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Smart Grid Knowledge Representation and Reasoning Based on Adaptive Neuro-Fuzzy Inference System

Sang-Hyun Lee [1], Sang-Joon Lee [2] and Kyung-Il Moon [1]

[1] *Dept. of Computer Engineering, Honam University, Korea,*
[2] *School of Business Administration, Chonnam National University, Korea*
{leesang64, kimoon}@honam.ac.kr, s-lee@chonnam.ac.kr

Abstract

Several models have been created for Smart Grid resource-allocation problem. The principal purpose of the models is to connect power sources with appropriate sinks when considering the input parameters of power balance and consumption size, etc. Fuzzy logic is representative of these models. When creating the fuzzy model, the parameters and rule construction play the most significant role. For the fuzzy Logic model, the rule base has been constructed considering the operator's general knowledge, the operator's activity and the experience. However, the fuzzy model did not have any clear boundary for the price, power, and distance values, so the model output was largely dependent on the contributions from individual portions. This paper introduces an Adaptive Neuro Fuzzy Inference System (ANFIS) approach to the smart grid problem. Learning is another attribute that can be incorporated into the current model. ANFIS is one way that the current model can be extended to. In ANFIS, the learning is done with the incorporation of a neural network. The Fuzzy system is trained over time to become self-adaptive. Once the training is complete, the system is capable of making intelligent changes based on a neural network. As a result, ANFIS has a distinct boundary for each segment. Hence, a little change along the boundary value pushed the value into the next segment.

Keywords: *Fuzzy logic, ANFIS, Smart grid*

1. Introduction

Ranganathan and Nygard formed a resource-allocation model for a smart grid in a binary integer programming concept [3]. The model can assign Distributed Energy Resources to available Regional Utility Areas or units that are experiencing power shortages. This approach is called capacity-based Iterative Binary Integer Linear Programming. All simulation results are computed using the optimization tool box in MATLAB. The results showed that the optimal value was reached after 163 iterations with 54 nodes participating in 1.22 seconds when using the capacity based Iterative Binary Integer Linear Programming based branch and bound method which maximizes the satisfaction of the DER preferences weighted by the model capacities. For another case, when the preferences of DERs were changed, then the optimal solution was reached with 13 iterations and 0.047 seconds with default node and branch strategies.

Today, with the increasing demand for electricity and the expanding scale of the power grid, smart grid fuzzy knowledge representation and reasoning method is particularly important. In the study of knowledge, the distinction of knowledge representation and processing is the foundation of the knowledge based processing. Some researchers have proposed medium logic research ideas and methods on the issue of representation and

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processing of uncertain knowledge and it's negative. The medium logic system distinguishes clear knowledge and fuzzy knowledge, and distinguishes the fuzzy privative relationship and opposition privative relationship of knowledge [1]. This theory has important implications for the construction of smart grid information platform. But, the predicate calculus proposition to represent the guidelines is not clear, and the characteristics of the parameter cannot be sure that have certain similarities in some degrees with the threshold value.

The current work automates the operator's decision making. Routing decisions are made by this study. The solution incorporates the self-healing characteristic of the smart grid. The decision comes in the form of picking the best power source for a particular demand area, so the model is capable of making the routing decisions about which source to connect with which sink or demand area. These decisions are made both by fuzzy Logic and neural network model. For developing both the models, the initial assumption is to have power sources with an adequate supply. Hence, the supply side always needs a higher amount of power than the demand side. Another assumption is that there should be always existed at least one electric transmission route between the region of interest and the power supply sources. The model picks the best power source to connect to a particular sink based on predefined parameters. Based on ANFIS (Adaptive Neuro-Fuzzy Inference System) [4, 9], this paper explore fuzzy knowledge and its negative representation and reasoning by a specific example of power transmission and distribution.

2. Fuzzy Logic and ANFIS Architecture

The smart grid fuzzy controller is capable of making automated decisions for resource allocation. It takes some predefined inputs, and then based on the given parameters it picks the best source to connect with a sink. First, the fuzzy variables are identified. In the smart grid model, the power capacity of source, the price to generate unit power and distance between the source-sink are considered as inputs for the fuzzy model. These three parameters are named as power, price and distance [2, 5]. After that, the membership functions are constructed. The power capacity is the first input parameter. The power of the source has been divided into three categories: Low, Normal and Big. The low power value starts at 0 and goes all the way up to 500 units; beginning at 300 units, it starts to overlap with normal. Similarly, the normal starts at 300 and overlaps with big at 500 units. After 700 units, all the values are considered as big. The unit of power is megawatts (MW) but the unit can be assigned as something else, too. All the input values of power are fuzzified using the membership function in the range of [0 1].

The price of power generation is the second variable and is also divided into three categories: Low, Normal and big. The low value starts at 0 and goes all the way to 6 units; beginning at 3 units, it starts to overlap with normal. Similarly, the normal starts at 3 and overlaps with big at 6 units. After 9 units, all values are considered big. The unit is dollars/day. All the input values of power are fuzzified using this function in the range of [0 1]. The last Fuzzy variable is the distance between source and sink. It is also divided into three categories: low, Normal and Big. The low value starts at 0 and goes to 5 units; beginning at 3 units, it starts to overlap with normal. Similarly, the normal starts at 3 and overlaps with big at 5 units. After 10 units, all the values are considered big. The unit is miles. All the input values of power are fuzzified using this function in the range of 0-1. We want to give priority to the source which is closer to the demand area, so a lower distance will get more priority.

The initial membership functions and rules for the FIS are designed by employing smart grid knowledge about the target system to be exploited. The ANFIS can then refine the fuzzy 'if-then' rules and membership functions to describe the input/output behavior of a complex system. In practical applications Sugeno type FISs have been considered more suitable for constructing fuzzy models due to their more compact and computationally-efficient representation of data than the Mamdani fuzzy systems. A typical zero-order Sugeno fuzzy system has the form: If power balance is A and actual consumption is B then level = c, where A and B are fuzzy sets and level is a crisply defined function.

3. Fuzzy Knowledge Representation of Smart Grid

Set the amount of electricity of the region is m, actual consumption is n, and power balance is t = n/m, then the monitoring level division depends on t, n according to the following rules:

Rule1: If t is small, whatever the actual output m and actual consumption are, we recognize it as a good level.

Rule2: If t is close to zero and n is low, we recognize it as normal.

Rule3: If t is close to zero and n is high, it is the critical degree, and we regard it as a control level, which means manual supervision is required.

Rule4: If t is close to one, we regard it as warning level. This means artificial debugging and maintenance treatment is strongly recommended.

In fuzzy reasoning systems, there are several different classes of hedge operators. There are hedges that intensify the characteristics of fuzzy set (very, extremely), that dilute the membership curve (somewhat, rather, quite) or that form the complement of a set (not). There are other types that approximate fuzzy region (about, near, close). Hedges can be combined with each other (not very high). Suppose that Takagi-Sugeno fuzzy system has two inputs, balance and consumption, and one output level. Linguistic labels are small, normal and big. If-then rules:

Rule1: if balance is very small then good=a_1·balance+b_1·consumption+c_1

Rule2: if balance is very small and consumption is more or less small or very small then normal=a_2·balance+b_2·consumption+c_2

Rule3: if balance is more or less small and consumption is more or less big then critical=a_3·balance+b_3·consumption+c_3

Rule4: if balance is more or less big then warning=a_4·balance+b_4·consumption+c_4

The outputs of layer1 are fuzzy membership grade of inputs. If the gauss membership function is taken, the fuzzy set (very small) of input variable balance is

$$\mu(balance) = \left(\exp\left[-\frac{(\alpha - balance)^2}{2\sigma^2}\right]\right)^2$$

Here α and σ are the center and width of the fuzzy set Small. Also, the fuzzy set (more or less small) is given by

$$\mu(balance) = \left(\exp\left[-\frac{(\alpha - balance)^2}{2\sigma^2}\right]\right)^{1/2}$$

For β(>0), there is a s(>1) such as $2\sigma^2=(s-1)/\beta$, and $g(x)=\exp(-x/\sigma^2)$ in terms of β and s is

$$g(x) = [\exp(\ \beta x)]^{1/(1-s)}$$

Also, for β>0, there is s (<1) such as $2\sigma^2=(s-1)/\beta$. Thus, g(x) in terms of β and s is

$$g(x) = [\exp(\ -\beta x)]^{1/(1-s)}$$

g(x) can be denoted as a monotone generating function $g_0(x)$. For every s>1, using a linear generating function $g_0(x) = x$, $g(x) = x^{1/(1-s)} \Leftrightarrow \mu(x) = g(x^2) = x^{2/(1-s)}$

Every node in layer2 is a fixed node. The output nodes can be presented as μ(balance)*μ(consumption), where * denotes T-norm. Nodes is marked by a circle and labeled Π. Using a linear generating function $g_0(x) = x+1$, $\mu_k = \prod_{i=1}^{2} [(\alpha_{ij} - x_i)^2 + 1]^{1/(1-s)}$

Here x_1 is input variable balance, and x_2 is input variable consumption. The membership function having the linear generating function has only an adjustable factor α_{ij} for a suitable s.

The output of layer3 can be presented as $\bar{u}_i = u_i / (\mu_1 + \mu_2)$

The outputs of layer 4 are given by $\bar{u}_i f_i = \bar{u}_i \left(\sum_{j=1}^{3} a_{ij} x_j + c_i \right)$

Finally, the output of layer5 can be presented as $level = \sum_{i=1}^{2} \bar{u}_i f_i = \left\{ \sum_{i=1}^{2} u_i \left(\sum_{j=1}^{3} a_{ij} x_j + c_i \right) \right\} / \sum_{i=1}^{2} u_i$

The hybrid learning algorithm is used for updating the parameters [8].

4. Application

We use 5 years data in 4 regions by Wang, *etc.*, [7]. The assumptions are divided into a, b, c, d four regions, and consumption magnitude is calculated by using low power generation. To comprehensive analysis survey data in the same area over the years, we can average them respectively. There are two fuzzy variables and for each variable, there are seven different outcomes. The used rules are 19 of the total rules. The outcome of the rules is considered in terms of decision level. This linguistic outcome clearly captured the notion of the input. The output with a good level would generally be preferred over more or less low or very low. Figure 1 denotes an ANFIS structure corresponding to these rules, and Figure 2 represents a decision making surface.

Table 1 denotes city power distribution results. Consumption size is calculated as weighted ratio (reflecting the distance among regions) between actual consumption in high power generation and actual consumption in low power generation. Consumption of region c is the highest, and all regions represents warning level. They need to lower the power balances below 0.6.

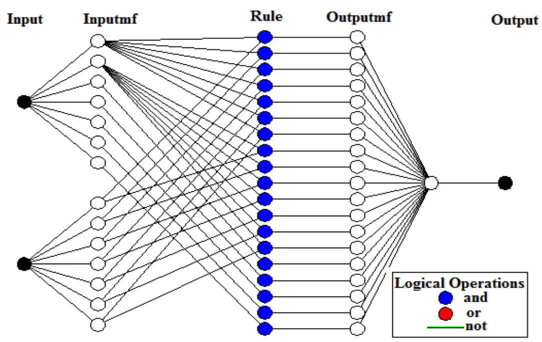

Figure 1. ANFIS Structure of Smart Grid

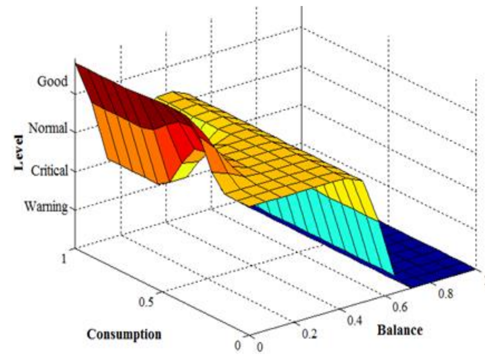

Figure 2. Decision Making Surface

Table 1. City Power Distribution Results

region	Power balance	Consumption size	level
A	0.7067	0.8411	Warning
B	0.6475	0.9696	Warning
C	0.6807	1.0439	Warning
D	0.7433	0.8436	Warning

5. Conclusion

It can be learned that both of the Fuzzy and ANFIS model can be applied in the smart grid decision-making. Both the Fuzzy and the ANFIS models are fast in computation, so they can be used to filter out the best source-sink combination when a decision is crucial in terms of time. This kind of situations may arise when a sudden power failure has occurred due to a bad weather or any other unanticipated occurrences. The model would pick the best solution quickly in those situations. In particular, ANFIS provides some specific boundaries. Boundary-value analysis is an approach that can be used to test any model. The idea of boundary-value analysis is to check if there has been any unexpected change in the output if the input values were changed close to the boundary. In Fuzzy Logic, the concept of a boundary is fluid, and it does not have any clear boundary. These models can also be applied in a distributed fashion because both the Fuzzy and ANFIS models are extremely scalable. In this way, the models can incorporate self-healing characteristic in the grid function. The time complexity is also in polynomial order compared to other mathematical models that generally have exponential-order complexity. Also, the models were straight forward and easy to implement.

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Authors

Sang- Hyun Lee, he received the BS and MS in Department of Computer Engineering from Honam University in 2002 and 2004, respectively. He received Ph.D. degrees in Computer Science from Chonnam National University in 2009. He has been a professor at Honam University since 2012. His research interests include artificial intelligence, Software Engineering, Early Warning System, claim analysis, intelligence automotive

Sang-Joon Lee, he received the BS, MS and Ph.D. degrees in Computer Science and Statistics from Chonnam National University. He was assistant professor in Seonam University and Shingyeong University. Since 2007, He has been with Chonnam National Univ. as an associate professor in the School of Business Administration. His research interests include MIS, SE, IT Service and Ubiquitous Business.

Kyung-li Moon, he is a professor at the Department of Computer Engineering, Honam University in Gwang-Ju, Korea. His theoretical work began at Seoul University as a statistical computing scientist, and then expanded into complexity science, chaos theory, and cognitive science generative sciences.

