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Measurement-based Static Load Modeling Using the PMU data Installed on the University Load

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Abstract – Load modeling has a significant influence on power system analysis and control. In recent years, measurement-based load modeling has been widely practiced. In the load modeling algorithm, the model structure is determined and the parameters of the established model are estimated. For parameter estimation, least-squares optimization method is applied. The model parameters are estimated so that the error between the measured values and the predicted values is to be minimized. By introducing sliding window concept, on-line load modeling method can be performed which reflects the dynamic behaviors of loads in real-time. For the purpose of data acquisition, the measurement system including PMU is implemented in university level. In this paper, case studies are performed using real PMU data from Korea Univ. and Seoul National University of Science and Technology. The performances of modeling real and reactive power behaviors using exponential and ZIP load model are evaluated.

Keywords: Load modeling, Measurement-based approach, Parameter estimation, PMU

1. Introduction

The accuracy of stability analysis has a significant influence on control and planning of power system. Accurate modeling of power system components is essential in simulating the power system stability. For stable operation of power system, the balance between power generation consumption has to be maintained all the time. Therefore, among all components of the power system, generators and loads are the most important factors. Much effort has been dedicated to understanding the dynamics of the generator as well as its related controls [1, 2]. However, study on load dynamics has not been performed sufficiently due to the complex nature of load. The load is an aggregation of various load components with different dynamic characteristics. And the load keeps changing with time in amount and composition.

However it is important to represent the load model as a simple aggregated form and not to distort the characteristics of loads [3]. To express the complicated load characteristics accurately, on-line load modeling algorithm is required.

Using the measurement-based load modeling technique, on-line load modeling is possible. In measurement-based load modeling, the task can be divided into two operations. One is determining the mathematical structure of load and another is estimating the parameters proper to the load model structure. It has been observed that different load models will lead to various conclusions on power system stability [4]. To capture the various characteristics of load under system disturbances, the structures of dynamic load models as well as static load models are needed. The combination of static and dynamic load model is called composite load model. In static load model, the real and reactive power of the load at any instant of time is expressed as functions of the voltage and frequency at the instant [5]. On the other hand, dynamic load models express the characteristics of load as functions of the time-dependent voltages and frequencies.

For static load model, exponential load model and ZIP load model are widely used. The ZIP model is a combination of constant impedance (Z), constant current (I) and constant power (P) components. As for the dynamic load model, motors typically consume 60 to 70 percent of the total energy supplied by a power system. Therefore, the dynamics attributable to motors are usually the most significant aspects of dynamics of the system load. Thus, induction motor models are generally employed as dynamic load models in the field of study.

In this paper, static load models are applied to the measurement-based load modeling. In addition, studies on modeling of dynamic load such as third-order induction motor are in progress for more accurate indication of load responses.

So as to calculate correct parameters of the predefined model structure, iterative optimization algorithm is applied. The task of parameter estimation is formulated as a

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nonlinear least squares problem where the output mismatch error is an objective function [6].

The concept of on-line load modeling is introduced by Rehtanz. With the idea of sliding window, the changing parameters of the dynamic loads can be represented [7]. Using the real time measurement equipments such as PMU (Phasor Measurement Unit), actual measurement data can be collected. The data obtained by the measurement equipments will be used to parameter estimation algorithm in real time.

Currently a PMU is set up at the load of university level. The records collected from the PMU are transmitted in TCP/IP type to the server system. In this manner, the transmitted information is represented through the software program and stored in the server. Recently, the data accumulation has been started and been in operation properly.

In this paper, case studies are performed using the collected data from Korea Univ. and Seoul National University of Science and Technology. PMUs are installed on 22.9kV loads in University. The validation of static load models representing the active and reactive power behaviors are carried out.

2. The Measurement-based Approach

In the measurement-based approach, the load behaviors are collected at the representative substation and feeders using the measuring equipment. The parameters of static load models are estimated using the measured data. The measured responses of active and reactive power, voltage are fitted to the polynomial and exponential expressions. To improve the estimation performance, preprocessing operation such as filtering noise of the collected data can be included in the algorithm.

2.1 Basic principle

The task of load modeling is to determine the appropriate mathematical relationship between power consumption and voltage/frequency at the designated buses. It should be noted that the active and reactive power are functions of both voltage and frequency. However, due to the fact that the system frequency generally varies little, the load characteristic recorder cannot record the load variation with respect to very small frequency variation. Therefore,

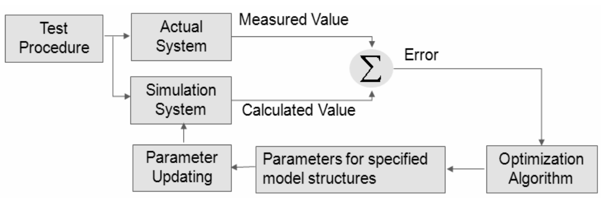


Fig. 1. The measurement-based approach algorithm

in this paper, only the relationship between the load and the voltage is considered.

The parameters of the assigned load model structure are estimated so that the error between the measured values and the predicted values based on measurement data is to be minimized. The basic algorithm of the measurement-based approach is described in following:

2.2 Measurement system setup and data acquisition using PMU

PMU offers the voltage and current information in phasor form. Using GPS (Global Positioning System), time tags are assigned on each data. Due to the time synchronizing by GPS, each data will have the exact same time information [8]. Currently a PMU (ABB model: RES521) is installed at main electric control station of Korea University (22.9kV load bus). The feature of PMU installed is represented in Fig. 2.

Fig. 2. The feature of PMU installed in Korea University

Using PT and CT, the PMU is connected to the distributing board. The wires using PT are composed of six lines representing three of each phase and three neutral points for the purpose of voltage measurement. Two lines for each phase, total six lines are utilized to measure the current using CT. The connection is shown in Fig. 3.

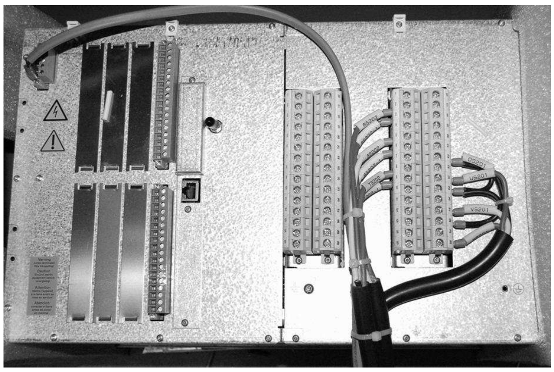


Fig. 3. Connection of three-phase wiring to PMU

The measurement data from PMU are transmitted to the server system which is called KU-WAMS (Korea University Wide Area Monitoring System) in the format of PC 37.118. By means of this program developed by Korea Electric Power Data Network, the dynamic responses of the load of Korea University are monitored and recorded. The server system currently in operation is shown in Fig. 4.

Fig. 4. The server system receiving data from the PMU

The KU-WAMS records active/reactive power and frequency in addition to voltage and current in phasor form. The data accumulation had been started two years ago. The measured data will be utilized in further study of on-line static and dynamic load modeling. In Fig. 5, the data recording in real time is represented.

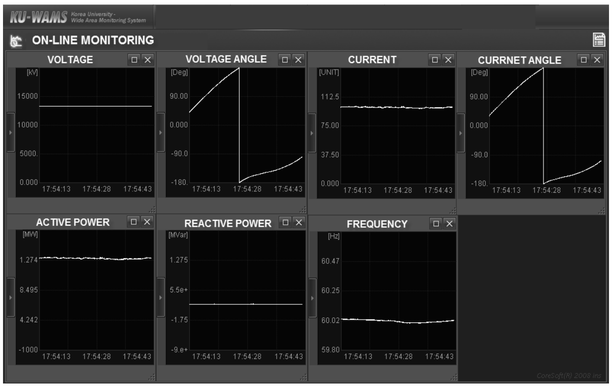


Fig. 5. On-line data recording feature in KU-WAMS

2.3 Load model structure

For static load model, exponential load model and ZIP load model are widely used. In this paper, we selected the ZIP model for load modeling for the simplicity of the estimation. The ZIP model represents the load power as a polynomial equation of the voltages. The model structure is described below.

$$P = P_0\left(a_z\left(\frac{V}{V_0}\right)^2 + a_i\left(\frac{V}{V_0}\right)^1 + a_p\left(\frac{V}{V_0}\right)^0\right) \tag{1}$$

$(a_z + a_i + a_p = 1)$

P_0 and V_0 are active power and voltage in steady-state respectively. In the parameter estimation, three parameters (a_z, a_i and a_p) are calculated.

2.4 Load modeling using the parameter estimation technique

In the measurement-based load modeling, the structure of the static load model is determined. Using the measured data as inputs to the model structure, the parameters of the load model are calculated. The objective of the parameter estimating task is to match the responses of developed model and the measured responses. In other words, the target is to minimize the error between the simulated values and the measured values. The objective function is as follows:

$$\min_{prm \in Prm} E(prm) = \sum_{k=1}^{N}\left(z_{act}(t_k) - z_{cal}(t_k, prm)\right)^2 \tag{2}$$

where
$E(prm)$: Error Function of parameter prm
$z_{act}(t_k)$: Actual data at t_k
$z_{cal}(t_k,prm)$: Calculated data at t_k with parameter prm
t_k : Time with k_{th} sample
N : Total number of samples
Prm : Parameter space

The least squares method is applied to optimize the matching of the measured and simulated responses. The parameter space Prm is defined as a permissible range of all parameters to be estimated. The parameters in the most minimized condition in Eq. (2) are considered as desired solutions. For error minimization, optimization techniques such as simple gradient based method, BFGS method and genetic algorithm can be also used [9].

2.5 Sliding window method

In order to estimate the parameters of the load model, the sliding window concept is introduced. At an instant of time, the parameter estimating procedure is performed using the data within the length of the window. In the next step, the time window moves a step forward and the parameter estimation is conducted. In this manner, the sliding window keeps advancing. With the idea of sliding window, it is possible to estimate the parameters of the load model which represents the varying load responses in real time.

For parameter estimation of static load modeling, the projection method and the least-squares method are frequently used [10]. The projection method shows, however, a poor performance in view of tracking accuracy and steady-state behavior. On the other hand, the least-squares of estimation methods show a good tracking property because of the linear optimal feature resulting from minimizing the sum of the squared prediction errors. When the parameters are time-varying, the recursive least-square is generally unsuitable because the adaptive gain often approaches.

To track time-varying parameters, it has been suggested to use some window on the data. Two popular windowing techniques in conjunction with recursive least-square are the exponential window and the sliding rectangular window. In the recursive least-square with the exponential window, the most recent data are treated as more important than the past data using a weighting factor.

To reduce the excess noise due to a finite set of data samples, however, one has to use a large weighting factor, which in turn causes the estimator to be not adaptive to time varying parameters.

2.6 Applying load changes

In general, in order to success the load modeling, fault data, that contains dramatic voltage deep, is needed. Because P_0 is fixed during the fault, load model structure such as Eq. (1) is works very well. But a fault is not occurring frequently, it is difficult to obtain data from university load level. Actually there were no contingencies yet since the PMUs are installed in Korea Univ. So all data obtained from the PMUs in KU are normal condition until now. It is not easy to derive the load modeling parameter using a normal condition data because of changing of load level. If load variations are not considered on load modeling, parameter estimation is not converged well and ZIP model constraint is not satisfied. Section 3 will show this situation.

In order to calculate the parameter using the data contained no contingencies, load changes should be applied in ZIP model formulation. In this paper, it is assumed that P_n does not vary in a window n. So the Eq. (1) is changing to Eq. (3).

$$P = P_n\left(a_z\left(\frac{V}{V_0}\right)^2 + a_i\left(\frac{V}{V_0}\right)^1 + a_p\left(\frac{V}{V_0}\right)^0\right) \quad (n_{th}\text{ window}) \tag{3}$$

Using the Eq. (3), we can obtain the parameter at every window that satisfies ZIP model equal constraint.

3. Case Study

PMUs installed on Korea University (KU) and Seoul National University of Science and Technology (SNUT) gather voltages, active power and etc. every day. Using a recent one day (twenty four hours) data of them, we tried to estimate the load parameters (ZIP).

3.1 Korea university data

Fig. 6 shows the one day voltage and active power of main building in Korea Univ. The voltage magnitude is oscillating all day since the transformer tap changing, shunt capacitor/reactor switching or etc. The maximum voltage was 1.02986p.u and the minimum voltage was 1.00257p.u. The active power starts to increase in the morning and decrease in the evening. It varied about 800kW to 1400kW. Using this data, the parameter estimation was performed.

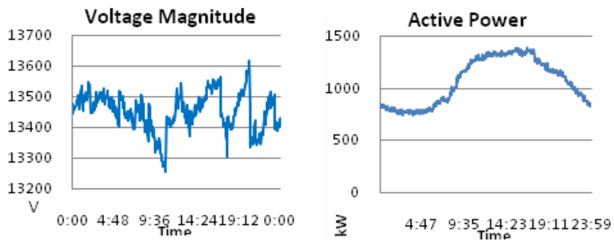
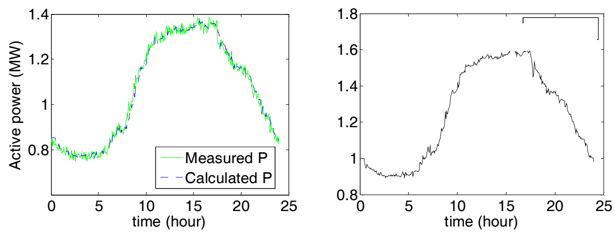


Fig. 6. Voltage magnitude and active power of main building in KU

3.1.1 Results



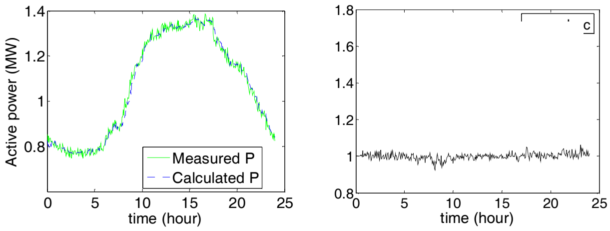
(a) (b)

Fig. 7. (a) Calculated active power; (b) sum of parameters

The measured P in Fig. 7(a) are original data from the PMU, and the calculated P are obtained from estimated parameter, measured voltage and Eq. (1). As shown as Fig. 7(a), the measured and calculated P are not significantly different.

But the estimated parameters are uneven and abnormally big. In addition, the sum of the parameter is varied 0.9 to 1.6, is not 1.0. In order to satisfy ZIP model condition, P_0 should be fixed when estimating the parameters. Since the data was not a contingency data, so the P_0 was changing, the parameter estimation is not succeeded. The composition of parameters does not comply with the ZIP model.

As mentioned as section 2.6, it is necessary to apply the load changes. Fig. 8 is the results using the Eq. (3) that is including the load variations. The graph of the sum of parameters, Fig. 8(b), is significantly improved than Fig. 7(b). They are not far from the 1.0 although they are oscillating.



(a) (b)

Fig. 8. Applying load changes: (a) Calculated active power; (b) sum of parameters

3.2 SNUT data

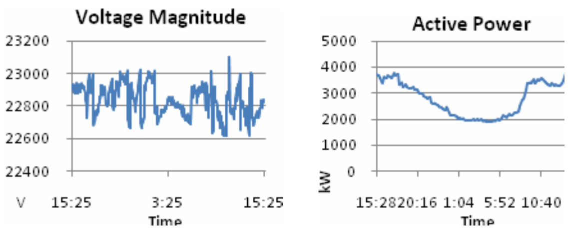
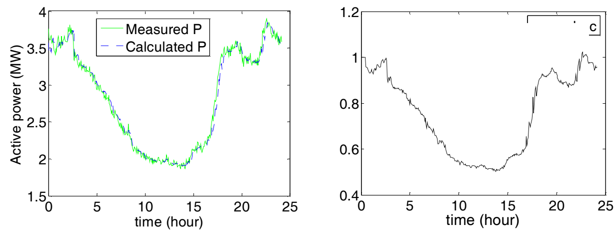


Fig. 9. Voltage magnitude and active power from SNUT

Fig. 9 shows the one day voltage and active power obtained from Seoul National University of Science and Technology. The data is not quite different with KU data. The data is starting from 3:00pm to 3:00pm next day. The parameter estimation was proceeding in the same process.

3.2.1 Results

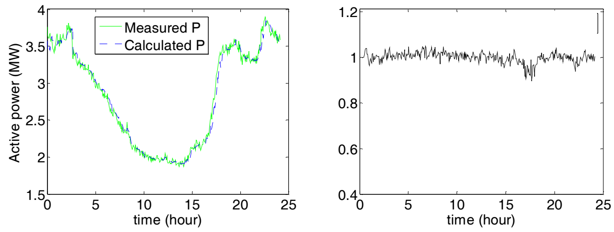


(a) (b)

Fig. 10. (a) Calculated active power; (b) sum of parameters

Fig. 10 shows the result of parameter estimation using the SNUT data. This results are not applying the load variation, the sum of parameters are not satisfied ZIP model criteria although the measured active power and calculated active power are almost same values. So we need to apply the load changes again.

Fig. 11 is the result from the parameter estimation using the SNUT data applied load variations. As shown as Fig. 11(b), the result applying the load changes is more accurate than no applying.



(a) (b)

Fig. 11. Applying load changes; (a) Calculated active power; (b) sum of parameters

4. Conclusion

This paper presents the result of the parameter estimation of load modeling using the real PMU data. The data is obtained from KU and SNUT. The least square method was using in order to calculate the parameters. There was no contingency yet, so all data stored were normal condition data. For the accurate parameter estimation, load changes are introduced to the ZIP model equation that brings about better results.

Actually, the parameter estimation from the normal condition data is not perfect because the composition of parameters is still varying from moment to moment. In order to obtain correct parameters, we need to get the fault data but it is very difficult to suffer a contingency in university level. Future works will include the abnormal condition data and re-enforced formulations in load model.

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