1$ is a time (number of years) parameter by which the forecast $F(t)$ is being affected. Various complicated computations of relation $R^w(t, t-1)$.

II. Strategy of fuzzy techniques based time Series

Below we will look at the forecasting process step by step

We will consider two series:

1. The series of annual production of power consumption by hydropower for the period 2007-2016.
2. The series of monthly production of power consumption by hydropower for the Jan-Dec 2016

Step1: initially compute the first order variation of the historical data

Step2: Define the universe of discourse, U based on the range of available variation of the historical data. U= [V_{min}-V1, V_{max}], where V_{max} is the maximum and V_{min} value of the first order variation of the data, V1 and V2 are two positive integers so:

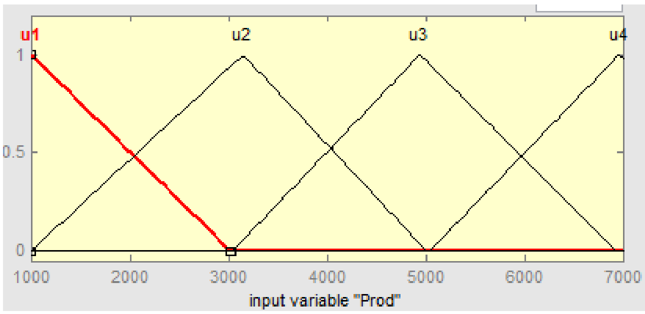
U= [V_{min}-V1, V_{max}+V1]

U= [100000, 700000]

Year	Production	First Diff	Fuzzy set
2007	109,355	-	v1
2008	130,569	21,214	v1
2009	168,756	38,187	v1
2010	235,174	66,418	v2
2011	181,479	(53,695)	v1
2012	312,159	130,680	v3
2013	401,820	89,661	v4
2014	437,694	35,875	v4
2015	487,109	49,415	v4
2016	661,797	174,688	v6

Table 1: The historical data of hydro power

Step3: Define Fuzzy sets Ai on universe of discourse U. then determine how many linguistic variables to be fuzzy sets.



Step4: Fuzzify the variations of the historical data and established the fuzzy logical relationship is represented by Ai → Aj as in table 1.

Step5: Regulation of forecasting follows: [Aj] is corresponding interval uj for which membership in Aj is
supremum (i.e.1) L [Aj] is the length of the interval uj for whose membership in Aj is supremum (i.e.1)
M [Aj] is the mid value of the interval uj having supremum membership value in Aj for a fuzzy logical relationship Ai →Aj

- A_i is the fuzzified enrollment of the current year n;
- A_j is the fuzzified enrollment of the next year n+1;
- D_i is the actual enrollment of the current year n;
- D_{i-1} is the actual enrollment of the previous year n-1;
- E_i is the variation enrollment of the current year n;
- E_{i-1} is the variation enrollment of the previous year n-1;
- F_j is the forecasted enrollment of the next year n+1;

(i) Forecasting hydroelectric for the year n+1 is obtained from modified computational algorithm as follows:

Obtain the fuzzy logical relationship Ai →Aj.

If Ei < M [Ai], then Fj=Di-1+ (M [Aj]-1/4*L [A]), Else if Ei > M [Aj], then Fj=Di-1+ (M [Aj] +1/4*L [A]), Else Fj=Di-1+M [Aj].

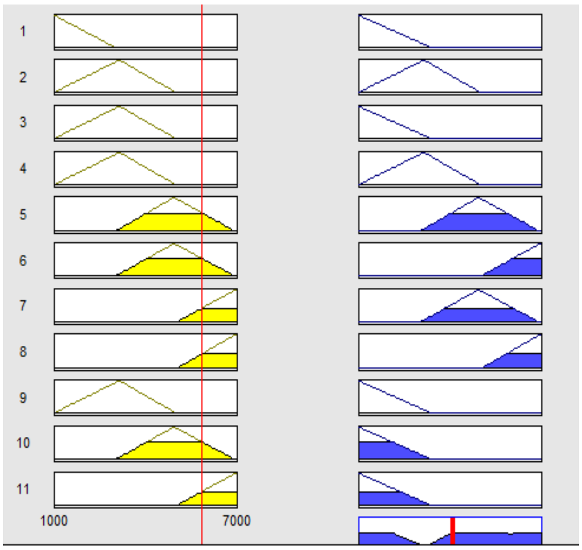
(ii) Obtain the mean square error is using actual values and forecasted values.

Step6: Variations in the Fuzzy Logic Relationships

V1→V1; V1→V1; V1→V2; V2→V1; V1→V3; V3→V4; V4→V4; V4→V4; V4→V6;

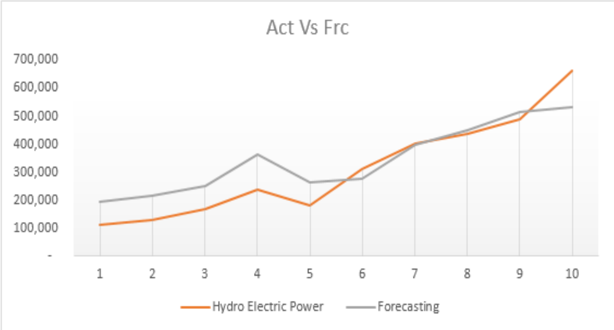
Fuzzy Logic Relationship Groups:

1 V1→V1, V2, V3
2 V2→V1,
3 V3→V4
4 V4→V4, V6



Year	Hydro Electric Power	Forecasting	Deviation
2007	109,355	192,000	82,645
2008	130,569	217,000	86,431
2009	168,756	252,000	83,244
2010	235,174	365,000	129,826
2011	181,479	262,000	80,521
2012	312,159	277,000	(35,159)
2013	401,820	397,000	(4,820)
2014	437,694	448,000	10,306
2015	487,109	516,000	28,891
2016	661,797	534,000	(127,797)

Table 2: The historical and forecasting data of Hydro Power plant



Graph 1: The historical and forecasting data

Define the universe of discourse, U based on the range of available variation of the historical data. U= [V_{min}-V1, V_{max}], where V_{max} is the maximum and V_{min} value of the first order variation of the data, V1 and V2 are two positive integers so:

U= [V_{min}-V1, V_{max}+V1]

U= [10000, 100000]

Month	Production	First Diff	Fuzzy set
Jan-16	66,536		V3
Feb-16	82,875	16,339	V4
Mar-16	91,447	8,572	V5
Apr-16	79,733	(11,713)	V4
May-16	88,496	8,763	V4
Jun-16	47,807	(40,689)	V2
Jul-16	21,481	(26,326)	V1
Aug-16	13,560	(7,922)	V1
Sep-16	24,333	10,773	V1
Oct-16	45,145	20,812	V2
Nov-16	64,561	19,416	V3
Dec-16	35,822	(28,739)	V4

Table 3: The historical data of hydro power

Variations in the Fuzzy Logic Relationships

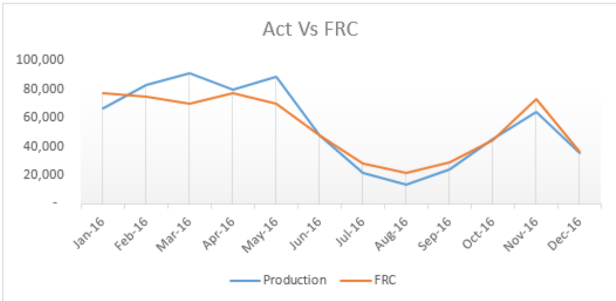
V3→V4; V4→V5; V5→V4; V4→V4; V4→V2;V2→V1; V1→V1; V1→V1; V1→V2; V2→V3; V3→V4;

Fuzzy Logic Relationship Groups:

1 V1→V1, V2,
2 V2→V1, V3
3 V3→V4
4 V4→V2,V4, V5
5 V5→V4,

Month	Hydro Electric	Forecasting	Deviation
Jan-16	66,536	77,100	10,564
Feb-16	82,875	74,800	(8,075)
Mar-16	91,447	69,700	(21,747)
Apr-16	79,733	77,600	(2,133)
May-16	88,496	70,400	(18,096)
Jun-16	47,807	47,900	93
Jul-16	21,481	28,100	6,619
Aug-16	13,560	21,300	7,740
Sep-16	24,333	29,400	5,067
Oct-16	45,145	44,800	(345)
Nov-16	64,561	73,700	9,139
Dec-16	35,822	36,600	778

Table 3: The historical and forecasting data of Hydro Power plant



Graph 2: The historical and forecasting data

I. CONCLUSION

The main objective of this work was to estimate different approaches applied to energy production forecasting for small hydropower plants and determine the best forecasting model analyzing the production of hydropower in Albania, in two series annual production for the years 2007-2016 and monthly production for the period Jan – Dec 2016. Energy production process on a hydropower plant are relevant for building an accurate prediction model. In this paper fuzzy time series method is designed to forecast the hydro power generation of Albania. This work can be extended to develop a method for relating fuzzy logic-linguistic variables with various efficient control of hydropower plant energy in future.

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