Annals of Electrical and Electronic Engineering, 2(7) 2019, Pages: 11-15

Published by IASE

Annals of Electrical and Electronic Engineering

Journal homepage: www.aeeej.org

The effect of different membership functions in power load flow

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ARTICLE INFO

Article history:
Received 5 February 2019
Received in revised form
10 June 2019
Accepted 14 June 2019

Keywords:
Power flow
Fuzzy logic
Generator
Terminal
Performance

ABSTRACT

Power load flow is one of the most important subjects in the electrical engineering field. There are several methods for this purpose. A fuzzy concept is one of the new and efficient tools in many applications. In last decade's fuzzy logic have vastly applied in control systems, pattern recognition problems, prediction problems, noise cancellation, function approximation, and many other problems. The fuzzy logic tools have excellent capabilities in function approximation and solving of nonlinear problems. Therefore, in this study application of fuzzy logic tools have been proposed for the power flow solution. There are some methods and algorithms for power flow solution, such as the Newton method. But these methods and algorithms are very sensitive to initial solutions of a problem. Therefore the algorithm simply traps to local minima. For evaluating the proposed intelligent method, the one real-world power system is applied. The mentioned power system has ten generators and thirty-nine terminals. The obtained results show that the proposed hybrid system has good performance and capability in solving of a power flow problem.

1. Introduction

With increasing the demand of electrical energy, the power networks become bigger and more complicated. The electrical energy is the best type of energy that has no pollution. In new and modern electrical power networks, the number of generators, transformers, breakers, loads, compensators, FACTS devices and other power devices are very plenty.

The other studies about power system are based on power flow problem. After power flow solution, the current of transmission lines, the amplitude of terminal voltages, the angle of terminal voltages and power transmission is achieved. By computing the power flow for one case study system, the normal and steady state situation are achieved (Rao and Kumar, 2015; Abdelouadoud et al., 2015; Kamel et al., 2015).

The classical and traditional power flow methods, such as Newton method, are based on initial solution and the repetitive process to achieve the satisfying solution. With development of computers in last decades, the application of these tools is vastly used in many areas. The computers have high calculation speed and excellent sensitivity to detailed problems. Therefore many time consuming algorithms become applicable for usage in many areas by aid of new computers. One of the most effective and efficient concepts in artificial intelligence is artificial neural networks or neural networks. This concept is inspired from human neural system. Like human neural system, artificial neural networks try to train the one special issue.

The artificial neural networks have many application s in much area such as control systems, pattern recognition problems, prediction problems, noise cancellation, function approximation and many other problems. The artificial neural networks have excellent capabilities in function approximation and solving of nonlinear problems (Wen et al. 2015; Kokkinos and Margaritis, 2015; Zhao et al., 2015). The artificial neural networks have simple structure and training algorithm. The artificial neural networks have some types such as radial basis function neural networks (RBFNN), multi-layer neural networks (MLPNN), probabilistic neural networks (PNN), concurrent neural networks, recursive neural networks, adaptive neural networks and Elman neural networks. Each of these types of artificial neural networks has its special features and capabilities. For example MLPNN has good features in pattern recognition and classification problems. The Elman neural networks have high capability in dynamic problems. The PNN has good features in forecasting problems. Based on published literature, it can be seen that the RBFNN has good characters in function approximation and nonlinear problem solution.

In last decades, the artificial neural networks vastly applied for power network problems. For example, the artificial neural networks have been applied successfully in power network security improvement. Also artificial neural networks are applied in FACTS device control problems. For example, artificial neural networks can be used as controller to control the fire angle of SVC, STATCOM, UPFC and other power electronic devices (Modi et al., 2007; Al-Masri et al., 2015; Gomes and Medeiros, 2015; Yap et al., 2014; Xiong et al., 2013). Also artificial neural networks can be applied as classifier for power network fault detection. The artificial neural networks have been successfully applied for induction motor fault detection. Aloui et al. (2013) method is applied for underground cables fault detection. Also ANFIS is one of the most new concepts in artificial intelligence field that has many applications in several areas (Zhu and Wu, 2014; Chen et al., 2013; Liu et al., 2015).

The power flow problem is complicated and multi modal problem. Therefore it is essential to have powerful and effective method to solve this problem. As mentioned in this paper we proposed the application of ANFIS for power flow solution. For this purpose the applied ANFIS must have simplest and optimized structure to have good calculation time. In ANFIS the radii parameter has high effect on its performance. Therefore in this study, the value of this parameter is selected after extensive simulations.

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https://doi.org/10.21833/AEEE.2019.07.003

2. ANFIS

The ANFIS is one of the most effective and powerful types of fuzzy controller. This type of fuzzy controller has five layer structures. The main schematic of fuzzy is illustrated in Fig. 1. Similar to other machine learning tools, ANFIS needs to train data to learn the specific problem. ANFIS has excellent features in function approximation, pattern recognition, classification, fault detection, chaotic signals prediction and many other applications.

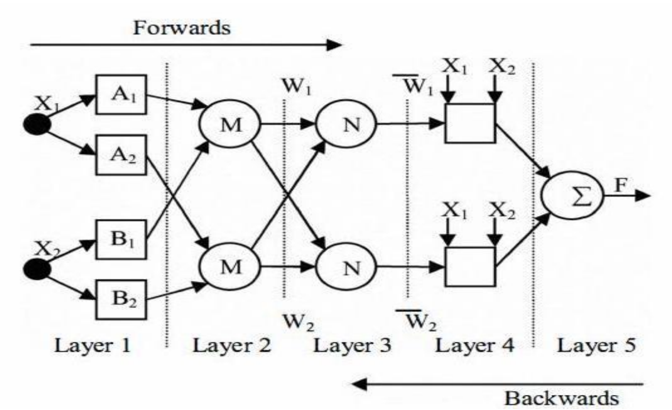

Fig. 1. ANFIS schematic.

In ANFSI, the type of membership function has vital role in its performance. In this study the following membership functions are considered. In the following lines, the mathematical formulation and shape of different membership functions are illustrated.

2.1. Sigmoid membership functions

This type of membership functions has two free parameters. The mathematical representation of this membership functions is shown by Eq. 1. The two free parameters have high effect on performance of final fuzzy system. Also in Fig. 2, the plot of this membership function is illustrated.

$$f(x; a, c) = \frac{1}{1+e^{-a(x-c)}} \qquad (1)$$

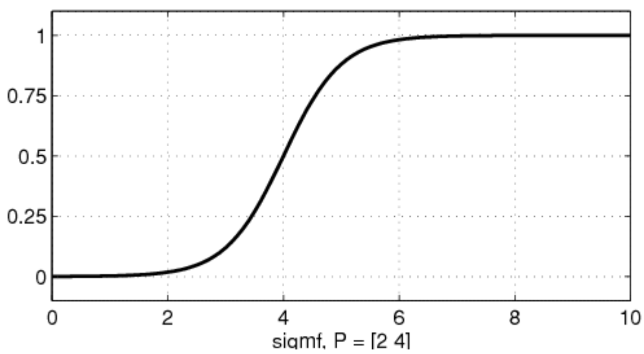

Fig. 2. Sigmoid membership function.

2.2. Gaussian membership function

Like sigmoid membership functions, Gaussian membership function has two free parameters, too. The mathematical representation of this membership functions is shown by Eq. 2. The two free parameters have high effect on performance of final fuzzy system. Also, in Fig. 3, the plot of this membership function is illustrated.

$$f(x; \sigma, c) = \frac{(x-c)^2}{2\sigma^2} \qquad (2)$$

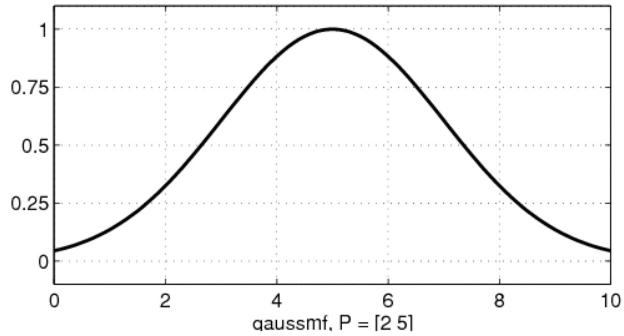

Fig. 3. Gaussian membership function.

2.3. Bell shape membership function

The shape of this membership function is like bell. In this membership function, there are three free parameters. In Fig. 4, the plot of this membership function is shown. It can be seen that this type of membership function is similar to Gaussian membership function. The Eq. 3 represents the mathematical formulation of bell membership function.

Also, in this paper we used some other membership function like π-Shape membership function, S-Shape membership function, Trapezoidal-shaped built-in membership function, Triangular-shaped built-in membership function and Z-shape membership function. More details regarding these membership functions can be found in Buragohain and Mahanta (2008).

$$f(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \qquad (3)$$

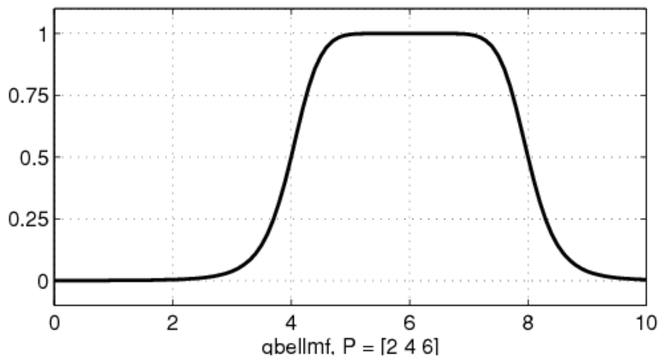

Fig. 4. Bell shape membership function.

3. Proposed method

The proposed method to solve the power flow in power network is presented in this section. The proposed intelligent method is applied in real world standard system. The test system contains ten generator node and thirty nine terminals. The mentioned power network is located in England. The proposed method can be used for any power network system in each country. The main scheme of test system is shown in Fig. 5.

The ANFIS has excellent features in function approximations. In the proposed intelligent method, the target of ANFIS is to approximate the power network operation. In the proposed method, we used the power networks operating situations as input of ANFIS. The output of the ANFIS is the power flow results. In each approximation problem, the input variables must be selected cleverly. For this purpose, the extracting the satisfying collection of input parameters is performed. This process is done as follow.

In each power network system, one node usually selected as slack terminal. In the studied case, the first node or terminal 1 is selected as slack terminal. In computing process, the amplitude of voltage for this terminal is fixed in 1. Also the angle of voltage for this terminal is clear parameter. Also the other terminals that are generator or machine nodes, the value of active and reactive power is known parameter. These nodes are known as PV buses. Other remaining nodes are known as PQ terminals. It can be seen that in terminal 25, one compensating capacitor is installed. This terminal is considered as PV bus. For simplicity, some conditions are considered. These conditions are as follow:

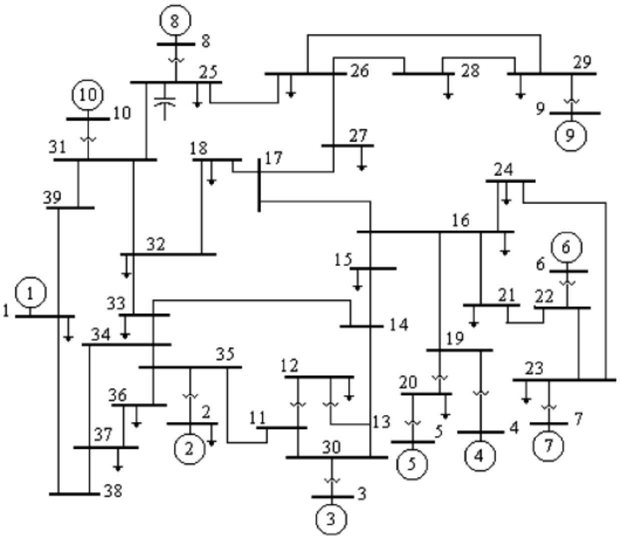

Fig. 5. The main scheme of test system.

a. The amplitude of voltage in PV terminals is called$V_n$and$n = 2,3,\ldots\ldots,10$.
b. The real power in generator terminals is called$PG_n$and$n = 2,3,\ldots\ldots,10$.
c. The magnitude of real power in load terminals is called$PD_n$and$n = 1,2,\ldots\ldots,39$.
d. The magnitude of reactive power in load terminals is called$QD_n$and$n = 1,2,\ldots\ldots,39$.
e. The magnitude of reactive power in compensating terminal (terminal 25) is calledQ_c.

With considering all the above mentioned parameters, we have fifty nine power network operating situation. The target of the proposed method in this paper is to approximate the relation function between the inputs and outputs by ANFIS. In the proposed method, the output will be achieved by one ANFIS. The main scheme of the proposed method is illustrated in Fig. 6.

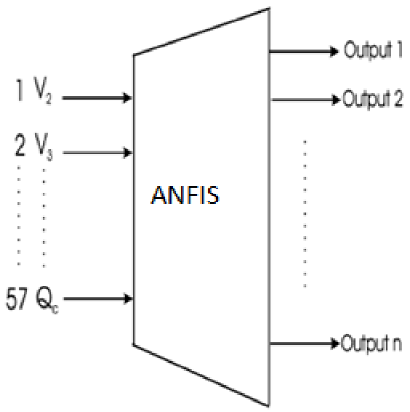

Fig 6. The main scheme of the proposed method.

From Fig. 6, it can be seen that the inputs variables are: $V_2, V_3, \ldots\ldots, Q_c$. It can be seen that we have fifty seven input variables. The inputs are voltage of nodes, the active and reactive of PV terminals and reactive power of compensator. The outputs are real and reactive power magnitudes in generator terminals, the real and reactive power value in slack node and the voltage amplitude in load terminals. With summing these parameters, it can be seen that we have seventy eight output parameters. The main step in neural network application in each problem is the training phase. For training we need to training data. The training data is achieved with simulating the test system. After training phase, the ANFIS is ready to use in real world system. The training phase may take some computing time, but after training, the operating of trained network is very fast. The input parameters for each condition can be achieved from control room. The main steps for achieving the input parameters are as follow:

Step 1) the boundaries for produced reactive power is fixed to [-0.2, 0.7].
Step 2) all simulation and calculations are based on following assumptions:

1. The value of voltage in nine generator terminals is varying independently.
2. The value of real power in nine generator terminals is varying independently.
3. The real and reactive power magnitude in all load terminals is varying independently.
4. The compensator bus, generate reactive power, independently.
5. The boundaries for voltage changes in PV terminals are [0.9, 1.1].
6. The boundaries for other operating situations can be changed in [0.6, 1.1].

Step 3) for each of variables that mentioned in previous step, an accidently value is assigned.
Step 4) the produced data from above procedure, the ANFIS can be trained. In each step, the all terms and conditions must be checked carefully.

4. Simulation results

In this section, the performance of proposed method is evaluated. As mentioned before, for this purpose we used real world standard power network system. This power network is placed in England and has ten generator terminals and thirty nine load nodes. The test system is simulated in four hundred different situations. This data set is used for training and testing the proposed method. The 75% of this data set is used for training the neural network and the 25% is used for testing the proposed method. For simplicity, the collected data set is normalized between [0, 1]. Based on the ANFIS training procedure, the input data is clustered. In this method, subtractive clustering algorithm is applied for clustering.

In ANFIS, the number of clusters and radii has high effects on the system accuracy. Therefore these parameters are selected based on vast experiments and simulations. The mean square error (MSE) criterion is chosen as fitness function. Eq. 4 shows the MSE mathematical formulation:

$$MSE = \sum_{i=1}^{n} (RBFNN_{output} - TARGET)^2 \quad (4)$$

The obtained results are shown in Table 1. In this experiment, effect of radii is investigated. For this purpose we used Gaussian membership function. It can be seen that radii has high effect on ANFIS performance. Therefore this parameter must be selected carefully. In Fig. 7, the effect of radii is illustrated. The best cluster number is 0.4. It is clear that there is no linear relation between MSE and radii value.

The obtained results with different membership functions are listed in Table 2. It can be seen that Gaussian membership function led to best results among other systems. In this experiment we used Mamdani fuzzy inference system. The parameters of ANFIS are selected based on trial and error method. In second experiment, we used Sugeno motor. The obtained results are listed in Table 3. It is clear that the first system has better performance.

Table 1
The obtained result or proposed method with different radii values.

Run	Radii	MSE
1	0.1	0.0003
2	0.2	0.0004
3	0.3	0.0009
4	**0.4**	**0.0002**
5	0.5	0.0007
6	0.6	0.0004
7	0.7	0.0006
8	0.8	0.0009
9	0.9	0.0006
10	1	0.0005

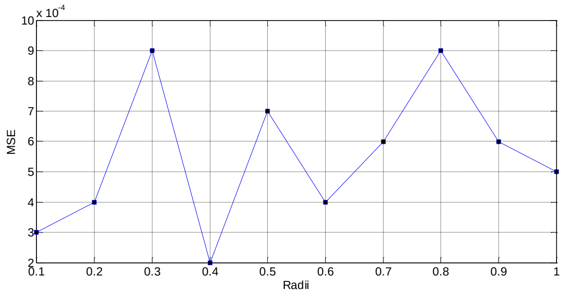

Fig. 7. The effect of radii on MSE.

Table 2
Results with Mamdani motor.

Row	Membership function	Parameters	Motor	MSE
1	Sigmoid	$a = 2, c = 4$	Mamdani	0.0065
2	**Gaussian**	$\boldsymbol{\sigma_1 = 2, c_1 = 5}$	**Mamdani**	**0.0002**
3	Bell	$a = 2, b = 4, c = 6$	Mamdani	0.0009
4	π	$a = 1, b = 4, c = 5, d = 10$	Mamdani	0.0028
5	S	$a = 1, b = 8$	Mamdani	0.0019
6	Trapezoidal	$a = 1, b = 5, c = 7, d = 8$	Mamdani	0.0016
7	Triangular	$a = 3, b = 6, c = 9$	Mamdani	0.0007
8	Z	$a = 2, b = 5$	Mamdani	0.0076

Table 3
Obtained results with Sugeno motor.

Row	Membership function	Parameters	Motor	MSE
1	Sigmoid	$a = 2, c = 4$	Sugeno	0.0012
2	**Gaussian**	$\boldsymbol{\sigma_1 = 2, c_1 = 5}$	**Sugeno**	**0.00026**
3	Bell	$a = 2, b = 4, c = 6$	Sugeno	0.00165
4	π	$a = 1, b = 4, c = 5, d = 10$	Sugeno	0.0054
5	S	$a = 1, b = 8$	Sugeno	0.00076
6	Trapezoidal	$a = 1, b = 5, c = 7, d = 8$	Sugeno	0.0006
7	Triangular	$a = 3, b = 6, c = 9$	Sugeno	0.0009
8	Z	$a = 2, b = 5$	Sugeno	0.0054

In next experiment, the changes of membership functions parameters are investigated. For this purpose we used Triangular and Gaussian membership functions. In Table 4, the details of experiment are clear. It can be seen that the changes of membership functions parameters have high effect on ANFIS performance.

5. Conclusion

In this paper, the application of ANFIS for solving the power flow in power networks is investigated. The ANFIS has good features in function approximations. In ANFIS, the value of radii and membership functions has high effects on its performance. Therefore in this study, this parameter selected carefully. The main step in application of ANFIS or each machine learning concept is the obtaining the training data. In the proposed method we used a proper collection of control variables that can be gained from control room. The proposed method is tested on real world standard power network system. The simulation results show that the proposed method has good performance in approximating the power flow.

Table 4
Investigation of parameters effect.

Gaussian	MSE	Triangular	MSE
$\sigma_1 = 1, c_1 = 4$	0.00028	$a = 3, b = 5, c = 9$	0.00085
$\sigma_1 = 2, c_1 = 4$	0.00026	$a = 2, b = 5, c = 9$	0.00102
$\sigma_1 = 2, c_1 = 5$	**0.0002**	$a = 3, b = 5, c = 8$	0.0018
$\sigma_1 = 2, c_1 = 4$	0.0003	$\boldsymbol{a = 3, b = 6, c = 9}$	**0.0007**
$\sigma_1 = 3, c_1 = 5$	0.00025	$a = 2, b = 6, c = 9$	0.0009

References

Abdelouadoud SY, Girard R, Neirac FP, and Guiot T (2015). Optimal power flow of a distribution system based on increasingly tight cutting planes added to a second order cone relaxation. International Journal of Electrical Power and Energy Systems, 69: 9-17. https://doi.org/10.1016/j.ijepes.2014.12.084

Al-Masri AN, Ab Kadir MZA, Hizam H, and Mariun N (2015). Simulation of an adaptive artificial neural network for power system security enhancement including control action. Applied Soft Computing, 29: 1-11. https://doi.org/10.1016/j.asoc.2014.12.006

Aloui T, Amar FB, and Abdallah HH (2013). Fault prelocalization of underground single-phase cables: Modeling and simulation. International Journal of Electrical Power and Energy Systems, 44(1): 514-519. https://doi.org/10.1016/j.ijepes.2012.07.067

Buragohain M and Mahanta C (2008). A novel approach for ANFIS modelling based on full factorial design. Applied Soft Computing, 8(1): 609-625. https://doi.org/10.1016/j.asoc.2007.03.010

Chen B, Matthews PC, and Tavner PJ (2013). Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. Expert Systems with Applications, 40(17): 6863-6876. https://doi.org/10.1016/j.eswa.2013.06.018

Gomes CR and Medeiros JACC (2015). Neural network of Gaussian radial basis functions applied to the problem of identification of nuclear accidents in a PWR nuclear power plant. Annals of Nuclear Energy, 77: 285-293. https://doi.org/10.1016/j.anucene.2014.10.001

Kamel S, Jurado F, and Mihalic R (2015). Advanced modeling of center-node unified power flow controller in NR load flow algorithm. Electric Power Systems Research, 121: 176-182. https://doi.org/10.1016/j.epsr.2014.12.013

Kokkinos Y and Margaritis KG (2015). Topology and simulations of a hierarchical markovian radial basis function neural network classifier. Information Sciences, 294: 612-627. https://doi.org/10.1016/j.ins.2014.08.025

Liu H, Tian HQ, and Li YF (2015). Comparison of new hybrid FEEMD-MLP, FEEMD-ANFIS, wavelet packet-MLP and wavelet packet-ANFIS for wind speed predictions. Energy Conversion and Management, 89: 1-11. https://doi.org/10.1016/j.enconman.2014.09.060

Modi PK, Singh SP, and Sharma JD (2007). Voltage stability evaluation of power system with FACTS devices using fuzzy neural network. Engineering Applications of Artificial Intelligence, 20(4): 481-491. https://doi.org/10.1016/j.engappai.2006.08.003

Rao BV and Kumar GN (2015). Optimal power flow by BAT search algorithm for generation reallocation with unified power flow controller. International Journal of Electrical Power and Energy Systems, 68: 81-88. https://doi.org/10.1016/j.ijepes.2014.12.057

Wen S, Huang T, Zeng Z, Chen Y, and Li P (2015). Circuit design and exponential stabilization of memristive neural networks. Neural Networks, 63: 48-56. https://doi.org/10.1016/j.neunet.2014.10.011

Xiong G, Shi D, Chen J, Zhu L, and Duan X (2013). Divisional fault diagnosis of large-scale power systems based on radial basis function neural network and fuzzy integral. Electric Power Systems Research, 105: 9-19. https://doi.org/10.1016/j.epsr.2013.07.005

Yap WK, Havas L, Overend E, and Karri V (2014). Neural network-based active power curtailment for overvoltage prevention in low voltage feeders.

Expert Systems with Applications, 41(4): 1063-1070. https://doi.org/10.1016/j.eswa.2013.07.103

Zhao ZS, Feng X, Lin YY, Wei F, Wang SK, Xiao TL, Cao MY, and Hou ZG (2015). Evolved neural network ensemble by multiple heterogeneous swarm intelligence. Neurocomputing, 149: 29-38. https://doi.org/10.1016/j.neucom.2013.12.062

Zhu F and Wu Y (2014). A rapid structural damage detection method using integrated ANFIS and interval modeling technique. Applied Soft Computing, 25: 473-484. https://doi.org/10.1016/j.asoc.2014.08.043