Impact of Measurement Selection on Load Model Parameter Estimation

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***Abstract*—Measurement-based load model parameter estimation uses measurements from a disturbance on the grid. Those measurements can include voltage and/or real and reactive power. In this paper, we show that the type of measurements used directly impacts the accuracy of parameter estimation. We look at four scenarios. With wide-area deployment of voltage sensors, such as PMUs, the resulting parameter estimation is very accurate at high signal-to-noise ratios (SNR), but is very poor at low SNRs, because voltage has low sensitivity to the parameters. With only local deployment of complex power sensors, the estimate is worse than the first scenario at all SNRs. However, with wide-area deployment of complex power sensors, the estimate becomes very robust to low SNR, because complex power has much higher sensitivity to the parameters. Combining wide-area voltage and power measurements produces the best results.**

I. Introduction

Aggregate dynamic load models are designed to be used in transient stability simulations of large areas, such as the entire Eastern Interconnect. In such a large simulation, it would be infeasible to model loads down to the device level, for example by implementing a separate induction motor (IM) model for each air conditioner or refrigerator compressor in every home. Instead, we use relatively few differential equations to represent the aggregate load at the bulk transmission level. This aggregation leads to many difficulties for the parameter estimation of the load model [1], [2], [3], [4]. The result is that our understanding of load models is relatively weak. For example, the authors in [5] found that in a survey of 97 electricity utilities globally, 70% of utilities were using static load models (e.g. constant power, ZIP, or exponential) for transient stability studies. Additionally, 60% of utilities had not updated their load models (static or dynamic) within the last 5 years. This lack of knowledge has made load models a source of major uncertainty in simulations [6]. For example, in [7], the authors showed that for their proposed power system stabilizer algorithm, the tie-line flow required for the algorithm to achieve a certain level of damping could vary by approximately 250% depending on the type of load model assumed. In the absence of an accurate and verified load model, we must err on the side of caution, thus potentially under-utilizing our available resources [8]. Clearly, load modeling is an issue which needs to be tackled.

The preferred method of load model parameter estimation is measurement-based estimation. In this approach, we wait for a disturbance on the system to excite the dynamics of the load. We can then use measurements obtained during the disturbance, and the following recovery, to estimate the parameters of the load model. In [4], [9], we found that the ability of a parameter estimation algorithm to determine the correct parameters of our test case was heavily dependent on the amount of noise in the synthetic measurements. This was due to parameter interdependency—when changing one parameter has a similar impact on the simulation results as another.

In this paper, we build on this work and investigate how the choice or availability of measurements can impact the accuracy of a parameter estimation algorithm in the presence of measurement noise. This is important because often we may not have access to our desired type of measurements. For instance, the definition of a load model is one that maps voltage inputs to real and reactive power (P and Q) outputs. Thus, direct parameter estimation would require measurements of P and Q for all the loads at a substation, which may not be available due to the limited placement of PMUs. In such cases, we may only have access to bus voltage measurements, and would thus have to perform estimation indirectly by examining the recovery of a fault induced delayed voltage recovery (FIDVR) event. In this paper, we will analyze several scenarios which differ in the type of measurements available, ranging from local to wide-area power and voltage measurements.

A. Outline

In Section II, we introduce the load model for our case study, the measurement-based load modeling algorithm, and the impact of measurement noise. In Section III, we present the scenarios we wish to study, the synthetic power grid we use, and the synthetic measurements. In Section IV, we show the results of the analysis, and finally conclude in Section V.

II. Background

Measurement-based load modeling involves the selection of a load model, followed by parameter estimation. The model we will analyze is the complex load (CLOD) model. This model and it's parameter estimation are described here.

A. CLOD Model

The CLOD model is a composite model defined in Siemens PSSE [10] and PowerWorld [11], which means that it combines several simpler submodels. The CLOD model contains both dynamic and static components, described here:

- **Induction motors** Two IMs labeled Large and Small which are each characterized by a d-q reference frame dynamic model.

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- **Discharge lighting** A piecewise polynomial that describes behavior during operating and extinguished states.
- **Transformer losses** Saturation and hysteresis losses.
- **Constant MVA** Constant real and reactive power.
- **PI/QZ** Constant current real power, constant impedance reactive power.

The CLOD model also includes a feeder with a feeder impedance. The parameters of the CLOD model are the percentages allotted to each submodel, summing to 100%. Since there are six submodels, we can set five parameters independently. Additionally, we can also set the feeder impedance, R and X, for a total of seven parameters. We chose to use the CLOD model for our studies because it contains a sufficient amount of dynamics but is still simple enough to understand.

B. Parameter Estimation of Load Models

Measurement-based parameter estimation seeks to produce a model that best emulates, in simulations, the same input-output characteristics of the real system. To do this, the estimation algorithm solves for the model parameters that minimize the difference between measured signals on the grid and simulated results. Since dynamic models are desired, steady state measurements are insufficient; we require an input of sufficient magnitude to observe meaningful outputs. Power system disturbances such as generator outages, load steps, and line faults are our best sources of input. While these events are near instantaneous, they are severe enough to result in a period of recovery, and the behavior of the loads during that time is used to determine their parameters.

For a given disturbance on the system, the traditional measurement based parameter estimation approach [12] is to find the parameters p which minimize the mean squared error (MSE) between the measurements, Y_{meas}, and the simulation results Y_p. Since there are usually measurements at multiple buses, we concatenate the measurements and simulation results for each bus i:

$$\begin{aligned} p^* &= \underset{p}{\operatorname{argmin}}\, \operatorname{MSE}(Y_{\text{meas}}, Y_p) \\ &= \underset{p}{\operatorname{argmin}} \left\{ \operatorname{mean}(||Y_{\text{meas}} - Y_p||^2) \right\} \\ &= \underset{p}{\operatorname{argmin}} \left\{ \frac{1}{I}\frac{1}{T} \sum_{i=1}^{I} \sum_{t=0}^{T} \left(Y^i_{\text{meas}}[t] - Y^i_p[t] \right)^2 \right\} \end{aligned} \tag{1}$$

The availability of Y_{meas}, the output (i.e. measurements) recorded during the recovery, is the focus of this paper. Possibilities include voltage magnitude, real power, reactive power, and combinations of those.

C. Measurement Noise

Whenever real measurements are used, we must be concerned about measurement noise and sensor inaccuracies. The IEEE standard for PMUs (STD C37.118.1) lists an accuracy requirement of 1% during steady state and 5% for voltage steps of up to 0.1 pu [13]. This is equivalent to 40 dB signal-to-noise ratio (SNR) and 26 dB SNR, respectively. There are not, however, requirements for larger voltage steps, which may often be seen during a fault. However, we may infer that measurement error will be higher than 5% (SNR lower than 26 dB) for larger disturbances.

In [9], we analyzed how measurement noise affects the accuracy of parameter estimation using a synthetic case and fault, by artificially adding white noise. Due to insensitivity of the simulation results to the parameters, the optimization problem in (1) is very ill-conditioned, in that the cost function is very flat near the optimal solution. As a result, the paper showed that as SNR dropped, the estimation error increased drastically. In that paper, the parameter estimation was done using voltage measurements, since those are the most widely available at the transmission level. In this paper, we will determine if parameter estimation can be improved with the use of other types of measurements, namely complex power. In other words, we are trying to find the Y that makes (1) most accurate and robust to noise. In the next section, four possibilities are described.

III. Simulation Setup

In this section, we define the four scenarios we will study, as well as the synthetic power system and load model we will use in our studies.

A. Description of Scenarios

The four scenarios differ in the type of measurements we have access to. Table I lists the measurements used for each scenario, the input-output relationship of the simulation, and the objective function of the parameter estimation. It is also illustrated in Fig. 1. Scenarios 1 and 2 are meant to represent the current level of monitoring: wide-area voltage monitoring, but limited power monitoring at only some feeders. In Scenario 1, we find the load model indirectly, by measuring the load recovery's impact on voltage, i.e. FIDVR. As opposed to voltage, which can be measured by a single PMU at the high voltage side, load power consumption is usually harder to monitor, because it requires PMUs on each distribution feeder. Thus, in Scenario 2, we assume we only have power measurements at a few buses. As a result, instead of using a

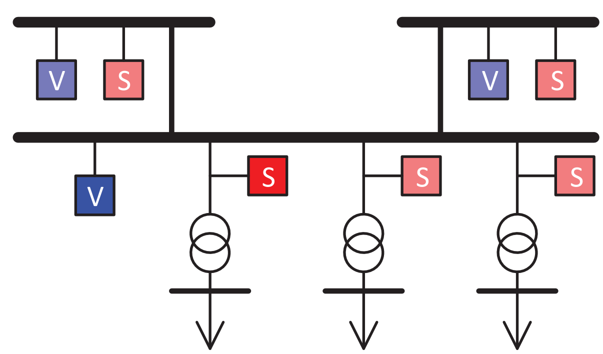

Fig. 1. Illustration of the voltage (V) and power (S) measurements of the 4 scenarios (color coding explained in Table I). The thick buses are part of the bulk transmission system, while the distribution feeders are connected to the thin buses.

TABLE I
SUMMARY OF SCENARIOS # 1 TO 4.

SCENARIO	MEASUREMENTS	SIMULATION	OBJECTIVE FUNCTION
1	Wide-area V	$fault \xrightarrow{system} V_p$	$\text{MSE}(V_{\text{meas}}, V_p)$
2	Local V, P, Q	$V_{\text{meas}} \xrightarrow{SMIB} P_p, Q_p$	$\text{MSE}(P_{\text{meas}}, P_p) + \text{MSE}(Q_{\text{meas}}, Q_p)$
3	Wide-area P, Q	$fault \xrightarrow{system} P_p, Q_p$	$\text{MSE}(P_{\text{meas}}, P_p) + \text{MSE}(Q_{\text{meas}}, Q_p)$
4	Wide-area V, P, Q	$fault \xrightarrow{system} V_p, P_p, Q_p$	$\text{MSE}(V_{\text{meas}}, V_p) + \text{MSE}(P_{\text{meas}}, P_p) + \text{MSE}(Q_{\text{meas}}, Q_p)$

Notes: $system$ means the network model of the system. $fault$ means the description of the disturbance. P and Q are normalized, based on the steady state consumption of each load.

wide-area simulation of the system, we use a single-machine-infinite-bus (SMIB) simulation of just the buses where power measurements exist. The machine in this model is set to "playback" mode, where the terminal voltage is set to the V measurements. Scenario 3 represents a system with improved wide-area complex power monitoring. In this case, we have power measurements at all loads so we can return to a full system simulation instead of using a SMIB. Finally, scenario 4 combines the wide-area measurements of scenarios 1 and 3 for the best possible case.

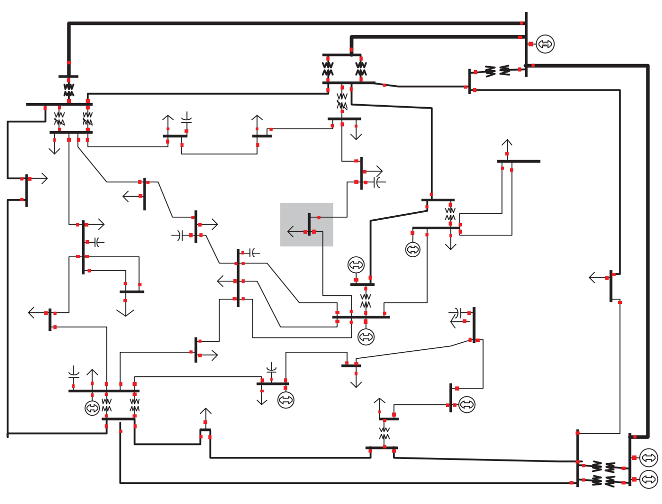

Fig. 2. 37 bus case from [14] used for validation (fault bus highlighted).

TABLE II
PARAMETERS DESIGNATED AS THE SYNTHETIC LOAD MODEL.
$p_{syn} = \begin{bmatrix} 0.24 & 0.19 & 0.3 & 0.09 & 0.18 \end{bmatrix}^T$

PARAMETER	VALUE
Large motor	**24%**
Small motor	**19%**
Discharge lighting	**30%**
Transformer losses	Neglected
Constant MVA	**9%**
PI/QZ	**18%**
Feeder R and X	Neglected

judge the algorithm's efficacy. Therefore, we use a synthetic model with fictional parameters, p_{syn}, to generate a set of synthetic measurement data: $Y_{\text{syn}}[t]$. The synthetic load model parameters are listed in Table II. The five bold ones are the parameters the algorithm will solve for. We choose to ignore the transformer and feeder losses, since those are relatively insignificant compared to the other five parameters [6], which represent the major classes of loads.

In order to quantify the performance of the algorithm, we need to define an error metric. Since the CLOD parameters are represented in a vector, a natural metric would be the Euclidean distance between the estimate and the correct solution $||p_{\text{syn}} - p^*||_2$, which we henceforth call the estimation error.

IV. RESULTS

We now investigate how the four scenarios described in Section III-A affect the accuracy of the parameter estimation under noisy conditions. In Fig. 3, we show the estimation error as a function of SNR. We vary the SNR from 0 dB to 90 dB, in 5 dB steps. For each noise level, we perform the test 5 times, each time with a new realization of white Gaussian noise added to V_{meas}. We expected that with low noise levels, the correct solution would be obtained. As noise increased (SNR decreased), the minimization of the MSE between V_{meas} and V_p may not converge to the correct solution. Upon first inspection, we can see that scenarios 1 and 2 matched our expectations, but scenarios 3 and 4 did not. Several of the scenarios also have unpredictable behavior at low SNR, most

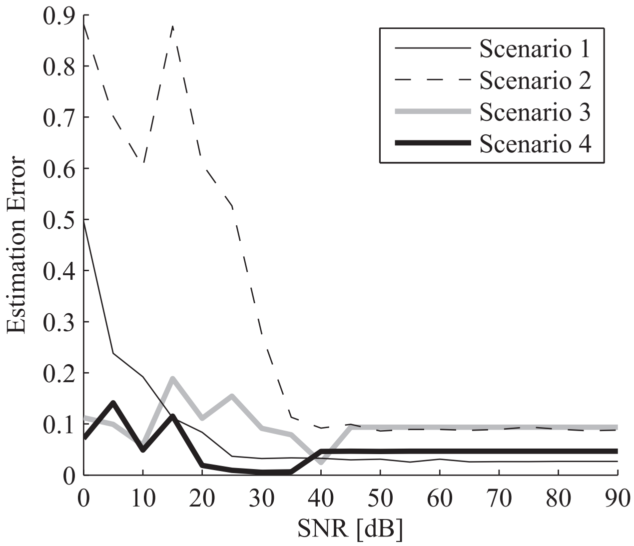

Fig. 3. The total estimation error as a function of the measurement SNR for the 4 cases.

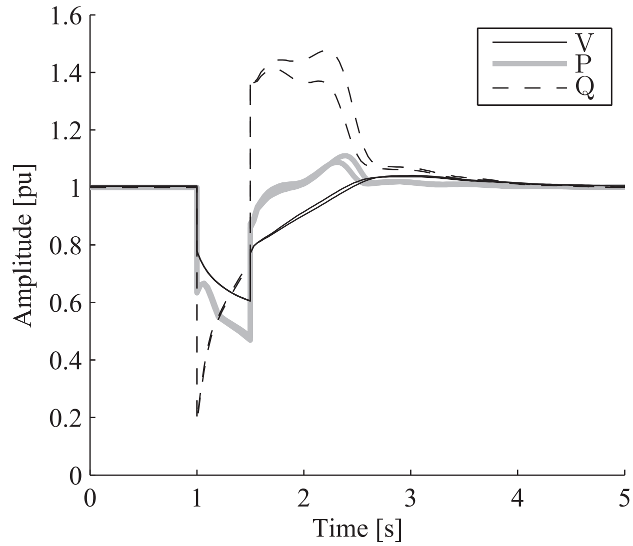

Fig. 4. Illustrating the sensitivity of V, P, and Q to different parameters.

likely because computational feasibility would only allow us to test 5 realizations of noise. Finally, at above 40 dB, the curves flatten out. This means that the noise has dropped to a low enough level as to not impact the algorithm's convergence to the correct global optimum. The following sections compare and elaborate on the performance of each scenario.

A. Scenario 1: Wide-Area Voltage Measurements

In scenario 1, we see the expected increase in estimation error as SNR drops. Above 25 dB, wide-area voltage measurements provide the best accuracy. However, as discussed in Section II-C, real measurements may not achieve the necessary SNR for this to matter.

B. Scenario 2: Local Power Measurements

Scenario 2 suffers from the same problem at low SNR, but even more so than scenario 1. This is because not only do the measurements of P and Q include noise, but so does the input to the simulation V_{meas}. Thus, when we perform the SMIB simulation, we obtain simulation results P_p and Q_p that are already degraded by the effects of noise. Then, when we compare that to the noisy measurements, the effect is exacerbated. At high SNR, scenario 2 also does not perform as well as scenario 1. This means that even in ideal conditions, P and Q still have a relatively flat objective cost near the optimum p^*, resulting in the optimization algorithm converging to an imperfect solution.

C. Scenario 3: Wide-Area Power Measurements

In scenario 3, the measurement SNR did not have much impact on estimation error, which was surprising. At low SNR, we find that scenario 3 performs much better than scenarios 1 or 2. What this points to is that when p is far away from p^*, P and Q are much more sensitive to p than V is to p. Fig. 4 illustrates this. In Fig. 4, one set of plots corresponds to the simulation results at a bus using the parameters in Table II. The other set corresponds to the results at the same bus, but with the percentages of Large and Small IMs swapped. While the V results are nearly overlapping, there is a visible difference in P and a significant difference in Q.

To further analyze this sensitivity, we can visualize it by contouring the $log(\cdot)$ of the cost function (1) by varying each pair of parameters in the CLOD model. Fig. 5 shows the contour for scenario 1. In the first subplot, Large and Small motors are varied, while Constant Power and Discharge Lighting are fixed to their correct values. The final parameter, PI/QZ, is used as a "slack" parameter, to ensure they add to 100%. The remaining five subplots show the other pairwise combinations of parameters, with PI/QZ always playing the role of "slack" parameter. Fig. 6 shows the same figures for scenario 3.

If we compare Figs. 5 and 6, we can see that, firstly, the contours for scenario 3 span more orders of magnitude. This confirms our hypothesis that P and Q are more sensitive to parameters than V. As a result, when using $P+jQ$, even when a high amount of noise exists, the optimization algorithm is still able to converge to a reasonable solution. Secondly, the contours for scenario 3 are much more circular than those for scenario 1, which are more elongated. More circular contours means that there is also less parameter interdependency: there is a single optimal value for both parameters, and not a range of optimal values for both. Both of these observations cause scenario 3 to perform well at low SNR. At high SNR, scenario 3 performed identically to scenario 2. Thus, simply widening our power measurements from local to wide-area does not improve performance under ideal conditions. This means that, while P and Q are most sensitive to p far away from p^*, V is most sensitive to p near p^*.

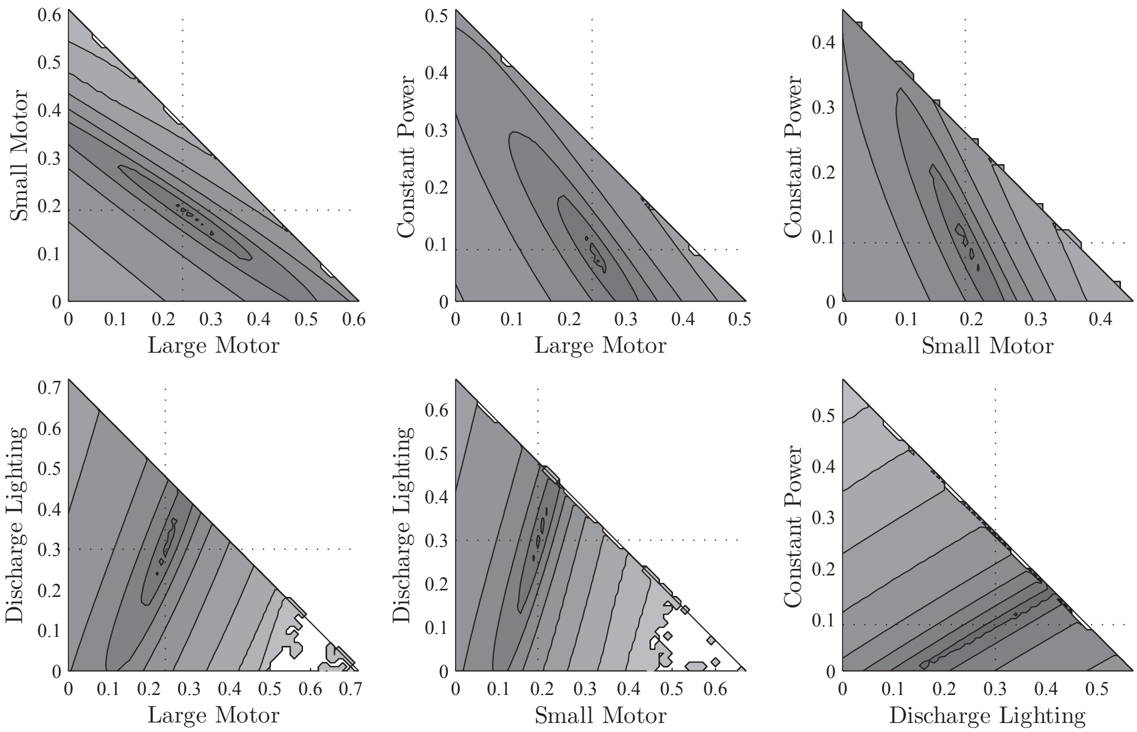

Fig. 5. Contours of the objective function cost (log scale) in case 1, for each pair of parameters. The white areas in the lower right corner of some plots represent parameter vectors for which the simulation could not be solved.

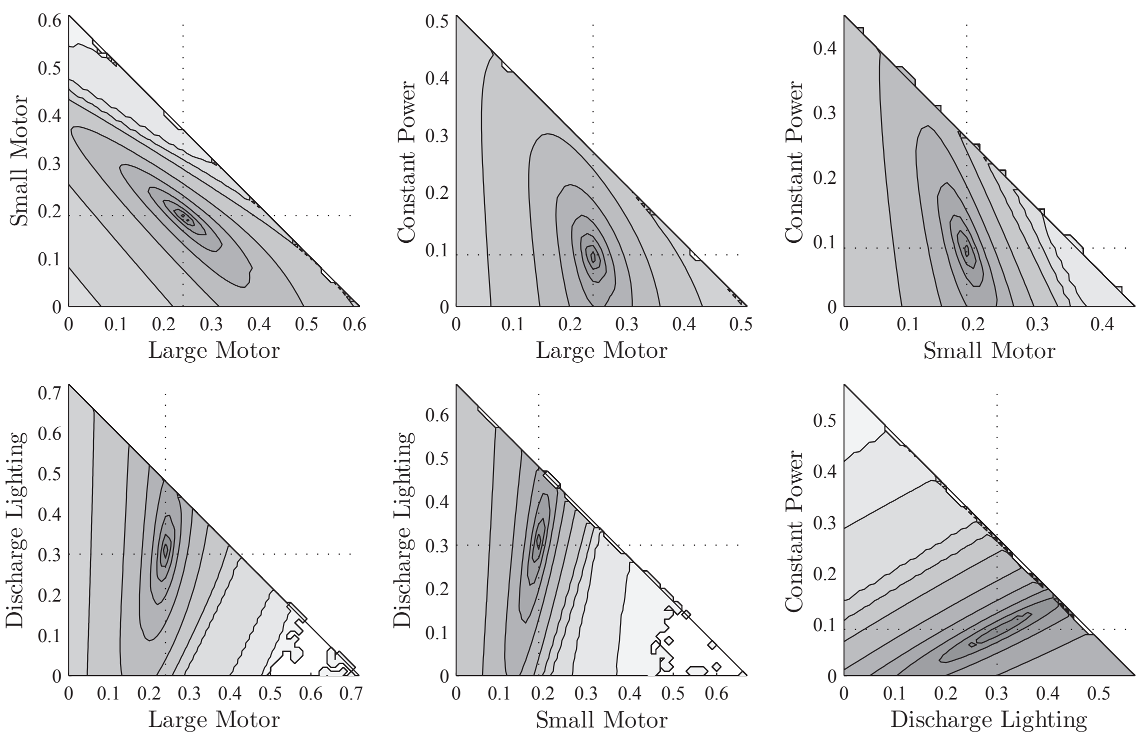

Fig. 6. Contours of the objective function cost (log scale) in case 3, for each pair of parameters. The white areas in the lower right corner of some plots represent parameter vectors for which the simulation could not be solved.

TABLE III
COMPUTATIONAL COST REQUIRED FOR CONVERGENCE, WITH STANDARD DEVIATIONS.

SCENARIO	RUNTIME/ITERATION	ITERATIONS
1	0.456 ± 0.187 s	78.2 ± 13.7
2	1.203 ± 0.045 s	76.9 ± 35.7
3	0.495 ± 0.187 s	104.2 ± 20.5
4	0.611 ± 0.187 s	88.7 ± 26.1

D. Scenario 4: Wide-Area Voltage and Power Measurements

We found in scenario 3 that wide-area power measurements are best for finding a reasonable p, but scenario 1 showed us that wide-area voltage provides the highest accuracy at low levels of noise. Scenario 4 tries to capture the advantages of both: the robustness of power to noise, and the accuracy of voltage at high SNR. While the objective function is the sum of the objective functions of scenarios 1 and 3, we can see that the estimation error for scenario 4 is slightly better than the average of the plots for scenarios 1 and 3. This is due to the use of a weighted sum. Through empirical tests, we found that weighting the MSE of voltage 5 times more than the MSE of P and Q gives the best results in this case.

E. Computational Cost

In the previous sections, we compared how the use of voltage or power affects the accuracy of parameter estimation. In this section, we look at the computational cost of each scenario. In scenarios 1, 3, and 4, we perform a single 37-bus simulation. In scenario 2, we perform 25 separate SMIB simulations, one for each bus which contains a load. Table III summarizes the time required to evaluate each iteration and the number of iterations required. For each of the four scenarios, we measured the running time of 630 evenly spaced sets of parameters, and the iterations required for convergence of 95 cases. The average and standard deviation of each scenario was then calculated. We can see that scenario 2 is by far the slowest. This can be attributed to the overhead required to initialize 25 simulations, even though each SMIB simulation is more simple than a 37-bus case. Scenario 4 requires slightly longer to run than scenarios 1 and 3, but we feel that the significant accuracy improvement justifies the small increase in computational expense.

V. CONCLUSION

Load modeling has become increasingly important, but the problem of load model parameter estimation remains unsolved. We have found that when the dynamic response of a load model is insensitive to its parameters, the parameter estimation's least-squares cost function becomes very shallow. When random measurement noise is present, the noise causes the optimization algorithm to converge to a random incorrect estimate. In this paper, we looked at four possible sets of input-output relationships that we can use for load modeling. The first requires wide-area measurement of voltage. The advantage of this first scenario is that voltage measurements are abundant, and the results of parameter estimation using voltage measurements are excellent for cases with low measurement noise. The second uses measurements of voltage and complex power at a local level, for example, at a single feeder. However, this method is extremely susceptible to noise since even the simulation results are contaminated by noise. The third case requires wide-area complex power measurements. The advantage of using complex power is that parameter estimation using power is much more robust to noise than using voltage, though it is not as accurate for low noise cases. Finally, by combining both wide-area voltage and wide-area power measurements, the best performance is achieved across all SNRs, and is well worth the extra computational time required. While we do not currently have the wide-area complex power monitoring required to implement this fourth case, thanks to the rapid expansion of the PMU network, this could be a reality in the near future.

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REFERENCES

[1] R. Bravo, R. Yinger, D. Chassin, H. Huang, N. Lu, I. Hiskens, and G. Venkataramanan, "Load modeling transmission research appendix H - load monitoring," California Energy Commission, Tech. Rep., 2007.

[2] J. D. Glidewell and M. Y. Patel, "Effect of high speed reclosing on fault induced delayed voltage recovery," *2012 IEEE Power and Energy Society General Meeting*, pp. 1–6, 2012.

[3] B. Lesieutre, P. Sauer, and A. Pai, "Development and comparative study of induction machine based dynamic P, Q load models," *Power Systems, IEEE Transactions on*, vol. 10, no. 1, pp. 182–191, 1995.

[4] S. Guo and T. J. Overbye, "Suitability of a dynamic load model to measurement-based parameter estimation," in *17th International Conference on Intelligent Systems Application to Power Systems*, 2013.

[5] J. V. Milanović, K. Yamashita, S. Martínez Villanueva, S. Ž. Djokić, and L. M. Korunović, "International industry practice on power system load modeling," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3038–3046, 2013.

[6] J. De Leon and B. Kehrli, "The modeling requirements for short-term voltage stability studies," *2006 IEEE PES Power Systems Conference and Exposition*, pp. 582–588, 2006.

[7] N. Modi, T. K. Saha, and N. Mithulananthan, "Design of wide-area damping controller and performance evaluation in presence of load model uncertainties," *2012 22nd Australasian Universities Power Engineering Conference: "Green Smart Grid Systems", AUPEC 2012*, 2012.

[8] R. Bravo, R. Yinger, D. Chassin, H. Huang, N. Lu, I. Hiskens, and G. Venkataramanan, "Load modeling transmission research," California Energy Commission, Tech. Rep., 2010.

[9] S. Guo and T. J. Overbye, "A maximum a-posteriori based algorithm for dynamic load model parameter estimation," in *Smart Grid Communications, IEEE International Conference on*, 2015.

[10] Siemens Inc., *PSS/E 33.0 Model Library*, 2011.

[11] PowerWorld Corporation, "Block diagrams," 2015.

[12] H. Renmu, M. Jin, and D. Hill, "Composite load modeling via measurement approach," *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 663–672, 2006.

[13] IEEE-SA Standards Board, "IEEE standard for synchrophasor measurements for power systems - Amendment 1: modification of selected performance requirements IEEE power and energy society," 2014.

[14] J. Glover, M. Sarma, and T. Overbye, *Power System Analysis and Design*, 5th ed. Stamford, CT.: Thomson Learning, 2008.