Spatial Load Forecasting Using Fuzzy Logic

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Abstract:

During the last four decades various load forecasting methods have been created. However, these methods cannot forecast future loads in case of sever lack of data, when only few loads are measured in nonconsecutive years. This paper proposes and describes the general methodology to use fuzzy logic to fuse the available information for spatial load forecasting. The proposed scheme can provide distribution planners other alternatives to aggregate their information for spatial load forecasting. A new spatial load forecasting method using non-uniform areas has been established. The result is a method that requires substantially less manpower and data than existing grid-based methods. In addition, this method results in a closed-form solution for spatial loading as a function of time.

The algorithm has been tested on the Ghaen City (North-East of IRAN), Khurasan Province as a benchmark for present and projected land uses. The results provide a reasonable projection of the loads in the Ghaen City area, in line with the expectations. The algorithm accurately constrained the growth within the forecast area to the overall projected demand.

Keywords: Power Systems, Spatial Load Forecasting, Fuzzy Logic

1. Introduction

Utilities are required to provide reliable power to customers. However, utilities do not want to overbuild their system because they need to bear the unnecessary cost. In ideal situations, utilities will build a reliable power system with just enough capacity (with proper reliability margins) to support their customers. Distribution systems are the retail part of utilities that supply power to their customers. Distribution system covers large geographic areas with substantial construction and operation costs. Proper information gathering, decision making, planning and design are all important towards a more cost-effective and reliable distribution system. In the design stages, utilities need to plan ahead for anticipated future load growth under different possible scenarios. They need to decide whether to build new lines and substations, or to upgrade the existing systems. Their decisions and designs can affect the gain or loss of millions of dollars for their companies as well as customer satisfaction and future economic growth in their territory. Therefore, utilities are very concerned about distribution planning. They would like to use as many tools as possible to help them achieve the best planning so that money, time, and human resources can be used effectively and efficiently. Different approaches, such as spatial load forecasting based on land usage and end-user load modeling, have been used to improve the performance of distribution load forecasting [1-3]. Land usage-based spatial load forecasting is based on objective predicts how the land will be used - Will it be a residential site, commercial site, or industrial site in the future? Each land usage is assumed to have a certain load growth characteristics [4].

The land usage-based spatial load forecasting compute simulation has been used to aggregate appropriate geographic information to simulate future load growth based on different anticipated scenarios [3]. Spatial load forecasting techniques have been shown to provide superior results compared to other distribution load forecasting techniques such as regression analysis of historical distribution load data [2]. The increasingly popular, accrete, and affordable Geographic Information Systems (GIS) technology provides an excellent data base platform for spatial load forecasting techniques [5]. The use of GIS can help the utilities save thousands of man hours that are spent on collecting relevant geographic data. Thus spatial load forecasting becomes even more attractive than before due to affordable costs and superior load forecasting accuracy.

2. Spatial Load Forecasting Modeling

Load forecasting in power systems is an important subject and has been studied from different points of view in order to achieve better load forecasting results. Techniques such as regression analysis, expert systems, artificial neural networks and multi-objective evaluations have been used based on different choices of inputs and available information. Distribution system load forecasting has been a challenging problem due to its spatial diversity and sensitivities to land usage and customer habits. Different tools have been developed [6-8] to asset utilities to simulate and estimate the future land usage and load growth in their territory, so that distribution system planners can plan according to their goals and interests. Many factors need to be considered for this purpose. To name a few:

- What type of land usage will be in their territory in the future?
- What type of power consumption will be in their territory?
- Should they build new feeders and substations or reinforce the existing ones?
- Where should they plan the new lines and structures?

Among different distribution load forecasting techniques, the one based on spatial distribution of land usage has yielded one of the best performances [9].

There are a few stages for spatial load forecasting. The process, as shown in Figure 1, involves: (1) gathering appropriate spatial information, (2) deciding what the land usage will be based on the collected information, and (3) predicting the future load growth. The land usage and load growth are then calibrated based on different constraints imposed on the areas [5]. The constraints include system load growth, budget available, future economy growth of the area, etc.

Figure 1. Land-use based spatial load forecasting

In the present era of information technology, we can access much more information than a few years ago. Availability of high resolution and more variety of GIS data, improved compute speed and reduction in cost are all helpful to provide better accuracy in distribution load forecasting. However, we also face the information explosion problem, in which we have so much information that humans alone cannot handle the huge amount of data without help from other appropriate technologies. Different technologies such as fuzzy logic, neural networks, and distributed data base have been developed to manage the large amount of data available and to best utilize the information provided in the data. In general, the better we utilize relevant information, the better results will be. One of the immediate challenges is what type of technology is suitable for us to appropriately process the information to improve our applications.

As shown in Figure 1, land usage decision making is an important part for spatial distribution load forecasting. Conventional linear weighting on feature maps have been used in the spatial load forecasting programs to infer land usage decision [3].

3. Application of Fuzzy Logic in Spatial Model

Heuristic, intuition, expert knowledge, experience, and linguistic descriptions are often used by engineers in distribution planning. For example, industrial sites prefer to be very close to highways. Land usage-based spatial load forecasting simulation programs are basically a tool to provide information to users to help them make decisions for different scenarios. Most of the linguistic description such as close and prefer are fuzzy in nature. The conventional feature map approach does not capture linguistic and heuristic knowledge in an effective manner.

The increasing popular fuzzy logic technology has achieved impressive achievements in engineering applications such as decision and control [10-12]. The basic nature of spatial load forecasting fits well into a fuzzy logic application that includes using membership functions, fuzzy rules, fuzzification and defuzzification processes.

This paper proposes and describes the general methodology to use fuzzy logic to fuse the available information for spatial load forecasting. Since the accuracy of spatial load forecasting depends on many different factors such the inference engine technique used and the quality of human calibration process [3], it will be difficult to demonstrate the quantitative results from the fuzzy information gathering. The approach will be discussed in terms of ease of heuristic implementation and feature resolution. The proposed scheme can provide distribution planners other alternatives to aggregate their information for spatial load forecasting.

3.1. Fuzzy Sets/Membership functions and fuzzification

Linguistic terms used in our daily conversation can be easily captured by fuzzy sets for computer implementations.

Linguistic terms such as Close and Far are often used to describe distances. The distance from the highway is an important factor for many Byers to determine whether the site is suitable as a residential, commercial, or industrial site. Since the descriptions of many linguistic terms are relative, we need to define the range that the membership functions of the linguistic variable are to cover. The range is termed the universe of discourse of the membership function. The membership values of each function are usually normalized between 0 and 1, where 0 indicates non-member and 1 indicated full member of the membership function, respectively. Figure 2 shows the membership functions of three linguistic variables: ***Very Close, Moderate Close, and Far,*** used to describe the distance from the highway. For example, 0 and 2000 meters cannot be considered as moderately close because they both have 0 membership values in the moderately close membership function. 900 meters is really moderately close because it has full membership value for being moderately close. 200 meters has 0.66 membership value of being very close.

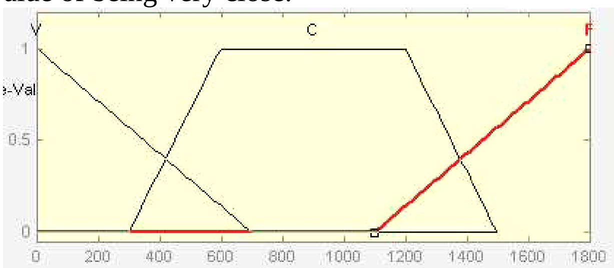

Figure 2. Distance membership functions.

Linguistic terms such as Strongly Against and Moderate Prefer is commonly used linguistic expressions in decision making processes. Assume that the level of preference is linearly mapped to [0,1], where 0 indicates absolutely against and 1 indicates absolutely prefer, then the corresponding universe of discourse is [0,1]. Fig 3 shows five membership functions that describe the different preferences: ***Strongly Against, Moderately Against, Neutral, Moderately Prefer, Strongly Prefer***. Again, the preference membership functions are normalized between [0,1]. A 0.2 preference value cannot be considered as moderately prefer (MP) because the corresponding membership value is 0. However, a 0.2 preference value can be considered moderately against because it has membership value 1 for the moderately against (MA) membership function.

Even though the choices of membership functions are subjective, there are some rules of thumb for membership function selection that can produce good results [13]. In general, we would like to choose the membership functions which overlap with other neighboring membership functions by 25-30%. In addition, we would like to select sensible membership values.

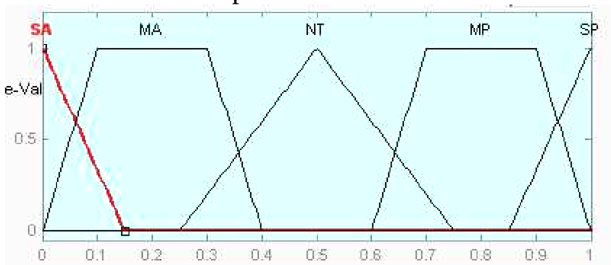

Figure 3. Prefernce Values

3.2. Fuzzy Rules

Heuristic and expert knowledge are often expressed linguistically in the form of IF-THEN rules. These rules can be extracted from common sense, intuitive knowledge, survey results, general principles and laws, and other means that reflect real-world situations. For example, the average home buyer generally prefers to buy a house that is close to highways for the convenience of commuting, yet not too close to highways in order to avoid the noises and air pollution generated by the traffic of the highways. The rules for selecting three various sites (residential, Commercial and Industry) with respect to distance to highway and also distance to urban pole are mentioned in tables 1-3 as follow:

Table 1: FAM matrix for residential site

Highway / Urban Pole	V	C	F
V	SA	MA	MA
C	SA	SP	MA
F	SA	MP	SA

Table 2: FAM matrix for Commercial site

Highway / Urban Pole	V	C	F
V	SP	SP	MP
C	MP	MP	MA
F	MP	NT	SA

Table 3: FAM matrix for Industrial site

Highway / Urban Pole	V	C	F
V	NT	MA	SA
C	MP	NT	SA
F	SP	NT	SA

3.3. Fuzzification, Inference, and Defuzzification method

After describing the problem in linguistic terms using membership functions and fuzzy rules, we can use fuzzy logic operations to compute and infer decisions. However, the actual measurement, such as 5 miles from the highway, in the physical world is usually in quantitative units rather than in linguistic form. We need to convert the 200 meters into linguistic terms such as very close in order to use the fuzzy inference techniques. The process to convert the actual numerical value (crisp) to its membership value (fuzzy) through membership functions is usually called the *fuzzification process*. For example, based on the membership functions in Figure 2, if the measured distance is 1200 meters, then we will say that the distance has 0 membership value for very close and cannot be considered very close at all. The distance has membership value 1 for moderately close; therefore, the distance is really moderately close. The distance has 0.2 membership value for far, therefore we can kind of consider the distance far, but not quite. These membership values will later be used in the fuzzy rule inference process.

After the fuzzy inference process, the results will be in membership units. There may be situations where the output of a fuzzy process needs to be a single scalar quantity as opposed to a fuzzy set. For example, the fuzzy rule inference based on different fuzzy rules may result in 0.7 strongly prefer, 0.5 moderate against, and 0.2 strongly against. We only want to know whether we should accept or reject the decision, which is a crisp decision. Therefore, a *defuzzification process* is used to convert the fuzzy value back to the actual scrip output value for the final decision making. Many different defuzzification methods have been proposed and used [12]. The centroid rule is one of the most popular defuzzification techniques and will be the one used in this paper.

The centroid rule approach can compromise and/or resolve the conflicts or inconsistencies of the different preferences of decision making. Therefore, the decision is not only based on some specific points of the membership curves but on the entire membership functions under consideration. Let the output described by membership function μ(p). The crisp value p* representing the membership function can be described by the centroid method shown in Eqn.(1)

$$p^* = \frac{\int \mu(p).pdp}{\int \mu(p)dp} \qquad (1)$$

Where $\int$ denotes an algebraic integration.

Eqn.(1) has been used to compute the center of gravity of a volume mass in different engineering areas. The center of gravity is then used as a point mass to represent the volume mass in mechanical system calculation for simplicity for simplicity and is often a good approximation. Similarly, p* is used as the crisp output representing the membership function μ(p). The centroid method is the most prevalent and physically appealing of all the defuzzification methods. The whole process is shown in figure (4) as follow:

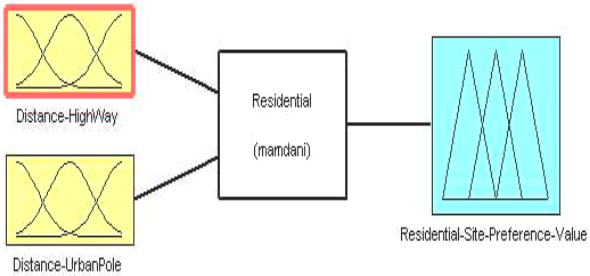

Figure 4. Fuzzy Inference Engine

4. Results

In this paper, we choose one of the North-Eastern cities in IRAN, Ghaen which is under developing according an infrastructure. Figure 5 shows satellite photo of city and we choose a typical area with a radius about 1 kilometer for our simulation which is shown in figure 6. The area is divided into 9*9 grids and there is a highway construction project and also an urban pole project which are shown in plot. All distances of each grid respect to these two projects are measured and are indicated as input to our fuzzy model. Results are gotten from defuzzification system and are indicted as a preference value for each utilization site. Surface of such a preference values are shown in figures 7-9.

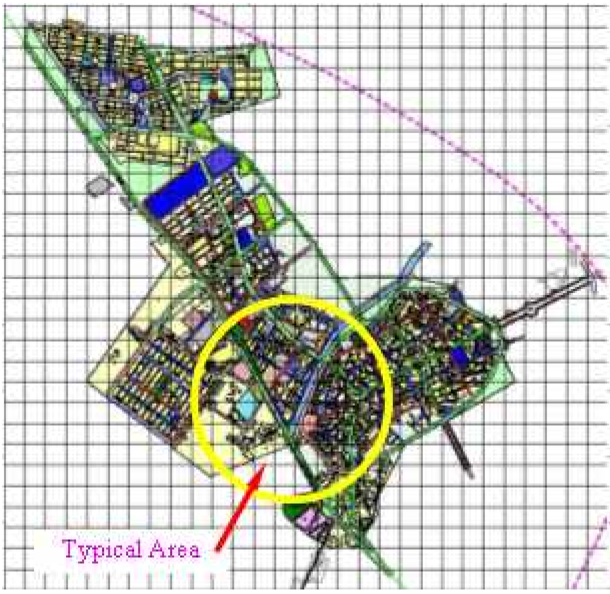

Figure 5. Satellite photo of Ghaen City

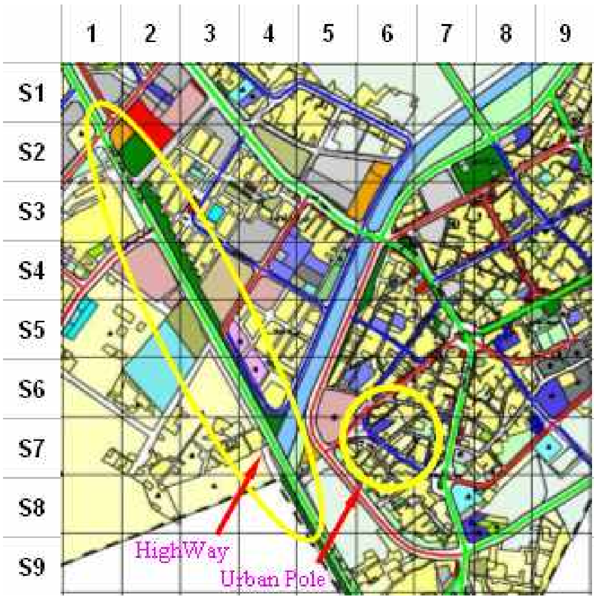

Figure 6. Typical area of simulation

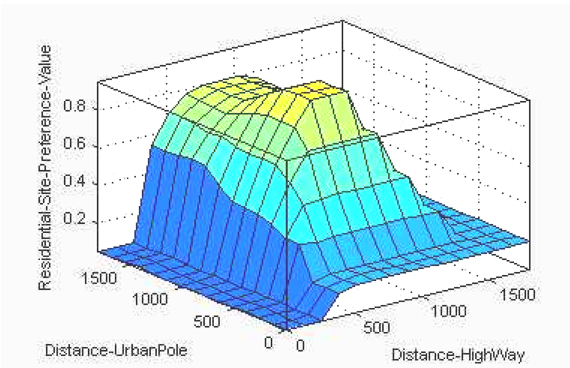

Figure 7. Residential preference value surface

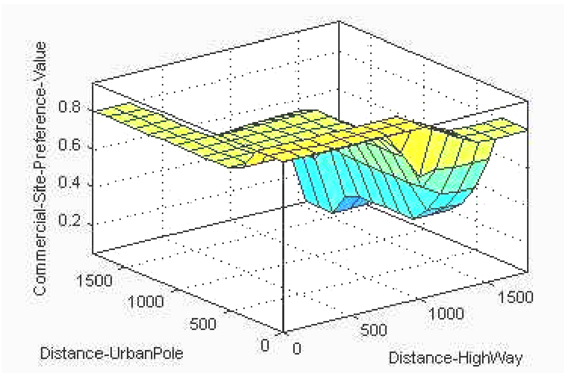

Figure 8. Commercial preference value surface

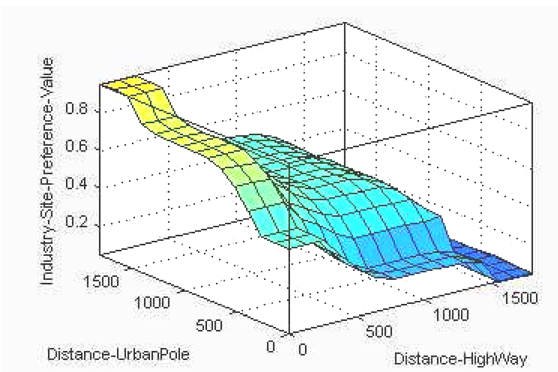

Figure 9. Industry preference value surface

Load growths of future years for 3 utilizations are shown in figures 10 to 13 in gray scale meshes. Black grids are respected to high preference and high load growth and white grids are respected to low preference and low load growth. As it is shown for example in figure 10, residential load growth along the highway and also very near to urban pole is too low.

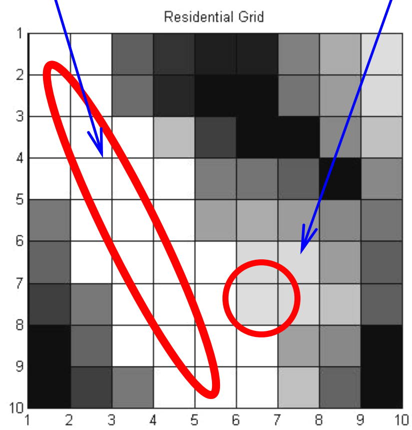

Figure 10. Residential Grid

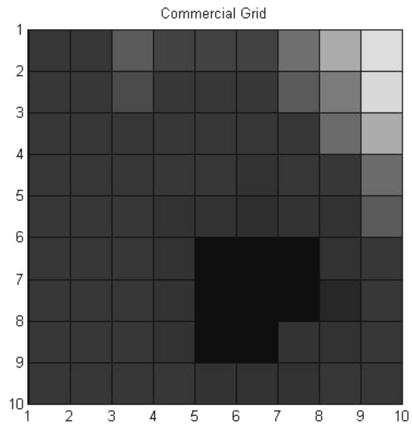

Figure 11. Commercial Grid

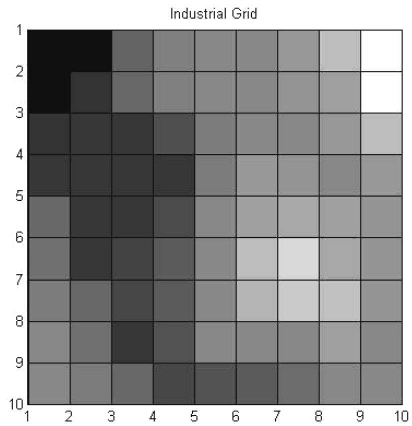

Figure 12. Industrial Grid

5. Discussion

The fuzzy rule approach is designed to closely describe to input-output relationship of the actual problem by using linguistic terms. The relationship can have significant interactions and nonlinearities. In the fuzzy logic approach, distance is described by three membership functions, and preference is described by five membership functions. Their relationship is systematically described by the fuzzy rule (FAM table in our case).

Fuzzy logic membership functions and fuzzy rules are designed to provide a simple technique to directly implement experience and intuition into a computer program. The membership functions and fuzzy rules in the fuzzy logic formulation provide an intuitive and straightforward manner to include heuristics into the spatial load forecasting land selection criteria. Fewer mistakes can be made.

In the fuzzy logic approach, the preference calculation is based on the entire profile of the membership functions rather than base on point values. This approach is much closer to people's decision making process in real life that we consider the preference around the environments before making final decision.

Fuzzy logic information fusion separates the information fusion step into membership functions and fuzzy rules. Three linguistic variables have been used to describe distance and five linguistic variables have been used to describe preference. In order to further increase the performance resolution of the fuzzy logic approach, more linguistic variables can be introduced. Note that the increase in linguistic variables used will also increase the dimension and complexity of the problem.

6. Conclusion

This paper has proposed and described the general methodology to use fuzzy logic to fuse the available information for spatial distribution load forecasting. The approach has been discussed in terms of ease of heuristic implementation and feature resolution. The proposed scheme can provide distribution planners other alternatives to aggregate their information for spatial load forecasting.

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References

[1] H. Lee Willis, Hahn Tram, "Distribution Load Forecasting, IEEE Tutorial on Power Distribution Planning, EH0361-6-PWR, 1992.

[2] H. Lee Willis, J.E.D. Northcote-Green, "Comparison Tests of Fourteen Distribution Load Forecasting Methods," IEEE Transactions on Power Apparatus and Systems, Vol. PAS-103, No.6, June 1984, pp.1190-1197.

[3] H. Lee Willis, Michael V. Engel, Michael J. Buri, "Spatial Load Forecasting," IEEE Computer Applications in Power, April 1995, p.40-43.

[4] H. L. Willis, R. W. Powell, H.N. Tram, "Computerized Methods for Analysis of Impact of Demand Side Management on Distribution Systems," IEEE Transactions on Power Delivery, October 1987, p.1236.

[5] Understanding GIS, ESRI, 1992.

[6] H. Lee Willis, Hahn Tram, "Distribution Load Forcasting," IEEE Tutorial on Power Distribution Planning, EH0361-6-PWR, 1992.

[7] Hesham K. Terraz, Victor H. Quintana, "Analytic spatial electric load forecasting methods: a survey," Canada Journal of Electrical and Computer Engineering, Vol. 17, No. 1, 1992, pp. 24-42.

[8] H. Lee. Willis, J.E.D. Northcote-Green, "Comparison Tests of Fourteen Distribution Load Forecasting Methods, "IEEE Transactions on Power Apparatus and Systems, vol. PAS-103, No. 6, June 1984, pp. 1190-1197.

[9] H.L. Willis, H.N. Tram, G.B. Rackliffe, "Short-Range Load Forecasting for Distribution System Planning-An Improved Method for Extrapolating Feeder Load Growth," IEEE Transactions on Power Systems, Vol. 7, No. 3, August 1992, pp. 1306-1312.

[10] Mo-yuen Chow, Fuzzy System, CRC Press Industrial Electronics Handbook, 1996.

[11] Robert N. Sharpe, Mo-yuen Chow, Steve Briggs, and Larry Windingland, "A Mehtodology Using Fuzzy Logic to Optimize Feedforward Artificial Neural Network Configurations, IEEE Transactions on System, Man, and Cybernetics, vol. 24, no.5, pp. 760-768, May, 1994.

[12] Timothy J. Ross, Fuzzy Logic with Engineering Applications, McGraw Hill, 1995.

[13] B. Kosko, Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence, Prentice Hall, 1992.