Investigating the Choice of Load Model and its Parameters for Different Voltage Response Scenarios in Large Power Systems

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SUMMARY

The aim of this paper is to investigate how different load models from static to more complicated dynamic ones can be optimized and what impact they can have on dynamic simulation results of high voltage side in real-life power systems. We focus on identifying the parameters for three practical and widely used load models including a static load model, CLOD composite load model and induction motor load model. These 3 models are practical and are implemented in large-scale simulators such as PSS/E. Real measurements recorded by Phasor Measurement Units (PMU) for some detected events at the study area are used and some possible voltage scenarios are resampled accordingly. Performance of the load models are analysed for all these resampled scenarios. To do so, we aim to minimize the error between resampled measurements and PSS/E simulation for each scenario and each of the mentioned load models. This is considered as a wide area model validation and therefore requires a proper off-line model building for simultaneous optimization of multiple load models in the study area. we use a combination of evolutionary-based methods along with heuristic methods like Levenberg Marquardt for the optimization. We then report the results and establish trends for performance of each load model towards generated scenarios. Some models with generic parameters are also considered and compared with simulation results of optimized models. This investigation can help power system operators to have some general insight into the impact of different load model types and parameters on high voltage level simulations of large-scale power systems.

KEYWORDS

Dynamic load modelling, Large-scale power system, Load model selection, Parameter optimization, Evolutionary algorithms.

1. Introduction

Load modelling in general and particularly its modelling in dynamic simulations have been a remaining challenge for system operators [1]. Despite all the efforts towards developing load models in recent years, still there are no general guidelines for dynamic load modelling in real-life power system operations. Different types of events observed in studies and therefore resulted in model identifications that are solely valid for their specific case. Additionally, some complex models that have been used for load modelling are not readily available in widely used commercial power system simulators and therefore are not practical for many numbers of loads in large power systems.

Different approaches for load modelling have been considered in the literature. Measurement-based and component-based methods have been mainly employed for model identification. Component-based methods try to build the mathematical description of the load based on their knowledge on load structure [2]. These methods may perform well for simple loads but cannot be a practical choice for more complex loads with unknown components in their structure. Measurement-based techniques assume a general model for load with some unspecified parameters and try to optimise these parameters to achieve the highest similarity with measured data [3]. Some studies have used measurements corresponding to artificially created events while others have utilized the data for real-life events. In any case, high resolution measurement devices such as Phasor Measurement Units (PMU) are necessary to achieve acceptable results.

Load models can be static, dynamic or a combination of both known as composite load models [1]. Constant impedance, current and power (ZIP) and exponential model have been broadly utilized to statically present loads in power systems [4]. According to the survey reported in [5], around 90 percent of system operators all over the world are still using basic static load models. As an example of static model validation, reference [3] applied a linear regression-based approach to find the ZIP model parameters. Artificial voltage events were created and used in this measurement-based approach. Dynamic modelling is usually more demanding and thereby recent literature is mostly focused on dynamics of loads. These models usually try to come up with different representations for induction motor loads as they have a major role in the dynamic response of loads. As an example of these dynamic models we can mention [6] and [7] which differ in the induction motor representation. Some studies used combination of static and dynamic models which often referred to as composite load models. A simple and widely used composite load model is a ZIP in parallel with an induction motor [8].

In this paper, we applied an area-wide measurement-based load modelling approach to a selected study area in Alberta. We have PMU data at a high voltage substation near this major load area. A real-life fault event in the study area is identified and its data is used for the simulations. This event followed by a very fast voltage response due to the nature of Alberta Interconnected Electric System (AIES) at the time of the event. We resampled this basic voltage event and generated some slower recovery scenarios for voltage. This can help to make the study results more representative and generalized. Three different load models are selected in this study, namely, PSS/E's static model as a pure static model, CIM5 Induction motor model as a pure dynamic model and CLOD composite model. All these 3 models are available in large-scale power system simulators such as Power System Simulator for Engineering (PSS/E) and PowerWorld. Selected models have a reasonable variety from static to dynamic as well. The objective of this paper is to investigate how these three different load models change the simulated voltage responses at the HV level, and which of them can possibly be a better choice for each of different voltage scenarios that can be observed in real-life networks.

To achieve this objective, each of these three load models replace the loads in the study area and their parameters are optimised for all voltage scenarios. As a result, we can observe how each of these models can perform in different scenarios. In addition, we compare the performance of each model with optimised parameters with that of typically used parameters for the selected model. This investigation can then assist system operators when it comes to selecting load model and its parameters for their operating power grids.

Other parts of this paper are organised as follows; Section 2 describes the voltage scenarios used in this study. Section 3 discusses each of the load models used in this study and reports the sensitivity analysis performed on these models. Some information on preparing the area-wide simulation along with the optimisation techniques used in this paper are given in the section 4. Numerical results are presented and analysed in section 5. Finally, section 6 concludes the paper.

2. Voltage Scenarios

Initially, we detected a fault induced voltage event and collected the PMU data for the selected interval around the time of the determined event. Thereafter, different voltage scenarios have been resampled based on this real-life data recorded in the study area. The event detection process can be found with more details in the fourth section. As the recovery of recorded event in Alberta is very fast, other samples are created by extending the signal and therefore producing a range of different signals from very fast ones to very slow recovery signals such as the ones reported in Fault Induced Delayed Voltage Recovery (FIDVR) events [9].

Fast Fourier Transforms Resampling (FFTR) [10] have been implemented for resampling the original PMU recorded signal. Ten scenarios have been resampled with recovery times from 0.1 to 5 seconds, but all maintain a similar shape to the original data. These scenarios cover a variety of possible voltage responses in large power systems ranging from very fast events like the ones in Alberta to very delayed responses such as the ones observed in southern parts of California [9]. Figure 1 illustrates the resampled scenarios that have been utilized in the present study. Resampled scenarios are only shown for 138 kV bus as the 240 kV ones have a similar pattern and are redundant to display here. The total length of signals is not same cause of the fact that each of them are generated with different recovery time but they all follow a same pattern.

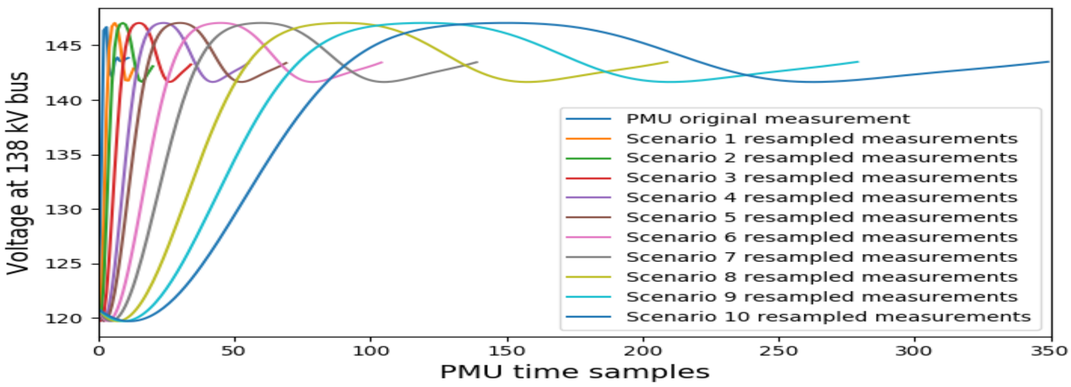

Figure 1. Resampled voltage scenarios at 138 kV bus

3. Load Models and Sensitivity Analysis

Three different load models have been employed in this study. These models are intentionally selected to vary from pure static to composite and pure dynamic load models. Each of these load models are optimised for all generated scenarios to evaluate their potential contribution towards more accurate dynamic simulation results. Each of these models are explained with more detail in following sub-sections. These sub-sections also report the sensitivity analysis results that performed on these models. Sensitivity analysis is necessary for assuring more efficient parameter selection and optimization in load modelling studies. To be consistent, half of the models' parameters are selected for optimization in each of the load models.

Sensitivity analysis is performed by using the Sobol method [11]. Sobol is a global sensitivity analysis method which relies on variance decomposition of returned values by the model. It has been considered as a successful method in application to large nonlinear systems [11]. Considering a black-box function Y=f(Xi), variance decomposition can be expressed as:

$$\sigma^2(Y) = \sum_{i=1}^{n} V_i + \sum_{i<j}^{n} V_{ij} + \dots \quad \text{where:}$$

$$V_i = \sigma^2(x_i).(E_{X_i}(Y \mid X_i)) \quad \text{and} \tag{1}$$

$$V_i = \sigma^2(x_i).(E_{X_i}(Y \mid X_i)) \quad \dots.$$

Where, σ2 shows the variance and E is the expected value or the conditional probability of output for different aggregations of inputs.

A. Static load model

The considered static load model is implemented in PSS/E and is a generalization for the well-known ZIP load model. There are totally 14 parameters for this model which their detail along with model equations and constraints can be found in [12]. This model has voltage and frequency dependency that can be controlled by user and it has two similar equations for active power part and reactive power portion of the load. This model can well generalize the performance of static models in large power systems. Generic assumptions for this static model parameters are recommended in [13]. Table 1 shows the sensitivity analysis results performed on this model. Sensitivity rankings are based on Sobol total effect index. Total effect indices are relatively more reliable than first order indices as they include parameter correlations. Results of sensitivity analysis show that parameters related to the active portion of the load are relatively more important than that of reactive part. This is mainly because of the higher concentration of active load in the area. We have selected five parameters from the active part and two parameters from the reactive part including a_1, a_2, a_7, n_2, n_3, a_8, n_4.

Table 1. Sensitivity analysis results for static load model

Parameter ranking	Total-effect index	Parameter ranking	Total-effect index
1. a_7	0.63	8. a_8	0.069
2. a_1	0.43	9. a_6	0.059
3. n_2	0.41	10. a_5	0.059
4. a_3	0.36	11. n_5	0.045
5. n_1	0.35	12. n_6	0.044
6. a_2	0.30	13. a_4	0.040
7. n_3	0.27	14. n_4	0.030

B. CLOD load model

CLOD is a composite load model supporting variety of loads at the connecting node. It also recognizes the physical distance between loads and the supplying feeder. This model does not provide the user with ability to manually change details for each of the model elements. As this model is relatively simple to implement, it has been widely used by system operators to simulate dynamic behaviour of loads in large-scale power systems. CLOD has separate models for large and small motors, static loads, discharge lighting and few other load elements. Details of each element are fixed in this model and only percentage of these components can be controlled. Generic assumptions for CLOD parameters are recommended in [14]. Table 2 shows the sensitivity analysis results based on the total-effect indices. The first half of the parameters are used for optimization, namely large motor, small motor, K_P and Discharge lighting.

Table 2. Sensitivity analysis results for CLOD composite load model

Parameter ranking	Total-effect index	Parameter ranking	Total-effect index
1. Large motor	9.42e-1	5. Constant power	2.09e-3
2. Small motor	2.99e-1	6. Transformer current	1.41e-3
3. K_p	4.21e-2	7. X	1.32e-3
4. Discharge lighting	5.10e-3	8. R	1.79e-4

C. Induction motor load model

Third group of load models that have been used in this study are induction motor loads. This model gives the user ability to control the induction motor with detail. It has total number of 19 parameters including the relay protection for the motor. This model replaces the corresponding load with the same size induction motor and does not have any static part. Details of this model can be found in [12].

Only 13 parameters are considered for sensitivity analysis as the other 6 parameters are either related to protection or motor ratings. Following the same trend as previous models, first half of the parameters are selected, namely X_A, D, X_1, R_A, R_2, H, X_m.

Table 3. Sensitivity analysis results for induction motor load model

Parameter ranking	Total-effect index	Parameter ranking	Total-effect index
1. X_A	0.36	8. X_2	0.11
2. D (load damping factor)	0.25	9. S(E_2)	0.087
3. X_1	0.22	10. E_1	0.083
4. R_A	0.17	11. E_2	0.081
5. R_2	0.16	12. S(E_1)	0.057
6. H(inertia)	0.14	13. R_1	0.013
7. X_m	0.136		

4. Off-line model building and optimization implementation

In this section, we briefly describe the event detection process, offline model building and implementation of evolutionary optimization to the problem. The event detection process combines the analysis of different sources including the Supervisory Control and Data Acquisition (SCADA), PMU measurements and control room notes. We first monitor SCADA data to notice sudden changes in the study area and determine suspected intervals. PMU data is then analysed for these intervals to confirm the events. To re-simulate the event for wide area simulation, Control Room data is also checked for suspected intervals and root cause of events are recognised. Following the mentioned procedure, a fault event on 17 October 2017 is recognised. This fault event is suitable for certain characteristics. This fault is on a long transmission line which upon tripping isolates the study area from non-PMU monitoring section. This study area is in the eastern parts of AIES and has high volume of loads with no generation near the PMU monitored substation making it a representative choice for the present study. The detailed diagram of study area is will not be presented here for confidentiality reasons.

As mentioned earlier, we are aiming to optimise the parameters of multiple load models in the study area. For this purpose, we need to have some load categorization in the area. Considering individual model for each load in the system is not feasible and can result in unsuccessful optimization. Based on the available load categorization in AIES, there are two main group of loads in the selected area. We consider same parameters for load models of same category. Given this, we have two sets of parameters for each optimization in this study area. As we are considering all the loads in large-scale power system model, it is not feasible to reduce the network and thereby it is necessary to build the off-line model as close as possible to power system prior to the event. Reasonable cross referencing between SCADA data and available AIES models have been made to build the best match. Fault analyses have been performed to have a relatively similar pattern to the actual fault recorded from the grid.

This paper applies a combination of Genetic Algorithm (GA) and Levenberg Marquardt (LM) as the optimization method. This combination is selected to speed up the simulation time while maintaining the accuracy. Use of GA or LM for load model parameter identification is very common trend in the literature such as the works reported in [8] and [15]. Our simulation shows that GA can optimise the problem with high accuracy but requires a very long simulation time if number of iterations are large. Simulation time is an important concern in this paper as there are eleven voltage scenarios along with three types of load models which gives 33 cases for optimization. Alternatively, LM is very fast but usually not very accurate and can only change a bit around the initial guess. Therefore, we first apply the GA optimization but to some limited number of iterations and then feed the outcome as the initial guess for LM. This way we can achieve a proper compromise between simulation time and accuracy. Detail discussion of this optimization methods are out of the scope of this paper and interested readers can find more information in [16].

5. Numerical results

The problem formulated in this paper is implemented to the case of Alberta. Optimization models are solved with the interactive use of Python and PSS/E for all resampled voltage responses considering the three mentioned load models. Python implements the optimization process and calls PSS/E in each iteration to solve the dynamic simulation for AIES. This process is followed repeatedly with parameter modification in each iteration until a stopping criterion has been satisfied. This optimization is implemented for all cases and MAEs of each optimization along with MAEs for generic models can be observed in the Figure 2. Presenting all detail results of simulations and voltage responses for each of these scenarios cannot fit in this paper. We present more important results and in a more compact way along with discussion and comparison between various cases.

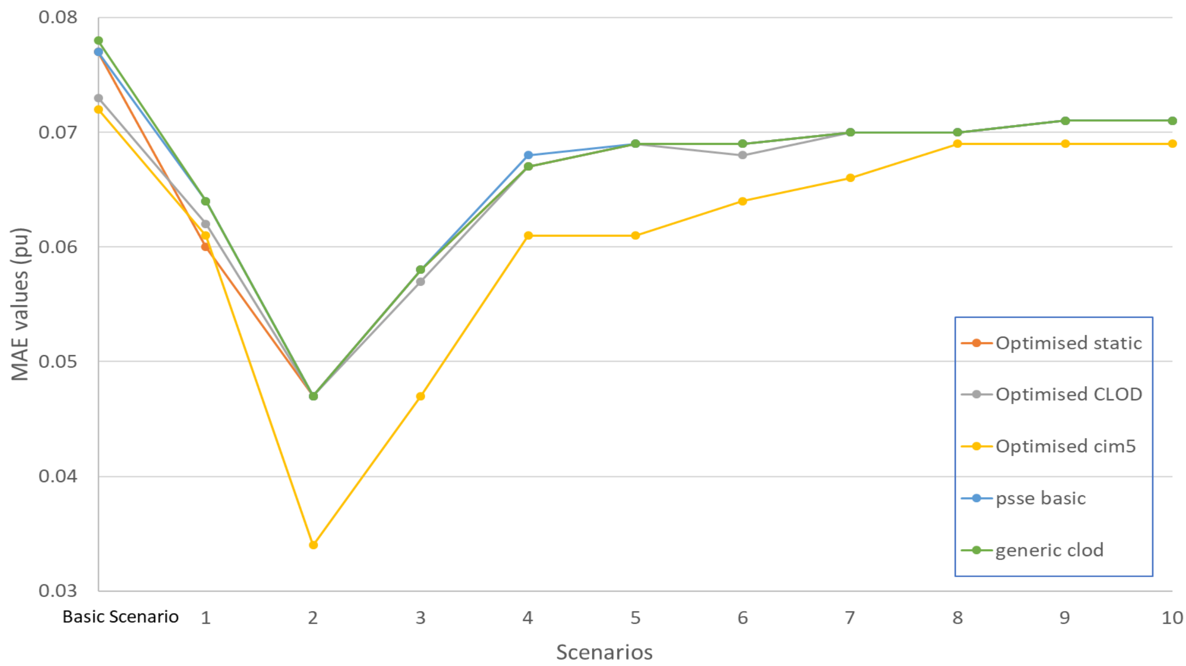

Figure 2. MAE pattern for five different loading conditions at generated scenarios

As can be seen in Figure 2, there is no substantial difference between MAEs of different load models in each scenario. All the models are performing relatively better around the second scenario. This is not related to load models, but it is because of the natural similarity of system response to scenario 2. It can be observed that induction motor load model can slightly perform better in most of scenarios. This better performance of induction motor load model is more evident for scenarios where simulation and resampled measurements are naturally closer such as the second scenario. In addition, MAE differences between generic CLOD or static models and that of optimised models is not significant in any of these scenarios which shows negligible impact of parameter selection on simulated voltage outcome for CLOD and static models. To better observe the reflection of these optimization results on actual simulated voltages, we can investigate Figure 3 which depicts voltage responses for some of the discussed scenarios.

Figure 3 shows the simulated voltages for 5 different conditions of load modelling, namely, optimised static, optimised CLOD, optimised induction motor, generic static and generic CLOD along with their corresponding resampled measurements. Four out of the ten scenarios including scenarios 1, 4, 7, 10 are given in sub-figures (a), (b), (c), (d), respectively. It can be observed that proposed models perform better for less delayed scenarios such as sub-figures (a) and (b), but completely fail to catch up with more delayed scenarios like sub-figures (c) and (d). To make simulations more comparable, simulation time is always twice the recovery time plus the clearing time (0.6 sec). Although MAE can be used as an appropriate quantitative measure for optimization, there is a need for more qualitative comparison to achieve informative conclusions from these results.

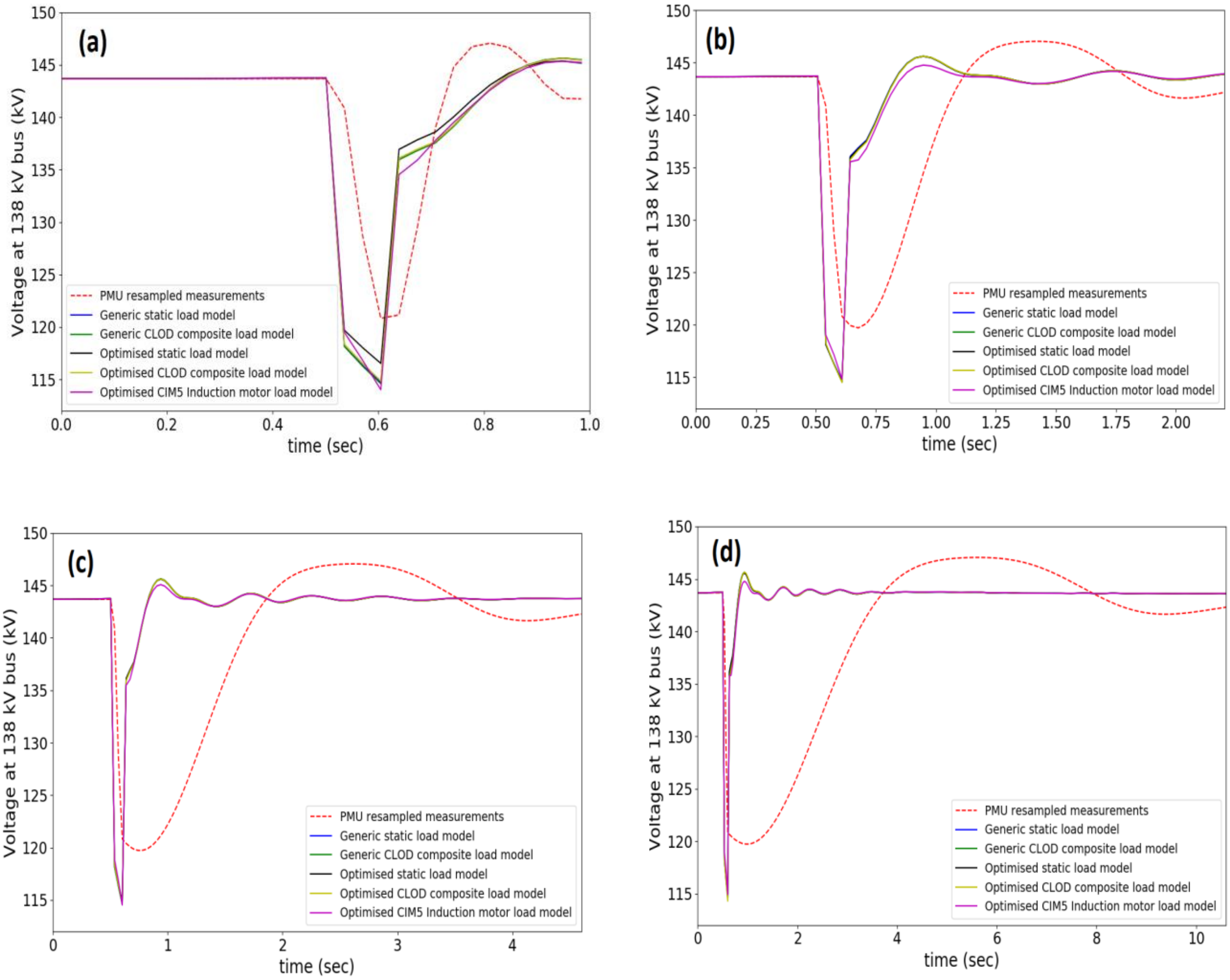

Figure 3. Voltage responses considering 5 different load presentation versus PMU resampled measurements; a. scenario 1; b. scenario 4; c. scenario 7; d. scenario 10.

Some of these important qualitative measures which are discussed here are characteristics like the initial drop or the recovery time of signals. Looking into Figure 3, the estimation of initial drop is almost same for all the models and its closed to initial drop of resampled measurements. Therefore, simulations are successful in predicting the drop independent of their load modelling conditions. Problem can be considered from two perspectives when it comes to accuracy of delay time anticipation. One is the time it takes for voltage to reach the first peak after the clearance and the other is time it takes for voltage to get back to acceptable boundaries (acceptable voltage range for this bus is 140 to 145 kV based on emergency minimum and maximum ratings). From the first perspective, recovery time is always around 0.35 seconds no matter models are trying to simulate fast responses or more delayed scenarios. The later perspective shows higher agreement in first scenarios but fails to predict the delay in other scenarios. The time it takes for voltage to come in the acceptable boundaries is almost same for other scenarios and models cannot peruse the delay. This shows that these models are not successful to change the natural response of signal to more or less delayed ones and therefore can only have acceptable performance for less delayed scenarios. Induction motor model can keep the voltage magnitude lower for a longer time, but this cannot make any important difference in results.

It should be noted that load models are only one of the contributing factors to the voltage response at the HV level. Achieving the perfect match requires proper dynamic modelling of other system elements such as generators and SVCs near the study area. Additionally, no matter how accurate we try to build the off-line model for the system prior to the event, there is always some unseen differences between actual system and modified base-cases.

6. Conclusion

In this paper, a comprehensive investigation on the impact of 3 different practical and widely used load models on simulation results of HV side of large-scale power systems is considered. A representative study area and fault event has been selected and 10 voltage scenarios have been constructed according to the real-life PMU data. Complete sensitivity analysis is performed prior to optimization of each load model and sensitivity rankings are established. Wide area model identification has been considered for load model parameter optimization in the study area. Optimizations are solved for each load model at generated scenarios using evolutionary optimisers resulting in MAEs reported as quantitative measure.

Simulation results considering different optimised or generic load models do not show any significant differences in the voltage response at the monitored HV substation. The improvement between generic and optimised models is minimal. Models can better simulate less delayed scenarios but are not successful in implementation to more delayed responses. Induction motor model can slightly perform better but this difference is not significant in terms of decision making for System operators. Future work can investigate the sensitivity of voltage response to some other factors such as load amount and dynamics of other elements.

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