Dynamic Load Modelling Using Real Time Estimated States

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***Abstract*—Dynamic load models are necessary for accurate monitoring and control of the system during various events as well as for better understanding the behavior and the characteristics of the system. In this paper, a realistic approach of load modelling using real time estimated states is studied. Since Phasor Measurement Units (PMUs) are not installed yet at every bus, a linear state estimator is used to provide the state of the buses without PMUs. The overall impact of the real time estimated states and the inaccurate load model parameters are studied on the IEEE 39-bus dynamic test system. In addition, the realistic approach of load modelling is enhanced by using various load types while errors that affect the estimated states, such as line parameter errors and measurement gross errors are also considered. Furthermore, a sensitivity analysis with inaccurate load model parameters is performed to show their effect on the results of load modelling.**

***Index Terms*—Dynamic load model, linear state estimation, real time monitoring.**

I. Introduction

Power systems are experiencing unprecedented changes in structure and topology. Environmental, economical, and political reasons have increased the system utilization, while utilities tend to operate systems closer to their limits [1]. In this sense, simulations and analysis have become more demanding and the models need to be more accurate than in the past in order to accurately monitor and control the system. Although a lot of studies have been performed for accurate modelling of the system components, such as generators, transformers, and lines, less effort has been given for modelling the loads. The need for accurate load models has been well recognized after the events in Sweden in 1983, Tokyo in 1987, and Western North America in 1996 [2] - [5]. Further, in many cases system operators realized that some events could not be reconstructed in post mortem simulations with the currently used load models [4]. It is therefore important to always have a detailed and realistic picture of the system's operation in order to take the appropriate actions when needed.

The percentage of electronic devices and motors in the grid is rising, affecting the composition, characteristics, and the behavior of loads. These changes have accented the need for load modelling as they affect more the power system stability. The significance of accurate load models, especially for predicting the operation of the protection devices, was shown in [6]. However, many load models are developed based on measurements [7], [8]. But once the load model is developed, it is important to study how the data given to the models affect the results. In [9] the authors apply different load models in order to examine the actual load to be shed. In [10] pseudomeasurements from load models are used for analyzing bad data in distribution state estimation. The impact of load modelling in distribution state estimation is studied in [11] where the authors developed a state estimation algorithm enhanced by the composite load model.

In general, loads are one of the most difficult components to model as it is not sufficient to use a single model in the whole system. This is because the load characteristics and behavior depends on the load composition that changes during the day and on the location of the load. As most of the time the model is an aggregation of loads, it is not possible to have enough data to know the exact composition that is also changing in time [12]. It is therefore more suitable to use different load models in the system depending on the location and the time that they are used.

A load model is defined as the mathematical representation of the active and reactive power with inputs of voltage and/or frequency. An error in the output of the model in comparison to the actual demand may come either from the use of an inappropriate model, inaccurate parameters for the current load composition or even a deviation of the available input values in relation to the actual ones. It is also important to ensure that the model used is chosen carefully so that all the details that need to be analyzed, are captured satisfactorily. As the requirements have increased and the behavior of the loads has become more complex, it is important to be able to capture as much as possible, the detailed behavior of loads during an event. For such cases the use of a dynamic load model is needed in which the measurements (voltage and frequency) from PMUs can be utilized as inputs. Although the deployment of PMUs is continuously increased, the installation of PMUs at every bus of the system is not feasible yet. This is mainly due to the high

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cost of these measurement devices, and the advanced communication and measuring infrastructure needed for installing a PMU in the substation. For this reason, there was a lot of research activity in the past years to determine the optimal PMU locations for rendering the power system observable [13].

In a PMU-observable system, a linear state estimator can be used for providing the power systems states in quasi real time. In general, the state estimator provides the power system states (i.e., voltage magnitude and angle of all the buses) in consecutive time intervals. Although the conventional state estimator is intended to capture the static behavior of the power system (due to the low reporting rate of the conventional measurements), a PMU-based state estimator can be used for capturing the dynamic behavior of the power system during a contingency [14]. In this sense, the estimated states (voltage magnitude) from a linear state estimator can be used as inputs to the dynamic load model for capturing the real and reactive power changes during an event.

In this paper, the use of the estimated states provided from a linear state estimator in load modelling is examined. An Exponential Dynamic Load Model (EDLM) takes as inputs the estimated states for calculating the changes of active and reactive power in each bus of the system. The effect of inaccurate load model parameters, the measurements gross error and the line parameter error on the output results of the models is also studied.

The paper is organized as follows. Section II focuses on load modelling and the EDLM that is used in this study, whereas, Section III explains the theory behind the linear state estimation. The study cases and the results are shown in Section IV while Section V presents the conclusions.

II. Load Modelling

There are various load models that can be used depending on the requirements of the utilities; however, all the models should present minimum deviation between the calculated and the real values of loads. The models may be developed as component based or measurement based [12]. The component based approach needs data of the load composition in order to model the aggregate load, whereas the measurement based needs data that are collected during a disturbance. The load models can be classified into static and dynamic, where static load models cannot capture the dynamic behavior of the load during an event whereas dynamic load models are especially needed for stability studies.

In this work, the dynamic load modelling will be considered. The most frequent used dynamic load models are the composite and the exponential model. The composite model is a combination of a static and a dynamic load. For the static part the ZIP or the exponential model is used and for the dynamic part an induction motor model is used. The composite model is usually used when induction motors are the dominant component whereas the exponential recovery dynamic load model is a mathematical function and it is usually used when the load recovers slowly. Other dynamic load models with higher complexity are also available but it is more difficult to accurately estimate their parameters [12].

A. Exponential Dynamic Load Model (EDLM)

In this study we are using the EDLM as it is widely used and is capable of effectively representing loads. Based on this model the active power can be expressed as,

$$T_p \frac{\partial P_r}{\partial t} + P_r = P_o \left(\frac{V}{V_o}\right)^{a_s} - P_o \left(\frac{V}{V_o}\right)^{a_t} \tag{1}$$

$$P_l = P_r + P_o \left(\frac{V}{V_o}\right)^{a_t} \tag{2}$$

where P_o is the active power consumption before voltage change, V_o is the voltage before disturbance, V is the measured voltage, P_r is the active power recovery, P_l is the total active power response, T_p is the active load recovery time constant, a_s is the steady state active load voltage dependence and a_t is the transient active load voltage dependence. The electrical quantities are in per unit, T_p is in seconds and the parameters a_s and a_t are dimensionless. It should be noted that similar equations are also valid for reactive power [15].

In the case of this paper the voltage (V) at each time step, the voltage before the disturbance (V_o) and the active and reactive consumption before the voltage change (P_o, Q_o) are taken from the linear state estimation results.

The equations show a nonlinear dependence of voltage for active and reactive power. The nonlinearities produce variations of power for large voltage changes. In Fig. 1 the load model behavior for a simple voltage drop is presented.

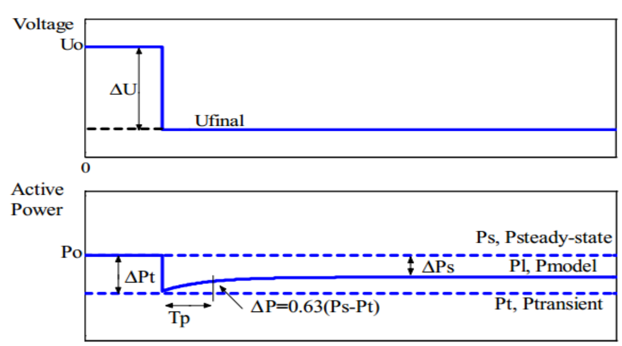

Fig. 1. Load response under ΔU step, from Uo level [16]

For a voltage drop of ΔU from Uo, the active power drops instantaneously, but starts recovering exponentially. The load may not totally recover to its initial value depending on the parameters used. If a_s is 0 then the load is fully restored after the event otherwise it is partially restored. The a_t parameter is used to show the load behavior during the event. The a_t values of 0, 1, and 2 correspond to a constant power, constant current and constant impedance load respectively. The T_p parameter shows the time needed for the load to reach 63% of its final value [16].

III. Linear State Estimator

The linear state estimator that is used in this paper is formulated in a Weighted Least Squares (WLS) formulation using the following measurement model [17],

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{e}, \tag{3}$$

where $\mathbf{z}$ is the measurement vector, $\mathbf{h}(\mathbf{x})$ is the vector containing the equations that relate the measurements to the system states, $\mathbf{x}$ is the state vector containing the power system states and $\mathbf{e}$ is the Gaussian noise in the measurements.

Based on the WLS formulation, the state vector can be determined by minimizing the function $J(\mathbf{x})$ as,

$$\min_{\mathbf{x}} \; J(\mathbf{x}) = [\mathbf{z} - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{z} - \mathbf{h}(\mathbf{x})], \tag{4}$$

where $\mathbf{R}$ is the measurement error covariance matrix.

In the case of a linear state estimator, the measurements that are provided by the PMUs and used in the estimator are the voltage phasors of the buses where the PMUs are installed as well as the phasors of the currents that flow through the transmission lines emanating from the PMU bus (assuming enough PMU measuring channels). In order to have a linear relationship between the power system states and the PMU measurements, the voltage and current phasors are transformed from polar to rectangular form and the measurements can be expressed as,

$$\mathbf{z} = \mathbf{H}\mathbf{x} + \mathbf{e} = \begin{bmatrix} \mathbf{V}_r^{meas} \\ \mathbf{V}_i^{meas} \\ \mathbf{I}_r^{meas} \\ \mathbf{I}_i^{meas} \end{bmatrix} = \begin{bmatrix} \partial \mathbf{V}_r / \partial \mathbf{V}_r & \partial \mathbf{V}_r / \partial \mathbf{V}_i \\ \partial \mathbf{V}_i / \partial \mathbf{V}_r & \partial \mathbf{V}_i / \partial \mathbf{V}_i \\ \partial \mathbf{I}_r / \partial \mathbf{V}_r & \partial \mathbf{I}_r / \partial \mathbf{V}_i \\ \partial \mathbf{I}_i / \partial \mathbf{V}_r & \partial \mathbf{I}_i / \partial \mathbf{V}_i \end{bmatrix} \begin{bmatrix} \mathbf{V}_r \\ \mathbf{V}_i \end{bmatrix} + \mathbf{e}, \tag{5}$$

where $\mathbf{V}_r$, $\mathbf{V}_i$, $\mathbf{I}_r$, $\mathbf{I}_i$ are the real and imaginary parts of the bus voltage phasors and the line current phasors, respectively, when they are expressed in rectangular form.

Due to the linear relationship between the states and the measurements, the states provided by the linear state estimator can be estimated non-iteratively as,

$$\hat{\mathbf{x}} = (\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \mathbf{z}. \tag{6}$$

It should be noted that using the estimated states the real and reactive power injection of each bus (which is actually the load of the bus (active and reactive power) in case of no other attached element on the bus) can be calculated as,

$$P_i = V_i \sum_{j \in \aleph_i} V_j (G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)) \tag{7}$$

$$Q_i = V_i \sum_{j \in \aleph_i} V_j (G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)) \tag{8}$$

V_i, θ_i the voltage magnitude and phase angle at bus *i*, $G_{ij}+jB_{ij}$ is the ij^{th} element of the bus admittance matrix, and $\aleph_i$ is the set of buses directly connected to bus *i*.

IV. Case studies

The case studies that are presented in this paper investigate the impact of using real time estimated states in the EDLM dynamic load model for calculating the actual power in the system during an event. Three case studies will be investigated in order to enhance the realistic approach of the study: *(1) sensitivity analysis for erroneous load model parameters (2) dynamic load model considering gross errors in PMU measurements (3) sensitivity analysis for erroneous line parameters*. The case studies are performed on the IEEE 39-bus dynamic test system [18] that is implemented in the DigSilent software. It should be noted that 16 PMUs are installed in the system and the estimated states provided by the linear state estimator are used. The location of the installed PMUs are shown in Table I. The PMUs were placed in such a way to have a full observable system by PMUs while 3 more PMUs in buses 3, 8, and 16 are added to enhance the measurement redundancy.

Table I. Locations of PMUs

Bus number
2, 3, 6, 8, 9, 10, 13, 14, 16, 17, 19, 22, 23, 25, 29, 34

Further, the simulated PMU measurements that are used in the linear state estimator are subjected to Gaussian noise added to the real PMU measurements due to the instrument transformers and the measurement device [19] as,

$$V_{meas} = V_{network} + N(0, u_{VT}^V) + N(0, u_{PMU}^V) \tag{9}$$

$$I_{meas} = I_{network} + N(0, u_{CT}^I) + N(0, u_{PMU}^I) \tag{10}$$

$$\theta_{meas}^V = \theta_{network}^V + N(0, u_{VT}^{\theta_V}) + N(0, u_{PMU}^{\theta_V}) \tag{11}$$

$$\theta_{meas}^I = \theta_{network}^I + N(0, u_{CT}^{\theta_I}) + N(0, u_{PMU}^{\theta_I}), \tag{12}$$

where u_{VT}^V, $u_{VT}^{\theta_V}$, u_{CT}^I, $u_{CT}^{\theta_I}$ are the voltage and current transformer standard uncertainties associated to the magnitude and the phase of the respective quantity. u_{PMU}^V, $u_{PMU}^{\theta_V}$, u_{PMU}^I, $u_{PMU}^{\theta_I}$ are the standard uncertainties of the PMUs associated to the magnitude and the phase of the voltage and current respectively. The instrument transformer and the PMU standard uncertainties in (9)-(12) are calculated as,

$$u_{VT}^V = |V_{meas}| \bar{e}_{VT}^V / 1.96 \qquad u_{PMU}^V = |V_{meas}| \bar{e}_{PMU}^V / 1.96 \tag{13}$$

$$u_{CT}^I = |I_{meas}| \bar{e}_{CT}^I / 1.96 \qquad u_{PMU}^I = |I_{meas}| \bar{e}_{PMU}^I / 1.96 \tag{14}$$

$$u_{VT}^{\theta_V} = \bar{e}_{VT}^{\theta_V} / 1.96 \qquad u_{PMU}^{\theta_V} = \bar{e}_{PMU}^{\theta_V} / 1.96 \tag{15}$$

$$u_{CT}^{\theta_I} = \bar{e}_{CT}^{\theta_I} / 1.96 \qquad u_{PMU}^{\theta_I} = \bar{e}_{PMU}^{\theta_I} / 1.96 \tag{16}$$

where $\bar{e}_{VT}^V$, $\bar{e}_{CT}^I$, $\bar{e}_{VT}^{\theta_V}$, $\bar{e}_{CT}^{\theta_I}$ are the instrument transformers maximum magnitude and angle errors defined by the manufacturer and are shown in Table II (assuming a 0.5 accuracy class transformers); $\bar{e}_{PMU}^V$, $\bar{e}_{PMU}^I$, $\bar{e}_{PMU}^{\theta_V}$, $\bar{e}_{PMU}^{\theta_I}$ are the PMU maximum magnitude and angle errors as shown in Table III [20]; $|V_{meas}|$ and $|I_{meas}|$ are the voltage and current magnitudes.

It should be noted that in this paper it is implicitly assumed that the measurement errors lie with a 95% probability in the interval bounded by the maximum errors defined in the manufacturers' data (Table II and Table III). Since the distribution of the measurement errors is assumed to be normal, the choice of this particular coverage probability leads to having the measurement errors lie between -1.96u to +1.96u. Therefore, in this case the coverage factor of the measurement error distributions is equal to 1.96 and the standard uncertainties for each measurement type can be calculated by dividing the maximum measurement error by 1.96 as in (13)-(16).

Table II. Maximum errors-0.5 accuracy class instrument transformers

Voltage transformers		Current transformers									
Percentage of voltage magnitude error	Phase displacement (degrees)	± Percentage of current error at percentage of rated current					± Phase displacement at percentage of rated current (degrees)				
±0.5	±0.333	1	5	20	100	120	1	5	20	100	120
		-	1.5	0.75	0.5	0.5	-	1.5	0.75	0.5	0.5

Table III. Measurement devices maximum errors

Voltage magnitude (%)	Current magnitude (%)	Phase angle (degrees)
±0.02	±0.03	±0.54

Moreover, the PMU measurements that are used in the linear state estimator are weighted by using the combined measurement uncertainty of each PMU measurement which can be calculated as,

$$u_{meas}^{V} = \sqrt{(u_{VT}^{V})^2 + (u_{MU}^{V})^2} \tag{17}$$

$$u_{meas}^{\theta_V} = \sqrt{(u_{VT}^{\theta_V})^2 + (u_{MU}^{\theta_V})^2} \tag{18}$$

$$u_{meas}^{I} = \sqrt{(u_{VT}^{I})^2 + (u_{MU}^{I})^2} \tag{19}$$

$$u_{meas}^{\theta_I} = \sqrt{(u_{VT}^{\theta_I})^2 + (u_{MU}^{\theta_I})^2}. \tag{20}$$

The EDLM (implemented in Matlab) uses the voltage magnitude (V) at each time step (provided by the linear state estimator) and the voltage magnitude (V_0) and the active and reactive power (P_0, Q_0) before the occurrence of the fault again taken from the state estimation results.

The Mean Absolute Error (MAE) is used as a metric of comparison between the actual active/reactive power and the calculated power either from the equations (7) and (8) or from the EDLM. The MAE is calculated as,

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| \tag{21}$$

where f is the computed active/reactive power in each case, y is the actual measurement and n is the number of time steps. It should be noted that the simulation duration was 20 s and the active power for each load was calculated every 0.02 s (time step) as the execution rate of the linear state estimator. The total MAE is an aggregation of all the individual MAEs (MAE for each load in the IEEE 39-bus system) for each case study.

A. Case study 1: Sensitivity analysis for erroneous load model parameters

In case study 1, a sensitivity analysis is performed for erroneous load model parameters. The sensitivity analysis of the error in the load parameters is significant since it will show how the results are changing with inaccurate load model parameters and how much error is acceptable in such simulations. In addition, in this case, multiple load models where used in the system in order to enhance the realistic approach of the case study. In reality not all loads of a power system have the same behavior and characteristics so they are represented with different parameters. Three sets of load model parameters are used as shown in Table IV.

Table IV. Assigned load model parameters of case study 1

Loads	a_s	a_t	T_p	b_s	b_t	T_q
3, 21, 23, 24, 25	-0.32	1.65	70	-0.48	2.22	78
4, 7, 15, 16, 18, 27, 31	0.44	4.02	1.78	4.9	148.7	55.5
8, 12, 20, 26, 28, 29, 39	0.79	4.84	4.6	5.03	363.8	73

In this case study, the generator G6 that is connected on bus 35 is disconnected from the system at t=2 s. A comparison between the actual active and reactive power of the system (taken from DigSilent) and the calculated active and reactive power is presented using: (a) equation (7) and (8), (b) EDLM with inaccurate parameters with a range of parameter error [-50%, 50%] and (c) EDLM with accurate parameters. The total MAEs for case 1 are tabulated in Table V.

Table V. Summarized results of case study 1

Case Studies			Total MAE P (MW)	Total MAE Q (MVAr)
(a)	Real and reactive power injection calculation using (7) and (8) vs Actual measurements		42.857	72.988
(b)	EDLM with parameter error vs Actual measurements	-50 %	53.564	38.608
		-40 %	43.086	31.915
		-30 %	32.703	25.311
		-20 %	22.646	18.821
		-10 %	13.481	12.590
		10 %	14.004	9.565
		20 %	23.994	12.991
		30 %	34.410	17.942
		40 %	44.875	23.849
		50 %	55.334	29.983
(c)	EDLM with exact parameters vs Actual measurements		8.378	8.692

As it is shown in Table II for a parameter error larger than -30% and 30% the EDLM model gives worst results than the power injection calculations (case (a)). In this sense, through this sensitivity analysis it is indicated how important it is to use a load model with accurate parameters but also the importance to frequently update the parameters used in a power system. Since load characteristics are changing during the year but are also changing during the day, parameter errors in the load models are usually expected. However, based on the sensitivity analysis, it is important to try to keep this error as small as possible to have accurate results. This is underlined in the case that EDLM has exact parameters where the MAE is considerably smaller than the respective one of case (a).

B. Case study 2: Dynamic load model considering gross errors in PMU measurements

In case study 2, the effect of PMU measurement gross errors on the dynamic load modelling is considered. In general, gross errors of measurements are due to telemetry failure, drift or bias of the measurement device, and in case of PMUs due to loss of GPS signal. In this case study, the same load parameters as shown in Table IV are used. The generator G6 is disconnected at t=2 s as in case study 1, but the effect of adding a gross error of 5%, 10% and 15% on the measurements (both in voltage and current magnitude) taken from PMUs connected on buses 2, 14 and 34 is studied. A comparison between the actual active and reactive power of the system (taken from DigSilent) and the calculated active and reactive power using: (a) equations (7) and (8) and (b) EDLM with accurate parameters is presented. The summarized results are tabulated in Table VI.

Table VI. Summarized results of case study 2

		Gross Error	Case Studies	
			(a) Real and reactive power injection calculation using (7) and (8) vs Actual measurements	(b) EDLM with exact parameters vs Actual measurements
Total MAE	P (MW)	0%	42.857	8.378
		5%	155.240	128.447
		10%	293.500	251.111
		15%	430.770	360.756
	Q (MVAr)	0%	72.988	8.692
		5%	142.671	93.042
		10%	237.983	176.565
		15%	327.487	255.136

As noticed from the results, the erroneous measurements captured by the three PMUs have a negative impact on the calculation of the active and reactive power using equations (7) and (8). Even a 5% gross error has significantly increased the total MAE of the active power. The use of the EDLM model is able to reduce slightly the MAE. However, this diminution is not significant and the error is still large. This large MAE is mainly due to the high dependence of EDLM on the accuracy of the P_o and Q_o provided by the linear state estimator. To reduce the effect of the inaccurate P_o and Q_o provided by the linear state estimator ((7) and (8)) to the EDLM, conventional real and reactive power injection measurements may be used for P_o and Q_o. The results with a 15% gross error using the EDLM with exact parameters and (a) P_o and Q_o calculated by (7) and (8) using the results from the state estimation and (b) P_o and Q_o from conventional measurements is presented in Table VII.

Table VII. Summarized results of case study 2 for 15% gross error considering conventional measurements

Case Studies		Total MAE	
EDLM with exact parameters vs Actual measurements		**P (MW)**	**Q (MVAr)**
(a)	P_o, Q_o from equations (7) and (8)	360.756	255.136
(b)	P_o, Q_o from conventional measurements	69.056	52.832

As shown in Table VII in subcase b) the MAE of the EDLM model is much smaller meaning that the active and reactive power are close to the actual. As a result, in case that there is a doubt for the accuracy of the PMU measurements it is better to use the EDLM model in combination with the conventional real and reactive power injection measurements (if they are available).

C. *Case study 3: Sensitivity analysis for erroneous line parameters*

In case study 3, except from the measurement noise that is already considered in all cases, the uncertainty of the line parameter errors is also considered. The uncertainty of the line parameter errors has been added to lines 3-4, 4-5, 7-8, 8-9, 15-16, 16-21, 20-34 and 25-26. A range of errors up to 30% is examined. In addition, static loads have also been added to the power system resulting with four load types in the system as shown in Table VIII.

Table VIII. Assigned load model parameters of case study 3

Loads	a_s	a_t	T_p	b_s	b_t	T_q
1,10,11,12,13	-0.32	1.65	70	-0.48	2.22	78
2,3,8,15,18	0.44	4.02	1.78	4.9	148.7	55.5
4,5,9,14,16,17,19	0.79	4.84	4.6	5.03	363.8	73
4,6,7,9,19	static					

In this case a load increase occurs at t=2 s. The active power of loads 15, 20 and 39 increases by 30% and their reactive power by 20%, whereas the active power of loads 8 and 16 increases by 20% and their reactive power by 10%. A comparison between the actual measurements and (a) the active and reactive power injection calculation using (7) and (8) and (b) the EDLM with exact parameters is shown in Table IX for 10%, 20%, and 30% line parameter errors.

Table IX. Summarized results of case study 3

		Line Parameter Error	Case Studies	
			(a) Real and reactive power injection calculation using (7) and (8) vs Actual measurements	**(b)** EDLM with exact parameters vs Actual measurements
Total MAE	P (MW)	0%	32.093	4.534
		10%	84.170	78.438
		20%	149.566	151.964
		30%	214.553	225.723
	Q (MVAr)	0%	61.711	6.293
		10%	86.933	40.606
		20%	126.503	80.392
		30%	159.414	127.426

As the results indicate, the line parameter error may significantly increase the error calculation of the active and reactive power. Even in some cases where the error is large, the use of the EDLM may not always improve the result but is still comparable to (a). As the line parameter error gets larger, the total MAE also increases. In order to reduce the effect of the inaccurate P_o and Q_o on the EDLM the use of conventional power injection measurements is also studied in this case. The results for a 30% line parameter error is shown in Table X.

Table X. Summarized results of case study 3 for a 30% line parameter error considering conventional measurements

Case Studies		Total MAE	
EDLM with exact parameters vs Actual measurements		**P (MW)**	**Q (MVAr)**
(a)	P_o, Q_o from equations (7) and (8)	225.723	127.426
(b)	P_o, Q_o from conventional measurements	50.265	14.051

In case (b) when P_o and Q_o for EDLM are taken from conventional measurements the MAE is significantly reduced. It is important to use the conventional measurements when the line parameter errors may be inaccurate. This will ensure that the active and reactive power calculation using the EDLM is close to the actual values.

V. CONCLUSIONS

This paper presents a realistic approach for load modelling, by using real estimated states in a dynamic load model. Multiple load types (with different parameters) are added to the system as in reality not all the loads have the same behavior and characteristics. In addition, except from the measurement noise that is considered in all cases, (1) erroneous load model parameters, (2) PMU measurement gross errors and (3) line parameter errors are also considered. All these are likely to be present in a real system so it is interesting to examine the effect of these factors on the accuracy of the calculated results as well as how the error between the calculated and the actual active and reactive power can be reduced. A sensitivity analysis is performed for each case to study the impact of the examined factors on the results. The sensitivity analysis of the error in the load parameters is significant since it shows how the results are changing with inaccurate load model parameters and how much error is acceptable in such simulations. As shown in the results, when no load modelling is used, the error is considerable while in the cases that the load models are used for computing the active and reactive power the total MAE decreases (even with error in the parameters). When the PMU measurements gross errors are considered, it is shown that the results may be much more inaccurate. Similar results are derived when the inaccurate line parameters are considered. The MAE may become large for both power injection calculations and EDLM when the line parameter error is also large. However in both case study 2 and case study 3 when using the EDLM in combination with conventional power injection measurements for P_o and Q_o, MAE is significantly reduced meaning that the active and reactive power are close to the actual. As a result, in case that PMU measurements contain gross errors or the line parameters are erroneous it is more secure to use conventional measurements for P_o and Q_o. In conclusion, it is important to minimize as much as possible the errors in the system, recognize erroneous measurements and have accurate load model parameters that must change during different periods and be frequently updated. It should be noted that the estimated states could also be used to obtain the EDLM parameters but their inaccuracy will be propagated to the parameters.

The results show the importance of using an accurate load model for the system simulations in order to have an accurate visualization of the power system operating condition in case of a contingency. In particular, considering that during an event a certain amount of load should be shed by the operator, in case of the power injection calculation the large MAE indicates that a large amount of load may be unnecessarily shed by operators (leaving a lot of customers without electricity). On the other hand, the correct load model may prevent the inconveniences and loss of revenue resulting from the unexpected loss of power for the customers.

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