

Chapter 4

Fuzzy Forecasting Methods for Energy Planning



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Abstract For energy planning, forecasting the energy demand for a specific time interval and supply of a specific source is very crucial. In the energy sector, forecasting may be long term, midterm or short term. While traditional forecasting techniques provide results for crisp data, for data with imprecision or vagueness fuzzy based approaches can be used. In this chapter, fuzzy forecasting methods such as, fuzzy time series (FTS), fuzzy regression, adaptive network-based fuzzy inference system (ANFIS) and fuzzy inference systems (FIS) as explained. Later, an extended literature review of fuzzy forecasting in energy planning is provided. Finally, a numerical application is given to give a better understanding of fuzzy forecasting approaches.

4.1 Introduction

Energy is one of the scarcest sources in the world. Energy planning helps you get better control over your energy resources. Thus, facing with an energy scarcity or excessive energy consumption costs in the future can be prevented. Forecasting the energy consumption costs or the required energy levels for a firm is very helpful for the planning of future.

Forecasting methods can be divided into two main categories. Qualitative forecasting methods and quantitative forecasting methods. Qualitative forecasting methods are based on judgments, intuition, or personal experiences and subjective in nature. They are not based on hard mathematical computations. Qualitative forecasting methods are based on mathematical models, and objective in nature. Classical forecasting methods use crisp data and generally do not care the possible

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changes in the data, which the future forecasts are based on. In case of incomplete data or uncertain data, we need some extensions in the classical approaches.

Incomplete and/or vague forecasting data require fuzzy forecasting methods to be used. The advantage of the use of fuzzy logic is in processing imprecision, uncertainty, vagueness, semi-truth, or approximated and nonlinear data. Forecasting data generally involve these kinds of characteristics. Ordinary fuzzy forecasting, intuitionistic fuzzy forecasting, hesitant fuzzy forecasting, and type-2 fuzzy forecasting techniques have been developed and applied to some forecasting problems.

Carvalho and Costa (2017) propose a fuzzy forecasting methodology of time series for electrical energy prices. They use triangular fuzzy membership functions and apply the extended autocorrelation function. Kumar and Gangwar (2015) use fuzzy sets induced by intuitionistic fuzzy sets to develop a fuzzy time series forecasting model to incorporate degree of hesitation (nondeterminacy).

Bisht and Kumar (2016) propose a fuzzy time series forecasting method based on hesitant fuzzy sets. The proposed method addresses the problem of establishing a common membership grade for the situation when multiple fuzzification methods are available to fuzzify time series data. Hassan et al. (2016) present a novel design of interval type-2 fuzzy logic systems by using the theory of extreme learning machine for electricity load demand forecasting.

The rest of the chapter is organized as follows. Section 4.2 summarizes the literature on fuzzy forecasting. Section 4.3 presents the fuzzy forecasting methods. Section 4.4 gives a numerical application on fuzzy forecasting. Finally, Sect. 4.5 concludes this chapter.

4.2 Literature Review

Forecasting is one of the most precious activities in planning because of define company's strategies. Planning activities in the energy sector are very important because the cost of investment is very critical. There are different techniques in energy planning in electricity (Piras et al. 1995), wind power (Lou et al. 2008), power system planning (Holmukhe et al. 2010), forecasting energy and diesel consumption (Neto et al. 2011), electricity consumption (Bolturk et al. 2012) short term load forecasting (Liu et al. 2010; Jain and Jain 2013), electricity demand estimation (Zahedi et al. 2013), long term load forecasting (Akdemir and Cetinkaya 2012). While traditional methods use crisp data to make predictions, Zadeh (1965) introduced fuzzy sets in order to integrate expert evaluations into the problem and to deal with imprecision or vagueness intrinsic to the decision problem (Kahraman et al. 2016). In this section, a literature review on fuzzy forecasting methods is provided.

Piras et al. (1995) examined heterogeneous neural network architecture in order to forecast electrical load forecasting in energy planning and use artificial neural networks (ANN) to get results. Mori and Kobayashi (1996) recommended an

optimal fuzzy inference method for short-term load forecasting (STLF) which mentions a structure of the simplified fuzzy inference. The structure is modeled to clasp nonlinear manner in short-term loads and its aim is to minimize errors.

Electric power system load forecasting has a significant function in the energy management that has a big effect in operation, controlling and planning of electric power system. The load estimation used in electrical systems planning has to think future loads and their geographical positions in order to allowing the creator for situating the electrical equipment. The load forecasting affects different features aspects like peak load demand period, transformer sizing, conductor sizing, capacitor placement, and etc. Cartina et al. (2000) used nonlinear fuzzy regression approach in distribution networks for forecast peak load for STLF is an important subject in the operative planning activities of companies devoted to the allocation and trade of energy. Tranchita and Torres (2004) proposed an original method which consists of LAMDA-fuzzy-clustering techniques, regression trees, classification and regression trees algorithm and fuzzy inference for the peak power, daily energy and load curve forecast. Another STLF paper is studied by Hayati and Karami (2005). They explore the use of computational intelligence methods and use the three important architectures of the neural network and a hybrid neuro-fuzzy network named Evolving Fuzzy Neural Network to model STLF systems. Zhao et al. (2006) use the ANN and fuzzy theory for STLF. An algorithm—a pace search for optimum to renew the weight value of fuzzy neurons applied STLF method to some area's power system. Lou et al. (2008) use similarity theory and fuzzy clustering method in order classifying various periods and select a result to substitute to the output of wind power. Holmukhe et al. (2010) use fuzzy logic systems for power system planning for STLF and aimed to define improved method for load forecasting.

Liu et al. (2010) use time-varying slide FTS method that reduces the load forecasting error in STFL. The proposed technique fits a study framework of FTS to exercise trend estimator and uses estimator to obtain forecasting values at forecasting step.

Neto et al. (2011) develop a determination support system for forecasting the cost of electricity production using non-stationary data by integrating the methodology of FTS in order to see uncertainty intrinsic in study of diesel fuel consumption. Li and Choudhury (2011) present a technique to embody a fuzzy and probabilistic load model in transmission energy loss evaluation to overcome uncertainty of load forecast.

Long-term forecasting is a leading issue in energy planning especially in the size of energy plant and location. Akdemir and Cetinkaya (2012) use adaptive neural fuzzy inference system using real energy data in long-term load forecasting. Bolturk et al. (2012) examine electricity consumption to predict possible electricity consumption in energy planning for a company and they use FTS and compare total values of three periods.

Zahedi et al. (2013) estimate electricity demand with ANFIS to get more reliable and accurate planning. Electricity demand is studied with ANFIS and the study includes some parameters such as occupation, gross domestic product, people,

dwelling count and two meteorological parameters. Jain and Jain (2013) develop a fuzzy model and similarity-based STLF using swarm intelligence because of uncertainties in planning and operation of the electric power system is the complex, nonlinear, and non-stationary system. Another paper is presented by Chen et al. (2013) to show a solar radiation estimate model established on fuzzy and neural networks to get well results.

Bain and Baracli (2014) investigate the practice of the ANFIS to predict the energy demand planning. The results showed that hybrid ANFIS technique based upon fuzzy logic and ANNs perform efficiently in forecast accuracy. Li et al. (2015) use STLF with the grid method and FTS estimating technique to better forecast truth in energy planning.

Atsalakis et al. (2015) forecast energy export to plan potential energy demand to the importance of accuracy. The forecasting system is established on two ANFIS use to forecast the optimum energy export forecast parameters. In order to obtain the upper and lower bounds of wind power, Zhang et al. (2016) use an ANFIS to get wind power interval forecasts and based on the system and singular spectrum analysis and the paper develops a hybrid uncertainty forecasting model, Interval Forecast- ANFIS -Singular Spectrum Analysis-Firefly Algorithm. Another wind prediction study present by Okumus and Dinler (2016) with ANFIS and ANN for one h ahead to predict wind speed. Matthew and Satyanarayana (2016) use fuzzy logic along with the results for checking the accuracy of the proposed work in load forecasting. Because there is a requirement of power planning for the proper utilization of electrical energy in electrical power system.

Monthly forecast of electricity demand in the housing industry is studied by Son and Kim (2017) on a precise model and the proposed method is consists of support vector regression (SVR) and fuzzy-rough feature selection with particle swarm optimization (PSO) algorithms. Zhang et al. (2017) present a new variable-interval reference signal optimization approach and a fuzzy control-based charging/discharging scheme to wind power system. Arcos-Aviles et al. (2017) propose a strategy based on a low complexity Fuzzy Logic Control for grid power profile smoothing of a residential grid-connected microgrid in the design of an energy management in order to show the presented work minimizing fluctuations and power peaks while keeping energy stored in battery between secure limits results, a simulation comparison highlighted. Chahkoutahi and Khashei (2017) propose a direct optimum parallel hybrid model is consists of multilayer perceptrons neural network, ANFIS and Seasonal ARIMA to electricity load forecasting in electricity load forecasting and aim of this study is put into practice upper hands of ANFIS and Seasonal ARIMA in modelling composite and equivocal systems in energy planning.

Fuzzy forecasting methods in energy planning have been extensively used and the analysis of them in Figs. 4.1, 4.2, 4.3 and 4.4; Table 4.1.

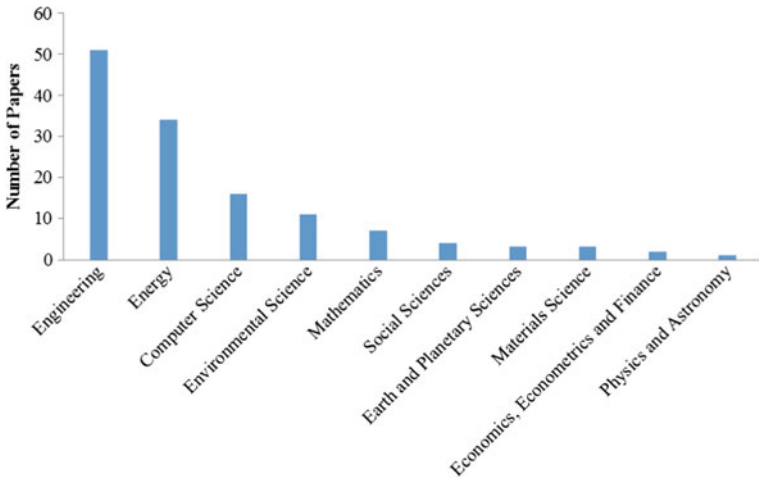


Fig. 4.1 Distribution of fuzzy forecasting methods in energy planning by subject area

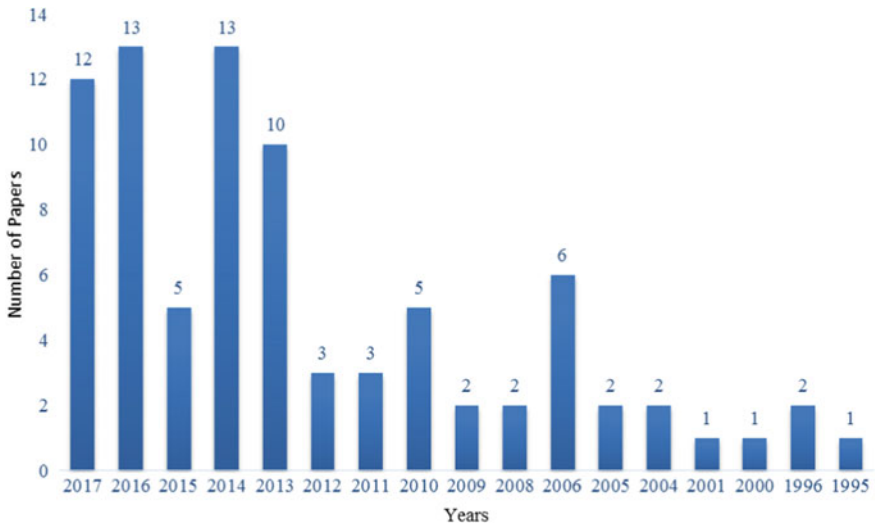


Fig. 4.2 Number of fuzzy forecasting methods in energy planning papers by years

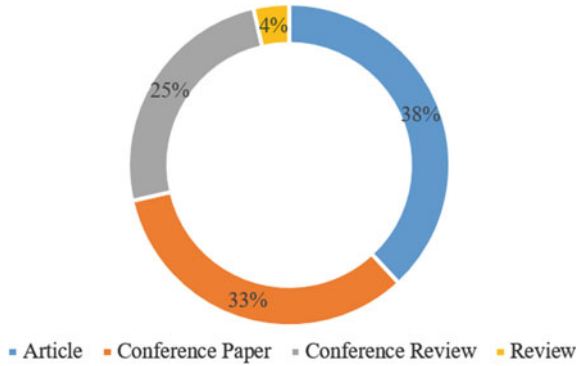


Fig. 4.3 Document type of fuzzy forecasting methods in energy planning

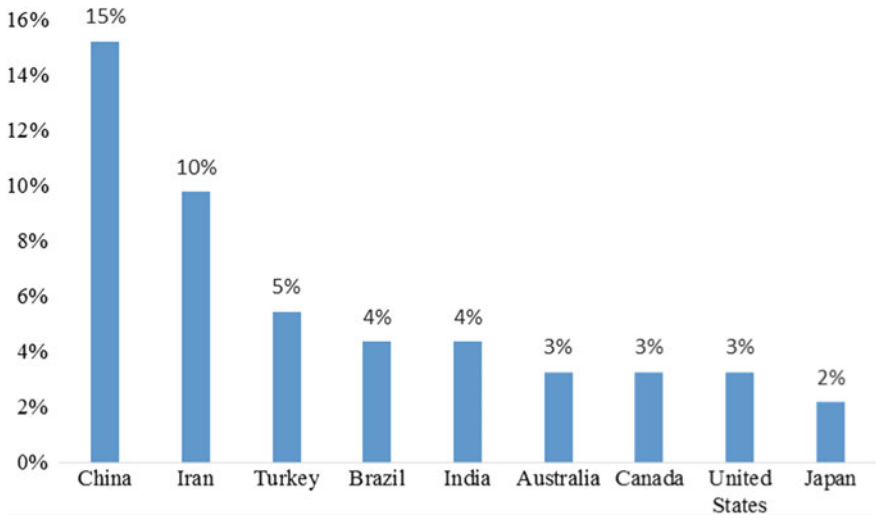


Fig. 4.4 Percentage of fuzzy forecasting methods in energy planning papers based on countries

4.3 Fuzzy Forecasting Methods

4.3.1 Fuzzy Time Series

A sequence of data is called time series if they are listed in time order. A time series refers to a sequence taken at successive equally spaced points in time. In statistics, time series models assume which forecast for the next time interval can be made

Table 4.1 Summarized literature review

Author (Year)	Subject	Method
Piras et al. (1995)	Electrical load forecasting	ANNs and weighted fuzzy average
Mori and Kobayashi (1996)	STFL	Simplified fuzzy inference
Cartina et al. (2000)	Peak load estimation	Nonlinear fuzzy regression approach
Tranchita and Torres (2004)	STFL	CART classification, fuzzy inference, LAMDA-fuzzy-clustering, regression trees
Hayati and Karami (2005)	STLF	Hybrid neuro-fuzzy network
Zhao et al. (2006)	STLF	ANN and fuzzy theory
Lou et al. (2008)	Wind power	Fuzzy clustering method and similarity theory
Holmukhe et al. (2010)	STLF	Fuzzy logic
Liu et al. (2010)	STLF	FTS
Neto et al. (2011)	Electricity production	FTS and optimization techniques
Li and Choudhury (2011)	Load forecast	Load model combined fuzzy and probabilistic
Bol Turk et al. (2012)	The consumption of electricity	FTS
Oztaysi and Ucal Sari (2012)	The forecasting of electricity demand	Seasonal FTS
Akdemir and Cetinkaya (2012)	Long-term load forecasting	ANFIS
Zahedi et al. (2013)	Electricity demand	Adaptive neuro-fuzzy network
Jain and Jain (2013)	STLF	Particle swarm optimization
Chen et al. (2013)	Solar radiation forecast	Fuzzy and neural networks
Bain and Baracli (2014)	Energy demand	ANFIS
Oztaysi and Bol Turk (2014)	Literature review on fuzzy forecasting	FTS, fuzzy regression, fuzzy inference systems, ANFIS
Li et al. (2015)	STLF	FTS forecasting method
Atsalakis et al. (2015)	Energy export forecast	ANFIS
Zhang et al. (2016)	Get daily average wind power interval forecasts	ANFIS

(continued)

Table 4.1 (continued)

Author (Year)	Subject	Method
Okumus and Dinler (2016)	One h ahead wind speed forecasts	ANFIS and ANN
Matthew and Satyanarayana (2016)	STFL	Fuzzy logic
Son and Kim (2017)	Electricity demand	SVR and PSO algorithm
Zhang et al. (2017)	Battery energy storage system	Variable-interval reference signal optimization approach
Arcos-Aviles et al. (2017)	Battery	Fuzzy logic
Chahkoutahi and Khashei (2017)	Load forecast	ANFIS and seasonal ARIMA

using the past set of values observed at the same time interval (Kahraman et al. 2010). Traditional time series model has been extended to fuzzy sets. Song and Chissom (1993) provide one of the initial FTS and propose a technique for linguistic data using fuzzy relation equations.

Let $Y(u) (u = .0, 1, 2, 3..)$ be a subset of $R1$, the universe of discourse. Fuzzy sets $f_i(tu) (i = 1, 2, 3, \dots)$ are identified on universe of discourse. A FTS, $F(u)$, on $Y(u)$ is defined as a collecting of $f_1(u), f_2(u), \dots, f_n(u)$. If $F(u)$ is affected only by $F(u - 1)$, it is represented by $F(u - 1) \rightarrow F(u)$. In this case we can say that there is a fuzzy relationship between $F(u)$ and $F(u - 1)$, and it can be shown as in Eq. 4.1. The relation R shown in Eq. 4.1, is called the fuzzy relation between $F(u)$ and $F(u - 1)$.

$$F(u) = F(u - 1) \circ R(u, u - 1) \quad (4.1)$$

Song and Chissom (1993) define two types of FTSs. If relation $R(u, u - 1)$ is individual of u , so $F(u)$ is called a time-changing FTS, in other cases, the relation is a time-variant FTS. Assume a FTS, $F(u)$, is stired up by $F(u - 1), F(u - 2), \dots$, and $F(u - n)$. Equation 4.2 epitomise this fuzzy relationship (FLR) is defined the n th order FTS forecasting mockup.

$$F(u - n), \dots, F(u - 2), F(u - 1) \rightarrow F(u). \quad (4.2)$$

Chen (1996) outlines the steps of FTS forecasting chniques. Process starts with partitioning the universe of discourse into exact intervals. Then historical data is fuzzified. The third step is to build the fuzzy relationship between historical fuzzy data. Finally, the forecasts are calculated using this relation.

4.3.2 Fuzzy Regression

Regression analysis is a statistical technique which is studied on widely. The technique focuses on exploring and modeling the relationship between an output factor and input factors. Traditional statistical linear fixation model is as given in 3.

$$y(x) = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \varepsilon_i, i = 1, 2, \dots, m \quad (4.3)$$

In this Eq. 4.3, $y(x)$ is the output variable, x_{ij} are the input variables. In the equation, β_j represents the coefficients of the formula and ε_i shows the random error term. In the original technique, all of the parameters, coefficients and variables are crisp numbers.

The classical technique is widely adopted both by the academia and the professionals. However, Shapiro (2004) reports some shortcomings of the classical

model for example an insufficient couple of observing, or missing data. Fuzzy regression models are proposed to overcome these issues. The literature provides various fuzzy regression models (Georg 1994; Sakawa and Hitoshi 1992; Tanaka et al. 1989; Wang and Tsaur 2000). In this chapter, we briefly explain Buckley's fuzzy regression model (Buckley 2004) study. In this model, the forecast is done based on confidence intervals. Buckley defines the fuzzy regression model is as in the following:

$$y(x) = a + b(x_i - \bar{x}) + \varepsilon_i \quad (4.4)$$

In this equation \bar{x} shows the mean value of x_i . Confidence intervals of a, b and σ are obtained using crisp numbers according to the technique $(1 - \beta) 100\%$. For this purpose the crisp estimators of the coefficients (\hat{a}, \hat{b}) should be found. $\hat{a} = \bar{y}$ and $\hat{b} = \frac{B1}{B2}$ are the values of the estimators where

$$B1 = \sum_{i=1}^n y_i(x_i - \bar{x}) \quad (4.5)$$

$$B2 = \sum_{i=1}^n (x_i - \bar{x})^2 \quad (4.6)$$

$$\sigma^2 = \left(\frac{1}{n}\right) \sum_{i=1}^n [y_i - \hat{a} - \hat{b}(x_i - \bar{x})]^2 \quad (4.7)$$

Using the above mentioned Equations, $(1 - \beta)100\%$ confidence interval for a and b are obtained using 4.8 and 4.9:

$$\hat{a} - t_{\frac{\beta}{2}} \sqrt{\frac{\hat{\sigma}^2}{(n-2)}}, \hat{a} + t_{\frac{\beta}{2}} \sqrt{\frac{\hat{\sigma}^2}{(n-2)}} \quad (4.8)$$

$$\hat{b} - t_{\frac{\beta}{2}} \sqrt{\frac{n\hat{\sigma}^2}{(n-2) \sum_{i=1}^n (x_i - \hat{x})^2}}, \hat{b} + t_{\frac{\beta}{2}} \sqrt{\frac{n\hat{\sigma}^2}{(n-2) \sum_{i=1}^n (x_i - \hat{x})^2}} \quad (4.9)$$

The fuzzy regression equation is can be written as;

$$\tilde{y}(x) = \tilde{a} + \tilde{b}(x_i - \bar{x}) \quad (4.10)$$

$\tilde{y}(x)$, \tilde{a} and \tilde{b} , are fuzzy, and x and \bar{x} are crisp in (4.10). For prediction, new fuzzy values for dependent variable can be calculated by new x values. Using the interval arithmetic and (α) -cut operation the predictions can be obtain using 4.11.

$$\tilde{Y}[x](\alpha) = \begin{cases} y(x)_1(\alpha) = \alpha_1(\alpha) + (x - \tilde{x})b_1(\alpha) & \text{if } (x - \bar{x}) > 0 \\ y(x)_2(\alpha) = \alpha_2(\alpha) + (x - \tilde{x})b_2(\alpha) & \\ y(x)_1(\alpha) = \alpha_1(\alpha) + (x - \tilde{x})b_1(\alpha) & \text{if } (x - \bar{x}) > 0 \\ y(x)_2(\alpha) = \alpha_2(\alpha) + (x - \tilde{x})b_2(\alpha) & \end{cases} \quad (4.11)$$

4.3.3 Fuzzy Inference Systems

Fuzzy inference systems (FIS) utilize expert evaluations expressed by rules and a reasoning mechanism for forecasting. Another usage of this label are “Fuzzy rule-based systems” or “fuzzy expert systems” (Jang et al. 1997). A set of rules, a database and an argumentative machine are three main components in FIS. The if-then rules used for reasoning is stored in the rule base. The membership functions used in these rules are stored in the database. The output of the system is obtained by the reasoning mechanism which uses rules and the given input values.

The expert evaluations about different conditions are transferred to the system by using fuzzy rules. The rules are defined by using if and then clauses. For example, “If the service is good then the tip is high” is an if-then rule representing the number of tips in a restaurant. Here, “service” and “tip” are linguistic variables, good and high are linguistic values.

Fuzzification, fuzzy rules, fuzzy inference and defuzzification are four steps of a typical FIS (Oztaysi et al. 2013). The first step involves fuzzification in which all crisp input data is transformed to fuzzy values. In the second step, the rules are obtained from the experts using linguistic terms and fuzzy operator. As the number linguistic variables and associated linguistic variable raise the amount of the rules rise exponentially. The third step is inference procedure which provides a conclusion based on rules above. The literature provides a various model for inference including Mamdani’s model (Mamdani and Assilian 1975), Sugeno’s model (Sugeno and Kang 1988) and Tsukamoto Fuzzy Model (Tsukamoto 1979). As the inference procedure obtains the results, the next step is defuzzification which transforms the fuzzy output to crisp values.

4.3.4 ANFIS

ANFIS uses expert evaluations, a dataset, and a learning mechanism to provide a relationship between inputs and outputs (Jang 1993). The system utilizes Sugeno

inference model and artificial neural networks (Yun et al. 2008). ANFIS learns the membership function parameters of linguistic variables utilizing input/output data set.

Jang (1993) defines the system with five layer feed forward neural network as follows:

1. 1st layer is composed of adaptive nodes which have a node function such as, $O_{1,i} = \mu_{A_i}(x)$ (for $i = 1, 2$). x shows input to node I , and lingual term is A_i . $O_{1,i}$ refers to the membership degree of a fuzzy set A .
2. 2nd layer is composed of fixed nodes which produce an output showing the firing strength of a rule.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2. \quad (4.12)$$

3. 3th layer is composed of linked nodes labelled N . The ratio of the i th rule's firing strength is calculated in order to sum of all rules' firing strengths as shown in Eq S. This layer produces normalized firing strengths as an output.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \quad (4.13)$$

4. 4th layer is composed of adaptive nodes with node functions given in 4.14. In this equation \bar{w}_i shows a regularized firing strength from 3th layer and p_i , q_i , and r_i show the parameter set for this node

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad (4.14)$$

5. Sum of all arriving signals is calculated by a single node as an overall output value in 5th layer.

$$\text{overall output} = O_{4,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (4.15)$$

4.3.5 Hwang, Chen, Lee's Fuzzy Time Series Method

A FTS technique proposed by Hwang et al. (1998) is for handling forecasting problems. To find the future demands via Hwang, Chen, Lee's FTS technique (Hwang et al. 1998) and the demand is known by yearly, the following steps are applied:

1. The variations are found in two consecutive years. For example the demand of year q is d and the demand of year p is e , then the variation is $e-d$.
2. Minimum increase D_{\min} and maximum increase D_{\max} are found.
3. Define the universe of discourse U , $U = [D_{\min} - D1, D_{\max} + D2]$, ($D1$ and $D2$ are appropriate positive numbers.)
4. Partition the universe of discourse U into several even length intervals.
5. Deciding linguistic terms delineated by fuzzy sets. The linguistic terms for the intervals can be described as follows: Big decrease, decrease and, etc.
6. Fuzzifying values of historical data.
7. Determining an appropriate window basis w , and output is calculated from the operation matrix $O^w(T)$. Criterion matrix $C(T)$, that T is year for which we want to forecast the data.
8. Fuzzy forecasted variations are defuzzified.
9. Final forecasted data is calculating by forecasted data plus the number of last year's actual data.

4.4 A Numerical Application

In this section we apply FTS Using Hwang, Chen, Lee's Method (Hwang et al. 1998) to energy forecasting problem. The actual spending values, variations and linguistic terms are given in Table 4.2.

Maximum variation = 6.504.394, and minimum variation is -3.268.290. Universe of discourse $[-3.500.000, 7.000.000]$ The linguistic terms for the intervals: {Big decrease, decrease, no change, increase, big increase, very big increase, too big increase}.

When we try to forecast Month 22 with a window size 5, the calculations are as follows:

$$O^5(22) = \begin{bmatrix} 0 & 0 & 0 & 0.5 & 1 & 0.5 & 0 \\ 0 & 0 & 0 & 0.5 & 1 & 0.5 & 0 \\ 0 & 0.5 & 1 & 0.5 & 0 & 0 & 0 \\ 1 & 0.5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & 1 & 0.5 & 0 \end{bmatrix} \quad (4.16)$$

$$C(22) = [0 \quad 0.5 \quad 1 \quad 0.5 \quad 0 \quad 0 \quad 0] \quad (4.17)$$

Table 4.2 Actual spending and variations of historical data

Months	Actual spending	Variation	Linguistic terms
Month 1	16.247.156		
Month 2	14.253.194	-1.993.962	A2
Month 3	20.757.588	6.504.394	A7
Month 4	20.192.911	-564.677	A2
Month 5	19.218.643	-974.268	A2
Month 6	18.242.756	-975.887	A2
Month 7	21.051.875	2.809.119	A5
Month 8	18.017.455	-3.034.420	A5
Month 9	19.851.723	1.834.268	A4
Month 10	18.690.696	-1.161.027	A2
Month 11	18.259.420	-431.276	A2
Month 12	21.060.161	2.800.741	A5
Month 13	20.228.593	-831.568	A2
Month 14	22.324.932	2.096.339	A4
Month 15	28.007.488	5.682.556	A7
Month 16	30.911.740	2.904.252	A5
Month 17	34.024.478	3.112.738	A5
Month 18	34.038.857	14.379	A3
Month 19	30.770.567	-3.268.290	A1
Month 20	33.148.083	2.377.516	A5
Month 21	32.873.582	-274.501	A3
Month 22	33.862.352	988.770	A3
Month 23	30.933.481	-2.928.871	A1
Month 24	34.080.836	3.147.355	A5

Table 4.3 Membership of months

Months	Actual	Forecast
Month 22	A3	A3
Month 23	A1	A3
Month 24	A5	A5

By applying the steps

$$F(22) = 0 \quad 0.25 \quad 1 \quad 0.25 \quad 0 \quad 0 \quad 0 \tag{4.18}$$

Since the maximum membership belongs to A3 (No change) the forecast for the next period is A3.

When we apply the method to the remaining three periods, we get the values as in Table 4.3.

4.5 Conclusion

Fuzzy forecasting methods present excellent tools for forecasting the future when incomplete, vague, and imprecise data exist in the considered problem. Fuzzy time series, fuzzy regression, fuzzy inference systems, and ANFIS are the most used fuzzy forecasting techniques in the literature. Forecasts for energy costs and energy production levels of the future are excessively important for both the energy producers and the energy consumers. Fuzzy forecasting provides the limits of possibilities in case of incomplete and vague data and a wider and deeper perspective of the uncertain future.

For further research, the recent extensions of fuzzy sets can be employed in the forecasting methods. Intuitionistic fuzzy forecasting techniques, hesitant fuzzy forecasting techniques, type-2 fuzzy forecasting techniques, and Pythagorean fuzzy forecasting techniques are possible research areas for future work directions.

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