Description of Power System QV Curve by Fuzzy Modeling

SHU-CHEN WANG
Department of Computer and Communication Engineering
Taipei College of Maritime Technology
Taipei, Taiwan
scwang@mail.tcmt.edu.tw

CHI-JUI WU,
Dep. of Electrical Engineering, National Taiwan University of Science and Technology
Taipei, Taiwan
cjwu@mail.ntust.edu.tw

Abstract: - The purpose of this paper is to study the description of power system QV curves by using the method of fuzzy modeling for analysis of voltage stability. Voltage instability of power system comes from increasing load rapidly, and causes bus voltage to drop. When voltage is out of control and it can be voltage collapse. The QV curve can identify voltage stability limit, and it determine robustness of power system. The method of fuzzy modeling has been proven to be well-suited for modeling nonlinear industrial processes described by input-output data. The fuzzy system model is basically a collection of fuzzy IF-THEN rules that are combined via fuzzy reasoning for describing the features of a system under study. In view of the nonlinear characteristic of power system QV curve, the method of fuzzy modeling is employed for representing the curve. Based on the Sugeno-type fuzzy model, various models with different numbers of modeling rules are used to describing the QV curve. It is found that such fuzzy model offers both quantitative and qualitative descriptions for the QV curve.

Key-Words: - Fuzzy Modeling, Sugeno-type, ANFIS, QV Curve, Voltage Stability, Voltage Collapse.

1 Introduction

Voltage security analysis should consider multiple scenarios, based on voltage instability and/or contingencies and often employ continuation power flow methods to determine voltage collapse margins [1], thermal limits, and voltage violations. Voltage stability [2, 3] is an important factor to be considered in power system operation and planning. Voltage Stability is the ability of a power system not to occur voltage collapse, the voltage of power system can be hold or resumed to allowable bound after being subjected to a physical little or big disturbance. The rule of judging voltage stability is that: In normal operating environment, for every bus of power system, the value of bus voltage will rise with reactive power injected this bus increasing. At least there is a bus, whose voltage will fall with reactive power injected this bus increasing, then the system is instability.

Voltage collapse may occur in a power system due to lost in voltage stability in the system. Therefore voltage stability analysis is important in order to identify critical buses in a power system i.e. buses which are closed to their voltage stability limits and thus enable certain measures to be taken by the control engineer in order to avoid any incidence of voltage collapse. Voltage collapse is more complicated than voltage stability, which refers to a process of voltage instability, the process leading to a blackout or very low voltages in a power system. Generally the severe bus voltage dips after a series of faults of power system, which include rotor angle instability and voltage instability. Here it should be pointed out that: The bus voltage gradual fall of the grid relates to the rotor angle instability, the fall of voltage only is the result of rotor angle loss of synchronization, but isn't the reason of the occurrence. When the voltage is unsteady to cause of the voltage collapse to take place, the rotor angle stability is not the focus of problem.

In the literatures, Fuzzy theory analysis produces a soft partition and provides more flexibility in describing the structure of the data points. Fuzzy sets allow for degrees of membership, the crisp classification can be extended into a fuzzy classification notion. There have been many successful applications of fuzzy set in various engineering disciplines [4, 5]. The fuzzy set approach is one of the most popular fuzzy algorithms and has been extensively used in related applications [6, 7]. A fuzzy system model is basically a collection of fuzzy IF-THEN rules that are combined via fuzzy reasoning for describing the features of a system under study [8, 9]. The fuzzy model not only offers the accurate expression of the quantitative information for a studied nonlinear system, but also can give a qualitative description of the physical feature. In view of the nonlinear characteristic of the power system QV curve, the fuzzy model is employed in describing the curve in that the method of fuzzy modeling is suitable for modeling nonlinear processes described by input-output data.

This paper aims to report an application of the Sugeno-type fuzzy modeling method [10, 11] to the description of nonlinear QV curves for the power system. Different numbers of modeling rules are adopted and compared in constructing the fuzzy models for representing the power system QV curves. The data points are fitted into the Sugeno-type fuzzy model by employing the algorithm of ANFIS (Adaptive Neuro-Fuzzy Inference System) [12]. The inherent IF-THEN structure can yield both numerical (quantitative) approximation and linguistic (qualitative) description for the studied system. It is shown from the study results that the obtained fuzzy models are capable of providing both quantitative and qualitative description of the power system QV curves. Those models can be helpful and useful in many advanced system studies of voltage stability to ensure voltage security.

2 The Power System QV Curve

In power systems, rotor angle stability had been the primary concern of the utilities for many decades. Since 1980s, many large interconnected power systems are increasingly experiencing abnormally high or low voltages and voltage collapse [13-18], power system short-term large-disturbance voltage stability has became one hot spot of power system research. Voltage collapse is a local or, at most, a regional phenomenon. Hence, identifying the system critical buses is important, in which including the problem is originated, or mostly related. These critical buses constitute the set of candidate buses for reinforcement against voltage collapse. Even when voltage collapse occurs much beyond thermal limits in some system branches, these critical buses together with the overloaded branches constitute the obvious set of candidates for reinforcement.

In recent years, with the evolution of research, people imminently want to establish the dynamic models of power systems to study its behavior characteristics, so that the nature of short-term large-disturbance voltage stability can be revealed and the explain of short-term large-disturbance voltage instability mechanism can be well made. Through research of more than twenty years, the problem of voltage stability has obtained big progress, the key factors affecting voltage stability have been clarified step by step, the mechanism of voltage stability are realized initially. In the earlier research, the phenomena of voltage stability was analyzed as a steady-state problem, many methods based on power flow simulation are put forward. Hereafter, the dynamic nature of voltage stability is known by people: Voltage collapse can be caused by all the dynamic factors, such as dynamic characteristics of load, control characteristics of HVDC, generator and excitation controls, characteristics of reactive power support devices, ULTC, etc. So, it is in reason to use dynamic viewpoint studying voltage stability problem. The analysis of steady-state voltage stability adopts inevitably simple system model for predigesting analysis and accelerating the speed of calculation. In this process some presumptions adopted do not consist with the real action of system. So, some result warp or wrong conclusion will be gained. In analysis of short-term large-disturbance voltage stability, the credible conclusion can be found by adopting detailed models, considering dynamic characteristics of load and using dynamic analytic methods.

The QV curve method [19] has been used as a planning tool by power system for analysis of voltage stability. Moreover, based on the reactive power (QV) curves obtained from the simulation, the system voltage control and stability issues are analyzed. Using the QV curve may help engineers to identify critical buses in the system as well as the reactive power injection needed at those buses to ensure voltage security.

3 Fuzzy Modeling

3.1 Fuzzy Set

The classical set notation strictly assigns each studied object into a relation of membership or non-membership. On the contrary, a set containing elements that have varying degrees of membership in the set is referred to as the fuzzy set [8, 9]. Based on fuzzy set theory, the fuzzy model [10, 11], which consists of a number of fuzzy IF-THEN rules, is used for describing the behavior or characteristic of the studied system. It typically expresses an inference such that if we know a premise, then we can infer or derive a conclusion. In a general nonlinear system, each of the fuzzy relational equations can be expressed in rule-based form. In modeling nonlinear systems, various types of fuzzy rule-based system could be described by a collection of fuzzy IF-THEN rules. The objective of this paper is to study an application of the fuzzy model to the description QV curve of power system for analysis of voltage stability

Among various types of fuzzy models, the Sugeno-type fuzzy model has recently become one of the major topics in theoretical studies and practical applications of fuzzy modeling and control. The basic idea of Sugeno-type fuzzy model is to decompose the input space into fuzzy regions and then to approximate the system in every region by a simple linear model. The overall fuzzy model is implemented by combining all the linear relations constructed in each fuzzy region of the input space. The main advantage of the Sugeno-type fuzzy model lies in its capability of smoothly interpolating linear functions in different regions of the system.

3.2 Model Structure

In this study, the single-input-single-output Sugeno-type fuzzy model consisting of n rules, as described in (1), $i=1,2,\cdots,n,$ is adopted for describing the power system QV curves:

$$R^i: \text{ IF } v \text{ is } A^i \text{ THEN } Q_i = a_i v + b_i,\ i=1,2,\cdots,n. \tag{1}$$

where v stands for the system input (the voltage) and Q_i (the reactive power) represents the output in the ith subregion. It is noted that the input domain is partitioned into n fuzzy subregions, which is described by a fuzzy set A^i, and the system behavior in each subregion is modeled by a linear equation $Q_i = a_i v + b_i$ of which a_i is the coefficient of voltage variation and b_i is a constant. Let $m_i(x)$ denote the membership function of the fuzzy set A^i. If the system input v attains a reading v^0 then the overall system output Q is obtained by computing a weighted average of all the outputs Q_i's from each rule as shown in (2) and (3).

$$Q = (\sum_{i=1}^{n} w_i Q_i)/(\sum_{i=1}^{n} w_i) \tag{2}$$

$$w_i = m_i(v^0),\quad Q_i = a_i v^0 + b_i. \tag{3}$$

3.3 Model Identification

Model identification can be defined as a process of recognizing structure in data by comparisons with known structure. The aim of model identification is to figure out all the parameters of the model. The tasks of model identification for the Sugeno-type fuzzy model are usually divided into two categories: structure identification and parameter identification.

(1) Structure identification: Set the number of model rules according to the system characteristics. Different numbers of model rules will yield different ways of description for the power system QV curve.

(2) Parameter identification: First select the type of membership functions depending on the shape described in each fuzzy set. Then the parameters of the linear function in each rule are to be identified. In this study, the Gaussian type membership function in (4) is employed for the fuzzy set in the IF-part of the rule:

$$f(x) = \exp[-\frac{(x-c_i)^2}{2\sigma_i^2}] \tag{4}$$

where the parameters c_i and σ_i define the shape of each membership function. Then the input/output data points of the system under study are put into an adaptive network structure, namely the "Adaptive Neuro Fuzzy Inference System" (ANFIS) [20-22], for the purpose of model training to calculate the parameters of the membership function (c_i, σ_i) in the IF-part and the coefficients of the linear function (a_i, b_i) in the THEN-part.

4 Voltage Envelope

4.1 Moving window for RMS values

The voltage magnitude envelopes contain the information of flicker components. The moving window method as shown in Figure 1 is used to calculate the RMS values of the instantaneous voltage $v(t)$ of a single-phase voltage waveform with N samples per cycle as a window [23]. To reduce the computation loading, h samples are shifted (jump-sampling) to reach the next window. The RMS values of all windows are calculated from

$$v_{rms}[i] = \sqrt{\frac{\sum_{m=(i-1)h+1}^{(i-1)h+N} v^2[m]}{N}}, i = 1,2,\cdots H \quad (5)$$

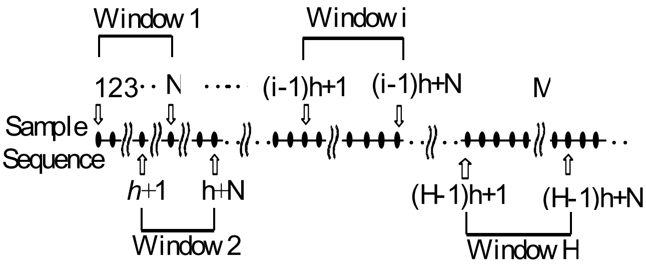


Fig. 1 Moving window to obtain RMS values

In the frequency spectrum calculation, the DC component in $v_{rms}[i]$ may cause spike and affect the accuracy of the flicker calculation. Consequently, the RMS deviation values can be obtained from

$$v_s[i] = v_{rms}[i] - v_{average}\ , i = 1,2,...,H. \quad (6)$$

Where $v_{average}$ denotes the average value of the RMS values during the measurement period and is given by

$$v_{average} = \left(\sum_{i=1}^{H} v_{rms}[i]\right)/H \quad (7)$$

The frequency components of $v_s[i]$ are the flicker components of $v(t)$.

In practical conditions, any phase of three-phase circuits may have different voltage flicker components. If it wants to obtain directly the three-phase voltage flicker equivalent values, the three-phase equivalent RMS deviation values must be obtained firstly. The arithmetic and geometric mean values to represent the three-phase equivalent RMS deviation values are, respectively, defined as,

$$v_A[i] = \frac{v_{s-R}[i] + v_{s-S}[i] + v_{s-T}[i]}{3} \quad (8)$$

$$v_G[i] = \sqrt{\frac{(v_{s-R}[i])^2 + (v_{s-S}[i])^2 + (v_{s-T}[i])^2}{3}} \quad (9)$$

Where $v_{s-R}[i]$, $v_{s-S}[i]$ and $v_{s-T}[i]$ are the deviation RMS values of corresponding phases.

4.2 Instantaneous voltage vectors

The instantaneous voltage vectors also can be used to obtain the three-phase equivalent voltage magnitude envelopes. For a three-phase circuit, the magnitude of the instantaneous voltage vector can be obtained from

$$|v_i(t)| = \left|\frac{\sqrt{2}}{3}[v_R(t) + v_S(t)e^{j\frac{2\pi}{3}} + v_T(t)e^{j\frac{4\pi}{3}}]\right| \quad (10)$$

Where v_R, v_S, and v_T are instantaneous voltages of the corresponding phases.

In order to explain this method, let phase-R have a single voltage flicker component and let the other two phases be purely sinusoidal. Then

$$v_R(t) = \sqrt{2}V_{rms}\left[1 + \frac{1}{2}\Delta V_{fn}\cos(2\pi f_n t)\right]\cos(2\pi f_{sys} t) \quad (11)$$

$$v_S(t) = \sqrt{2}V_{rms}\cos(2\pi f_{sys} t - \frac{2\pi}{3}) \quad (12)$$

$$v_T(t) = \sqrt{2}V_{rms}\cos(2\pi f_{sys} t + \frac{2\pi}{3}) \quad (13)$$

Then the magnitude of instantaneous voltage vector is given by

$$|v_i(t)| = \frac{2V_{rms}}{3}\left|\begin{array}{l} \left[1 + \frac{1}{2}\Delta V_{fn}\cos(2\pi f_n t)\right](\frac{e^{j2\pi f_{sys}t} + e^{-j2\pi f_{sys}t}}{2}) \\ +[\frac{e^{j(2\pi f_{sys}t - \frac{2}{3}\pi)} + e^{-j(2\pi f_{sys}t - \frac{2}{3}\pi)}}{2}]e^{j\frac{2\pi}{3}} \\ +[\frac{e^{j(2\pi f_{sys}t + \frac{2}{3}\pi)} + e^{-j(2\pi f_{sys}t + \frac{2}{3}\pi)}}{2}]e^{j\frac{4\pi}{3}} \end{array}\right| \quad (14)$$

It can be obtained from (14) that

$$|v_i(t)| = V_{rms}\{1 + \frac{1}{2}[\frac{\Delta V_{fn}}{3}\cos(2\pi f_n t) + \frac{\Delta V_{fn}}{3}\cos(2\pi f_n t)\cos(2\pi f_{sys} t) + \frac{\Delta V_{fn}^2}{9}\cos^2(4\pi f_{sys} t) + \cdots]\}$$

Thus

$$|v_i(t)| \cong V_{rms}[1+\frac{\Delta V_{fn}}{6}\cos(2\pi f_n t)+\frac{\Delta V_{fn}}{6}\cos(2\pi f_n t)\cos(2\pi f_{sys} t)] \tag{15}$$

The frequency spectrum of (15) has four components. The second contains the useful information to obtain the corresponding flicker component. Then the sampled data sequence of $|v_i(t)|$, that is $v_i[i]$, can be used in FFT to obtain the three-phase voltage flicker equivalent values.

5 Characteristics of Fluctuating Load

Voltage fluctuation and power quantities fluctuations are major power quality disturbances caused by fluctuating load. They are used to reveal loading condition, respectively, as follows.

5.1 Voltage fluctuation

In a short duration, a voltage fluctuation waveform can be described as

$$v(t)=\sqrt{2}V_{rms}[1+\frac{1}{2}\sum_n \Delta V_{f_n}\sin(2\pi f_n t+\varphi_n)]\sin(2\pi f_{sys} t) \tag{16}$$

where f_{sys} is the fundamental frequency (power frequency), V_{rms} is the RMS value, and ΔV_{fn} is fluctuation component of the amplitude modulation frequency f_n. For the voltage fluctuation limitation, we only need to consider f_n in the range of 0.1Hz~30Hz. The definitions of voltage deviation ΔV is

$$\Delta V=\sqrt{\sum_n(\Delta V_{f_n})^2} \tag{17}$$

5.2 Power Quantities [24]

It is required to preserve several values of power quantities after data compression to represent the characteristics of fluctuating load. For a three-phase three-wire load under non-sinusoidal and unbalanced conditions, the arithmetic apparent power is

$$S_A=S_R+S_S+S_T=V_R I_R+V_S I_S+V_T I_T \tag{18}$$

If only fundamental components are considered, the fundamental active power and reactive power are, respectively, as follows.

$$P_1=P_{R1}+P_{S1}+P_{T1} \tag{19}$$

$$Q_1=Q_{R1}+Q_{S1}+Q_{T1} \tag{20}$$

Therefore, the corresponding fundamental apparent power is given by

$$S_1=\sqrt{P_1^2+Q_1^2} \tag{21}$$

To reveal harmonic condition, the non-fundamental arithmetic apparent power can be defined as

$$S_{AN}=\sqrt{S_A^2-S_1^2} \tag{22}$$

Additionally, the effective representation of three-phase fundamental voltages and currents can be given by

$$V_{e1}=\sqrt{\frac{V_{R1}^2+V_{S1}^2+V_{T1}^2}{3}} \tag{23}$$

$$I_{e1}=\sqrt{\frac{I_{R1}^2+I_{S1}^2+I_{T1}^2}{3}} \tag{24}$$

Then the fundamental effective apparent power is defined as

$$S_{e1}=3V_{e1}I_{e1} \tag{25}$$

It is noted that S_{e1} is different with S_1. When there is an unbalanced situation, the fundamental positive-sequence apparent power is defined as

$$S_1^+=3V_1^+I_1^+ \tag{26}$$

Where V_1^+ and I_1^+ are the fundamental positive-sequence components. Therefore the unbalanced condition can be represented by the fundamental unbalanced apparent power as follows.

$$S_{1U}=\sqrt{S_{e1}^2-S_1^{+2}} \tag{27}$$

6 Example

In the study case, it is a medium-sized system with longitudinal structure, covering 400 km distance from north Taiwan to south. The power system QV curves at the rated output $Q_{\max}$ as 3,124 MVAR. The power system QV curves can be represented as (28) where the voltage in Volt is v and Q is the output reactive power of the generator in MVAR.

$$Q = \begin{cases} FM(v), & v \geq v_C \\ Q_{MAX} - FM(v), & v < v_C \end{cases} \tag{28}$$

As the power falls until the collapsed voltage v_C, the output power $FM(v)$ is to be described by the Sugeno-type fuzzy model. Note since $FM(v)$ is the nonlinear part of the power system QV curves that the approach of fuzzy modeling will be suitable in the analysis of curve description.

To better understand the performance of the Sugeno-type fuzzy model, comparative studies are conducted under conditions of different numbers of modeling rules. Fuzzy models with two, three, four, five and six rule are shown as follows. All parameters of models with different numbers of modeling rules are shown in Table 1 to Table 5. The mean-squared errors under different numbers of modeling rules are tabulated as Table 6. Moreover, the membership functions as well as data points with fuzzy models are drawn for the purpose of comparison as shown from Figure 2 to Figure 6. It is observed that more modeling rules will yield a model with higher degree of fitting accuracy.

Table 1. Parameters of two-rule model

Rule	(σ_i, c_i)	(a_i, b_i)
1	(0.11, 1.21)	(100, 3124)
2	(0.07, 0.89)	(100.20, -1317)

Table 2. Parameters of three-rule model

Rule	(σ_i, c_i)	(a_i, b_i)
1	(0.02, 1.12)	(100, 2500)
2	(0.08, 0.95)	(100.20, -3790)
3	(0.06, 0.92)	(0.60, 2052)

Table 3. Parameters of four-rule model

Rule	(σ_i, c_i)	(a_i, b_i)
1	(0.04, 1.14)	(100, 2950)
2	(0.09, 0.97)	(100.20, -4100)
3	(0.06, 0.93)	(0.60, 2252)
4	(0.06 0.88)	(0.51, -1500)

Table 4. Parameters of five-rule model

Rule	(σ_i, c_i)	(a_i, b_i)
1	(0.04, 0.89)	(0.50, -1500)
2	(0.06, 0.93)	(0.60, 2252)
3	(0.09, 0.96)	(100.2, -4100)
4	(0.04, 1.01)	(0.12, 0.05)
5	(0.04, 1.14)	(100, 2850)

Table 5. Parameters of six-rule model

Rule	(σ_i, c_i)	(a_i, b_i)
1	(0.03, 0.86)	(0.11, 0.05)
2	(0.04, 0.89)	(0.52, -1500)
3	(0.06, 0.93)	(0.60, 2252)
4	(0.08, 0.96)	(100.20, -4100)
5	(0.04, 0.99)	(0.12, 0.05)
6	(0.04, 1.14)	(100, 2850)

Table 6. Mean-Squared Error

Rule	Error Rate (%)
2	6.5084
3	2.9815
4	2.3945
5	1.1629
6	0.3609

Each fuzzy modeling rule can be converted into a linguistic rule by referring the parameter c_i to the Beaufort scale to give the fuzzy set in the IF-part a linguistic label. For example, $c_i = 1.21$ in the first rule of the two-rule model shown in Table 1. According to the fuzzy set we can have a Gaussian membership function with $c_i = 1.21$. Each rule can be considered as a label for the fuzzy set with a c_i value in Table 1. Therefore, we can convert every fuzzy rule in Table 1 to Table 5 into a rule whose IF-part bears a linguistic description and THEN-part is in the form of a linear function. The IF-THEN rules for models with various numbers of rules are as following.

(1) The two-rule models are as following:

R^1 : THEN Q_1=100v+3124 (MVAR);

R^2 : THEN Q_2=100.20v-1317 (MVAR);

(2) The three-rule models are as following:

R^1 : THEN Q_1=100v+2500 (MVAR);

R^2 : THEN Q_2=100.20v-3790 (MVAR);

R^3 : THEN Q_3=0.60v+2052 (MVAR);

(3) The four-rule models are as following:

R^1 : THEN Q_1=100 v +2950 (MVAR);

R^2 : THEN Q_2=100.20 v -4100 (MVAR);

R^3 : THEN Q_3=0.60 v +2252 (MVAR);

R^4 : THEN Q_4=0.51 v -1500 (MVAR);

(4) The five-rule models are as following

R^1 : THEN Q_1=0.50 v -1500 (MVAR);

R^2 : THEN Q_2=0.60 v +2252 (MVAR);

R^3 : THEN Q_3=100.20 v -4100 (MVAR);

R^4 : THEN Q_4=0.12 v +0.05 (MVAR);

R^5 : THEN Q_5=100 v +2850 (MVAR);

(5) The six-rule models are as following:

R^1 : THEN Q_1=0.11 v +0.05 (MVAR);

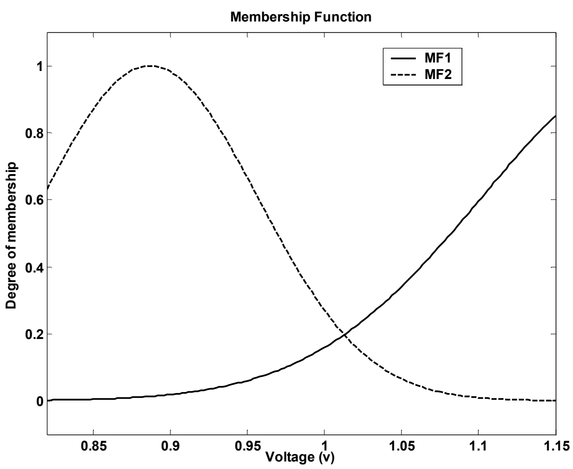
R^2 : THEN Q_2=0.52 v -1500 (MVAR);

R^3 : THEN Q_3=0.60 v +2252 (MVAR);

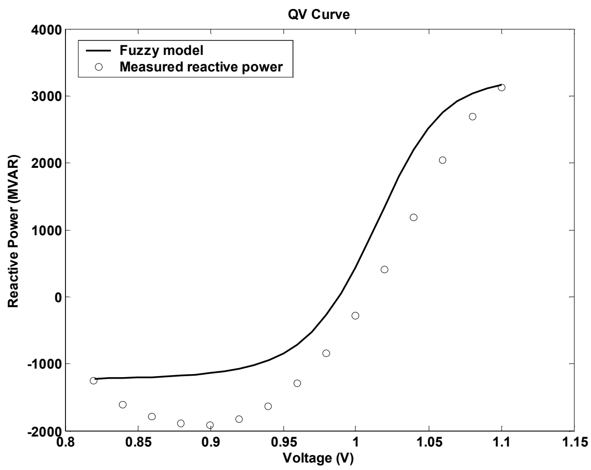
R^4 : THEN Q_4=100.20 v -4100 (MVAR);

R^5 : THEN Q_5=0.12 v +0.05 (MVAR);

R^6 : THEN Q_6=100 v +2850 (MVAR);

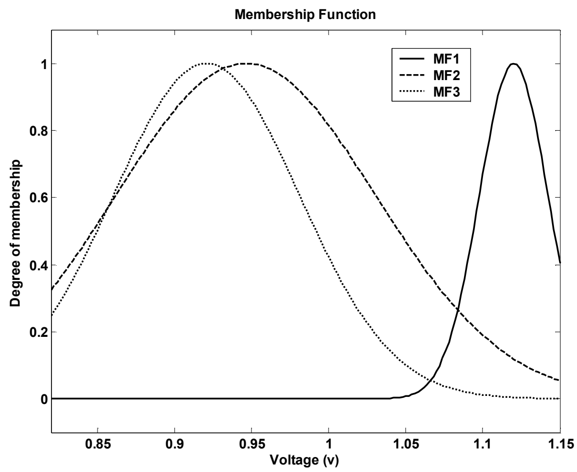


(a) Membership function

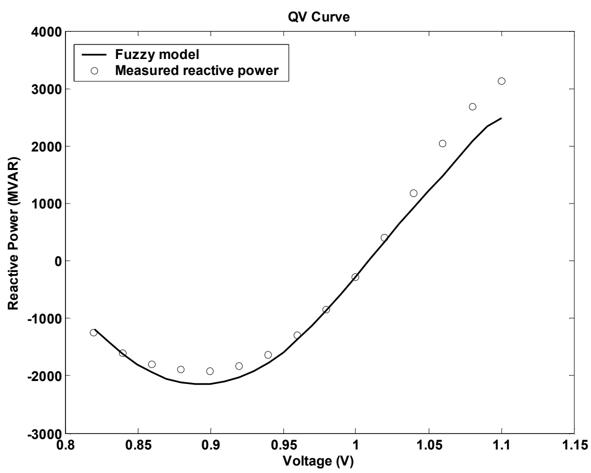


(b) Fuzzy model and measured reactive power data

Fig. 2 Two-rule model

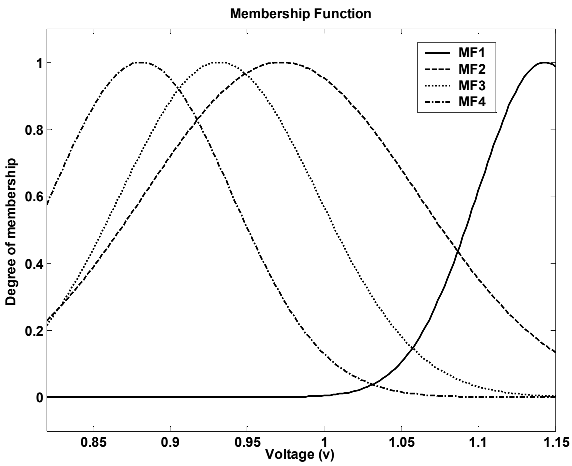


(a) Membership function

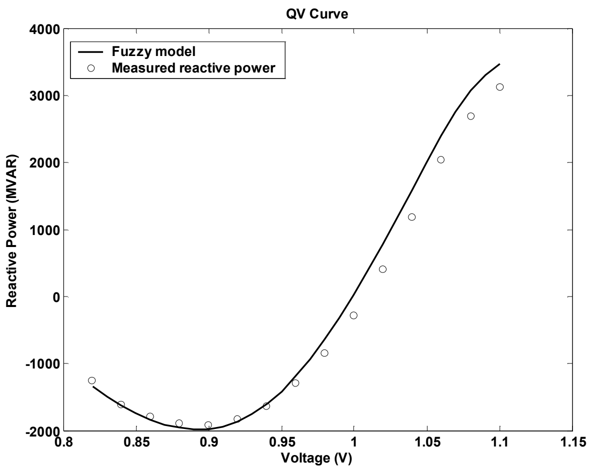


(b) Fuzzy model and measured reactive power data

Fig. 3 Three-rule model

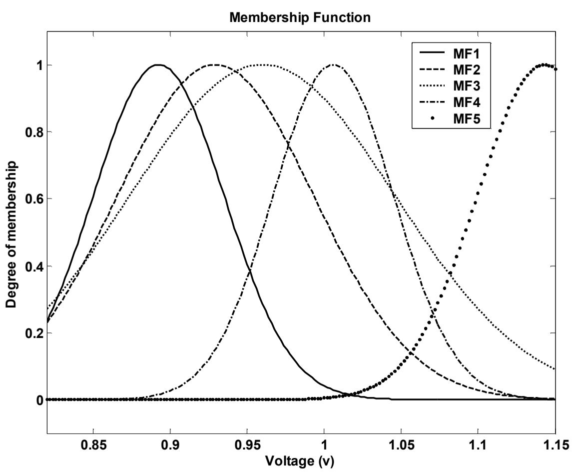


(a) Membership function

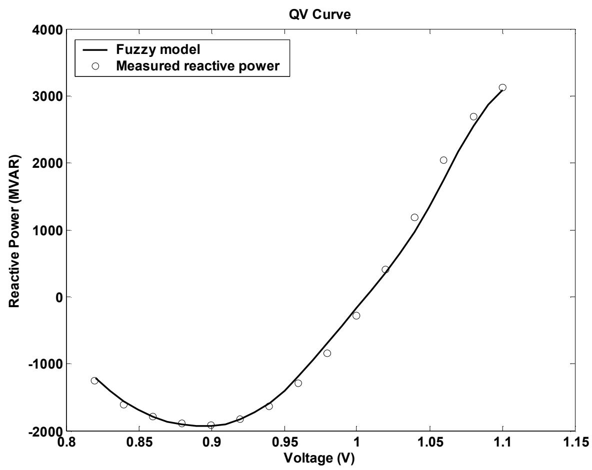


(b) Fuzzy model and measured reactive power data

Fig. 4 Four-rule model

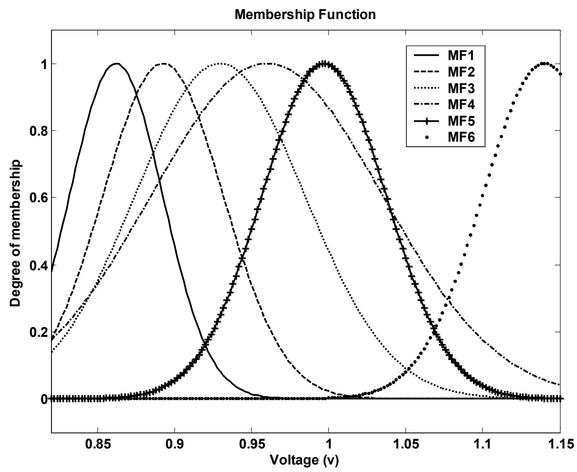


(a) Membership function

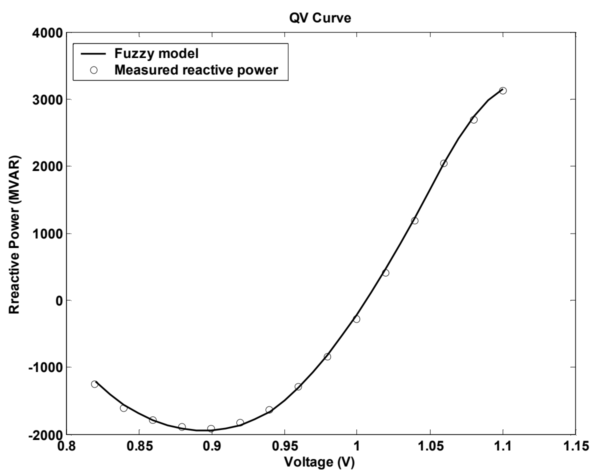


(b) Fuzzy model and measured reactive power data

Fig. 5 Five-rule model



(a) Membership function



(b) Fuzzy model and measured reactive power data

Fig. 6 Six-rule model

7 Conclusion

The main purpose of this paper is to present the description of the power system QV curve by fuzzy modeling. In view of the nonlinear characteristic of the QV curve, the method of fuzzy modeling is employed for representing the curve. Based on the Sugeno-type fuzzy model, various models with different numbers of modeling rules have been identified to describe the QV curve. It is found that such fuzzy model offers both quantitative and qualitative descriptions for the power system QV curve. The validity of the Sugeno-type fuzzy model in the analysis of the QV curve has been verified in this study.

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