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Small Local Dynamic Fuzzy Logical Models For Large-Scale Power Systems[*]

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***Abstract*— In the power system stability problems the primary actors in the mathematical system model are the differential equations defining the dynamic state variables of generation and load. These differential equations are coupled together by load flow equations. Mathematically the load flow equations are nonlinear algebraic equations. These differential equations and nonlinear algebraic equations form the mathematical Differential Algebraic Equations (DAE) model for the power system. The fuzzy set theory is commonly used in analysis of dynamical nonlinear systems. In this paper, we build a set of local dynamical fuzzy logic models for the differential equations, thus transforming the differential equations into nonlinear algebraic equations, the DAE into nonlinear algebraic equations. We try to simulate the system by solving the nonlinear algebraic equations rather than by solving the DAE model. We also compare the application of two types of dynamical fuzzy models: the discrete-time model and discrete-event model in this approach. First we explain the approach by a small DAE example, then we apply it to a 10-bus power system.**

I. Introduction

Voltage instability is an important subset of the power system stability problems. Voltage stability analysis tools can be classified into two primary types: static and dynamic. Dynamic voltage stability analysis, also referred to as transient voltage stability analysis, utilizes nonlinear methods of analysis, primarily relying on time simulations of the system. This allows for accurate analysis of specific situations. Static voltage analysis methods are numerical and predominantly based upon computation of indices. This method is less computationally intensive, [1–6]. The time simulation of a power system involves the solution of thousands of differential and algebraic equations. These equations exhibit nonlinearity and time constants that differ by several orders of magnitude. Thus the numerical simulation of power systems over extended periods of time is very time consuming. Furthermore, in the planning and operation of the power systems, the engineers face the uncertainties of the loads in the buses and other disturbance events. Many simulations of power flows will be necessary to be performed to estimate an adequate level of static voltage security. In the literature, an important method referred to as fuzzy power flow to model the uncertainties has been reported. This method uses fuzzy numbers to model the generation and load to deal with the uncertainties, [7].

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The complexity and size of power systems rule out the possibility of building a single fuzzy logic model to represent the dynamics of a large-scale power system. A general dynamic model for voltage analysis is similar to that for transient stability analysis. The overall system model consists of a set of algebraic equations and a set of differential equations. The set of algebraic equations describe the instantaneous response of the network portion of the system. It can be expressed as:

$$0 = g(X, Y), \tag{1}$$

The set of differential equations describe the dynamics of the system. The dynamic portion of the power system comprises synchronous generators, induction motors and so on. The dynamics can be captured by the following equation.

$$\dot{X} = f(X, Y). \tag{2}$$

where X is a vector consisting of the corresponding state variables of the synchronous generators and so on, Y is a vector of the algebraic variables such as bus voltages and angles.

Form the above Equation (1) and Equation (2), we know that the dynamics of a power system is the dynamics of the components of the power system coupled together by the network. For every component of the power system, the dimension of the differential equations are very limited, even though the dimension of the whole system is very large. Thus we can build small local dynamic fuzzy logical models for the individual components and coupled them together by algebraic equations to represent the whole system. By doing so, we do not need integration process to simulate the system. The main purpose of building fuzzy logic model for the dynamic power system is to explore the possibility of quick estimation of a power system stability by computing some dynamic indices and by using fuzzy logic to take some uncertainties into consideration. The fuzzy modeling that this paper presents is the first step. In Section II, the paper presents a small linear DAE example to show the approach. In Section III, the paper implements the approach in a 10-bus power system to show the results. In Section IV, some conclusions are made and some future work are mentioned.

II. Small Linear DAE Example

The small linear DAE example consists of 4 differential equations and 2 algebraic equations. The state variables are x_1, x_2, x_3 and x_4, and the algebraic variables are y_1 and y_2. The differential equations are as follows:

$$
\begin{cases}
\dot{x_1} = -x_1 - x_2 - 0.3y_1 \\
\dot{x_2} = x_1 + 0.5x_2 + 1
\end{cases}
\tag{3}
$$

$$
\begin{cases}
\dot{x_3} = -x_3 - x_4 - 0.25y_2 \\
\dot{x_4} = x_3 + 0.45x_4 + 1
\end{cases}
\tag{4}
$$

The algebraic equations are:

$$
\begin{cases}
0 = x_1 + kx_2 - y_1 - y_2 \\
0 = x_3 + 0.2x_4 - y_1 + y_2
\end{cases}
\tag{5}
$$

where k changes from 0.1 to 0.2 at time $t = 0$.

We can write the DAE in the form of

$$
\begin{cases}
\dot{X} = AX + BY + E \\
\ \ 0 = CX + DY
\end{cases}
\tag{6}
$$

where matrices A and D are invertible.

The solution of the DAE is

$$
\begin{aligned}
X(t) &= -(A - BD^{-1}C)^{-1}E \\
&\qquad + e^{(A-BD^{-1}C)t}[X_0 + (A - BD^{-1}C)^{-1}E] \\
&= X_0 + \left((A - BD^{-1}C)X_0 + E\right)t \\
&\qquad + (1/2)\left((A - BD^{-1}C)^2X_0 \right. \\
&\qquad\qquad \left. + (A - BD^{-1}C)E\right)t^2 \\
&\qquad + (1/6)\left((A - BD^{-1}C)^3X_0 \right. \\
&\qquad\qquad \left. + (A - BD^{-1}C)^2E\right)t^3 + \cdots \\
Y(t) &= D^{-1}CX(t)
\end{aligned}
$$

where X_0 is the initial condition.

The first two differential equations (3) form a dynamic system, the last two differential equations (4) form another dynamic system. The paper builds two dynamic fuzzy logical models for these two groups of differential equations. Two types of fuzzy logical models are used. The first type is the discrete-time model, and the other is the discrete-event model.

A. Discrete-Time Dynamic Fuzzy Logical Model

We construct two discrete-time dynamic fuzzy logical models for the above two groups of differential equations. The procedure to build the first fuzzy logical model is as follows:

- Define complete fuzzy sets to cover the input and output spaces. Suppose that $U = [\alpha_1, \beta_1] \times [\alpha_2, \beta_2] \times [\alpha_3, \beta_3]$, where $[\alpha_1, \beta_1]$ for variable x_1, $[\alpha_2, \beta_2]$ for x_2, and $[\alpha_3, \beta_3]$ for variable y_1. For each $[\alpha_i, \beta_i](i = 1, 2)$, define N_i fuzzy sets $A_i^{l_i}(l_i = 1, 2, \ldots, N_i)$; for $[\alpha_3, \beta_3]$,defineN_3 fuzzy sets $B_1^{l_1}$. For example, we choose the triangular fuzzy sets. Because the state variables x_1 and x_2 have dual roles in the fuzzy model, that is, they are not only the input variables but also the output variables, we define $\Pi_{i=1}^{3} N_i$ fuzzy sets $A_1^{l_i*}$ over $[\alpha_1, \beta_1]$ and $A_2^{l_i*}$ over $[\alpha_2, \beta_2]$ as output fuzzy sets for the state variables x_1 and x_2 respectively.
- construct the fuzzy system from the following $\Pi_{i=1}^{3} N_i$ fuzzy IF-THEN rules:

  R^l: IF x_{1_i} is $A_1^{l_i}$, x_2 is $A_2^{l_i}$, and y_1 is $B_1^{l_i}$;
  then x_1 is $A_1^{l_i*}$, and x_2 is $A_2^{l_i*}$.

  where the fuzzy set center points $\bar{A}_1^{l_i}$, $\bar{A}_2^{l_i}$, $\bar{B}_1^{l_i}$ are the initial conditions of the first group of differential equations (3), the fuzzy set center points $\bar{A}_1^{l_i*}$, $\bar{A}_2^{l_i*}$ are the outputs of the equations (3) at $t = 0.01$ second.
- Construct the fuzzy system based on the fuzzy rule base.

Similarly we can construct the other dynamic fuzzy logical model for the second group of differential equations (4). From the procedure of the construction, we know that when we construct a fuzzy model, we do not consider the influence of the rest of the system. Specifically, we do not consider the dynamics of algebraic variables $y_i(i = 1, 2)$ during one integration period when we construct the fuzzy rules. The small dynamic fuzzy logical models are approximating the equation (7) with initial conditions being X_0 during a integration period. Therefore, we have to take this affect into consideration when we try to solve the whole system by defuzzifying the two fuzzy models.

We go back to the DAE model (6), now we set Y to be Y_0, we get the model:

$$
\dot{X} = AX + BY_0 + E \tag{7}
$$

$$
0 = CX_0 + DY_0 \tag{8}
$$

During one integration period, the solution of Equation (7) is as follows:

$$
\begin{aligned}
X(t) &= X_0 + (AX_0 + BY_0E)\,t \\
&\qquad + (1/2)\left(A^2X_0 + A(BY_0 + E)\right)t^2 \\
&\qquad + (1/6)\left(A^3X_0 + A^2(BY_0 + E)\right)t^3 + \cdots
\end{aligned}
$$

It is obvious that these two solutions are equal in the first order term. If we need the higher order accuracy, the defuzzification process will be more complicated, but we can make the sampling time longer and fuzzy sets larger. In our example, we only considered the first order approximation. To solve the fuzzy system, we just regard it as a group of nonlinear algebraic equations. The advantage is that we do not need to integrate online by using rule base. We can see the accuracy of this fuzzy model compared to the original system from simulation results later. Figs. 1, 2, and 3 are the simulation results of the discrete-time method compared to the original system. The sampling time interval is 0.01 second. We plot the two corresponding trajectories, one calculated with the fuzzy model and the other with the original model, of every state and algebraic variable of the system together. Because they match each other very well, we plot their corresponding error aside.

B. Discrete-Event Dynamic Fuzzy Logical Model

In the above subsection, we set the integration interval before the integration starts. This method has a disadvantage that the speed is limited if we set the time too small, but if we

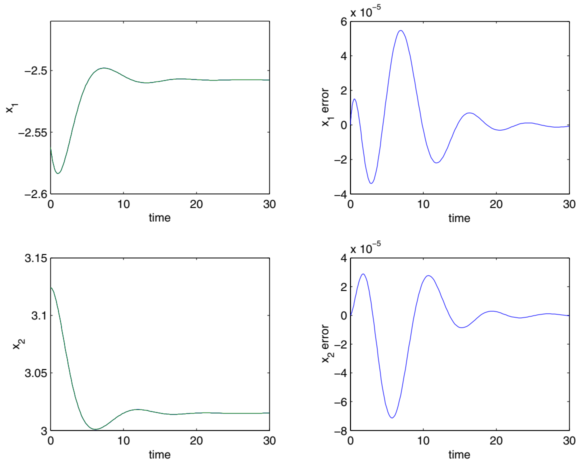

Fig. 1. State variables x_1, x_2, and the error.

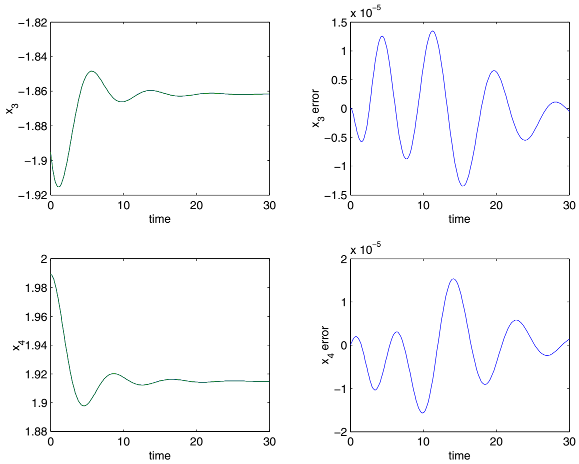

Fig. 2. State variables x_3, x_4, and the error.

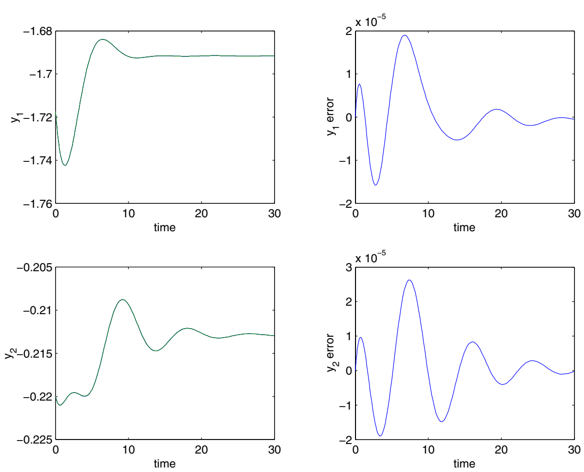

Fig. 3. Algebraic variables y_1, y_2, and the error.

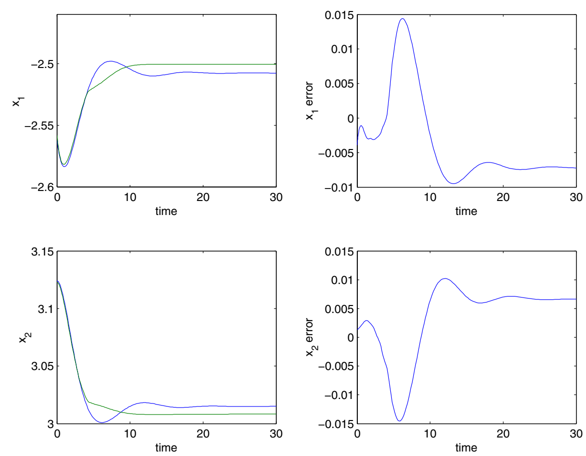

Fig. 4. State variables x_1, x_2, and the error.

set the time too large, the accuracy will be affected much. It's very difficult to select the time interval. Therefore we choose to construct the discrete-event dynamic fuzzy logical model for the differential equations (3) and (4). The procedure is similar to the above discrete-time model.The difference lies in the second step and the defuzzification:

- Define complete fuzzy sets to cover the input and output spaces as the above discrete-time procedure.
- Construct the fuzzy system from the following $\Pi_{i=1}^{3} N_i$ fuzzy IF-THEN rules:

  R^l: IF x_1 is $A_1^{l_i}$, x_2 is $A_2^{l_i}$, and y_1 is $B_1^{l_i}$;
  then x_1 is $A_1^{l_i *}$, and x_2 is $A_2^{l_i *}$ at $t = t^{l_i}$.

  where the fuzzy set center points $\bar{A}_1^{l_i}$, $\bar{A}_2^{l_i}$, $\bar{B}_1^{l_i}$ are the initial conditions of the first group of differential equations (3), the fuzzy set center points $\bar{A}_1^{l_i *}$, $\bar{A}_2^{l_i *}$ are the outputs of the differential equations (3) at $t = t^{l_i}$, where t^{l_i} is variable according to the events that the integration trajectory surpasses the limits of the fuzzy sets where they belong initially.
- Construct the fuzzy system based on the fuzzy rule base.

Similarly we can build another fuzzy model for the other group of differential equations (4). Because the time is different for each rule, the fuzzy logic should have to deal with this factor when the system is defuzzified. First we find out the fired rules, and select the smallest time $t^{l_i *}$, then we set the time of the other fired rules to be $t^{l_i *}$. Since we adopt the first order approximation, we make the outputs $A_1^{l_i *}$ and $A_2^{l_i *}$ of the other fired rules shrink according to the same proportion as the time does. Now we can solve the fuzzy system as the discrete-time model. Figs. 4, 5, and 6 are the simulation results of the discrete-event method compared to the original system. The figures are arranged in the similar way as the discrete-time method.

From the above figures, we see the error is relatively large, especially at the end of the trajectories. This error is due to

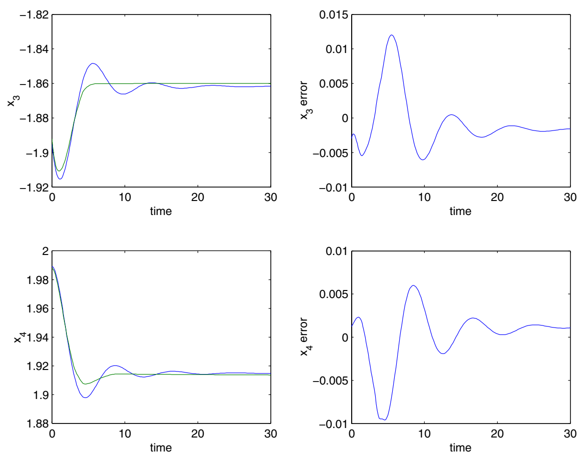

Fig. 5. State variables x_3, x_4, and the error.

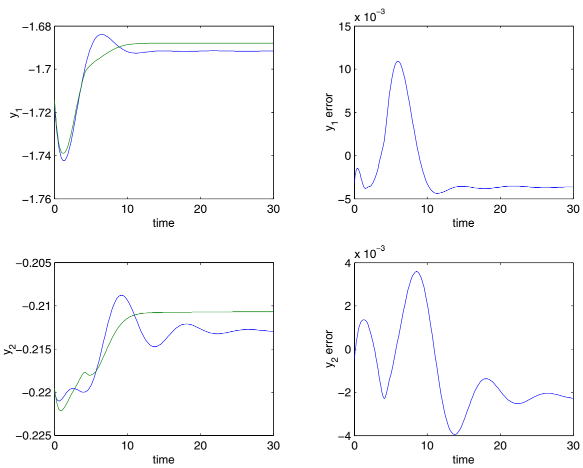

Fig. 6. Algebraic variables y_1, y_2, and the error.

the definition of the event, that is, an event happens when the integration trajectory surpasses the limits of the fuzzy sets where they belong initially. As the system converges, the trajectories do not surpass the limits of the sets where they belong initially, so during this period of time, the rules regard the the system as static. Therefore the event is redefined as that the trajectories surpass the limits of the fuzzy sets where they belong initially or the duration of time they stay in the corresponding initial sets is over 0.1 second. In this way, we set the largest time interval to 0.1 second, while the time for each rule is still variable. The rule matrix is similar as before, but the accuracy improves much. Figs. 7, 8, and 9 show the better results.

III. Application to a 10-Bus Power System

The 10-bus power system and the system data can be found in [8]. In this system, two loads are fed from a 500-kV bus

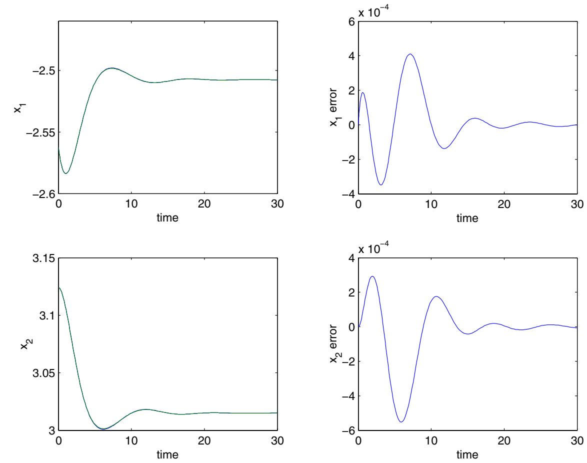

Fig. 7. State variables x_1, x_2, and the error.

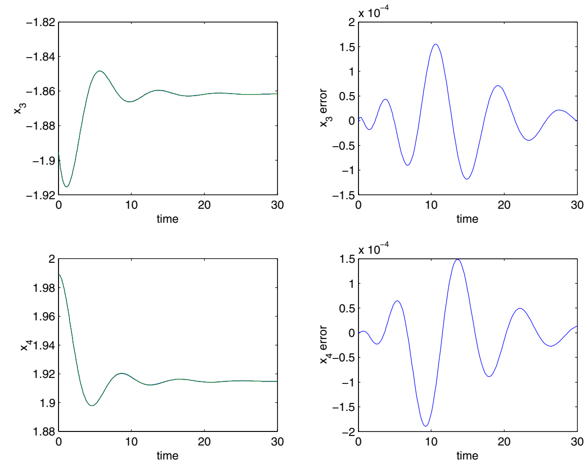

Fig. 8. State variables x_3, x_4, and the error.

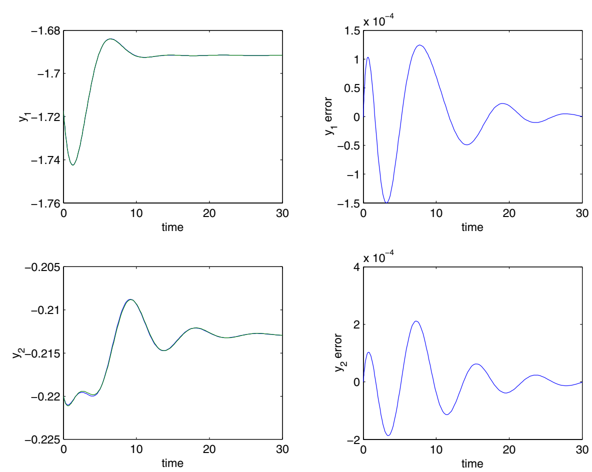

Fig. 9. Algebraic variables y_1, y_2, and the error.

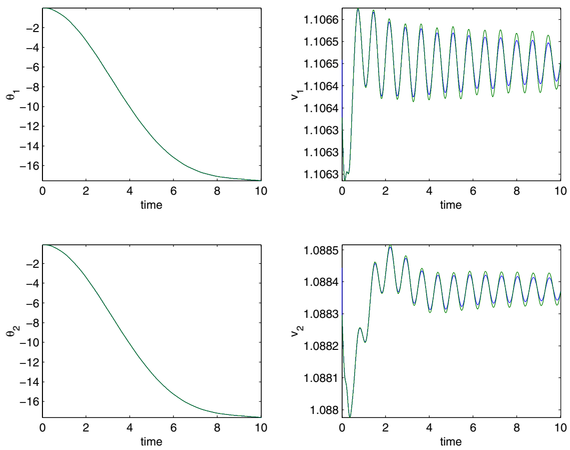

Fig. 10. Bus variables θ_1, v_1, and θ_2, v_2.

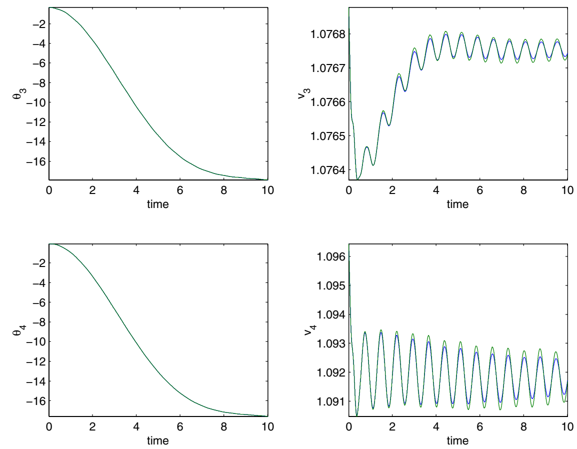

Fig. 11. Bus variables θ_3, v_3, and θ_4, v_4.

in the load area. An industrial load is served directly via a ULTC transformer at bus 7. Residential and commercial load is served at bus 10 via two ULTC transformer. The load area is heavily shunt compensated and includes a 1600 MVA equivalent generator. Two remote generators deliver 5000 MW to the load area over five 500-kV transmission lines. The system is disturbed by a 20 percent load increase at bus 10.

The load at bus 10 is equivalent to a 3rd order induction machine. The generators have 10-order dynamic models. Actually for such voltage stability analysis, it is unnecessary to use such high order dynamic generator model. Because of the highness of the order, the rule base requires too much memory. We simulate the system by first finding the fuzzy sets to which the inputs belong, then construct the fuzzy rules according to the discrete-time procedure online and lastly defuzzifying the system. The computation burden is very heavy. Anyway, the approach works. Later we will reduce the generator's model order, by doing so, the computational speed is supposed to increase exponentially, and try to construct higher-order dynamic fuzzy logical models. Figs. 10, 11, 12, and 13 show the results that the magnitudes and angles of the bus voltages of the system calculated with the fuzzy model match those calculated with a numerical analysis software. In each figure, there are two trajectories plotted one on top of the other. One of the plots is the result of the fuzzy model and the other is the result of a full time domain dynamical simulation.

IV. Conclusion

The paper studies a new method to construct small local dynamic fuzzy logical models to represent large-scale DAE systems such as large-scale power systems. The paper shows that the independent construction of local fuzzy logical models can approximate the original system by one order accuracy without linearizing the nonlinear system. For the small example, the approach works perfectly, the computation speed is very fast when the discrete-event method is applied. For the

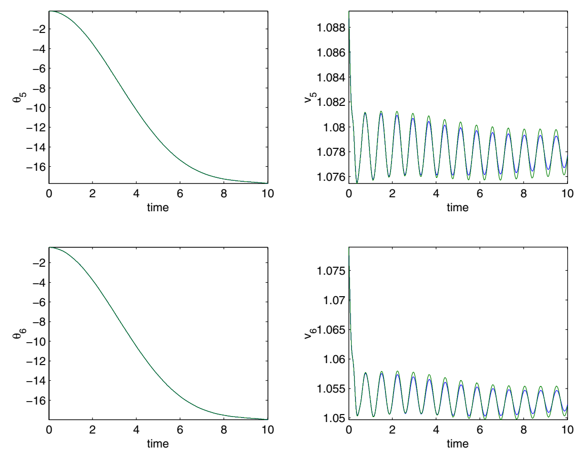

Fig. 12. Bus variables θ_5, v_5, and θ_6, v_6.

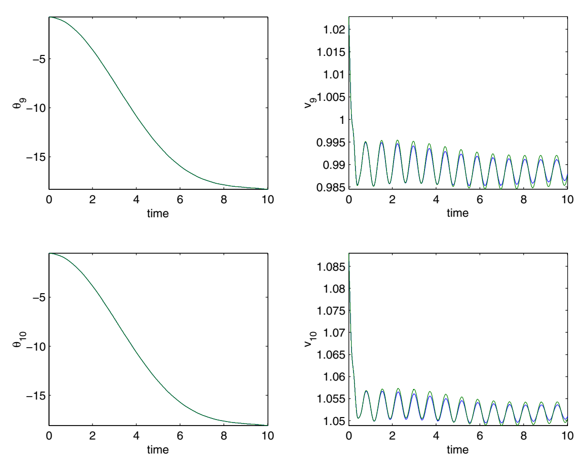

Fig. 13. Bus variables θ_9, v_9, and θ_{10}, v_{10}.

power system, the approach still works although the computation burden is heavy. This approach shows that it is feasible to construct a fuzzy model for a large-scale system such as a power system. This is a way to solve the dimension problem in the application of fuzzy theory. When Taylor's series of the solution are used, the solution is in polynomial form, the fuzzy logic can approximate it accurately. By comparing the higher order terms of Taylor's series of the solutions of the fuzzy logical model and the original model, we can set up rule base directly related to those terms to achieve higher order accuracy and faster solution of the fuzzy model because we can use larger fuzzy sets. This remains to be done in the future. We will also explore the possibility to use fuzzy logic to take the uncertainties into consideration.

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Mariesa L. Crow received her BSEE from the University of Michigan and her Ph.D. from the University of Illinois - Urbana/Champaign in 1989 both in Electrical Engineering. She is currently Associate Dean for Graduate Studies and Research and a Professor of Electrical and Computer Engineering. Her area of professional interest is bulk power transmission systems analysis and security. She is the Vice President for Education/Industry Relations of the IEEE Power Engineering Society. She is a Registered Professional Engineer in the State of Missouri.