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Load models for modeling dynamic behaviors of reactive loads: Evaluation and comparison

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ABSTRACT

Load modeling has a significant impact on power system dynamic analysis. Currently, static load models are commonly used in the power industry to model dynamic behaviors of reactive loads. Dynamic and composite load models are recommended to possibly improve modeling accuracy for reactive power. In this paper, the performance of six load models proposed in the literature for modeling dynamic behaviors of reactive loads are evaluated and compared. The issues of estimation accuracy and model complexity are compared to evaluate the estimation performance of each model. Numerical results indicate that static load models do not adequately model dynamic behaviors of reactive loads. A first-order induction motor model can satisfactorily capture the dynamic behaviors of reactive loads, while composite load models can accurately capture the dynamic behaviors of reactive loads. In addition, the issue of the incorporation of dynamic load models increasing the dimension of system representation is addressed.

1. Introduction

Load modeling has a significant impact on power system dynamic analysis results [1]. Accurate load models can result in precise determination of operational limits. On the other hand, inaccurate load models may lead to a power system being operated in modes that result in system collapse or separation [2]. The voltage collapse that took place in Japan in 1987 was mainly due to reactive power characteristics of air conditioning loads [3]. Voltage stability analysis and simulation results are greatly affected by the use of different load models [4]. For small signal analysis, it has been reported that the constant impedance load model tends to overestimate system damping by about 25% when compared with a more accurate load representation [5]. In the transient stability analysis of a Chinese power system, the power output of some power plants and its cost were affected by 4–6% depending on the load model used [6]. Because of its importance, the subject of load modeling has drawn significant research and development efforts from both academia and power industry.

Different dynamic analyses may require different load models. Load models adequate for some types of power system dynamic analyses may be not adequate for others. For example, voltage stability analysis is more concerned with dynamic behaviors of reactive loads while transient stability analysis is more concerned with dynamic behaviors of real loads. Hence, representative load models should be developed for certain types, not all types of power system dynamic analyses. Load models for certain types of power system dynamic analyses were developed in [7–11]. A dynamic load model and a composite dynamic–static load model are developed for dynamic stability analysis in [8,9]. The accuracy of using nonlinear static load models for transient stability analysis is examined in [10]. Load models for power flow and transient stability are investigated in [11].

Currently, static load models are commonly used in the power industry to model dynamic behaviors of reactive loads. Dynamic load models and composite load models, which can accurately capture dynamic responses of the loads to disturbance, are recommended to possibly improve the accuracy of modeling dynamic behaviors of reactive power. In this paper, the performance of six load model structures proposed in literature for modeling dynamic behaviors of reactive loads are evaluated and compared. These six model structures include two nonlinear static load models (ZIP and exponential), two induction motor models (first-order and third-order), and two composite load models (ZIP-induction and GZIP-induction). We derive the parameters of the six load models based on multiple actual measurement data sets. The issues of estimation accuracy and model complexity are examined to evaluate the estimation performance of each model.

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One key result derived from numerical studies with actual measurement data indicates that static load models do not adequately model dynamic behaviors of reactive loads. The first-order induction motor model can satisfactorily capture the dynamic behaviors of reactive loads while composite load models can accurately capture the dynamic behaviors of reactive loads. In addition, the issue of the incorporation of dynamic load models increasing the dimension of system representation is addressed.

2. Measurement-based parameter estimation

The measurement-based parameter estimation problem for reactive loads is formulated as a nonlinear least squares problem

$$\begin{aligned} &\min_p \varepsilon_Q(p) \\ &\text{s.t. } g(p) = 0 \\ &h(p) \leqslant 0 \end{aligned} \tag{1}$$

where p is a vector of model parameters, $\varepsilon_Q(p)$ is the output error function of reactive loads, and $g(p)$, $h(p)$ represent equality and inequality constraints for p. The objective function $\varepsilon_Q(p)$ is defined as follows:

$$\varepsilon_Q(p) = \frac{1}{2}\sum_{k=1}^{n} \varepsilon_{Qk}^2(p) \tag{2}$$

where n is the total number of sampling points used for parameter estimation. $\varepsilon_{Qk}(p) = Q_k - \widehat{Q}_k$ is error between the measured reactive power Q_k, and the model output $\widehat{Q}_k$ at the kth sampling point.

After model parameters are estimated, the model response is simulated with measured input to evaluate the developed load model. The residual calculation is used to evaluate the accuracy of the developed model by the following popular index:

$$\sigma_Q = \frac{\left(\frac{1}{n}\sum_{k=1}^{n} \varepsilon_{Qk}^2(p)\right)^{\frac{1}{2}}}{\left(\frac{1}{n}\sum_{k=1}^{n} Q_k^2\right)^{\frac{1}{2}}} \times 100\% \tag{3}$$

If σ_Q is less than a desired value, the developed load model is then acceptable; otherwise, remedial actions should be taken. It is desirable to evaluate the model on a different set of measurement data since parameter variance error may not be detected from the data used for parameter estimation. We next discuss a scheme to select the number of points n in the residual calculation (3).

A set of measurement data for a load model usually consists of three periods: pre-disturbance period, transient period, and post-disturbance period. Since a load model can always model pre-disturbance and post-disturbance periods accurately, the residual σ_Q will become smaller if more residual calculation points are selected from pre-disturbance and post-disturbance periods, according to (3). Then, even for a model structure that cannot model dynamic behaviors of reactive loads accurately, σ_Q will be less than the desired value if enough residual calculation points are selected from pre-disturbance and post-disturbance periods. In order to evaluate the performance of load models accurately, we present a scheme for selecting the number of points n in residual calculation (3), including the following steps:

Step 1: Determine the starting point i of the transient period. That is, the first point at which the voltage variation is larger than a threshold, say 2%.

Step 2: Determine the end point j of the transient period. That is, the last point at which the voltage variation is larger than the threshold.

Step 3: Select partial pre-disturbance period, point $i - m$ to point $i - 1$, and partial post-disturbance period, point $j + 1$ to point $j + m$, for residual calculation.

Step 4: Residual is calculated as follows:

$$\sigma_Q = \frac{\left(\frac{1}{n}\sum_{k=i-m}^{j+m} \varepsilon_{Qk}^2(p)\right)^{\frac{1}{2}}}{\left(\frac{1}{n}\sum_{k=i-m}^{j+m} Q_k^2\right)^{\frac{1}{2}}} \times 100\% \tag{4}$$

where $n = j - i + 2m + 1$.

When multiple measurement data sets are available (for example, m measurement data sets), the parameter estimation problem for reactive loads can be further formulated as a weighted nonlinear least squares problem

$$\begin{aligned} &\min_p \sum_{i=1}^{m} w_i \varepsilon_{iQ}(p) \\ &\text{s.t. } g(p) = 0 \\ &h(p) \leqslant 0 \end{aligned} \tag{5}$$

where w_i is a weighting factor for the ith error function $\varepsilon_{iQ}(p)$, and $\varepsilon_{iQ}(p)$ can be calculated according to Eq. (2). By introducing weighting a factor w_i, the importance of each measurement data set can be weighted.

We apply a quasi-Newton-type method to solve the above parameter estimation problem. Among the quasi-Newton methods, the Levenberg–Marquardt method is robust for nonlinear least squares problems. However, quasi-Newton methods suffer from finding a local optimal solution instead of a global optimal solution. Since the objective function is generally a non-quadratic function of p, several local minima may exist. This issue of several local optimal solutions needs to be resolved and requires more investigation.

In the following sections, parameters of the six load models: two static load models, two dynamic load models, and two composite load models, are estimated and evaluated using multiple online measurement data sets under different loading conditions.

Nine sets of self-acting monitoring systems are currently installed at primary substations and distribution substations of the Taiwan power system. When a (natural) system disturbance occurs, the monitoring system at the relevant substation is triggered automatically to record the three-phase currents and voltages of the substation (i.e. the load bus) and store the data on a local computer. In this study, ten sets of measurement data belonging to certain loading conditions are selected from the data recording system of a substation of the Taiwan power system for reactive load parameter estimation. Based on the recording time of each measurement data set, we classify the loading conditions into three categories: summer medium (SM), summer light (SL), and winter light (WL). Table 1 summarizes 10 sets of measurements at the substation. For the purpose of illustration, a set of measurement data (three-phase voltage and current) and its corresponding computed real and reactive powers are shown in Fig. 1.

Table 1
Ten measurement sets at a substation

No.	Time			Loading condition	Voltage variation (%)
	Month	Day	Hour		
1	8	9	11:34	SM1	9.1
2	6	18	11:03	SM2	11.4
3	8	2	00:24	SL1	5.6
4	8	2	00:39	SL2	5.5
5	8	2	01:43	SL3	5.5
6	8	2	02:39	SL4	5.2
7	1	11	04:27	WL1	9.0
8	1	11	06:06	WL2	9.1
9	1	10	03:08	WL3	12.6
10	1	6	06:51	WL4	9.8