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Chung-Liang Chang
Department of Electrical Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C, c47216@gmail.com

Pei-Hwa Huang
Department of Electrical Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C

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Key words: power system, load modeling, measurement data, load model parameter derivation.

ABSTRACT

The modern power system is an integrated complex dynamic system. Due to its scale and complexity, the power system operation and control heavily rely on numerical simulations based on power system models which includes load models. It has been observed that using different load models in the power system simulation may produce quite different, and even contradictory simulation results. Although the importance of load modeling on system dynamics has been well known, load modeling is still a very challenging problem. Thus, there remains a strong necessity for the development of an accurate dynamic load model for power system dynamic analysis because an inaccurate load model may mislead system operators and planners to make incorrect decisions. A Load Model Parameter Derivation (LMPD) program developed by EPRI has been used to investigate the measurement based approach of modeling loads.

This paper presents the study results of deriving the load parameters by using measured data of the events from Taiwan Power system. Thirteen disturbance events from over 500 events in the Taiwan power system have been selected, and then the load model parameters are derived via the measurement data of those events. In this paper, the LMPD method is first introduced. Then the procedures of data processing and event selection are briefly discussed. Study results, which provide the static and dynamic parameters of load at each substation, and observations are presented and analyzed. The final part is conclusions.

I. INTRODUCTION

The load model is one of the most important elements in power system simulation and it has been observed that different load models may produce different, and even contradictory simulation results [3, 9]. Although the importance of load modeling on system dynamics has been well known, load modeling is still a very challenging problem [5-8, 10, 12]. The difficulties lie in the following facts:

- There is a tremendously large number of loads connected to the power system at any given moment.
- There is a tremendous diversity of the types of loads connected to the power system at any given moment.
- It is an insurmountable task to pursue “accurate” information on the composition and mix of loads continuously.
- Loads have temporal variations from hour to hour, day to day, and season to season and thus there cannot be an “all-purpose” load model.

When it comes to modeling load, we need to model both static and dynamic properties of loads. Generally, there are two ways to represent the static load: ZIP model and exponential model. ZIP model comprises three different parts: constant impedance (Z), constant current (I), and constant power (P). On the other hand, dynamic loads consume 60% to 70% of the total energy supplied by a power system. There are two common approaches to represent the dynamic load: induction motor and differential equation. Industrial power engineers prefer to use ZIP model to represent the static load and induction motor to represent the dynamic load respectively. For this combination allows physical representation of load characteristics.

However, the ZIP + Induction Motor model, a typical load model structure, cannot capture some of actual complicated dynamic load behaviors because of the inherent inaccuracy. Thus, it is required to improve the structure of the dynamic load model and develop the corresponding optimization algorithm to estimate the load model parameters in order to produce more precise system study results, and to avoid misleading system operators and planners to make incorrect decisions.

Normally there are two ways to specify the parameters of the composite load models. One is to use the default and typical parameters [3, 9]. Since the load model is the aggregation of various load components, the selection of these typical parameters is not convincing. The other way is to

Paper submitted 04/01/13; revised 12/20/13; accepted 01/10/14. Authors for correspondence: Chung-Liang Chang (e-mail: c47216@gmail.com).
Department of Electrical Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C.

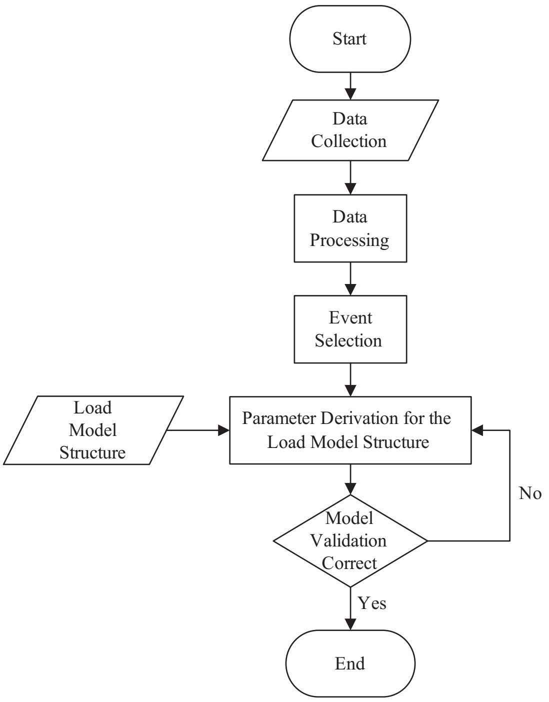


Fig. 1. Measurement based load modeling approach.

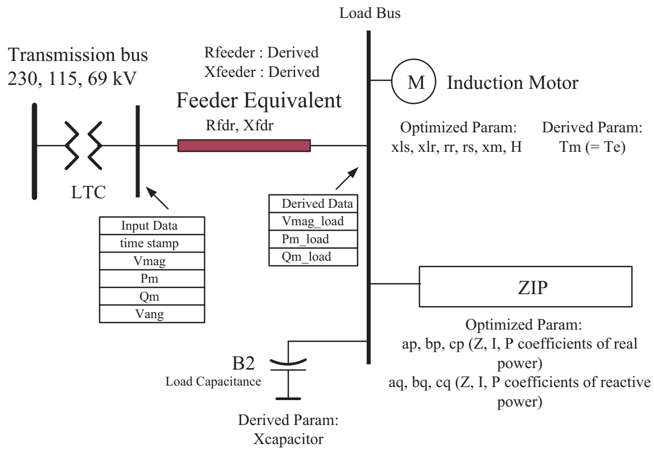


Fig. 2. Single machine structure with distribution feeder.

identify the parameters from field measurements, which is widely used in measurement based load modeling practices [1, 2, 4, 8, 11, 12]. The main purpose of this effort is to come up with a systematic methodology for developing load models from system measurements.

Based on the suggestions from the power industry, this work aims to enhance ZIP + Induction Motor load model to include LTC, feeder equivalent and load capacitance etc. This enhancement in load model structure allows for more precise representation for load characteristics. A Load Model Parameter Derivation (LMPD) program has also been developed to derive the load model parameters by using the measurement data [13].

Up until now a prototype method of load modeling has been developed and validated by the data collected from TVA, CenterPoint and Oncor. In line with an effort of validating this LMPD algorithm for various systems, we applied LMPD algorithm to model the loads of the Taiwan Power system by using its collected measurement data [3, 9] and the study results are presented in this paper. The LMPD approach process is shown in Fig. 1.

This paper is organized as follows: I. Introduction; II. LMPD Method; III. Data Processing and Event Selecting; IV. Study Results; V. Conclusion.

II. LMPD METHOD

1. Load Model Structure

The load model structure is illustrated in Fig. 2. This model has the following characteristics:

- For static load representation, the conventional ZIP load structure is selected. Although there is no distinct advantage in using a ZIP structure over an exponential, it is intuitive to consider static loads to be one of constant impedance or constant current or constant power.
- The model uses an induction motor model to represent dynamic load characteristics. The induction motor representation is preferred over the differential equation because an induction motor model allows physical representation of electrical and mechanical dynamic characteristics.
- The model represents feeder impedance explicitly.
- The model includes the capacitor bank at the load bus. This capacitor represents the total amount of shunt compensation on the feeder (in the form of substation capacitors as well as pole top capacitors on feeder). Of course, accurate information should exist on the exact amount of shunt compensation in a substation, or on a feeder, and this can be modeled explicitly instead of being estimated in the model.

The philosophy behind the load model structure is based on the assumption that the user has some information about the feeder to be modeled. In particular, the user is expected to have some ideas as follows:

- Feeder length;
- Approximate voltage drop across the feeder;
- Load composition (approximate mix of residential, commercial and industrial customers) at the time of the event;
- Status of capacitor banks at the time of the event.

Here the "feeder" refers to either a single feeder or the aggregate of multiple feeders, that is indeed under monitoring. The more information a user has about the feeder when the event occurs, the better the chances of finding a more accurate set of model parameters from the estimation process can be. While an effort has been made to get practical values of load model parameters for most of the cases, the use of a set of unreasonable input data may result in unrealistic parameters for the load model.

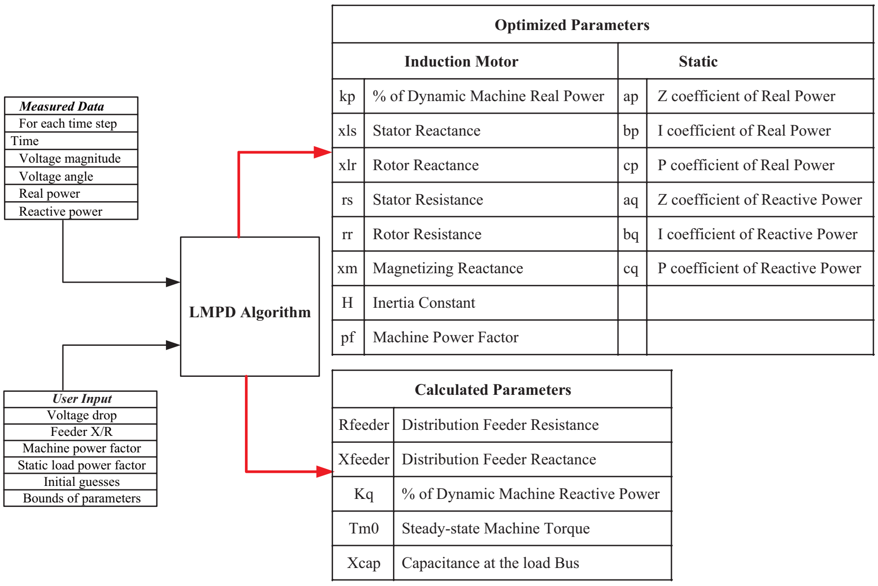


Fig. 3. Measurement based load modeling approach.

As shown in Fig. 2, "Optimized" parameters are those which are adjusted during the nonlinear optimization process. For these parameters, the user has to provide an initial guess or estimate. "Derived" parameters are those which are not optimized but calculated either based on user input or during the optimization process. "Input Data" is typically the voltage and current at the secondary side of the substation transformer where monitors are frequently located. The "Derived Data" node is the bus where the actual load response is modeled. The complete set of input and output parameters required for the single machine structure is shown in Fig. 3.

The optimization process is very sensitive to the initial guess and the bounds on the parameters to be optimized. To obtain reasonable estimates for all of the load model parameters, it is highly desirable to use a reasonable initial set of estimated parameters from which the optimization algorithm starts and is also essential while equipped with a reasonable set of bounds for each parameter. Therefore, a thorough literature review has been conducted to come up with different sets of machine and static parameters that have been used in the efforts of previous load modeling. These parameters can be used as initial guesses. Default values of lower and upper bounds are also based on practical considerations. However, these can be changed by the user if needed.

2. Load Model Parameter Estimation

The overall procedure of the load model parameter estimation process is shown in Fig. 4. A least-square based nonlinear iterative optimization process has been adopted for this study. The basic procedure includes the following items:

- Read input data – Read measurement data (instantaneous quantities).
- Perform data conversion and synthesis – Perform data

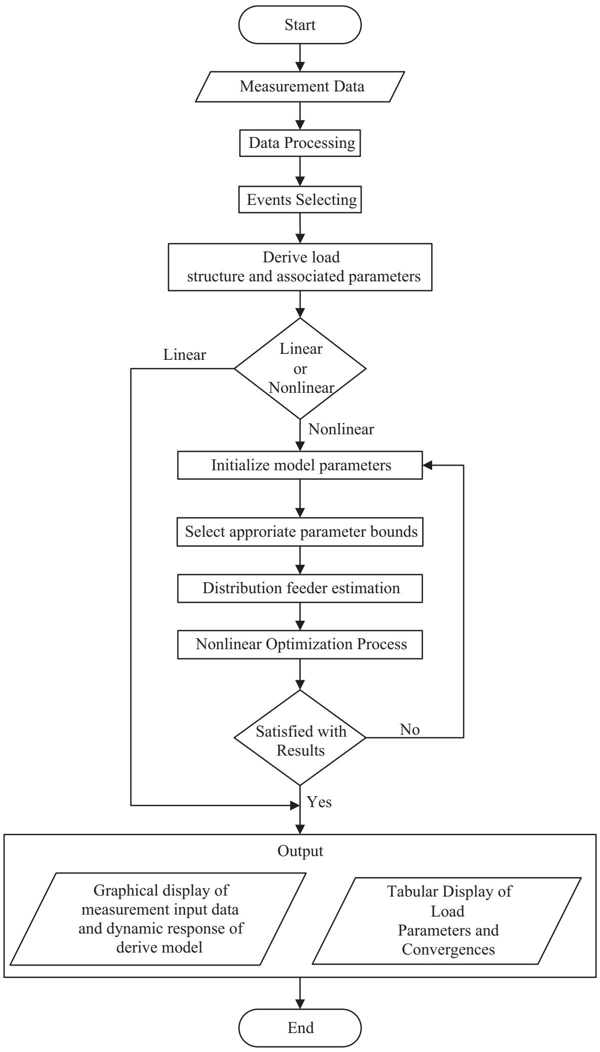


Fig. 4. Flowchart of LMPD algorithm.

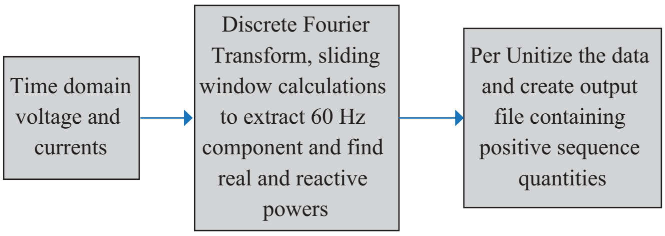


Fig. 5. Data processing.

processing to obtain per-unit positive sequence quantities of voltage, real power and reactive power at each time step;
- Conduct parameter initialization.
- Provide initial estimates of dynamic and static parameters.
- Assign appropriate lower and upper bounds of dynamic and static parameters.
- Estimate distribution feeder impedances by using user-defined performance criteria – Undertake a simple iterative process to evaluate distribution feeder impedance based on the following user-defined performance data:
  - Voltage drop along the feeder,
  - X/R ratio of the feeder.
- Initiate convergence parameter values (optimization tolerance).
- Start optimization algorithm:
  - Derive the initial values of the 3 states variables (rotor q-axis flux, rotor d-axis flux, rotor speed);
  - Perform numerical integration by using a fixed time step (Runge Kutta 4 is adopted for this purpose);
  - Calculate P and Q by using initial values;
  - Compute objective function (function=[P Q]);
  - Solve nonlinear least squares problems using the Levenberg-Marquardt method;
  - Check for parameter convergences;
  - If it meets the convergence demands, the nonlinear optimization process is finished and the program goes to data output. If not, then the initial parameter estimates are updated with the converged parameters and the process is repeated.
- Tabulate the output of calculated load model composition and associated parameters.

The procedure described above have been successfully implemented using MATLAB® and its Optimization Toolbox. This development tool, described here as LPMD program, was initially developed by EPRI [13].

III. DATA PROCESSING AND EVENT SELECTING

1. Data Processing

The data processing steps are shown in Fig. 5. The process has been automated by using a script written in MATLAB® environment. The important steps in data processing are stated below.

The input data required for the LMPD algorithm includes pre-event, during event, and post-event data. Typically, the following durations are used: 2-5 cycles of pre-event data (enough to initialize the load model to represent pre-disturbance conditions); entire duration of event data; 2-5 cycles of post-event data.

2. Event Selecting

The LMPD algorithm requires a balanced 3-phase event for parameter estimation. Balanced 3-phase events are the least common of all events in a power system. Even if a balanced 3-phase response is captured, the event may not be applicable because the location and performance of the conventional monitoring devices may be inappropriate or limited. Unfortunately, less than 1% of the total captured events are found to be useful in deriving parameters for load models. Some of the criteria used for selecting suitable events are as follows:

- The interests are not to collect fault data but in the response of loads to voltage sags occurring because of a balanced 3-phase fault (voltage depression) in the system. For the purposes of this study, an event was considered to be useful if voltage or current unbalance among three phases is less than 10%.
- The event should not be a momentary interruption. That is, voltage should not drop down to zero.
- The voltage dip should last at least 4 cycles or longer. Typically, shorter duration sags will not cause as much perturbation as longer sags.
- The voltage should drop down to at least 80% of the nominal during the sag (i.e. a depression of 20% from the pre-disturbance voltage). Motor dynamics will be pronounced for deeper voltage sags. Therefore, deeper sags will allow for calculation of more realistic characteristics of dynamic loads. Static loads will also be characterized better for deeper sags. However, the event is not useful if some or the entire load drops off as a result of the deep voltage depression. A drop in load (for example motor contactors, power electronic loads and discharge lighting typically will drop out at a certain voltage) is a step change in the input data which cannot be used in the LMPD algorithm. For this reason, slow voltage recovery events lasting several seconds are not useful in deriving parameters.
- Pre-disturbance data (a few cycles) should be available. Pre-disturbance data is essential to establish steady state values of machine state variables and other load model parameters as well.

3. Taiwan Power System Data Collection

Taiwan Power provided various events recorded on 9 different sites. Based on the selection criteria, 13 events were selected. The events are selected from five sites - A (69kV), B (161kV), C (69kV), D (69kV) and E (161kV). Sites A and B have four and six events that occurred in different time, respectively. These events are tabulated as Table 1.

Table 1. Taiwan power system event list.

Site	Voltage Base (kV)	Duration (sec)	Date	Time
A	69	13	12/7/2006	19:20
B	161	13	12/21/2006	8:40
C	69	13	12/7/2006	19:20
D	69	13	12/7/2006	19:21
E	161	13	12/7/2006	19:21

IV. STUDY RESULTS

Thirteen balanced disturbance events out of over 500 events are selected to derive load model parameters using the measurement data collected at the substations of Taiwan Power system. The study results and key observations are summarized in this section.

1. Overall Optimization Approach

The flowchart of the LMPD algorithm is shown in Fig. 4. The choice of initial estimates and the upper and lower bounds of the parameters are the most important factors in obtaining good fits and numerically reasonable parameters. Since each substation has its own load characteristics, each substation needs a load model structure. The initial estimates of load model parameters are documented. Upper and lower bounds of each parameter are set as the same for all the events, which are also documented.

The sampling rate of the measurement data is 3,840 Hz for every event. Without knowing the voltage drops along the feeder, five voltage drops (1%, 2%, 3%, 4% and 5%) are tested in order to find an optimal solution. The X/R ratios are set as 2.0 for all the events. According to the inputs from Taiwan Power system, the power factor of motor is set as 0.95 and the power factor of static load is set as 0.98 for all the events. The constant torque is used to model the mechanical torque characteristics for the motor load.

2. Modeling Loads

Based on the information provided by Taiwan Power system, different dominating dynamic loads connected at each substation can be identified. Hence, different initial values will be used to derive the load model parameters.

After testing five initial voltage drops along the feeder (1%, 2%, 3%, 4% and 5%) for each event respectively, we determine the voltage drop for each event according to the minimum average active power and average reactive power mismatch. Then the parameters of dynamic model and static model are optimized and the parameters of the feeder are calculated.

The optimized as well as the calculated results are presented in Table 2 for one event in each substation.

After the load model parameters are obtained, we simulate the dynamic response of the derived load models. Then, we compare the simulated results with the measured data, as shown in Fig. 6.

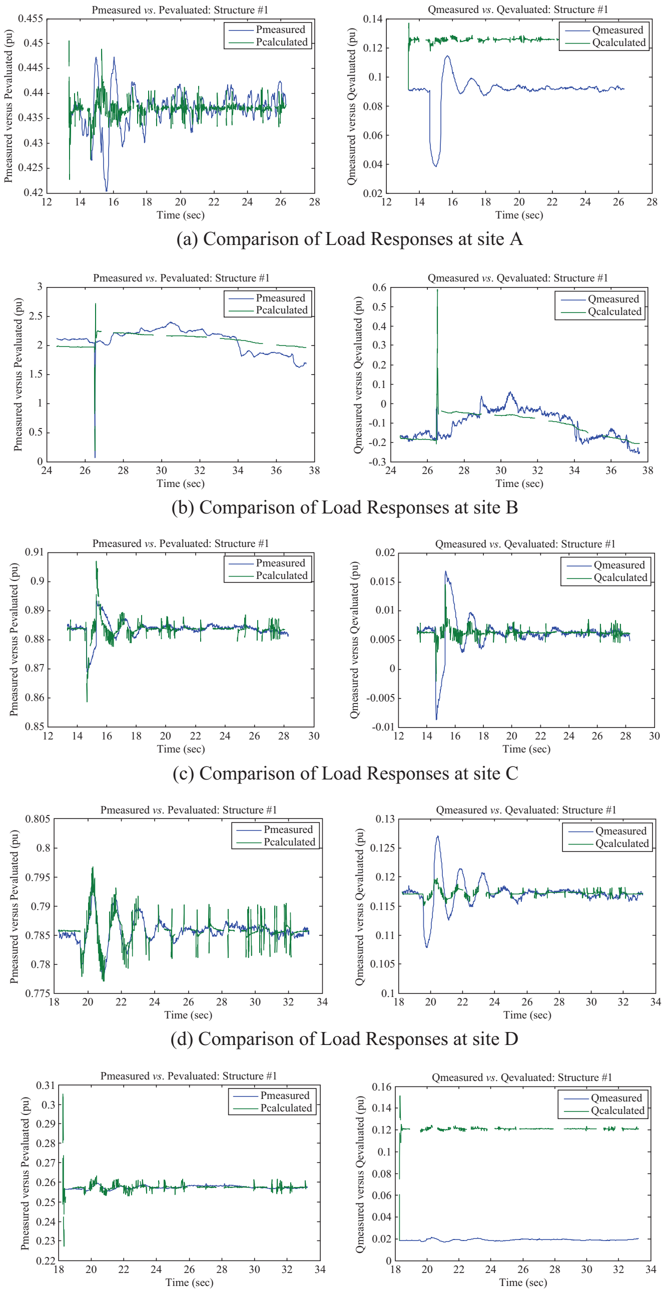
Table 2. Summary of converged parameters for the measurement cases.

Event	A	B	C	D	E
Time	12/07/06 19:20	12/21/06 8:40	12/07/06 19:20	12/07/06 19:21	12/07/06 19:21
Model used	13	6	13	16	16
Initial Guess for Feeder Voltage drop	5%	1%	2%	1 %	4%
Machine Parameters:					
Kp	0.80000	0.65957	0.59258	0.74107	0.80000
Kq	0.86621	0.75822	0.70188	0.82246	0.86621
rs	0.30000	0.26584	0.29527	0.24590	3.00000
rr	0.05263	0.02662	0.04459	0.04598	0.04325
xls	0.01000	0.08402	0.01393	0.02384	0.01000
xlr	0.01000	0.08372	0.01346	0.03808	0.01000
H	0.39160	1.71465	0.46267	1.27910	1.49992
xm	5.0000	3.68772	4.00435	4.32090	5.00000
Tm	0.29416	0.80419	0.41975	0.48666	0.18520
Steady State Speed	0.97835	0.93262	0.97074	0.96932	0.99055
Time Constant	0.25253	0.37579	0.23903	0.25147	0.30727
Motor pf	0.95000	0.95000	0.95000	0.95000	0.95000
Static Load Parameters:					
ap	0.40391	0.26540	0.43269	0.39787	0.35364
bp	0.30598	0.27498	0.31715	0.30144	0.25708
cp	0.30775	0.28102	0.29485	0.30143	0.25702
aq	0.02545	0.87483	0.24637	0.16107	0.94735
bq	0.00000	0.99019	0.00000	0.00003	1.00000
cq	0.00000	0.54259	0.00000	0.00081	1.00000
Static pf	0.98	0.98	0.98	0.98	0.98
Feeder Parameters:					
Rpu	0.08422	0.00572	0.02261	0.00989	0.12027
Xpu	0.16844	0.01144	0.04521	0.01979	0.24054
Xcapacitor	-17.06961	-0.95890	-4.28370	-10.91977	-10.40497
MVAR(pu)	-0.05288	-1.01613	-0.21474	-0.09141	-0.09171
Distribution Loss	0.01674	0.02596	0.01848	0.00613	0.00779
Utilization Voltage	0.95010	0.98710	0.95910	0.99910	0.97683
Voltage Drop	0.04990	0.00990	0.01990	0.00990	0.03317

The average and maximum mismatches of the real power and reactive power between the simulated and measured responses are listed in Table 3.

3. Factors Affecting Optimization Results

It should be noticed that the user input data has significant effects on the accuracy of the estimated load model parameters optimized based on the given measurement data. Since the LMPD optimization process finds a local minimum for the problem, there are certainly multiple solutions for optimizing



(a) Comparison of Load Responses at site A

(b) Comparison of Load Responses at site B

(c) Comparison of Load Responses at site C

(d) Comparison of Load Responses at site D

(e) Comparison of Load Responses at site E

Fig. 6. Comparison of load response of the derived and measured load models.

the load model parameters. Therefore, it is required that sound engineering judgment should be applied during the selection of initial estimates and bounds for individual parameters. All of the information such as the type of system (weak versus strong), the approximate location where the fault occurs, a sense of loading on the feeders, seasons and time of each day, the amount of shunt capacitors on the distribution feeder (i.e. the feeder is either over- or under-compensated) when the event occurred should be factored into the selection of initial estimates and bounds of individual parameters.

Table 3. Summary of mismatches between simulated and measured responses.

Event	A1	B1	C	D	E
Average mismatch of P	0.28 MW	12.66 MW	0.14 MW	0.28 MW	0.099 MW
Maximum mismatch of P	1.98 MW	80.43 MW	1.88 MW	1.98 MW	5.22 MW
Average mismatch of Q	3.52 MVar	3.9 MVar	0.14 MVar	3.52 MVar	10.18 MVar
Maximum mismatch of Q	8.83 MVar	77.73 MVar	1.45 MVar	8.83 MVar	13.31 MVar

V. CONCLUSION

This paper, based on the application of the LMPD program developed by EPRI, has presented the load modeling study using measurement data for Taiwan Power system.

The objective of this study is to model the loads at five different substations (A-E) using the measurement data from Taiwan Power system with the load model structure developed by EPRI. The study results provide the static and dynamic parameters for the load at each substation. The dynamic responses of the calculated loads are compared with the measured responses of the actual local loads at each substation. It has been observed that not all simulated load responses closely match the actual measurement. There are two reasons causing such mismatch. One is that the load model structure may not be adequate enough to fully represent load characteristics. The other reason is that the initial value chosen for optimized process may not be close enough to the actual value.

The load model and its derived parameters can be used for Taiwan Power system to engage in future studies.

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