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Application of PMU Data in Power Systems Load Modeling

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Application of PMU Data in Power Systems Load Modeling

by

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Abstract

Loads are one of the important components in the power system modeling. Accurate load models are necessary to ensure realistic simulation results for different large power systems. Detailed load representation has been a challenge for power system operators, especially for transient and dynamic simulations. The main objective of this thesis is to explore the application of Phasor Measurement Unit (PMU) data for power system load modeling. A general review on load modeling is initially presented. The presented review elaborates on different types of models and identification approaches utilized in the literature. Static and dynamic models are discussed with more emphasis on the dynamic ones. Several examples of studies based on the models for the industry-level practice are provided. Additionally, important points are concluded based on a practical point of view.

A measurement-based load modeling approach relying on the PMU data collected at the Alberta's grid is defined. A major load center with availability of PMU data is selected as the representative case-study. A breaker event near the PMU monitored substation is detected. Moreover, cross-referencing between available data sources is considered to match the simulation with the actual state of the grid as close as possible. CLOD complex load model parameters are optimized and voltage responses considering optimized and generic values are compared. Furthermore, several other industry-level load models along with potential voltage scenarios are investigated to extend the scope of study. PMU data for the original event is re-sampled and ten scenarios with different voltage recovery times are generated. Four different load models namely, IEEL static, CLOD complex, Induction motor CIM5, and WECC composite load model are implemented. The performance of these models are compared for the generated scenarios. These results yield guidelines for choice of load model structure and parameters in large power systems.

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To my beloved parents, Banafsheh and Ahmad.

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List of Symbols, Abbreviations and Nomenclature

Abbreviations	**Definition**
AC	Alternative Current
AESO	Alberta Electric System Operator
AIES	Alberta Interconnected Electric System
ANN	Artificial Neural Network
DC	Direct Current
DFR	Digital Fault Recorder
FIDVR	Fault Induced Delayed Voltage Recovery
GA	Genetic Algorithm
GPS	Global Positioning System
HV	High Voltage
IM	Induction Motor
LM	Levenberg Marquardt
MAE	Mean Absolute Error
NERC	North American Electric Reliability Corporation
PMU	Phasor Measurement Unit
PSO	Particle Swarm Optimization
PSS/E	Power System Simulator for Engineering
SA	Sensitivity Analysis
SCADA	Supervisory Control and Data Acquisition
WECC	Western Electricity Coordinating Council
WECC CLM	WECC Composite Load Model

Chapter 1

Introduction

1.1 Research Motivation

A power system is composed of different components such as generators, transformers and loads. Each of these components need to be modeled to reflect their behavior in power system simulations. More accurate simulation results will be achieved if more accurate models are available for different components in the power grid. Loads are one of the power system components that are often oversimplified in power system modeling [1]. Despite the recognized importance of accurate load modeling in power systems [2], still many operators find it difficult to update their models for simulations [3]. This difficulty is mainly due to several challenges such as model complexity in implementation for large-scale power systems, lack of measurements for model validation or uncertainties on model type and parameters' selection [4]. Compromising between model accuracy and complexity is another challenge for power system engineers. Highly complex models are able to capture the power system behavior more precisely, but they require more resources for implementation [5]. This thesis is motivated by the importance of load modeling in practice and the availability of new measurements in the system by means of the Phasor Measurement Unit (PMU) devices. In particular, the main research question that motivated this research was to explore if load models could be fine tuned given the partial availability of PMU measurements in today's power systems.

1.2 Literature Review

There are several reviews available on the concept of load modeling. General reviews on methods and the importance of load modeling were first considered in early 90s [6–8]. Reference [3] conducted an international survey on load models used by different power system operators. The reported survey revealed that most power system operators have not updated their load models since 2013. Another review was later published by CIGRE focusing on load aggregation in flexible power networks [9]. [5] provided a comprehensive review on the newly available load modeling practices. In [5], the importance of sensitivity analysis prior to parameter identification and compromising between models' accuracy and complexity was mentioned. Additionally, it has been emphasized on investigating the potential utilization of PMU data for more accurate load modeling.

Load models can be categorized as static and dynamic types from the modeling perspective [10]. Static models are only dependent on the current state of the system while dynamic ones are a function of current and past states. Static models are often simpler than dynamics in terms of implementation, but may fail to realistically simulate the power system voltage behavior in some events [11]. The significance of selecting the type of load model with focus on voltage response characteristics has been addressed in the literature [12], [13]. Importance of accurate dynamic load modeling became more known following the observation of Fault Induced Delayed Voltage Recovery (FIDVR) events in some parts of the North American power grid [14]. The type of voltage responses observed in different power systems can considerably vary. For example, recovery time is one of the characteristics that may significantly change for different case studies. Unseen voltage behaviors can lead to blackouts and very costly consequences as reported in [15] and [16]. Observing the mentioned discrepancies between actual and simulated voltage responses motivated many parties, such as the Western Electricity Coordinating Council (WECC), to conduct a new set of studies on the load modeling concept [17].

Building a load model is a two-step process. The specific model structure is chosen in the first step. Selection of model type depends on different factors such as the pattern of observed contingencies and load composition data [6]. Moreover, the second step is to find parameters of the selected model using either component-based or measurement-based approaches. Component-based approaches require exact information on load structure to build up a mathematical representation for the selected load. This method has been broadly investigated in the literature and has been reported to be successful in implementation to some loads [18], [19]. The detailed information required for component-based approaches is sometimes difficult to collect, especially for some modern aggregated power system loads. As a result, the measurement-based technique has gained a considerable interest in recent literature [20], [21]. Benchmarking the simulations with the available measured data at monitoring substations is a common practice in all measurement-based studies. However, these approaches may utilize different types of measurements for model validation such as SCADA system [22], Digital Fault Recorders (DFR) [23] or PMUs [24]. These devices have different sampling ratios. Some types of validation studies, such as the ones related to transient and dynamic load models may take advantage of a higher data resolution. Hence, the growing availability of high resolution PMU devices in power networks has motivated more investigations on their application in load modeling studies [25], [26]. However, the PMU data was usually collected from laboratory events.

Building load models is demanding for large power systems hosting many number of loads. A smaller portion of the literature have concentrated on the load modeling problem for large power systems. References [27] and [28] considered load modeling in one of the large-scale areas in the north-eastern China grid. Load models are categorized at the first step and then parameters for one of the loads in each category is identified and assigned to other loads in the same group. Validation is done based on PMU recorded data from artificially created laboratory events. These studies solely focused on one particular load and usually did not consider the simultaneous optimization of multiple loads in the power network.

There are several load models which are popular for large-scale power systems. These load models are readily available in industry-level simulation tools. When selecting the load model structure for large-scale power systems is considered, this availability makes them a rational choice over some other complex models developed in the literature. CLOD complex load model [29], induction motor load model [29] and WECC composite load model (WECC CLM) [30] are among the popular choices for dynamic load modeling in industry-level studies. [31] considered a template-based approach to find CLOD model parameters. Parameters were selected based on the load composition data. A compare and re-simulate based optimization for CLOD model was presented in [32]. However, validations were only for a single load and based on completely fictional data. Induction motor load model structures are used in many studies to address the dynamic behavior of loads [33], [34]. WECC CLM is the most recent among the mentioned models and has been the focus of several technical reports [1], [35]. Despite of the consideration of these models for individual loads in the grid, suggestions on choice of the model structure or identifying the parameters have not been presented in the literature. To the best of author's knowledge, there is no comprehensive comparison available on the performance of these load models versus the real-life PMU data.

This thesis considers a measurement-based load modeling approach in large power systems. Alberta Interconnected Electric System (AIES) is the case-study utilized in this thesis. PMU data is available in several high voltage substations at the AIES. A platform is designed to investigate the performance of several practical load models in the Alberta's grid. Furthermore, the study scope is extended by exploring the problem in some re-sampled PMU scenarios.

1.3 Research Objective and Contributions

The main objective of this thesis is to explore the application of PMU data in load modeling of large power systems. In particular, real-life PMU measurements are used to evaluate the voltage response of the system at a high voltage bus surrounded by a number of loads. A system planning model is developed and a system event is simulated. The main contribution of the thesis is that a process is designed to determine how the simulated system based on alternative load models mimic the observed response of the system recorded by PMU devices. More specifically, in Chapter 4, a procedure is designed to simultaneously optimize multiple load models in power systems. The process involves event detection and off-line model building procedure which are explained for the Alberta's grid. Finally, evolutionary methods are applied to optimize CLOD model parameters.

Building on the procedure designed in Chapter 4, the scope of the study is expanded to include other models and alternative system responses. Four load models, namely, IEEL static, CLOD, induction motor CIM5 and WECC CLM are considered in Chapter 5. Using the original PMU measurements at Alberta's grid, ten scenarios are created with different voltage recovery times. Performances of the selected load models are compared in accordance to these scenarios. Models are optimized and their simulation results are compared with those of the generic structures. The choice of load model parameters has been usually arbitrary and solely based on available generic values or engineering judgments. The investigation in this thesis provides a platform to find optimized parameters and test if any updates to model parameters used in day-to-day system studies are required, compared to the generic parameters. The significance of the research conducted in this thesis is that it helps power systems' engineers to determine if and how load models can be updated based on PMU measurements, and which models better match the actual system responses.

The thesis also presents an up-to-date review of the literature on different load modeling techniques. It is attempted to maintain a practical point of view during the conducted review. Static and dynamic models are discussed with more focus on dynamic ones. Models are divided into different categories based on their identification techniques or type of measurements being used. Finally, the possibility of implementing these models for industry-level practices are discussed.

1.4 Thesis Organization

The rest of this thesis is organized as follows:

Chapter 2 provides basic information on the load models, methods and devices used in this thesis. The four load models used in this thesis are explained to perceive their structure and mathematical representation. Subsequently, PMU devices, software tools and optimizers that are used in the thesis are elaborated.

In Chapter 3, different model structures which have been used in the literature are investigated. This chapter aims to maintain a practical point of view during the review. Eventually, a discussion on the practicality of the reviewed models along with a several suggestions for future research based on the identified gaps are provided.

A representative base-case and an event detection procedure is required prior to conducting the proposed measurement-based load modeling approach. This is done in Chapter 4. This chapter first provides the process for making the case ready based on the mentioned requirements. In the second step, the optimization problem is described and applied for CLOD complex load model. Detailed information on the simulation preparation and the optimization implementation is provided. The performance of CLOD model is completely analyzed and simulations with optimized parameters are compared with that of generic ones.

In Chapter 5, new voltage response scenarios are generated by re-sampling the originally detected breaker event. Four different load models available in large scale power system simulators are considered and analyzed for generated voltage scenarios. Sensitivity analysis and following optimization, similar to the general procedure described in the previous chapter, are presented for each model at different scenarios. Voltage simulation results are compared for different model structures. Furthermore, performance of WECC CLM is considered as a possible mitigation for more delayed scenarios.

Chapter 6 provides a summary of the work and elaborates on specific contributions.

Chapter 2

Background Review

This chapter provides a background on the models, methods and devices that are used in this thesis. It is an attempt to address the most important concepts in different models or methods which are used in this work. Digging into full detail for all the sections is out of the scope of this thesis, but informative references are provided whenever it is necessary.

2.1 Load Models

In this section, the load models which are used in this study are elaborated. There are four general load models used in this thesis varying from pure static ones to more complex dynamic load models. We selected these four load models based on two main criteria. Firstly, all models are available in large-scale power system simulators and thus, can readily be implemented for power system simulations by system operators. Secondly, these load models are selected in a way to cover a variety of different elements at the loading node. From the modeling perspective, they vary from static to dynamic and composite load models. In what follows, each of these load models are illustrated with more details.

2.1.1 IEEL Static Load Model

This static load model combines the constant power, constant current and constant admittance aspects of static loads. The IEEL static load model is known as "IEELXX" family of models for its representation in PSS/E. The model can mathematically be expressed as given in (2.1), (2.2) and (2.3).

$$P = P_{load}(a_1 v^{n_1} + a_2 v^{n_2} + a_3 v^{n_3})(1 + a_7 \Delta f) \tag{2.1}$$

$$Q = Q_{load}(a_4 v^{n_4} + a_5 v^{n_5} + a_6 v^{n_6})(1 + a_8 \Delta f) \tag{2.2}$$

$$a_1 + a_2 + a_3 = 1 \quad and \quad a_4 + a_5 + a_6 = 1 \tag{2.3}$$

P and Q stand for active and reactive power respectively. a_1 to a_6 parameters are voltage coefficients while a_7 and a_8 are the frequency dependency coefficients. n_1 to n_6 parameters are for different exponents of voltage. Considering these exponents to be 2, 1 and 0 for each part of the active and reactive part, this model can converge to the commonly used ZIP load model, [36]. This is the load model which is considered for static load modeling in this thesis.

2.1.2 CLOD Complex Load Model

CLOD complex load model [29] is a composite load model implemented in many commercial power system simulators such as PSS/E. This model respects the diversity at the load side and also considers the distance between load and the High Voltage (HV) bus in the model. CLOD model is often used to represent loads in real-life power networks, because it provides a trade-off between complexity and accuracy. Given this, CLOD has been one of the popular options for load modeling studies [37].

Figure 2.1 illustrates the CLOD model structure. The transformer and feeders connecting system bus to the load bus are modeled as an impedance. At the load bus, percentages of large and small motors, percentage of discharge lighting loads, percentage of constant power loads and transformer saturation current are among the model parameters. Remaining part of the load is modeled as given in (2.4) and (2.5) where active power is modeled by exponential model and reactive power is modelled as constant admittance.

$$P = P_R \times V^{K_p} \tag{2.4}$$

$$Q = Q_R \times V^2 \tag{2.5}$$

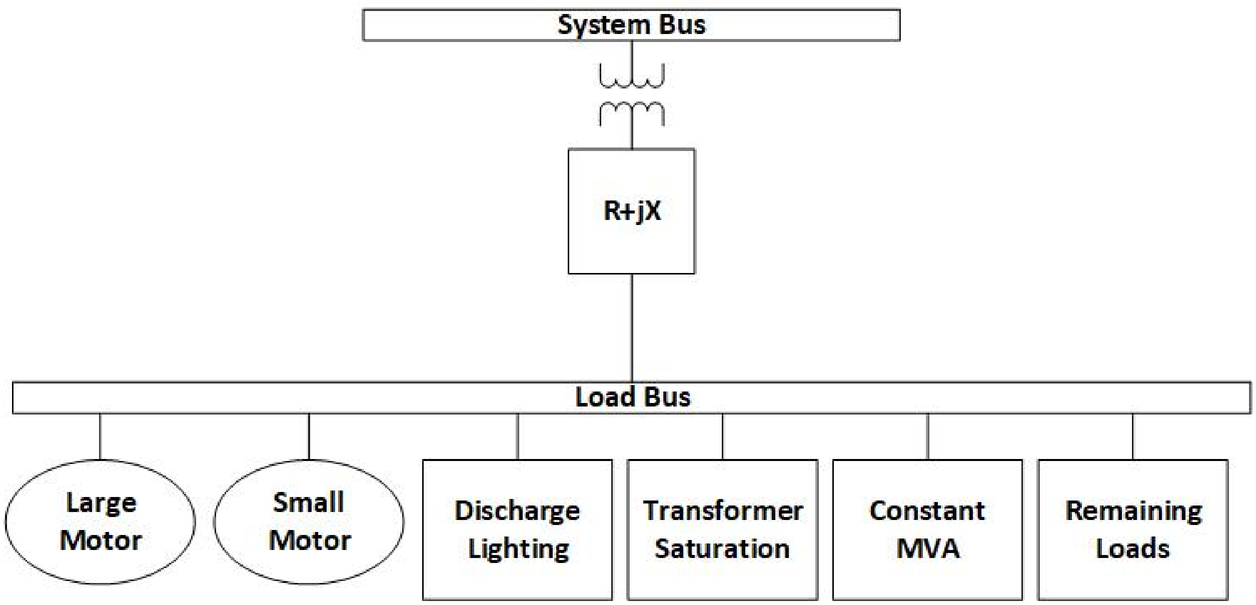

Figure 2.1: CLOD model structure.

P_R and Q_R are the active and reactive portion for the remaining load and V is the load bus voltage. K_P is the voltage exponent for active power in the exponential static model. It can provide constant power, constant current, constant admittance or a combination of these models. An analysis on typical ranges of this parameter for some different load types is available in [38]. The large and small motor parts of the model are three phase induction motor loads. User can only define the percentage of these motors but cannot control their details of the modeling. The main difference between the small and large motor is their inertia constant value which is assumed 0.6 and 1 for small and large motors respectively. Normal three phase induction motor models which are presented in more detail at the following subsection are used for these small and large motors. This model assumes that all elements are connected at 0.98 pu in the load bus and accordingly adjusts the feeder transformer. Then initialization adjusts the transformer tap to match the system bus voltage. Transformer current can simulate the saturation impacts of transformers. The discharge lighting part of CLOD has a real part modeled as a constant current. Voltage exponent of 4.5 is considered for the imaginary part. If the voltage is between 0.65 to 0.75 PU, a linear reduction is also applied to discharge lighting. More information on CLOD complex load model can be found in [29].

2.1.3 Induction Motor Load Model

The induction motor load model is a pure dynamic model which allows the user to model the three phase induction motor with higher level of detail. This model is also known as "CIM5XX" family of models in PSS/E. In contrast to the CLOD model which only allows the user to change percentages of components, this model allows the user to change the detail of the modeling. However, it does not have different components at the loading node and only considers a single induction motor model. The induction motor model can use two different types of equivalent circuits based on the user preference. The main difference between these two circuit types is the location of stator reactance in the equivalent circuit.The stator reactance is in series with R_1/S in the first type while it is in between the magnetizing reactance and R_1/S in the second type. More information can be found in [29].

The main equations describing the induction motor model can be written as (2.6), (2.7) and (2.8) [39]. It is worth mentioning that similar equations describe the motor load part in the CLOD complex load model with fixed parameters for large and small motors.

$$T_0'(de_q'/dt) = -T_0'(w - w_0)e_d' - e_q' - (L_s - L')i_d \tag{2.6}$$

$$T_0'(de_d'/dt) = -T_0'(w - w_0)e_q' - e_d' + (L_s - L')i_q \tag{2.7}$$

$$w(2H/w_0)dw/dt = (e_q' i_q + e_d' i_d) - T_{nom}(w/w_0)^D \tag{2.8}$$

T_0' is the rotor transient time constant. e and i show the stator transient voltage and current in different quadratic and direct axes. w is the rotor speed, while w_0 is the synchronous speed of the motor. L_s and L' are synchronous and transient inductances of motor respectively. T_{nom}, H and D are sequentially for nominal mechanical torque, motor inertia constant and model exponent.

2.1.4 WECC Composite Load Model

WECC composite load model is a complex load model which addresses a variety of components at the load bus. This model also provides user with the ability of detailed control over each of the model components. Figure 2.2 illustrates the structure of this load model. As can be seen, a variety of motors are considered at the loading node. Motor A, B and C are different three phase motors and motor D has the single phase air conditioner motor model. Motor A models the 3-phase compressor motor loads, while motor B addresses fan-motors connected across the line. Motor C is for pump motors which are rare in most power system loads. Models for these 3-phase motors are validated through different tests performed by WECC parties. Motor D is representative for residential single phase air-conditioners. stalling and running are two different states for this motor which are recognized based on the motor voltage. There are also separate models for static and Power Electronic loads. A constant impedance is assumed for resistive static loads and constant current is considered for lighting static loads. Power electronic components are modeled as constant power regarding to the relation with voltage and frequency. This model respects the distance between the system bus and load bus. This distance is modeled by a transformer and impedance. Moreover, reactive compensation is considered at both ends of the feeder. More detailed description of each of the models' components can be found in [37].

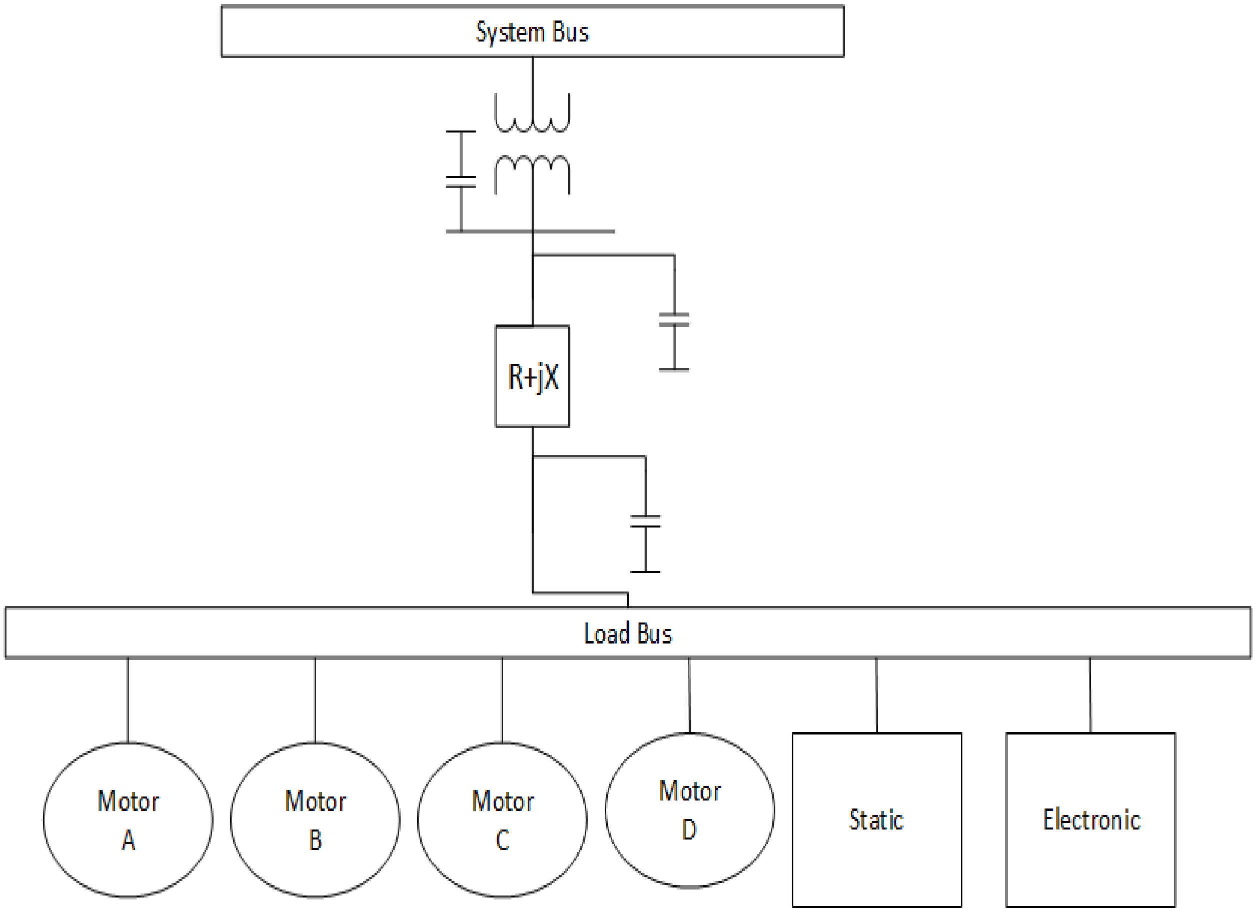

Figure 2.2: WECC composite load model structure.

2.2 Optimization Methods

The optimization methods which are related to this thesis are briefly described in this section.

2.2.1 Genetic Algorithm

Genetic algorithm (GA) is based on the natural selection theorem. It is fundamentally inspired from the genetics' evolution throughout different generations. This method can be used for constrained or unconstrained optimization problems. GA is a population based approach which iteratively attempts to modify each generation of answers. This modification results in new generation being closer to optimal answer compared to the old generations.

It is obvious that if these generation modifications are performed repeatedly, the algorithm converges to a final optimum solution which necessarily could not be guaranteed as the global optimal answer for all kinds of optimization problems.

There should be a logical process to ensure the effective modification from each generation to the next one. The process of transferring current generation to the next generation can generally be divided into three aspects. The first part of the population with the highest fitness score in comparison with other individuals. This part of the population stays unchanged and transfers to the next generation as it is. This part is often called as elite population. The second part of the population experiences a mutation process using different available mutation functions . In fact, this part tries to randomly create new individuals. Mutation can often be helpful for problems with higher risk of getting trapped in local optimal. It can help the algorithm to have a wider search in the solution space. Crossover is the third aspect of the process which usually effects a larger portion of individuals in a population. Considering the characteristics of individuals along with their corresponding fitness score, crossover functions try to mix the characteristics of individuals in current generation to create new individuals with better characteristics in the next generations. These new individuals are potential for having a better fitness score.

As any other evolutionary optimizer, GA needs a stopping criterion. There are two common stopping criteria for GA: 1) limitation on maximum number of iterations. 2) limitation on the number of iterations in which the best individual remains unchanged. Mathematically speaking, there are different fitness function available and each of them might be suitable for specific type of problem. It should be noted that in this section we only discussed some basics of genetic algorithm and this method can be improved in many different ways. Interested readers can find more detail on GA in [40]. Figure 2.3 depicts the iterative procedure for GA as described in this section. The Pyevolve Python package is used for GA implementation in this thesis [41].

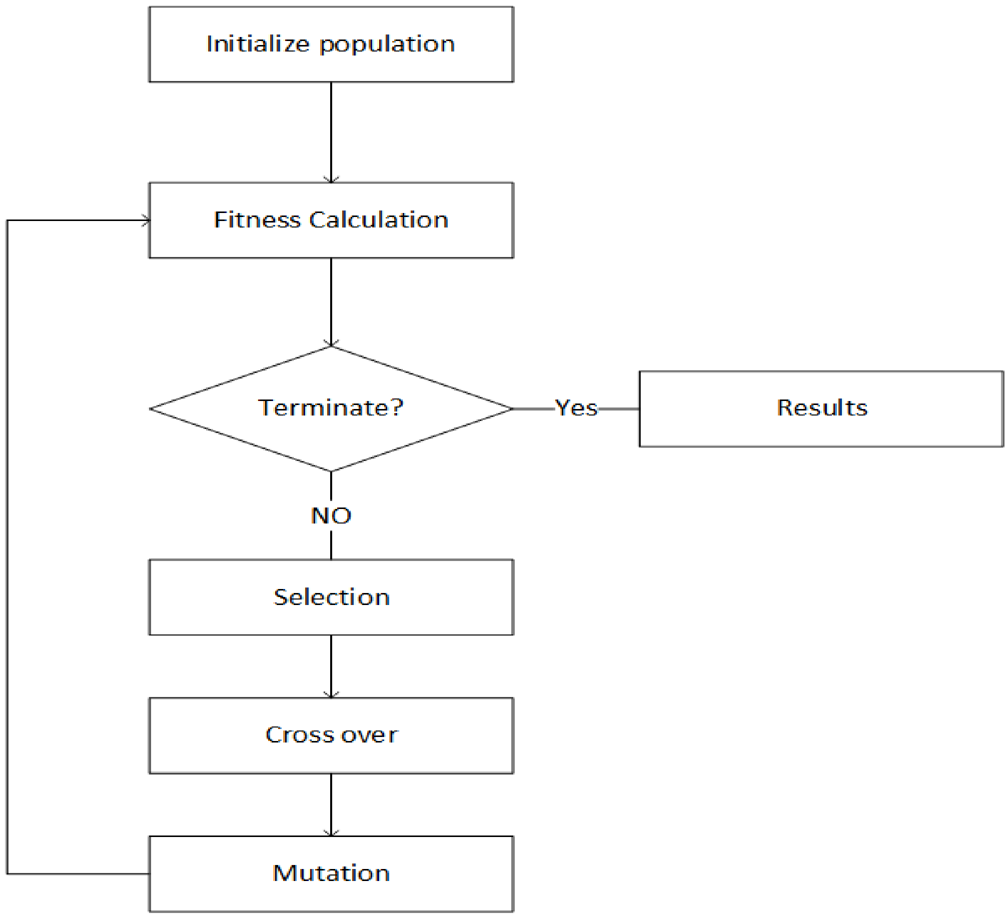

Figure 2.3: General process for Genetic Algorithm.

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2.2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is another population based evolutionary optimizer which can handle constrained or unconstrained optimization problems. Similar to the GA, it aims to improve a candidate population of solutions based on a score measurement mechanism. Each of these candidates in the population are often called as particles. In contrast to GA, PSO has no crossover functions for the evolution procedure. Generally, particles fly in the solution space with consideration of the optimal particles' scores at the present population. There are multiple optimal particles for different swarms in each population and a global optimal between the available solutions of all swarms. Particles consider all these optimal answers when flying to find better optimum points. This process continues iteratively until a stopping criteria is satisfied. Finally, the optimal solution is collected from the final population.

This process that PSO uses for iterative update of population is inspired by natural patterns observed for bird flocking. Figure 2.4 illustrates this process in a flowchart. As it can be seen from the flowchart, firstly an initial population along with local and global bests at this population are considered. Thereafter, velocity and direction of search are updated and process is repeated until an improvement in local and global bests are observed. This process continues iteratively and stops when a termination criterion is satisfied. More discussion on PSO algorithm can be found in [40]. The Pyswarms Python package is used for PSO implementation in this thesis [42].

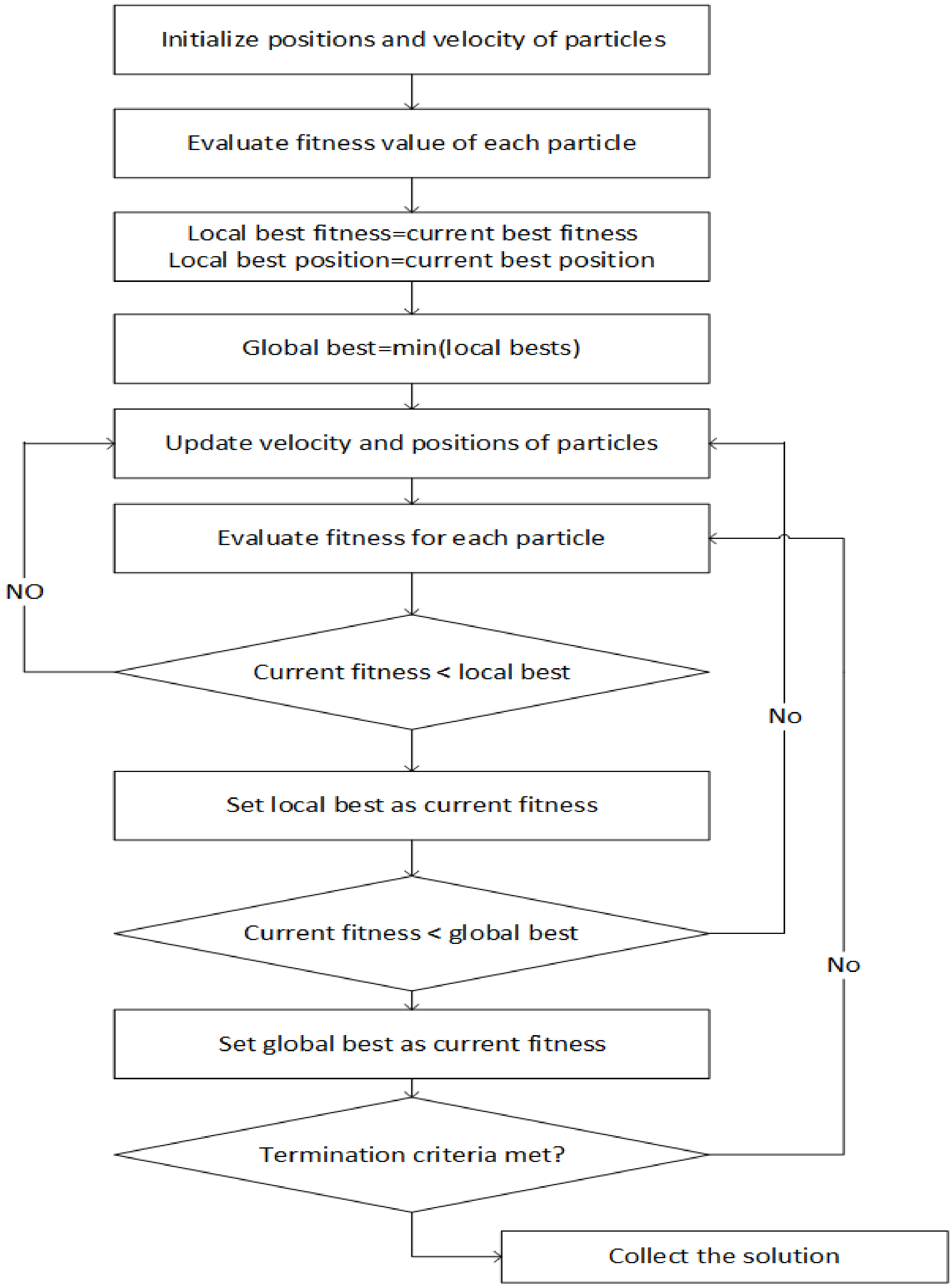


Figure 2.4: General process for Particle Swarm Optimization.

2.2.3 Levenberg Marquardt Algorithm

Levenberg Marquardt (LM) algorithm is generally used for non-linear least square problems. It is a common choice with generic curve-fitting problems. Same as GA and PSO, this algorithm does not guarantee to find the global optimal. LM can usually have an acceptable performance for well behaved functions, but it usually just converges to a local optimal near the initial guess for more complex functions. Hence, the choice of initial guess is very important for problems with multiple optimum answers. LM is not a population-based algorithm, in contrast to GA and PSO, and it only aims to modify a single solution candidate to find more promising solutions.

LM is considered as an alternative to Gauss Newton method and can be expressed as (2.9). This algorithm tries to iteratively find a new answer based on the previous solution. J stands for the Jacobian matrix and M is the damping factor for the algorithm. LM main contribution compared to other similar least-squares methods is in introducing the damping factor. Damping factor usually decreases with a specified division ratio after a better solution is reached and this process continues repeatedly until convergence. If a solution is not improved, then the damping factor increases iteratively upto a certain value and then either the initial guess is changed or the algorithm diverges, if no improvement is observed in the answer. More information on this algorithm is available in [43].

$$X_{k+1} = X_k - [J^T(X_K)J(X_K) + M_k I]^{-1} J^T(X_k)V(X_k) \tag{2.9}$$

2.2.4 Trust Region Reflective Algorithm

Trust Region Reflective Algorithm is mainly designed for large-scale constrained least squares problems. Most relevant explanation of the TRF algorithm can be found in [44]. Similar to other least squares techniques, the objective is to minimize a given function. Boundaries with finite or infinite bounds can be considered for the inputs of a function. Considering the general local optimality conditions and following several modifications, as described in

[44], the trial step to update current guess, x, to a new guess , $x + k$, for the trust region algorithm can be found by minimizing (2.10). Good algorithms are available for solving such equations [45].

$$1/2k^T H_k + k^T g \ \ such \ \ that \ \ ||D_s|| \leq \Delta \tag{2.10}$$

where k is the step to update the solution, H shows the Hessian matrix and g stands for gradient of function at the given input. D is scaling matrix and Δ is positive value to handle the boundary of a problem. If there is no modification in the answer, Δ decreases and process repeats. These steps are followed iteratively to converge to an optimal answer. The suggested method gives acceptable results for large-scale non-linear problems [46]. The exact structure of the Trust Region Reflective algorithm is available in python libraries [47] and is used in a part of this thesis.

2.3 Sensitivity Analysis

Sensitivity Analysis (SA) is usually necessary to ensure an efficient optimization. SA helps to better understand the system under study. In addition, SA provides the ranking of parameters for a model. The ranking can help different studies which are performed on the same system. It can also provide information about potential correlation between different parameters. Having this information helps to reduce the size of optimization problem. This is helpful to reduce the risk of converging to local optimal answers in non-linear problems as well. The use of SA for load modeling is considered in this thesis. It is applied to three of the load models utilized in this study. SA results provide useful information on importance of different parameters in these load models which different system operators can use in their modeling studies. Sobol method [48] is implemented as the SA technique in the current study.

Sobol [48] is a broadly used global sensitivity analysis approach and works based on the variance decomposition of model outputs. This method has been proved to be consistent for sensitivity analysis of large non-linear systems [49]. Given the black-box model ($Y = f(Xi)$), the mathematical expression for the variance decomposition in the Sobol method can be observed in (2.11), (2.12) and (2.13). The symbol σ^2 stands for variance and E shows the expected value which here is conditional probability of output for the occurrence of different combinations of inputs. Performing this sensitivity analysis provides first and total effect indices along with some correlation measures between model parameters. It is then possible to decide which parameters are better to choose for optimizations. It is worth mentioning that solely having a higher effect index value does not mean that a parameter is a better candidate for optimization. Sometimes there is a high correlation between two parameters with high ranking and hence, it is better to choose one of them for optimization. This is because choosing highly correlated parameters can simply result in different locally same combinations for the solution. The SAlib Python package is used for sensitivity analysis performed in this thesis [50].

$$\sigma^2(Y) = \sum_{i=1}^{n} V_i + \sum_{i<j}^{n} V_{ij} + ... \;\; where: \tag{2.11}$$

$$V_i = \sigma^2(X_i) \times E_{x_i}(Y|X_i) \;\; and \tag{2.12}$$

$$V_{ij} = \sigma^2(X_{ij}) \times E_{x_{ij}}(Y|X_i, X_j) \;\; and \;\; etc. \tag{2.13}$$

2.4 Alberta Interconnected Electric System

Alberta Interconnected Electric System (AIES) is the sample large-scale power system that is used in this thesis. The transmission network of Alberta is equipped with high voltage transmission lines transferring power from generators to different types of consumers, such as large industrial loads or low voltage distribution consumers within the cities. AIES has three interconnections to neighbor provinces, namely, Saskatchewan, Montana and British

Columbia.The Connection to Saskatchewan is with a DC link which is considered as one of the points of WECC separation from the other electric council in North America. Two other tie-lines are AC lines and are located within the WECC area.

The selected study area in this thesis is located on one of the eastern areas in AIES. The reason behind choosing this study area is its representativeness for the type of study that is performed. It is one of the areas with PMU data available at two transmission voltage levels. PMUs are surrounded by a number of loads and there is no generation in the area. This can better isolate the effect of loads in power system simulations. The AIES connection to Saskatchewan is through a DC line near the selected study area. Hence, it is attempted to concentrate on intervals which this DC link is switched off to better be able to isolate the effects of load models on the voltage behavior.

2.5 PMU Data

Phasor Measurement Unit (PMU) is a high resolution measurement device which has become more available in power systems in recent years. It has a higher sampling rate than normally available measurement devices in power systems. PMUs can record the magnitude and phase angles of voltage and current along with the system frequency at the point of installation. PMUs vary in terms of the number of samples they can record in each second. Their sampling rate is usually between 30 to 120 per seconds. This high sampling rate provides data for many power system studies, such as model validations for improvements in dynamic simulation accuracy. The PMU data available at AIES provides 30 samples per second. In other words, the system characteristics are recorded on an average of every two cycles by PMUs installed in AIES.

In power systems, phasor refers to the complex number made by the magnitudes and phase angles of voltage or current sinusoidal wave. The complex number presents the wave behavior in a simple manner. In order to analyze wave phasors in a time varying scale, a synchronized system needs to be applied. Hence, synchro-phasors have been suggested to identify the voltage and current in the entire power grid. It is clear that these phasors can be representative of waves as long as the frequency of system is constant. However, noises always exist in the system. Given this, the analog inputs of currents or voltages are first entering to anti-aliasing filter for error minimization. Filtered signals are then feed to analog to digital (A to D) converter. Digitalized outputs will then transfer to a phasor microprocessor for calculating their positive sequences. Positive sequences are mainly identified by a recursive algorithm using discrete Fourier functions. At last, phasors data can be sent to the centralized monitoring section of the power grid for further processes. It is worth mentioning that a phase lock oscillator is also attached to the A to D converter for locking the output of filters to acquire synchronism from the Global Positioning System (GPS). This is necessary for synchronization of phasors. Furthermore, the phase lock oscillator changes the sampling rate of recorded data for adjustments to different levels of exactness. The structural diagram of PMU devices is also illustrated in Figure 2.5. Interested readers who investigate more information on PMU basics and history can refer to a new review given in [51]. IEEE standards for Synchro-phasors can be found in [52] and [53].

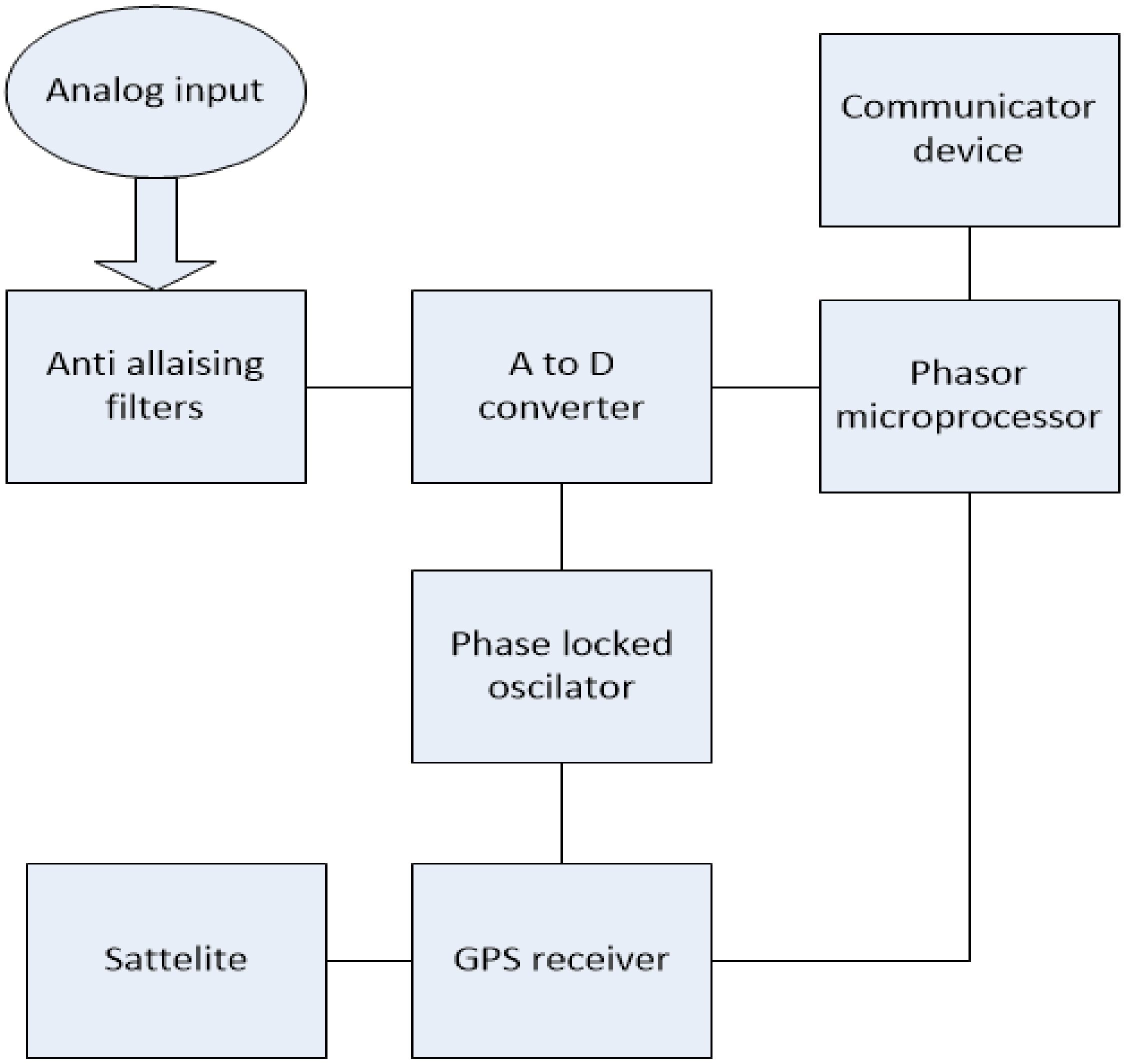


Figure 2.5: PMU structure diagram

The PMUs installed in AIES have the sampling rate of 30 per second. PMUs are installed in several different locations at the Alberta system. However, all of them are located at the high voltage transmission level and therefore, they are not recording the exact data at load nodes.

2.6 PSS/E

Power System Simulator for Engineering (PSS/E) is a commercial power system simulator widely used for large-scale power system simulations. The software is capable of performing variety of power system studies including transient and dynamic simulations which is mostly used in this research. PSS/E is also known as high performance transmission planning and analysis software and thus, it is a reliable choice for many power system operators when it comes to planning studies. PSS/E can interactively work with Python. This interaction is used in this thesis to solve the dynamic simulation by PSS/E and the optimization part of the problem with Python.

2.7 Summary

This chapter provided a background on different models or methods that are used in the thesis. Four different load models are considered in this thesis. These models namely IEEL static, CLOD complex load model, CIM5 induction motor model and WECC CLM are explained in this chapter. A brief review on different optimization methods, related to this thesis, is presented as well. Moreover, several general concepts used in the thesis such as the AIES structure, PMU data and PSS/E software were discussed.

Chapter 3

A Review on Load Modeling

This chapter provides a general review on load modeling. Discussions based on a practical angle are also provided in some sections. This chapter is organized as follows: the first section represents a background on load modeling problem. The second section provides a review on static load models. Additionally, the third section presents a detailed review on different dynamic load modeling approaches. This section categorizes dynamic models to four main groups. The first and the second categories are focused on input-output models and evolutionary based methods respectively. The third category concentrates on Artificial Neural Network (ANN) load models and the fourth category reviews PMU data applications in measurement-based load modeling techniques. The fourth section reviews several advanced techniques for identification. Load modeling for the industry-level simulations are discussed in the fifth section. Finally, summary and conclusions from a practical point of view are given in the final section.

3.1 Background

Load modeling has always been regarded as one of the important and complex problems in power system analysis [2], [54]. The load modeling complexity is mainly due to the uncertainties derived from limited information on load components' identification and seasonal changes of the climate. Uncertainty increment is the inevitable consequence of transforming the traditional power system into a modernized network hosting a number of volatile elements, such as complex loads. Thus, improved load modeling techniques are necessary to achieve realistic results in dynamic or static modulation of modern power systems. To mitigate these challenges and achieve precise methodologies for load modeling, different approaches have been considered in the literature.

There are two main approaches for load modeling: 1) component-based approach. 2) measurement-based approach. Component-based methods build the mathematical representation of the load based on the knowledge of different components participating in the load structure [18], [19]. Measurement-based methods attempt to fit a model with unknown parameters to the field recorded data. The latter method is more promising for the modeling of complex load structures, but requires the availability of measurements. Due to the increasing installation of high resolution measurement devices and the growing complexity of loads, measurement-based approaches have become more popular in the literature [21], [27]. These models may vary based on their different parameter identification techniques or their recording devices. PMU data are used as a measurement in some studies (e.g., [21], [25]). In general, field measurements are used to identify load model parameters.

Most of the industry-level load modeling methods are based on the static models. Utilization of dynamic models or composite structures are less frequent [3]. Figures 3.1 and 3.2 provide a detailed comparison of different load models used by different power system operators. The difference between model distributions is mainly the result of different technologies and load types. Distribution of models reveals that about ten percent of load models have deployed detailed model structures.

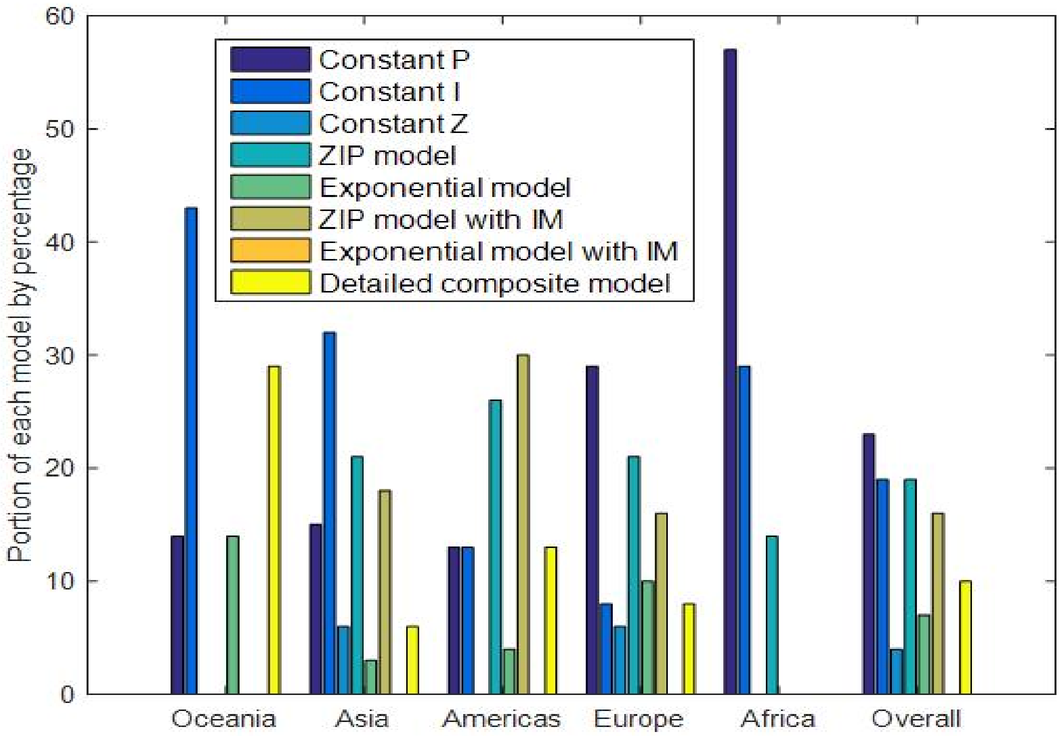


Figure 3.1: Load models for active power used in different geographical regions [3].

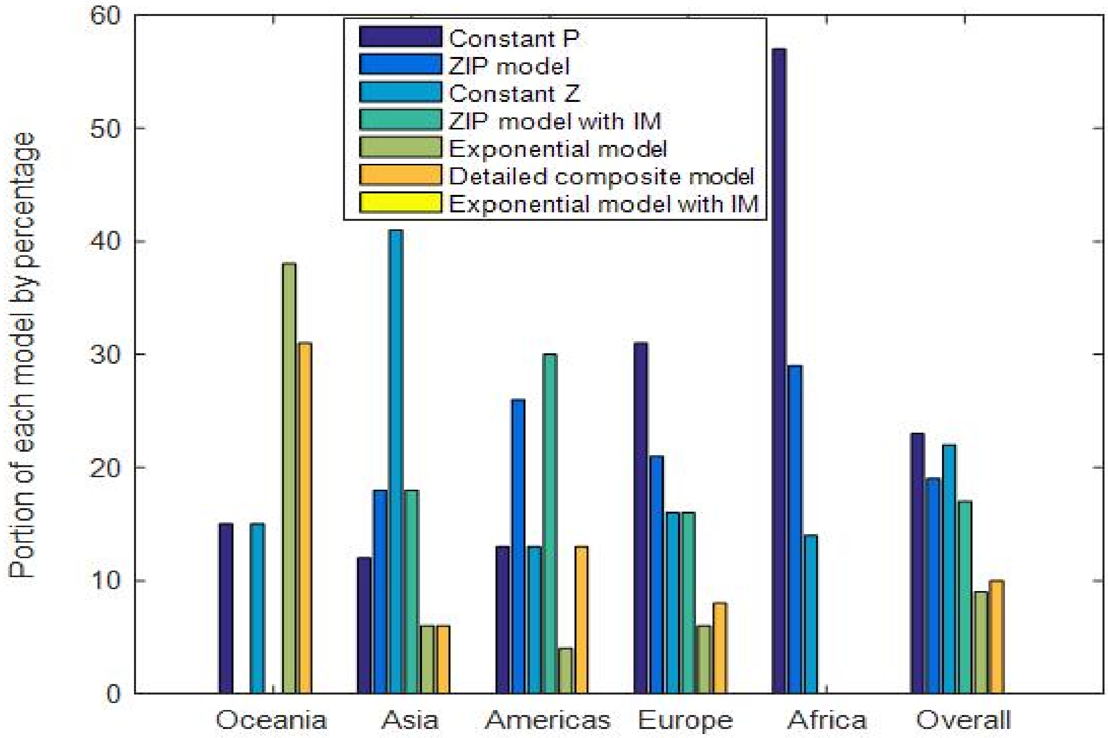


Figure 3.2: Load models for reactive power used in different geographical regions [3].

3.2 Static Load Models

Static load models are usually simpler to implement compared to the dynamic ones. As a result of this simplicity, these models have been used more often for practical cases. The ZIP load model [36] was widely used in the static load modeling structures. This model has constant power, constant current and constant impedance terms. The exponential load model was a popular choice in many static load modeling problems as well [55]. This model has exponents which vary for different types of loads. The following equations show the basic models for the mentioned static load modeling structures. (3.1), (3.2) and (3.3) present the ZIP model, while (3.4) and (3.5) are for the exponential load model.

$$P = P_0(a_1(V/V_0) + a_2(V/V_0)^2 + a_3)(1 + \alpha_{pf}(f - f_0)) \tag{3.1}$$

$$Q = Q_0(a_4(V/V_0) + a_5(V/V_0)^2 + a_6)(1 + \alpha_{pf}(f - f_0)) \tag{3.2}$$

$$a_1 + a_2 + a_3 = 1 \quad and \quad a_4 + a_5 + a_6 = 1 \tag{3.3}$$

$$P = P_0(V/V_0)^{n_p} \tag{3.4}$$

$$Q = Q_0(V/V_0)^{n_q} \tag{3.5}$$

By considering the $\alpha_{pf} = 0$, (3.1) and (3.2) become independent from frequency. This model converges to different constant components by tuning the parameters. For example, by neglecting the constant current and constant power parts of the voltage dependent polynomial ($a_2, a_3, a_5, a_6 = 0$), the model converges to the constant current structure. The exponential load model, given in (3.4) and (3.5), was mostly employed for mixed loads [56]. Indeed, the model exponents might vary due to changes in load types. To maintain the exponents within their reasonable limits for the model, a method based on exponents' correlations with voltage and frequency was suggested in [57]. Several studies considered field measurements and then applied different curve fitting methods to find coefficients of the models. For instance, authors in [54] employed a linear regression method to approximately find the coefficient values for the ZIP model. Coefficients were detected by implementing a sudden change in voltage and recording the data in multiple tests. Large deviations from realistic responses were observed in some cases, especially at low voltages. The problem was due to ferromagnetic devices which reached their saturation points. The model was applicable for less than 1.1 pu voltages. Hence, static models might only be applicable to specific voltage ranges.

In [58], small voltage deviation disturbance tests on a residential network were performed to calculate the ZIP model coefficients. Coefficient values were consistent in different switching tests. It was concluded that load responses could be approximated by linear and quadratic terms of the ZIP model. Reference [59] considered a medium voltage distribution system and estimated the parameters for both ZIP and exponential models under two classes, transient and steady state. The data was acquired by tap changing in different periods of time during the year. Least square technique was utilized as a solution method for parameter identification. Results claimed to be satisfying for the tested residential networks. Authors in [60] considered distribution networks where loads were supplied by utility voltage. It was claimed that traditional methods of applying large voltage disturbances are not acceptable for such cases and therefore, a taylor series approximation method was used to model the system with ZIP. The focus of [36] was on the experimental determination of ZIP model parameters in modern loads. Different load types such as commercial, industrial and residential were monitored in New York City. Changing the voltage between 0 and 1.1 pu, it was revealed that the ZIP load model of modernized loads have many differences with that of traditional loads. Hence, static models could be useful to model specific load types mostly at the distribution level. However, more considerations are necessary for complex and modern loads as mentioned in [36].

3.3 Dynamic and Composite Load Modeling

A very simple example of a dynamic load is an induction motor or a combination of induction motors. An induction motor in parallel with a static load has been vastly used as a composite load model in studies. A configuration of such a composite load model is given in the figure 3.3.

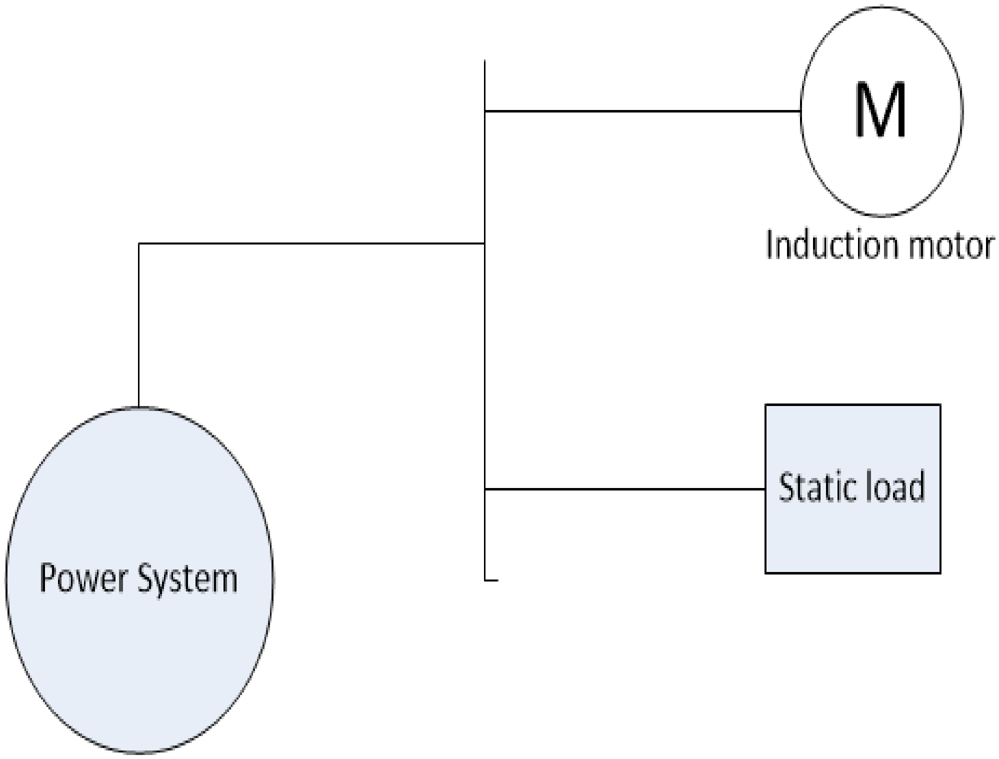


Figure 3.3: Simple composite load model.

In this section, dynamic load models are investigated in four main categories. A group of models used input-output mathematical functions to simulate system responses in case of a disturbance. The second group employed evolutionary-based optimization techniques to estimate load model coefficients. The third group utilized ANNs as their load models and trained them based on measured data. The last group concentrated on the PMU measured data to estimate parameters and build the models. In what follows, each of these groups are reviewed.

3.3.1 General Input-Output Models

A large portion of the input-output models have investigated different approaches to estimate the parameters of an induction motor as a dynamic load model. As an example of simulating induction motors' dynamic behavior by using equivalent circuits, [61] estimated the model parameters by performing normalized tests such as rotor-locked and running light.

Tests were carried out on two classes of loads based on whether they include compressor loads or not. This classification made it simpler to model induction motors with different slip characteristics. The approach considered in [61] resulted in an equivalent circuit model yielding satisfactory results in comparison with actual field tests. Reference [62] considered a sequential parameter estimation for a simplified induction motor. The sequential approach included five steps starting with a random assumption for the inertia time constant, rotor critical and initial slips. An output error minimization methodology was implemented for parameter estimation in [63]. An interactive numerical simulation software program was utilized to simulate the dynamic behavior of induction motors. Real time data of the system, consisting of phase voltages, motor speeds and motor currents, was recorded and the difference between measured data and modeled outputs was minimized by solving the optimization problem. The model derived from estimated parameters agreed closely with realistic results in the case of disturbances. Authors in [64] highlighted the role of motor size in choosing the modeling method. Small induction motors were mostly modeled by a first order speed differential equation. However, a first order voltage differential equation was established for larger induction motors' characterization. It has been claimed that this simplified first order voltage model has a privilege in voltage stability analysis of power systems with large induction motors. These studies show that the selection of parameters, size of the motor and type of the motor are important factors when input-output functions are considered for induction motors.

A portion of the input-output group of models focused on voltage response characteristics. In [65], a generic dynamic model was proposed for voltage stability analysis. An integrator feedback model was described. The difference between output and static power was given as an input to the integrator block producing state variables. The state variable stayed constant during the static period, but gradually changed and reached a new steady position during the transient time. Results asserted the effectiveness of this method for precise voltage stability analysis. The aim of [66] was to form a new composite load model which was mainly effective in voltage stability analysis. In fact, the goal of this paper was to address a modeling method for high voltage buses of power systems. As the dynamic model for induction motors is highly non-linear and is not compatible for parameter estimation, an exponential recovery was implemented to simplify the load model estimation. The first order model was assumed to be solely voltage dependent and the frequency impact on load models was neglected. The proposed simplified load modeling methodology was successful in load model estimation, but there was a need for higher order models in cases where oscillatory responses were observed in the recovery period [67]. In [68], a generalization of the method presented in [66] was considered. This generalization was expressed in higher order models or first order models containing more dimensions. The measurement-based approach was utilized relying on the data gathered from different parts of the load. Non-linear least squares was implemented to estimate the optimal load model. The dynamic model was applied to a test system located in Sweden which yielded satisfactory results in comparison with field measurements. A reactive load model aiming to simulate voltage stability dynamics was suggested in [69]. Parameters related to delayed elements and capacitor banks were taken into account. Using a hierarchical parameter estimation method, required parameters were identified in three steps and applied to two Pennsylvania power and light companies. The agreement between measured and simulated data asserted the effectiveness of this reactive dynamic load model. To sum up, voltage response characteristics, in particular for delayed events, were anticipated by different load model structures. Methods are varied based on the voltage level or amount of delayed recovery observed in the responses.

The component-based approach was considered by several studies in this group. Load class mix information, load characteristics and load composition must be known for component-based load modeling. As an example for component-based methods, an approach was presented in [70] with emphasis on voltage stability analysis. It was claimed that detailed dynamic analysis of the power system is not essential, while a comprehensive dynamic load model could completely show the voltage behavior in exposure to small or large disturbances.

It was observed that loads with constant power characteristics produce more impact on voltage stability dynamics. A simple first order delay model was structured for modeling the dynamic part. Power-voltage curves were analyzed in different contingencies and stability of the system in the post disturbance period was evaluated based on stability region determination. It is worth mentioning that component-based approaches were not as popular as measurement-based methods in the literature. However, according to their lower cost of implementation and independence from measurements, some operators still find component-based methods useful for their applications.

Another group of studies implemented composite load models. Induction motors in parallel with popular static models, such as ZIP, were broadly used in the literature. The uncertainty problem in dynamic load models was regarded in [71] and modeled by probabilistic collocation method to monitor dynamics of power systems. A ZIP static model in parallel with an induction motor, modeled with 13 parameters, was considered. If the probability density function of uncertain parameters was known, this method could find an accurate estimation of other parameters derived from it by a recursive process. The suggested process was faster than traditional methods, such as Monte Carlo. Tests implemented on the north eastern power grid of China highlighted the point that different load models can result in diverse simulation outcomes in some buses. Hence, an uncertainty analysis by the mentioned method was able to identify more sensitive sections of the grid. An improved composite load model using a parameter identifier program was introduced in [20]. A common ZIP model in parallel with an induction motor was considered. This improved load model could describe the load over long periods of time. Applying new parameters to the model was only necessary if the load composition experienced major changes. After implementing the improved model to case studies in China, it was proven that this model had a better performance than the typical load model for the reactive power analysis. A machine learning based methodology for composite load modeling of aggregate loads was regarded in [72]. Initially, both active and reactive powers were considered as a function of voltage and frequency. Thereafter, a factious node was considered to avoid unnecessary detailed load modeling. An error function was constructed by considering the difference between measured and modeled data. Test results validated the applicability of the proposed model. As pointed out in the reviewed studies, induction motor in parallel with static loads is a common choice for composite load models. These models can be used for a broader extent of loads as they have both static and dynamic characteristics. However, they usually require more parameters and thus, model validation and implementation is more difficult compared to other structures.

3.3.2 Models Based on Evolutionary Optimization Identification

Evolutionary computational algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have shown promising compatibility for the parameter identification of complex load models. High speed, robustness and simplicity of these optimization techniques have made them a popular choice among the solution methods. Nearly all studies benefiting from optimization techniques in load modeling have focused on converging to parameters which yield the closest outcomes to recorded data from the field measurements. Figure 3.4 depicts the general flowchart of these optimization procedures. Several important studies of this field are pointed out below.

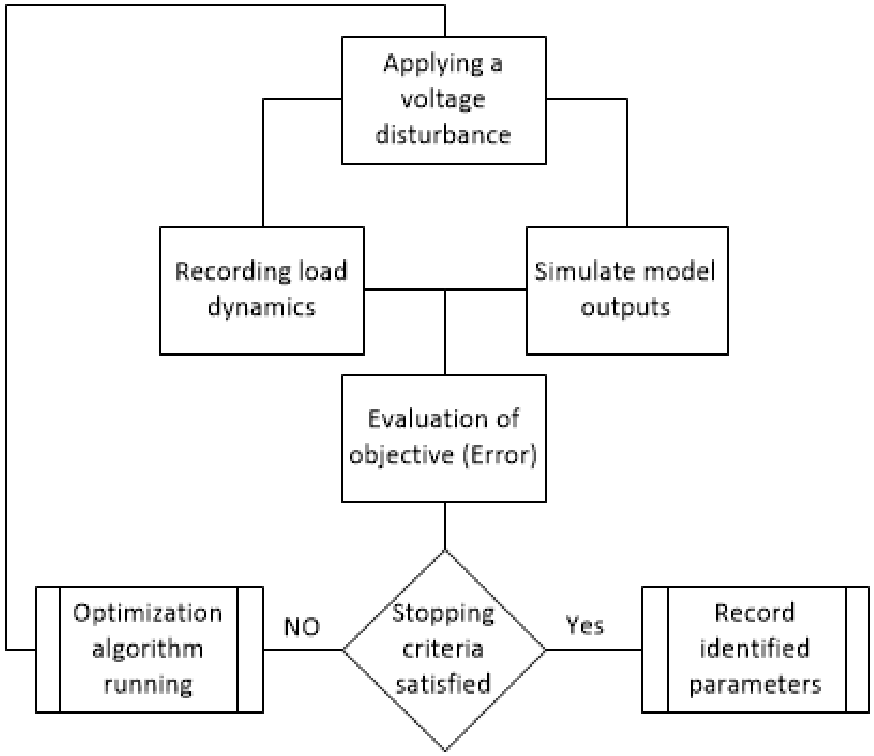


Figure 3.4: General flowchart of optimization based load modeling.

In [73], a measurement-based load modeling approach was described using GA for the parameters estimation. As a common trend in other studies, an induction motor in parallel with the ZIP static model was utilized as the composite load model structure. The ZIP part was modeled only as a function of voltage and the dynamic part was represented by a third order equation consisting of the flux and rotational dynamics of the induction motor. The objective of GA was to minimize the error between measured data and outputs of the model. It was claimed that GA, or evolutionary optimizers in general, are highly compatible for dynamic load modeling problems. Two main reasons were considered for this compatibility. First, the recorded data originated from the steady, dynamic and recovery states and not all algorithms are able to find the correct set of parameters in such a broad extent. Second, GA was less dependent on the accuracy of the initial guess. Test results on the IEEE 10 machine 39 bus and Hushitai power substations confirmed the applicability of GA in load model estimation. A comparison with the least square method was also considered and

GA showed better performance in realistic model estimation. Similar to [73], an improved GA was considered in [74]. Measurement-based load modeling approach was implemented on a 23-bus system. The load model used in [74] was the same as [73], but the GA was improved in order to mitigate problems such as the slow convergence speed and sticking in local optimal answers. To do so, four main changes were applied to the conventional GA. Direct transfer to the next generation occurs only for the individuals with the best fitness values, called elite individuals. Other individuals had the same statistical chance in the new selection strategy. Furthermore, crossover proportionally produced more children in the new generation and advanced immigration strategy was applied once every ten generations. Optimal searching direction based on damping factor detection was added to the GA as well. Numerical tests and comparisons with results from non-linear least square techniques, particularly Levenberg-Marquardt (LM), asserted that GA was more successful in finding the optimal answer. Nevertheless, the LM method had a faster convergence to the optimal solution.

Although GA has been the most commonly used evolutionary optimizer for load modeling, several studies have focused on the other evolutionary techniques for load model parameter identification. To mention a few, an Improved PSO was used in [25] as an optimization technique. Similar to the previous works, the same objective function seeking to minimize the mismatch between measurements and modeled data was defined. The Improved PSO was built up by a combination of the traditional PSO and a cross over operator. The cross over operation allowed particles to share their characteristics with the best individuals. Thus, it was more likely for PSO to explore more promising areas in the solution space. Authors in [25] argued that implementing this approach reduces the risk of stucking in local optimums and requires less computational time in comparison with traditional PSO. Consequently, the considered PSO was recommended as an alternative to GA. Authors believed that the modified PSO had an adaptation to time-critical operations due to its controllability for convergence properties. Another measurement-based method using Ant Colony Search (ACS) optimization was suggested in [75]. Several sets of equipment were installed to record the dynamics of the grid. The bus voltage was monitored and dynamics were recorded in case of a disturbance of more than five percent in nominal values. A sensitivity analysis was conducted to perform a more precise optimization in a shorter amount of time. The motor percentage in the total load, initial rotor slip and leakage reactance of the stator were selected to be optimized based on the sensitivity analysis results. A normal ACS, as described in [76], was applied for error minimization. The model derived from computed parameters was used for critical clearing time and power transfer capacity calculation of the Henan Electric Power Grid. Authors reported a significant improvement in the referred transient characteristics by using these parameters instead of the default settings. Reviewing this part of the literature shows that different evolutionary optimizers, such as GA and PSO, have been successfully used for parameter identification in the load modeling problem.

The critical role of sensitivity analysis for parameter reduction prior to optimization implementation was emphasized in [77]. A comprehensive sensitivity analysis was carried out by utilizing the hessian matrix which, for simplification, derived from the Jacobian matrix and its transpose multiplication. With respect to this sensitivity analysis, the number of parameters were reduced. Optimization required less computational time without jeopardizing the accuracy of the estimated model. Hence, sensitivity analysis is always recommended for load model optimization problems in the literature [78].

3.3.3 Artificial Neural Network Models

References [79] and [80] were among the first studies to consider the potential application of Artificial Neural Networks (ANN) in dynamic load modeling. Because of the high-level approximation ability of ANNs, they were considered as a logical choice for complicated load modeling problems. ANN is a computational model widely used in machine learning. In general, the ANN method is based on the biological processes of the brain and is popular for its trainable features and its massive parallelism [81]. In what follows, several examples for ANN applications in load modeling are provided.

A layered network forward type including one hidden layer was utilized for conducting a measurement-based approach on two load models in [80]. The ANN was trained with small disturbances, but showed acceptable performance for large disturbances by extrapolation. Due to the satisfactory results achieved in this study, ANN based load models were introduced as a possible substitute for other dynamic load models. A survey on voltage stability analysis of traditional load models was first conducted in [82] aiming to show their potential faults in dynamic emulation and consequently damaging the system by an unanticipated voltage collapse. A feed forward neural network load model was deployed for both static and dynamic analysis of system voltage stability and results on IEEE 14 bus system were satisfying. Power system stability analysis by dynamic load models derived from ANNs has been the goal of [83]. As an example for ANNs with feedback, a recurrent neural network containing feedback from present layers to previous ones formed the first step in the methodology. This model was updated in the second step in accordance to field measurement data. A case study on an induction motor proved the effectiveness of this ANN based approach. Mentioned works show the potential applicability of forward type or ANNs with feedback for load modeling. However, training these models require large amount of recorded data from the grid. Otherwise, these methods are prone to overfilling. Additionally, these studies are focused on a single load and not considered the application of ANNs for multiple loads in industry-level simulations. These ANN structures seem to be overly complicated for such practical applications.

A portion of the literature focused on ANNs with back-propagation learning algorithms for the load modeling problem. A three-layer feed forward ANN attached with back propagation learning was assessed in [84]. A measurement-based method which relied on the recorded data at a north-eastern China power system was considered and then compared with differential equations models. Different sets of neuron numbers were considered for input, hidden layer and output. Interpolation and extrapolation were implemented for both models. The reported results showed that ANNs had better adjustment to the non-linear behavior of dynamic loads. It was noted that exploring more effective learning rules for ANNs should be investigated in future research. A new ANN-based load model, called adaptive back propagation network, benefiting from modification in traditional ANNs was introduced in [85]. The new model had new error and activation functions. As the new error function had energy constraints in addition to the conventional error function, the proposed model was helpful in speeding up the convergence procedure. A linear back-propagation was also applied for parameter identification of several common load models, such as differential, polynomial and exponential functions. Models derived from this developed algorithm were verified and substantial savings in computation time were reported. Reference [86] criticized the widely used back propagation ANNs mainly due to the absence of feedback in their structure and shortcomings in their training algorithms. To mitigate the mentioned drawbacks, a recurrent ANN was suggested for composite load modelling. Simulations on a 220 KV substation yielded two major conclusions: 1) although back propagation ANNs showed strong abilities in static mapping; they were not the best choice for dynamic simulations. 2) the recurrent neural network model had a simple structure with fewer parameters and thus, it had a better non-linear mapping performance compared to the criticized models.

3.3.4 Load Modelling Based on Phasor Measurement Unit (PMU) Data

The importance of improved measurement devices has grown dramatically in recent years by the emergence of smart grids. The implementation of comprehensive smart grid applications in current and future networks is not possible without modern monitoring devices installed in power systems. Wide area technologies including monitoring, protection and control are one of the emerging methods that performs an essential role in real-time monitoring of new smart electrical systems. PMUs are among the important devices being used in this new monitoring environment. First introduced in 1988 by Phadke at Virginia polytechnic [87], PMUs have been used for phasor measurements of voltage or current. Later and following the 2003 blackout in the United States of America, the necessity of equipping power systems with PMU devices attracted more authorities in the US and Canada. Thus, a large budget was allocated to PMU installation in power systems and the number of PMUs substantially increased until 2013 [87]. The high resolution data acquired by PMUs has opened new doors for many model validation problems in power systems, such as dynamic load modeling. Several measurement-based load modeling approaches investigated the use of PMU data for model validation studies.

Authors in [25] presented a measurement-based load modeling by using the data collected by three different PMUs. Firstly, the conventional third order induction motor in parallel with the ZIP static part was considered. An abrupt voltage disturbance was applied and comparisons between simulation outcomes and PMU results were made. In the case of modeling small induction motors, none of the PMUs were able to record data with reasonable accuracy, but two PMUs were successful in recording the data for larger induction motors. The third PMU was not successful in capturing the dynamics because of its filtering settings. Hence, it was concluded that there is a direct relation between the time constant of an induction motor and the accuracy of PMU measurements. Testing the exponential recovery load model, mentioned in the input-output group of models [66], showed the same results. Hence, PMUs have better performance in measurement-based load modeling if the time constant of the dynamic period is not too short. Furthermore, the PMU type and its filtering effects must be taken into account. Another PMU-based measurement approach was recommended in [21] for parameter identification. It was emphasized that PMUs have a very high ability in making the dynamics of the power system visible. Test results on a five-bus system located in Tennessee confirmed the effectiveness of this PMU based methodology for capturing dynamics of the network. A wide area protection system aiming to identify different types of contingencies, with more concentration on the voltage instability issue, was investigated in [88]. Synchronized PMUs were installed to capture the dynamic behavior of the power system. The exponential recovery load model was used. After collecting the real-time data via PMUs, it was verified that operators could predict remedial actions by implementing this approach. These studies show the potential applicability of PMU data for better dynamic observability and load model development in power systems.

3.4 Complex Identification Techniques

A group of studies mainly focused on the parameter identification of load models. These studies usually attempted to either reduce the optimization time or increase the accuracy of solutions. Introducing a new two-step method, [89] simplified the composite load model by dominant parameters recognition and reducing the order of motor equations from three to two. As the first step, electrical parameters were defined and thereafter, mechanical parameters were evaluated using newton method. Estimated model showed acceptable results for stability studies. The computational time for this approach was about 50 times shorter than that of GA and PSO for the same case. As a result, this model was claimed to be applicable for real-time power system simulations. This model was designed for stability studies but could not necessarily be accurate for other types of studies. To address this problem and present a more generalized identification method, authors in [90] combined the binary tree with non-linear auto-regressive algorithms. The proposed method showed a reasonable agreement to real case results in different types of studies. This model did not require any prior knowledge of the load and it was adaptable to different types of power system studies. These complex identification techniques are often considered as overly complex for implementation to large-scale power system applications. However, they might be a reasonable option for time-critical studies, such as the real-time dynamic monitoring of power systems.

3.5 Load Models Used in Power System Simulations by the Industry

There is a difference between load models used for industry-level studies and the models considered in the literature. There are several non-static models that are more often used by the industry. CLOD complex load model, induction motor load models, such as CIM5 model in PSS/E, and the more recent composite load model developed by WECC, WECC CLM, are among the popular choices for power system operators. Popularity of these models is mainly due to the availability in large-scale power system simulators. A portion of the literature focused on the applications of these industry-level load models.

A template based study was considered in [31] as an example of CLOD implementation for industrial facilities. This study aimed to find the load compositions based on surveys. CLOD model parameters were identified according to the reported survey and used for simulations. The WECC CLM is more complex than other models. Thus, the WECC CLM implementation for large scale power systems is demanding. Authors in [91] performed a comprehensive dependency analysis on the model parameters based on the k-means method. This study resulted in parameters clustering and ranking which provided a useful insight into the importance of different parameters for the WECC CLM. Another study compared the simulation results, using the WECC CLM, with PMU measurements mostly for regions where delayed voltage recovery events were observed [1]. These studies usually used either some generic parameters or selected parameters based on conducted surveys on load compositions.

From the practical angle, finding efficient methods to facilitate load model building for large power systems is very important. Most of the available literature focused on methods to find parameters for one specific load. However, real-life power systems have large number of loads with unknown parameters and performing studies for each of these loads is not feasible. Authors in [27] and [28] concentrated on load modeling in large-scale power systems. They suggested methods for load type classification and aggregation. Parameter identification was performed on a single load and then generalized for other loads based on the available load classification.

3.6 Summary and Conclusions

A complete review on load modeling based on different perspectives was presented in this chapter. From modeling perspective, static, dynamic and composite models were investigated. Two main model building approaches namely component-based and measurement-based were discussed. Dynamic models were elaborated in four categories, namely, input-output models, evolutionary based models, ANN-based models and models using PMU data for their validation. Additionally, several complex identification techniques were mentioned. Furthermore, load modeling for the industry-level simulations were reviewed and several popular models, used by power system operators, were discussed.

A number of important points can be concluded based on the reviewed literature. Static models have been dominantly used by system operators because of their simpler structure compared to dynamic ones. The ZIP has been the most commonly used static model based on the available studies. It was common to only use one term of the ZIP polynomial as the static model as well, such as the constant power term. Exponential static model has been used less as a result of uncertainties on the selection of exponent values. Dynamic models were often more difficult to implement. Hence, these models required more investigations. Simple input-output dynamic models were usually concentrated on different induction motor representations. It was observed that first order equations can simplify motor representation without sacrificing simulations accuracy in many simulation cases. Reviewing the literature showed that dynamic models were more important in voltage response characteristics, especially in delayed cases. Induction motor sizes and types, such as pump or compressor motors, played an important role in the process of a model type selection. The developed input-output models have potential for integration to industry-level composite load models, such as CLOD and WECC CLM. Future research should investigate this integration as a possible mitigation to deficiencies of current models.

Least squares and evolutionary optimization methods were broadly used as the solution method for load model parameter identification. Evolutionary techniques, such as GA, showed better success in finding the optimal answer. Less dependency on the initial guess and better ability to treat the system as a black-box model are important advantages of these methods. Hence, a portion of the literature recommended evolutionary algorithms as a promising choice for parameter identification. The major drawback of these models was the high computational time. Thus, least-squares or hybrid approaches were suggested for time-critical problems. Despite of availability of these identification methods in the literature, industry usually preferred generic or arbitrary choices for load model parameters. This preference is mainly due to complexities for implementing these algorithms for large-scale systems. Furthermore, performing such identifications require the interactive use of large-scale power system simulators and available optimization tools. Future research needs to explore the necessary adjustments to facilitate the use of these techniques for the industry-level practice.

To the best of the author's knowledge, reported ANN-based load modeling studies were only applicable to small systems and were mostly based on laboratory tests' data. These models were complex for implementation to large power systems hosting many loads. Furthermore, ANNs need large amount of data to be successfully trained. There is limited data available for training and validation of neural networks in power systems. Thus, over-fitting is very probable. Despite the mentioned difficulties for ANNs implementation for industry-level applications, they might be a reasonable choice for complex loads with limited data available on their structures. If other models fail to represent such a load and upon availability of enough data for training, ANNs could be considered as the only solution for such cases.

Availability of PMU data motivated a group of studies to consider the collected data for measurement-based dynamic load modeling. These studies claimed that PMUs can be useful in validation of dynamic load models. Filtering effect and sampling rate of PMUs are important when comparing the data with simulations. Generally, it was observed that PMUs can capture the dynamics of larger induction motors with more accuracy. As for now, most of the literature have used PMU data based on the artificially created events. Data that is collected in the laboratory might be very different from what is observed in actual power grids. Moreover, PMUs can exactly record the state of substations which they are installed, but finding the exact state of a large-scale system prior to events can be challenging. Further research is required to investigate the use of PMU data in real-life power systems hosting many number of loads.

Chapter 4

The Impact of CLOD Load Model Parameters on Dynamic Simulation of Large Power Systems[1]

The objective of this chapter is to explore how optimal load model parameters impact the results of dynamic simulations in power systems. The focus is to identify the parameters for CLOD composite models that are widely used in power industry to represent major loads in dynamic simulations. This model accounts for the diversity of load components by representing a variety of elements, including large and small motors and static loads, as mentioned in Chapter 2. The off-line model building process for making the simulation case ready is elaborated in this chapter. Evolutionary-based optimization methods are used to minimize the error between PMU measurements and dynamic PSS/E simulations. The simulation results obtained using optimized load models are compared with those of generic models.

The rest of this chapter is organized as follows: a background review for the chapter is provided at the first section. Study area selection, event detection procedure and process

[1]Based on the materials presented in this chapter, a conference paper entitled "The Impact of CLOD Load Model Parameters on Dynamic Simulation of Large Power Systems" is published in IEEE [92].

for building the off-line model are given in the second and third sections respectively. The fourth section provides the problem formulation including the fitness function, constraints and the recursive process in which the selected evolutionary algorithms are applied to the problem. The fifth section illustrates the results of sensitivity analysis performed on the CLOD model prior to the optimization. The numerical results and comparison between generic and optimized CLOD are presented in the seventh section. Finally, the summary of the chapter is provided in the last section.

4.1 Background

Having an accurate model of load dynamics is a challenge for power companies. Despite the importance of loads in dynamic behavior of power systems, only 10 percent of system operators from around the world have reported to use detailed composite load models by 2013, [3]. The surveyed power companies mainly use generic models. However, these models are not necessarily the optimum match for all operating conditions. Most of the load modeling studies regarded small test systems or concentrated on finding optimum parameters for a single load in a power grid. However, there is a need for models being capable of estimating load parameters in large-scale power systems with many number of loads for which, no detail dynamic models necessarily exist. Only a few studies considered load modeling for large-scale power systems. References [27] applied measurement-based load modeling to North-eastern China grid as an example of large-scale power system. A common ZIP and induction motor equivalent circuit was used as the load model and parameters were identified based on artificial three-phase disturbances. Detailed review of the literature is available in Chapter 3.

CLOD complex load model [29] is a practical model widely used by system operators. Some generic assumptions have been usually considered for CLOD by system operators, but the question of whether optimizing parameters can yield different results from the generic ones needs to be answered. In this chapter, a measurement-based approach is implemented to investigate if and how CLOD composite load model parameters impact the simulation results of transient events in large power systems. The reason of focus on CLOD is that this model is implemented in popular power system simulation tools, such as PSS/E, and is widely used by practicing engineers to represent loads. The challenge that system engineers face is that many of the loads that are connected to the system are composite loads with no detail dynamic load models. Thus, power system modelers use generic CLOD load models to represent the dynamics of such loads. CLOD model is essentially a composite model that includes a large motor, a small motor, and a constant MVA model, and a few other components as described in Chapter 2. Power system engineers use typical coefficients for each component based on their best estimate of the load's nature. In this chapter, the main objective is to investigate how such somewhat arbitrary choices of the CLOD model components' parameters impact the results of system dynamic simulations. This is an important question that could be answered now that PMU data is available in power systems.

To answer the aforementioned question, measurements from a PMU on one of the high voltage substations at AIES are used. Well-established evolutionary optimization methods are utilized to identify the optimal values of model parameters, such that simulated voltage magnitude responses mimics the measured values as much as possible. Results are then compared with those of generic parameters, arbitrary CLOD models. The main contribution of this chapter is that it investigates to what extent CLOD model parameters' optimization impacts the results of dynamic simulations of large-scale real-life power systems. The significance of the contribution is that power systems engineers can decide how much effort and resources should be spent on modeling the dynamics of such composite loads where minimal information about their behavior is known.

4.2 Study Area Selection and Building the Off-line Model

Prior to formulating the problem and performing the simulations, it is necessary to select an appropriate study area for the simulations. Upon selection of the study area which can satisfy the requirements for the study, the off-line system-wide model of the AIES should be built. Following subsections describes each of these steps with more detail.

4.2.1 Study Area Selection

Selecting the appropriate study area is critical for this study. Study area should be selected in a way to be as representative as possible from the load response perspective. Most of the installed PMUs in Alberta are on generation centers. A major load center with no generation is identified. This major load area has three links to the rest of the system, 240/138kV substation which is monitored by a PMU, a back-to-back HVDC link and one long 138kV transmission line. One challenge of using data at the high voltage side of the system for load modeling is that the measured dynamic response is dominated by the transients of other system elements, such as generators and DC links, as mentioned in [27]. In particular, the load dynamics might be a minor contributing factor in the observed behavior. In order to isolate the effects of load dynamics, events have been investigated for the time intervals that this DC link is switched off and a fault that disconnects the area from non-PMU monitored line is selected. The event is collected near this major load area which has high volume of loads near the PMU and thus, there is more potential for observing the impact of load model changes on the HV buses of the system.

A line fault on the long 138kV transmission line linking this load area with the rest of the grid and its following recovery occurred in Fall 2017 has been considered. This line fault isolated the load area except for the PMU monitored 240/138kV substation. The full map of AIES is provided in 4.1. The focus of this study is on area 48, Empress. A more detailed map of the study area is illustrated in 4.2. These maps are publicly available and can be found in [93] and [94]. The PMU data is collected from Amocco substation located on the eastern part of Empress area. The rest of PMU data available in AIES is mostly at generation sites which makes this major load area the most promising choice for the current study.

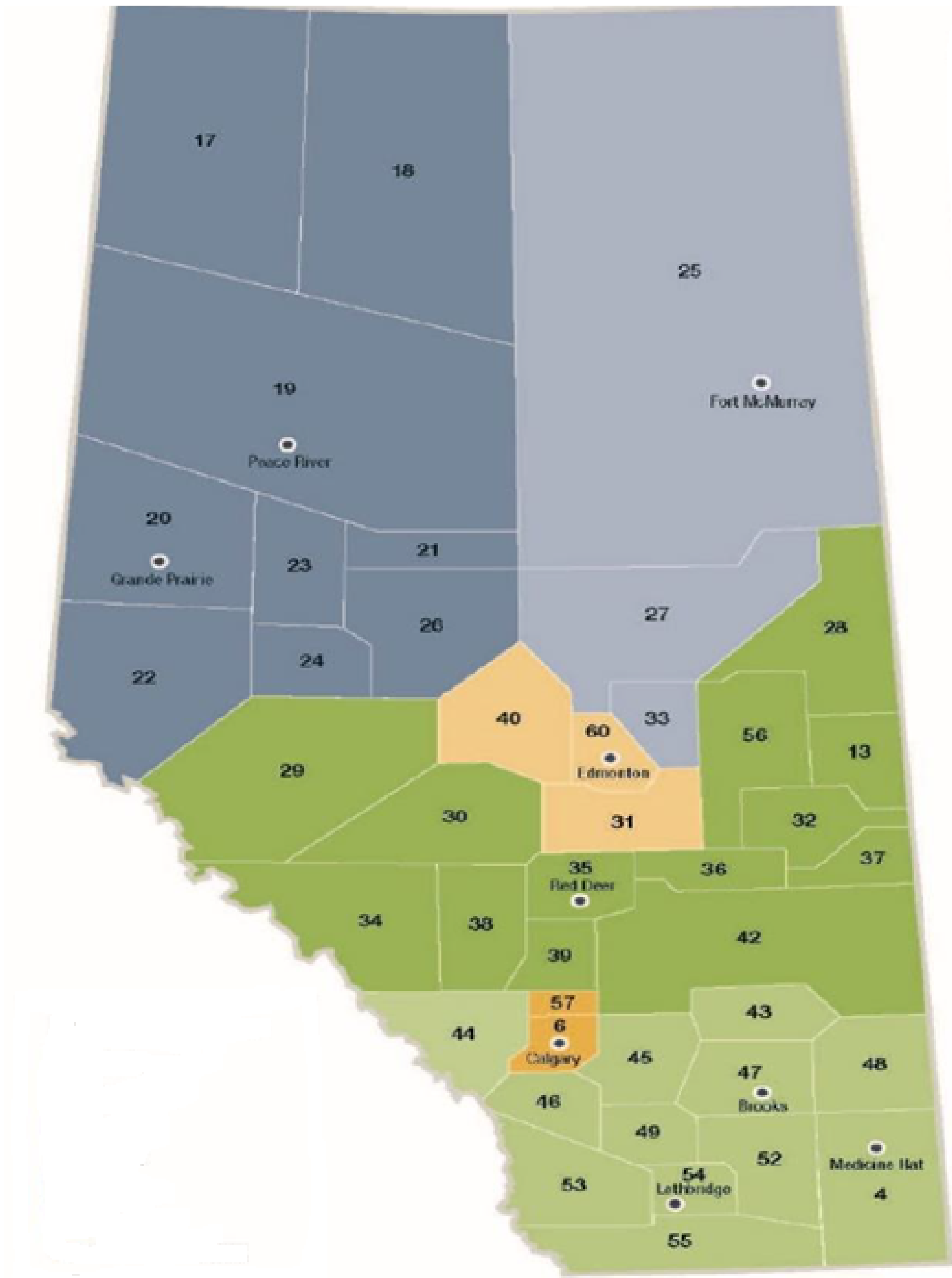


Figure 4.1: Alberta Interconnected Electric System.

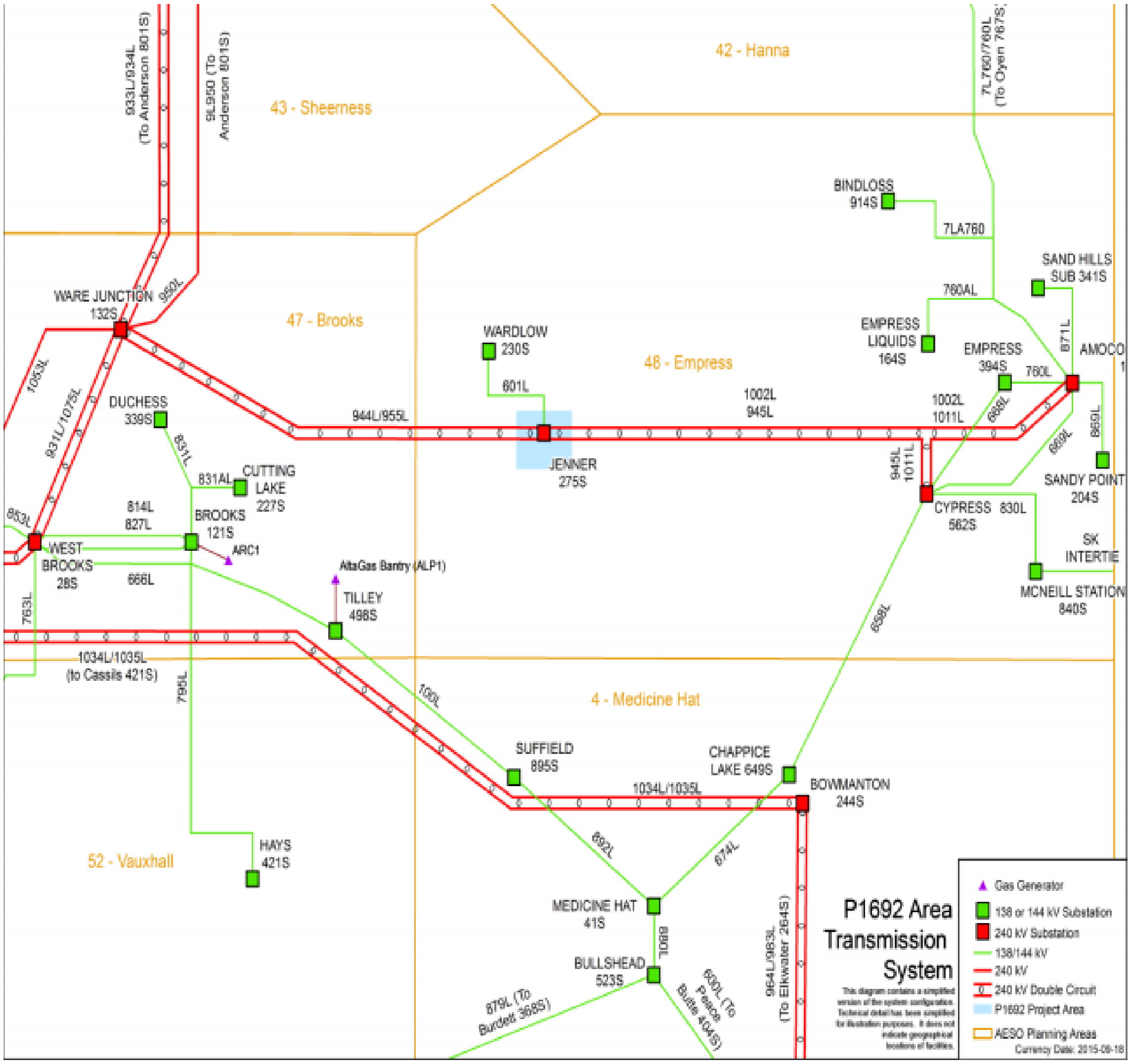


Figure 4.2: The study area map.

4.2.2 Building the Off-line Model

Using generator playback models to generate PMU recorded events has been a common trend for previous literature as mentioned in [24]. Although these models can accurately generate the voltage and frequency recorded by PMUs, they have two drawbacks for the current system-wide modeling. Firstly, generator playback models substitute the major portion of the power system with one generator model. Therefore, it is not an appropriate option when it is desired to simultaneously model a large number of loads in large-scale power systems.

Second, this model feeds the recorded voltage. Thus, an out-of-sample voltage comparison between simulation results and the PMU data is meaningless. Therefore, studies usually try to compare other characteristics, such as power and angle, which cannot necessarily guarantee the best match for voltage. As the aim of this study is to simultaneously optimize multiple load models, the system model cannot be reduced to equivalents. Hence, in order to have valid simulations, it is required to have estimates of the system model as close as possible to actual power network prior to the event. AIES has a peak demand of 11,697 MW served by 26,000 km of transmission lines. Given this, it is not feasible to have a base-case which perfectly matches with the AIES prior to the event. Reasonable cross-referencing between SCADA and PMU data have been considered to get more realistic results.

Alberta's operation coordination base case is used near the time of selected events. This base case has the closest match to the actual case as it contains all the changes and adjustments in AIES at the selected time. SCADA data is analyzed for system elements near the PMU monitored substation. Switching condition of lines and dispatching of nearby generators is checked and adjusted in the off-line model. The steady state voltage difference between PMU data and simulation base case was not significant after performing this cross-referencing. Less than half a pu voltage difference were observed between the developed steady state base-case and the PMU measurements at monitored substation.

4.3 Event Detection and Simulation Process

It is required to collect events based on the available data. In order to re-simulate the event, it is also necessary to know the location and type of the event. The general procedure for event detection and following fault analysis for re-simulating the event is described in this section.

4.3.1 Event Detection

The first step to investigate the performance of CLOD load model in simulations is to find a real event in the study area. Many previous studies are based on artificial events, but we try to find and re-simulate a real event in the study area. The event should have especial characteristics in order to qualify for this study. It should cause a relatively significant voltage drop in the area, specifically at the PMU monitored substation. Additionally, the more area isolation at the fault time helps to better capture the load dynamics. It is also necessary to understand the location of the event so it can be accordingly simulated. A combination of PMU and SCADA data analysis has been conducted for this purpose.

In this study, the actual structure of the AIES is kept intact by maintaining and using the full model that represents the system at the time of the event as reasonably close as possible. Note that system models are developed off-line and they do not fully reflect the state of the system at the time of the event. However, a reasonable cross-referencing among the available information from the Alberta's system for the time of the event is implemented to have a reasonable model, as mentioned in the previous section. The Alberta's Operations Coordination base case which is the most realistic real time system model available for Alberta has been used. The SCADA data is analyzed to identify sudden transmission line switching in the study area. Some of these suspected events were not tripping due to faults in the power system and were only scheduled outages. Upon reviewing notes from the control room and confirmation of fault events, with detail on type and location from the event log, PMU data were collected for the recognized time-lines. Hence, knowing the exact events, they can be simulated realistically and be compared with the available PMU data for that event. Figure 4.3 depicts the described process for the event detection. It is worth mentioning that several other events in the study area were detected as well. However, they all followed the same pattern and the voltage responses observed in different events were similar.

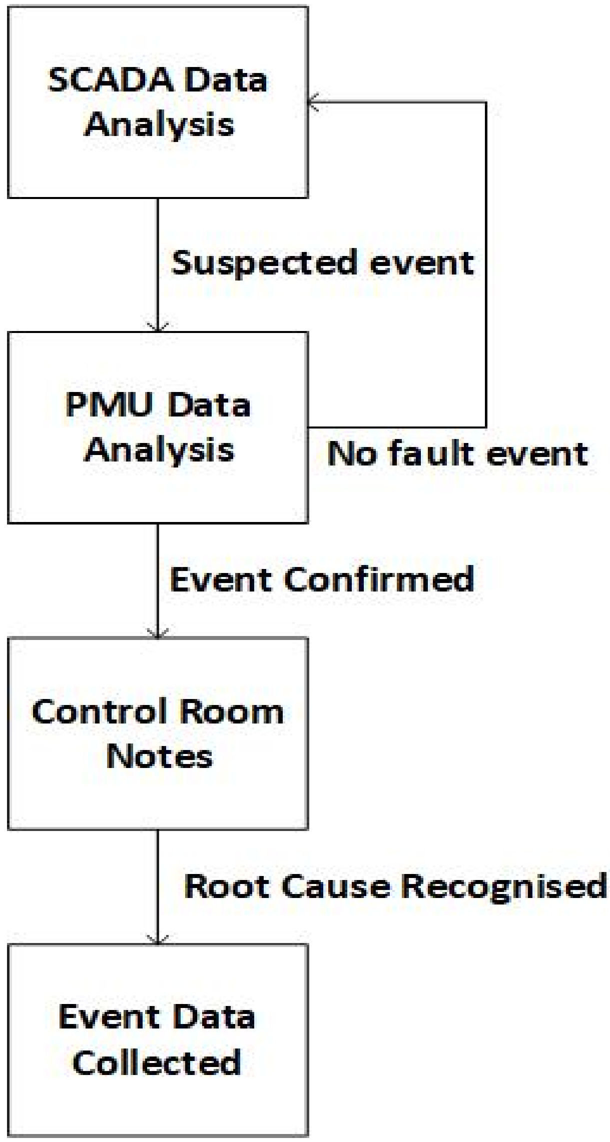


Figure 4.3: Event detection process.

4.3.2 Fault Analysis

A fault is detected near the study area according to the procedure described in the previous section. The selected fault is on one long 138kV transmission line linking this load area with the rest of the network. The clearing time is six cycles based on the available data. To simulate the event, a fault has been applied to the same line in the off-line model. Fault is cleared following by a line tripping after six cycles. Fault impedance is tuned to simulate the voltage drop reasonably close to the actual voltage drop recorded by PMU devices.

4.4 Problem Formulation

Dynamic load modeling problem is generally a highly non-linear problem and this non-linearity is more severe for complex load structures, such as CLOD. Given this and regarding the complexities for large-scale power systems hosting many loads with non-linear behavior, model independent optimizations, such as evolutionary techniques are a logical choice for these types of optimization problems. As mentioned in Chapter 3, meta-heuristic optimization methods have been widely used for load model parameter identification, but have not been utilized for simultaneous optimization of multiple dynamic load models in large-scale power systems.

The objective of this optimization problem is typically to minimize the Mean Absolute Error (MAE) between measured voltage magnitudes and those of the dynamic simulations generated by the software tool, in this case by PSS/E. Hence, the fitness function can generally be written as the (4.1). As the PMU recorded data is available for two HV buses in the area, i.e., 138 and 240 kV, the summation of MAE for each of these two buses is considered as the fitness function for the optimization problem.

$$\sum_{k=1}^{N}\sum_{t=1}^{M}(1/M)\times|V_{simulated}(t,k)-V_{measured}(t,k)| \tag{4.1}$$

Where N shows the number of available measurement devices in the study area and M accounts for the number of measurement points to be compared at each of these available measurements. The number of monitored voltage levels are two for the case of this thesis. The optimization algorithm attempts to minimize the calculated error. This problem is subject to following constraints:

$$0 \leqslant K_p \leqslant 5 \tag{4.2}$$

$$0 < Transformer\ exciting\ current(\%) < 10 \tag{4.3}$$

$$0 \leqslant \sum(\%based\_parameters) \leqslant 100 \tag{4.4}$$

K_p is the voltage exponent of the active part in the static load. Based on our broad simulations performed on AIES, model cannot work properly for K_P values higher than 5 and consequently results in convergence problems. Additionally, the range considered in (4.2) does not seem to miss any realistic load behavior regarding the diverse search on K_p values performed in [38] and standard ranges given in [39]. (4.3) emphasizes that transformer saturation current should stay within its reasonable limits as outlined in [29]. It is obvious that summation of percentage-based parameters of the model should not exceed 100 as written in (4.4).

GA and PSO are among the population-based evolutionary optimizers and can perform a diverse search in the solution space. Both these methods are employed to minimize the fitness function given in (4.1) with regards to constraints. Fundamental concepts supporting these optimization algorithms are similar, but each of them has different procedure for searching the solution space and converging to the optimal answer, as elaborated in Chapter 2. Figure 4.4 shows the flowchart for the measurement-based load modeling optimization problem described for this thesis.

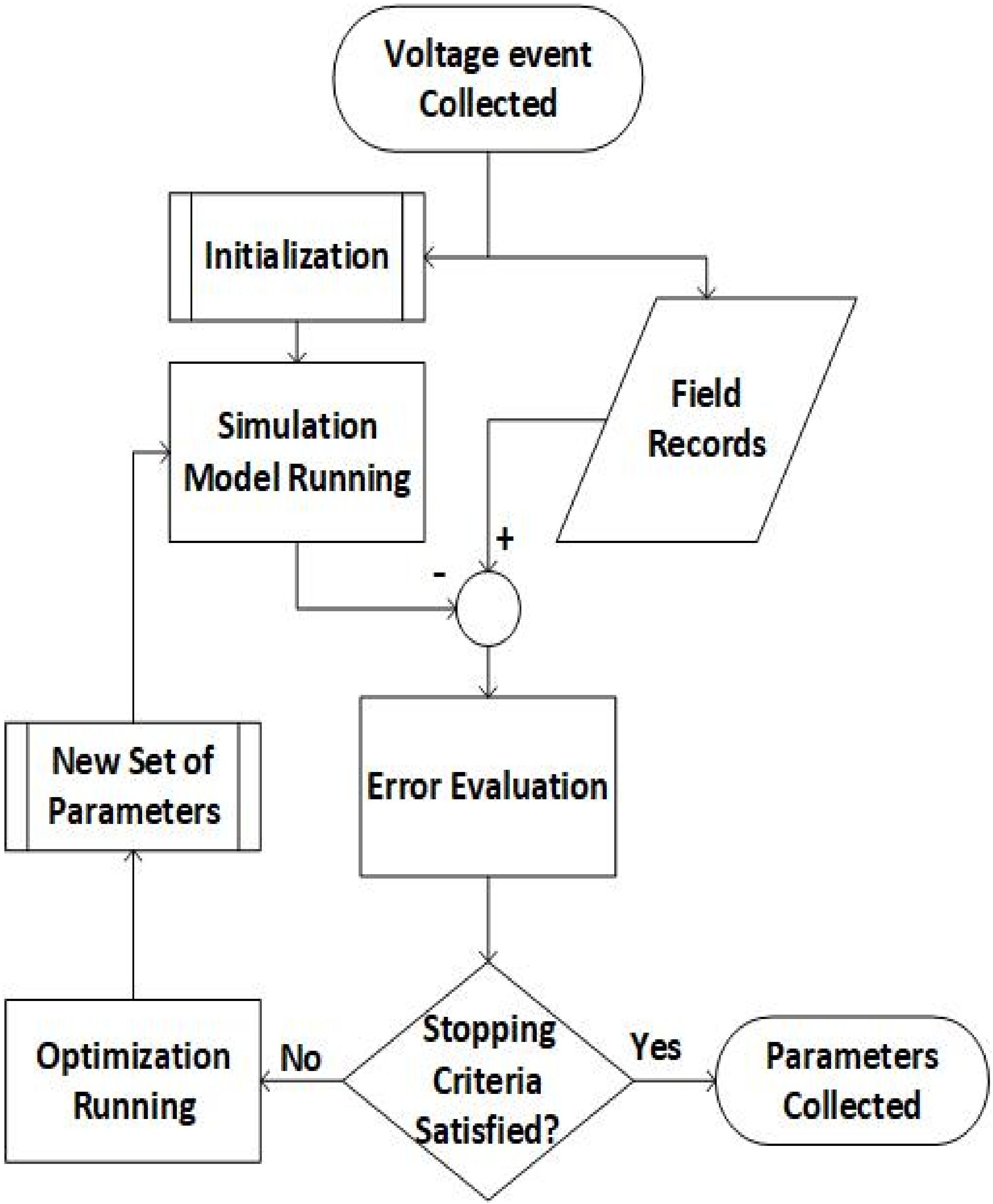


Figure 4.4: Flowchart diagram for evolutionary-based load model identification.

4.5 Performing the Sensitivity Analysis

Considering the large number of loads contributing in dynamic responses of the system, it is helpful to reduce the problem dimension by conducting a sensitivity analysis for the model.

This can also reduce the risk of being trapped in local optimal values by selecting more important parameters. Variance-based sensitivity analysis, referred as the Sobol method [48] and explained in Chapter 2, is utilized for sensitivity analysis of the proposed load model.

One of the large loads in the study area is considered and diverse samples of CLOD model are created for the sensitivity analysis. Comparisons between simulations with created load samples and the basic PSS/E results, with no specific load model, are considered at the selected load bus. First order and total-effect Sobol indices for CLOD model parameters in dynamic simulations of AIES are presented in the Table 4.1. As there are some correlations between model parameters, total-effect indices are more reliable than the first order indices. Therefore, model parameters are ranked based on the Sobol total-effect indices reported in Table 4.1. Large motor, small motor, and KP of the remaining loads are by distance the most important parameters. Further analysis on the second order correlations shows a very high dependency between large and small motors. This significant dependency can substantially increase the risk of getting stuck in local optimal solutions. Hence, large motor, with higher total-effect index, is chosen for optimization and small motor is fixed to its generic parameters.

Table 4.1: Sensitivity analysis result on CLOD.

Parameter ranking	total effect index	first-order index
Large motor	9.42e-1	6.83e-1
small motor	2.99e-1	4.04e-2
K_p	4.21e-2	3.44e-3
Discharge lighting	5.1e-3	3.83e-4
Constant power	2.09e-3	7.32e-4
Transformer current	1.41e-3	9.93e-4
X	1.32e-3	1.08e-4
R	1.79e-4	1.23e-4

4.6 Simulation Results and Discussion

This section provides the voltage simulations and results of the optimization problem which is performed on the AIES as the case study. The assumptions for modeling the loads, comparisons and complete discussions are presented in following sections.

4.6.1 General Assumptions and Simulation Description

The approach presented in the previous sections is implemented to the case of Alberta. Most of the installed PMUs in Alberta are on generation centers. A major load center with no generation is identified, as mentioned earlier, to isolate the impacts of load modeling as much as possible. Simulation is implemented based on the previously mentioned off-line model building process on AIES.

For performing the simulations, we distinguish between the different load types that are in the study area. Based on available information at the AIES database, there are three load categories near the monitored substation, namely, normal manufacturing loads, light manufacturing loads and non-class loads. About 82 percent of all loads in AIES fall into these three categories. Individual CLOD models are considered for each category. Thus, all loads in this area are modeled by either of the three CLOD models for which the parameters will be identified.

Table 4.2 gives the generic CLOD model parameters for AIES as outlined in [95] and originally suggested for WECC in [39]. These assumptions are valid for the area which we have access to PMU measurements at both 240kV and 138kV levels of one of the substations. The simulations that are presented based on generic CLOD model follows the same assumptions for model parameters.

Table 4.2: WECC 2001 generic parameters for CLOD model.

small motor(%)	10
Large motor(%)	10
Discharge lighting(%)	0
Transformer Saturation(%)	0
Constant MVA(%)	0
Kp	1
R	0
X	0

4.6.2 Numerical Results_ Case of Alberta

According to the sensitivity analysis on CLOD model, GA and PSO are applied to the proposed problem in case of a line fault event, at 17 October 2017 15:45 Mountain Time, to optimize large motor percentage and K_P for the three different load categories in the system. Other parameters are set to their generic values as given in Table 4.2.

Optimization results are reported in Table 4.3. Results show that all optimized CLOD models have a relatively higher static part than motor loads with a high voltage exponent in the exponential static model, remaining load part of CLOD. This can also be confirmed based on the fast voltage recovery responses observed by PMUs which show loads have more static nature in the area.

Table 4.3: CLOD parameter optimization results for AIES.

Categoies & Parameters	Non-class loads		Light manufacture		Normal manufacture	
	GA	PSO	GA	PSO	GA	PSO
large motor	5.06	7.52	18.01	14.73	11.55	13.02
K_p	4.09	4.31	4.61	4.83	4.25	4.13

Results are consistent between GA and PSO. Figure 4.5 shows the convergence diagrams for both optimization methods. PSO has a bit higher convergence speed while GA offers a better final solution. Figures 4.6 and 4.7 show the four second and zoomed one second comparison between PMU measured voltages, GA optimized CLOD simulated voltages and generic CLOD simulated voltages for 138 kV and 240 kV buses respectively.

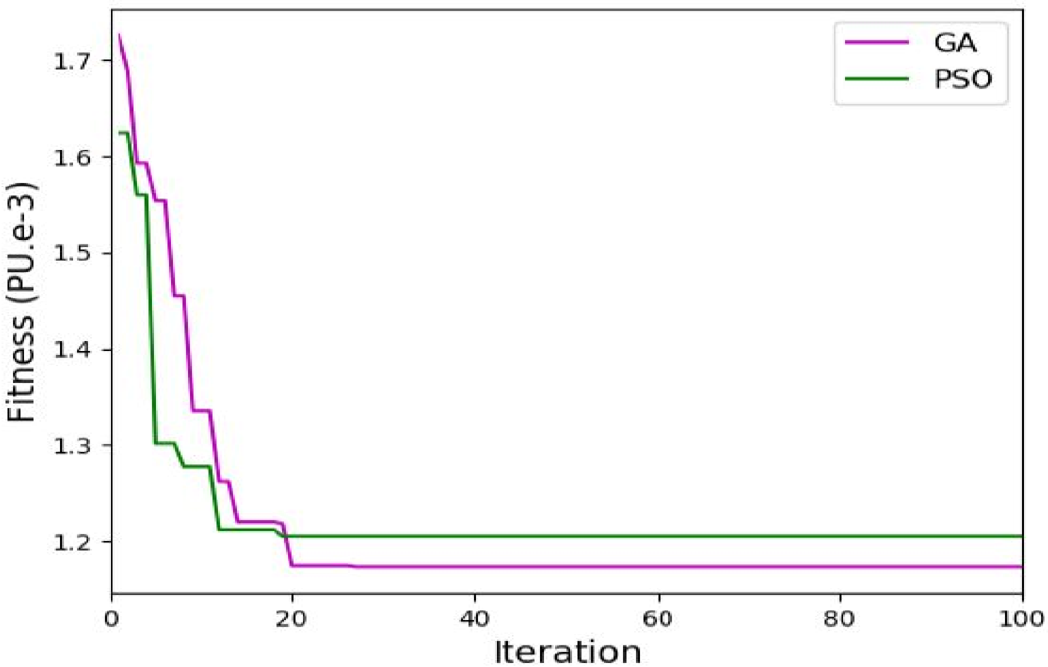


Figure 4.5: Convergence diagrams of GA and PSO.

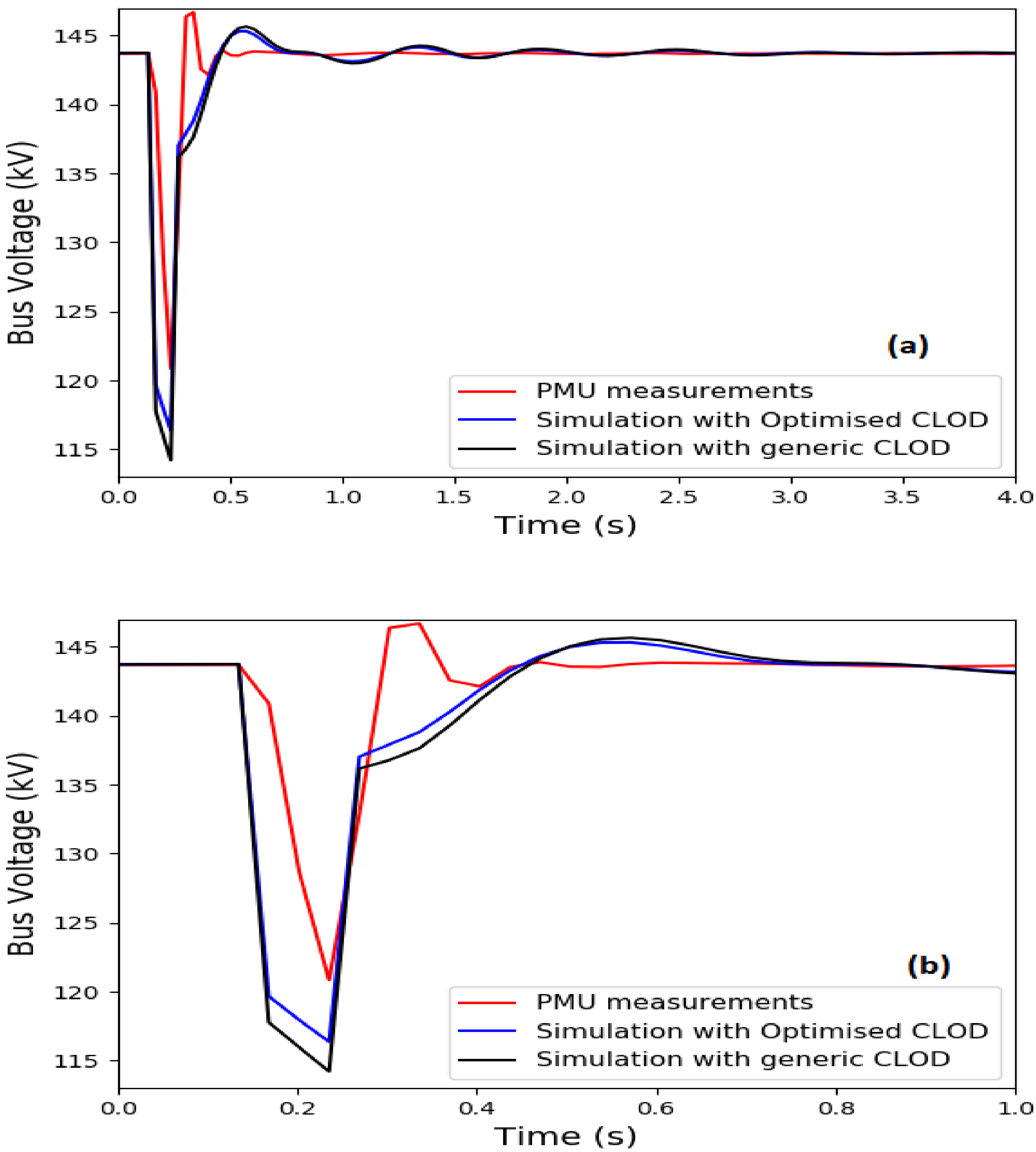
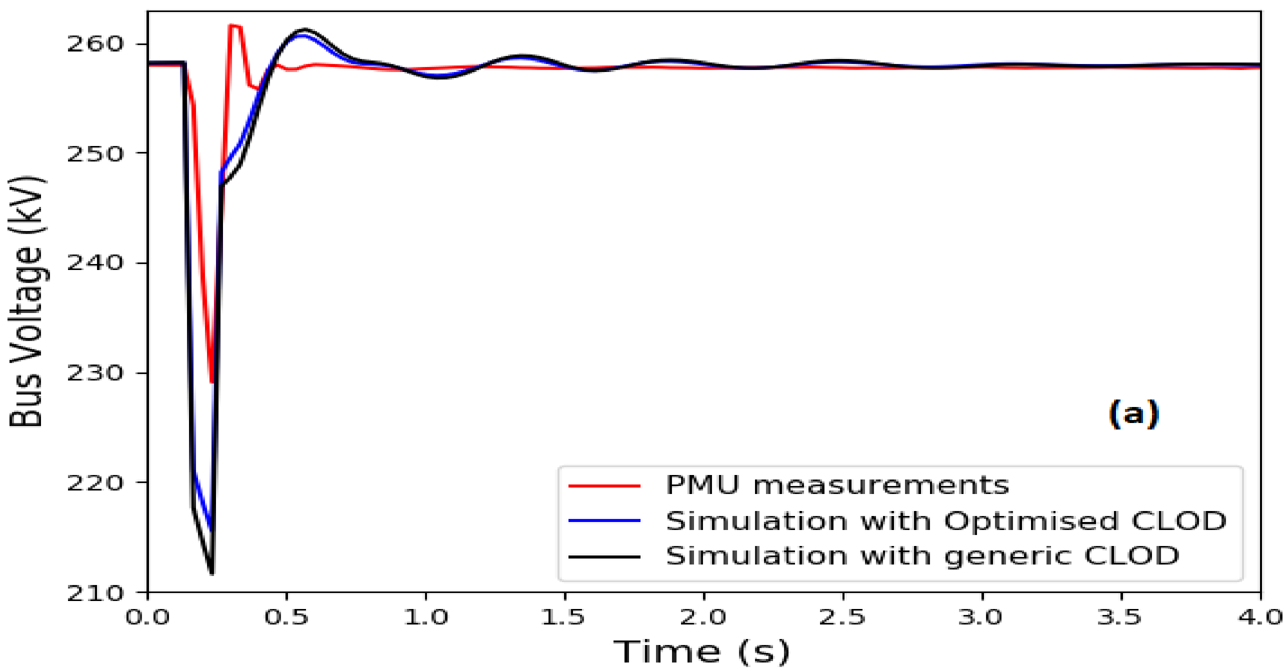


Figure 4.6: PMU voltage measurements, simulations with optimized CLOD and generic CLOD at 138 kV bus; a. for 4 secs, b. zoomed in to 1 sec.



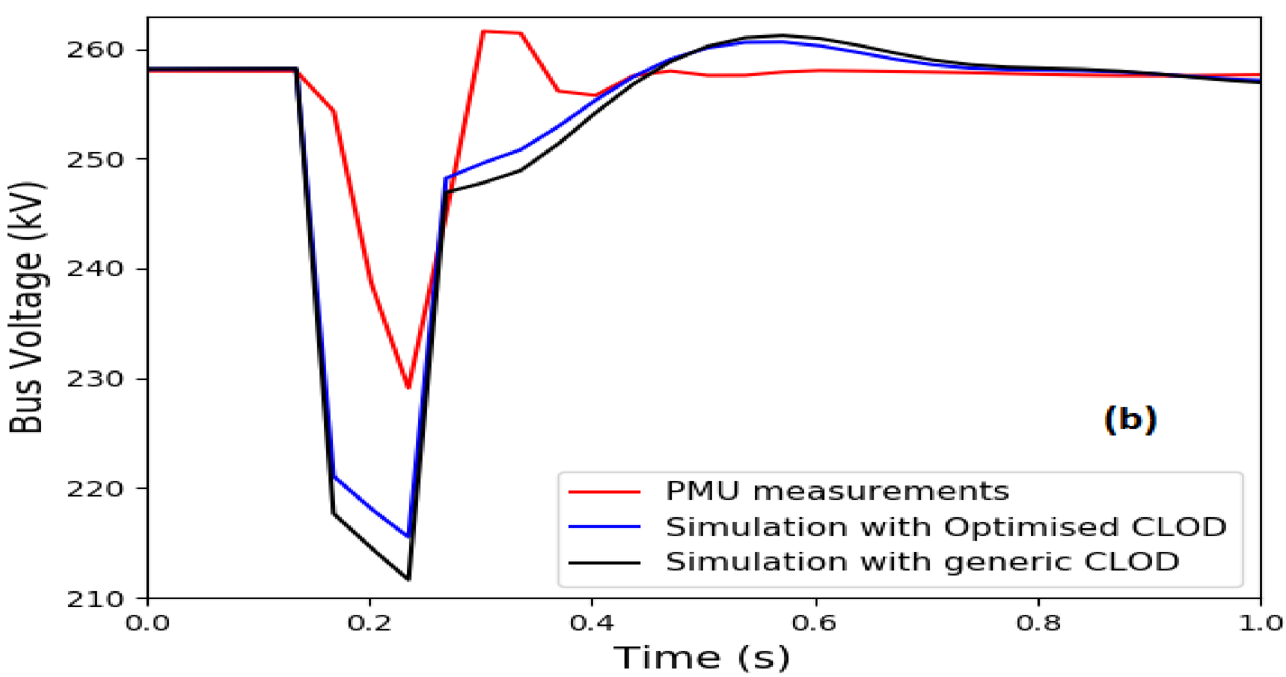


Figure 4.7: PMU voltage measurements, simulations with optimized CLOD and generic CLOD at 240 kV bus; a. for 4 secs, b. zoomed in to 1 sec.

4.6.3 Discussion on the Results

As the simulation is system wide, the comparison should be both qualitative and quantitative to better understand the difference in performance of these models. From the quantitative perspective, summation of MAEs for the two buses with available measurements are 1.59e-3 PU and 1.17e-3 PU for generic and optimized model respectively. Although these measures show 26 percent improvement which may seems significant at first, the performance of the generic and optimized models are almost the same from a qualitative point of view. Both models have close estimates for peak voltage at the first voltage swing. These models are not completely successful in predicting the recovery time and both are more delayed than PMU recorded recovery times. Optimized model can better predict the voltage drop at very first cycle after the fault. Correlation coefficients of each model in comparison to PMU measures are also calculated as another quantitative measure. Results for MAE and correlation coefficients are given in Table 4.4. Both optimized and generic model show strong positive correlation with measurements, but the improvement in optimized model is not significant.

Table 4.4: Quantitative voltage measures for optimized and generic CLOD in comparison to PMU data.

Type of measure	Optimized CLOD and PMU data	Generic CLOD and PMU data
MAE	1.17e-3 PU	1.59e-3 PU
Correlation coefficient	0.8188	0.8130

Given the quantitative and qualitative comparison presented based on the investigations on the case of Alberta, improvements achieved by using optimized CLOD models instead of the generic ones are not significant. Eventually, there is no general rule to know which model is practically more reasonable to use and the model preference is highly dependent on engineer's point of view.

4.7 Summary and Conclusions

In this chapter, the simultaneous optimization and validation of multiple CLOD models in AIES has been considered. Wide model validation can be very complicated due to uncertainties on system operating point before the event. We have built the Off-line model of the Alberta system to represent the real grid as close as possible to the time of the event. We collected PMU data for two voltage levels in the area at the time of the detected event. CLOD model parameters have been optimized using evolutionary optimizer for three different major load categories. Additionally, a Sobol sensitivity analysis has been applied to CLOD which can measure sensitivity rankings for model parameters. Eventually, quantitative and qualitative comparison between optimized and generic models have been made.

Simulated voltage responses considering the optimized model does not show significant improvements compared to generic models. It should be noted that this response is in high voltage level and is greatly influenced by transients of other system elements as well. Therefore, all elements should be examined to find the perfect match as loads may only have a minor contribution to this response. This method is general and can be applied to any large-scale power system. Results can substantially differ for different load structures and network topology. Upon following the proposed process, power system operators can clearly understand how much time and resources are reasonable to be spent for transforming their load models from generic ones to optimized CLOD.

Chapter 5

Investigating the Performance of Different Load Models in Various Scenarios[1]

This chapter investigates the performance of four load models in different PMU response scenarios. These scenarios are re-sampled based on the original event, used in Chapter 4, to have different recovery times. This chapter is organized as follows: section one provides a background on the chapter. section two describes the process for generating voltage scenarios. The detailed problem description is given in the third section. The implementation of optimization methods for this study is explained in the section four. Sensitivity analysis results for different load models are given in the fifth section. Section six provides the Numerical results for the static, CLOD and induction motor load models in each of the voltage response scenarios. An especial observation on the second scenario is presented in the seventh Section. The performance of WECC CLM is considered and analyzed in the chapter eight. the ninth chapter provides a summary along with a comparison and discussion on the

[1]Based on the materials presented in this chapter, a conference paper entitled "Investigating the Choice of Load Model and its Parameters for Different Voltage Response Scenarios in Large Power Systems" is accepted for publication in CIGRE 2019, Canada.

performance of load models used in this study.

5.1 Background

Load modeling in general and particularly its modeling in dynamic simulations have been a remaining challenge for system operators. Despite all the efforts towards developing load models in recent years, still there are no general guidelines for dynamic load modeling in real-life power system operations. Different types of events are observed in studies and thus, resulted in model identifications that are solely valid for their specific cases. Additionally, some complex models that have been used for load modeling 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.

Load models with different characteristics ranging from pure static to pure dynamic have been considered in this study. All selected load models are available in broadly used commercial power system simulators such as PSS/E which is employed in this study. The static load model used in this study is IEEE static load model which is known as "IEELxx" family of models in PSS/E. CLOD model, as considered in the previous chapter, has both static and dynamic parts and is known as a complex load model which is not providing the user with a lot of room for controlling the detailed behavior of model components. The induction motor model, known as "CIM5xx" family of models in PSS/E, is the third model that is used in this study. This model provides more parameter tuning ability for the induction motor characteristics. The WECC composite load model is the last model utilized in this chapter. Please note that all these models are introduced in the chapter 2 with more detail on their structure. The parameters for each of the mentioned load models are optimized for different voltage scenarios. WECC composite load model is more complicated to optimize. Hence, this model is studied for only some specific scenarios to draw a major conclusions on its performance. Optimizations are solved by a combination of GA and trust region reflective least squares aiming to minimize the MAE for each case. Upon completion of the optimization, performance of these load models are compared and important conclusions are yielded to provide generalized recommendations for model structure and parameter selection in different voltage response scenarios.

To investigate the proposed problem, an area-wide measurement-based load modeling approach, similar to the study presented in Chapter 4, is implemented. A major load area with PMU data available on one of its transmission level substations is selected. A recorded fault event in the study area is identified. This event followed by a very fast voltage response due to the nature of AIES at the time of the event. This basic voltage event is re-sampled and several slower recovery scenarios are generated for voltage. These created scenarios reserve an identical shape, but vary in terms of recovery time. This is helpful to make the study results more representative and generalized. The objective of this chapter is to investigate how these 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 the different voltage scenarios that can be observed by PMUs in real-life networks. To achieve this objective, each of these load models replaces the loads in the study area and their parameters are optimized to match with re-sampled voltage responses. As a result, it is possible to judge how each of these models can perform in different scenarios. Furthermore, the performance of different models with optimized or typically used parameters are compared. This investigation assists system operators when it comes to selecting a load model and its parameters for their operating power grids.

5.2 Scenario Generation

Initially, a fault induced voltage event is detected, as explained in Chapter 4, and the PMU data is collected for the selected interval around the time of the determined event. Thereafter, different voltage scenarios are re-sampled based on this real-life PMU data recorded in the study area. As the recovery of recorded event in Alberta is very fast, other samples are created by extending the signal producing a range of different signals from very fast ones to very slow recovery responses, such as the ones reported in Fault Induced Delayed Voltage Recovery (FIDVR) events [96].

Fast Fourier Transforms Re-sampling (FFTR) [97] is implemented for re-sampling the original PMU recorded signal. Ten scenarios are generated with recovery times ranging from 0.1 to five seconds, but all maintain a similar pattern 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 [96]. Figure 5.1 illustrates the re-sampled scenarios that are utilized in the present study. Re-sampled scenarios are only shown for 138 kV bus, the 240 kV ones have a similar pattern and are redundant to display here. The total length of signals is not same because of the fact that each of them are generated with a different recovery time but they all follow a same pattern. Figure 5.1 shows the created scenarios. It is worth mentioning that an exact delay voltage response recorded in a real-life grid might be slightly different from the generated scenarios. However, it was not feasible to observe all types of events in AIES. Therefore, delayed response behaviors are considered based on the created scenarios which maintain same shape as the original event.

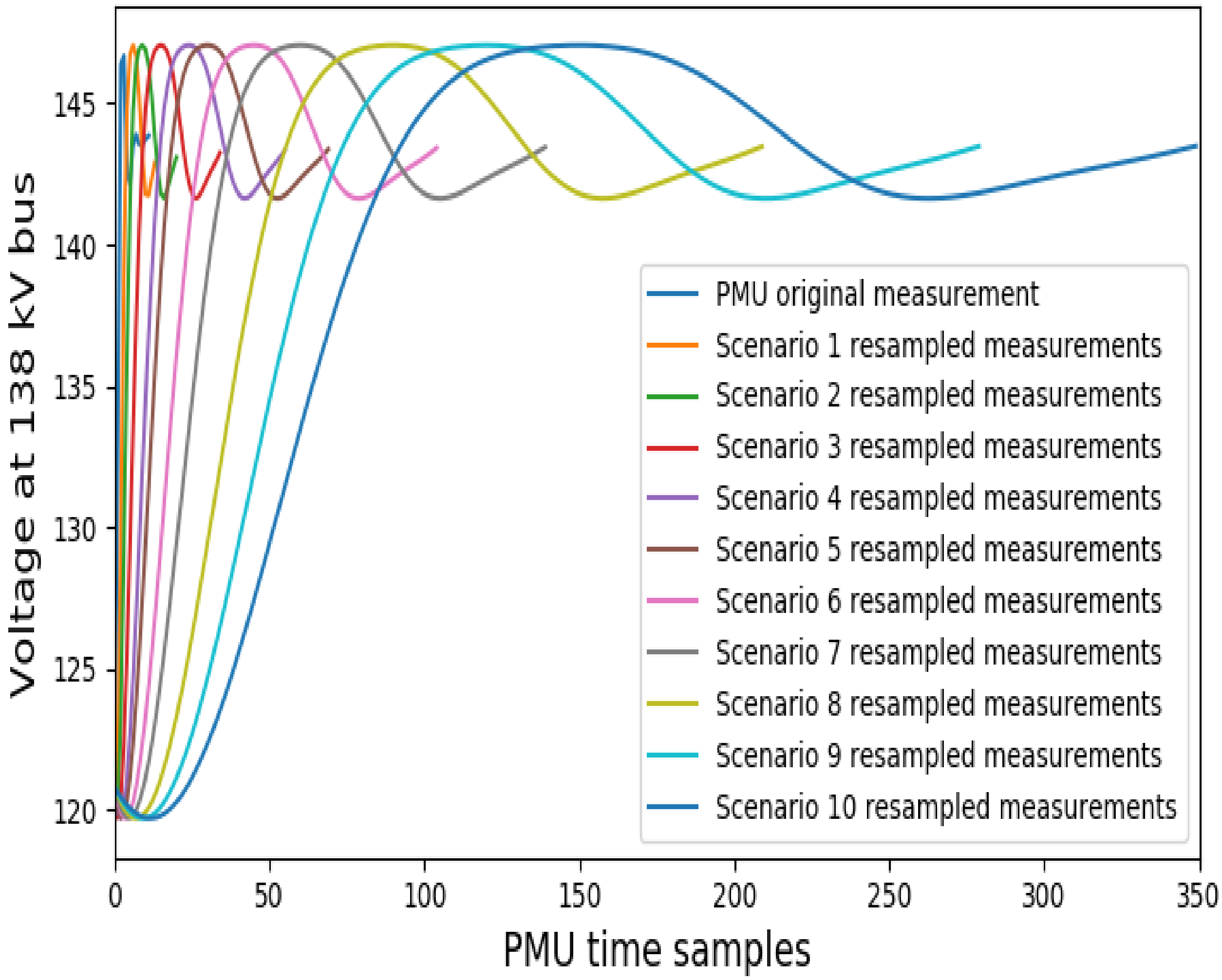


Figure 5.1: Re-sampled PMU voltage scenarios at 138 kV level.

5.3 Problem Description and Simulation Assumptions

Selection of correct load model and choosing correct parameters for each model is a difficult task when it comes to large-scale power systems. As a result, most power system operators are still using some very basic load models. To answer the question of how load model selection can improve the accuracy of dynamic simulations, it is necessary to consider different load models and test their performance for different voltage scenarios, as it is presented in this chapter. Load models are selected considering two important points. Firstly, models are selected in a way to be diverse. Load models can be categorized into static, dynamic and their combination known as composite models. The selected load models cover all these categories. Secondly, all these models are available in common used large-scale power system simulators. Hence, these models can be considered as a practical choice for power system operators.

The event detection process combines the analysis of different sources including the SCADA, PMU measurements and control room log data to find breaker-events in the study area. This process is same as what is described in the previous chapter and is redundant to be repeated in this section. One of the aims of this study is to optimize the parameters of multiple load models in the study area. For this purpose, it is needed to have load categorization in the study area. Considering individual models for each load in the system is not feasible and results in unsuccessful optimizations. Based on the available load categorization in AIES, there are three main group of loads in the selected case-study. However, further analysis shows that two of these categories account for more than 90 percent of the load in the selected area. Only these two major categories are considered in order to reduce the problem size and simulation time for optimizations. This is one of the differences in the simulation assumptions between the current and previous chapter. Same parameters are considered for load models of the same category. Given this, Two sets of load model parameters for each of the optimizations are assumed. It is not feasible to reduce the network to equivalents, because all the loads in the large-scale power system model are considered. Hence, it is necessary to build the off-line model as close as possible to the state of the power system prior to the event. Reasonable cross referencing between SCADA data and available AIES models has been made to build the best match for the off-line base case. More exact information on the of-line model building processes are given in Chapter 4.

5.4 Implementation of Optimization

The procedure in which the optimization is applied to this problem is slightly different from what is considered in the fourth chapter. As it is required to solve optimizations for many scenarios, it is necessary to reduce the optimization time to a reasonable amount. One approach to significantly reduce the simulation time is by using the least squares c methods such as trust region reflective algorithm instead of the meta-heuristic ones. Least square methods have been widely used in the literature for load modeling [98]. However, simulations for AIES show that trust region reflective or LM methods are very dependent on the initial guess and are usually converged to an optimal answer close to the initial guess. Population-based algorithms, such as GA, are usually more successful, but require more function evaluations and more simulation time. A combination of GA and trust region least squares is used to mitigate this issue. Trust region least squares is chosen because of its better performance for non-linear and large-scale problems. Simulations from previous chapter show that GA and PSO can converge to an answer near their final optimum in the first 10 to 15 iterations. Given this, running simulation up to 100 iterations is not as beneficial as the time it takes. Hence, the hybrid approach seems to be a reasonable choice when simulation time is a concern. Please note that time was a concern in this thesis mainly because it was needed to perform simulations on a number of scenarios in a limited time. As these simulations are mostly used for off-line purposes, the limitation on number of iterations might not be a concern for other users. Hence, higher number of iterations can be considered which can potentially reduce the error.

GA as the meta-heuristic algorithm is applied first upto a several generations. The final best individual of GA is passed to the Trust region least squares algorithm as the initial guess. This method can help to achieve a compromise between simulation time and accuracy. This compromise is important to current study as a number of optimizations need to be solved for different scenarios. It is worth mentioning that the number of GA generations might differ for various scenarios. Other assumptions for the optimization including the fitness function are exactly same as the Chapter 4.

5.5 Sensitivity Analysis on Different Load Models

Four different load models are implemented in this study. Each of these load models are considered for optimization in different voltage response scenarios to evaluate their potential contribution towards more accurate dynamic simulation results. SA is necessary for assuring more efficient parameter selection and optimization in load modeling studies. To be consistent, half of the models' parameters are selected for optimization of each load model. Following sections report the SA results that are performed on these models except for the WECC CLM. The WECC CLM has 132 parameters and is mainly considered in this study to address the delayed recovery events. Therefore, performing SA on this model is not feasible in this thesis. However, some available references are used to highlight more important parameters for the WECC CLM. For example, a comprehensive dependency analysis on the WECC CLM is presented in [91] showing that parameters which control the stalling characteristics of the model are more important for the purpose of delayed voltage recovery events. Most of the other parameters are fixed as mentioned in [1].

5.5.1 Sensitivity Analysis on the 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 Chapter 2. 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 power systems. Generic assumptions for this static model parameters are recommended in [38]. Table 5.1 shows the sensitivity analysis results performed on this model. Sensitivity rankings are based on Sobol total effect index.

Results of sensitivity analysis show that parameters related to the active portion of the load are relatively more important than that of the reactive part. This is mainly because of the higher concentration of active load in the area. Five parameters from the active part and two parameters from the reactive part including $a_1, a_2, a_7, n_2, n_3, a_8, n_4$ are selected for optimization.

Table 5.1: Sensitivity analysis result for the IEEL static load model.

Parameter ranking	total effect index	Parameter ranking	Total effect indices
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. a_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

5.5.2 Sensitivity Analysis on the CLOD Complex Load Model

CLOD is a complex load model supporting variety of loads at the connecting node. This model does not provide the user with the 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 behavior 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 [39]. SA results performed on CLOD load model are already presented in Chapter 4, as given in the Table 4.1. To be consistent with other models used in this chapter, the first half of the parameters are used for optimization, namely large motor, small motor, K_P and Discharge lighting.

5.5.3 Sensitivity Analysis on the Induction Motor Load Model

The other load model that is used in this study is the induction motor load model, specifically CIM5 model in PSS/E. 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. Only 13 parameters are considered for sensitivity analysis as the other six parameters are either related to protection or motor ratings. Table 5.2 shows the parameter ranking for this induction motor load model. 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 5.2: Sensitivity analysis result for the induction motor load model.

Parameter ranking	total effect index	Parameter ranking	Total effect indices
1. X_A	0.36	8. X_2	0.11
2. $D(damping factor)$	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		

5.6 Numerical Result for the Static, CLOD and Induction Motor Models

The problem formulated in this chapter is implemented to the case of Alberta. Optimization models are solved with the interactive use of Python and PSS/E for all re-sampled 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 is 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 5.2.

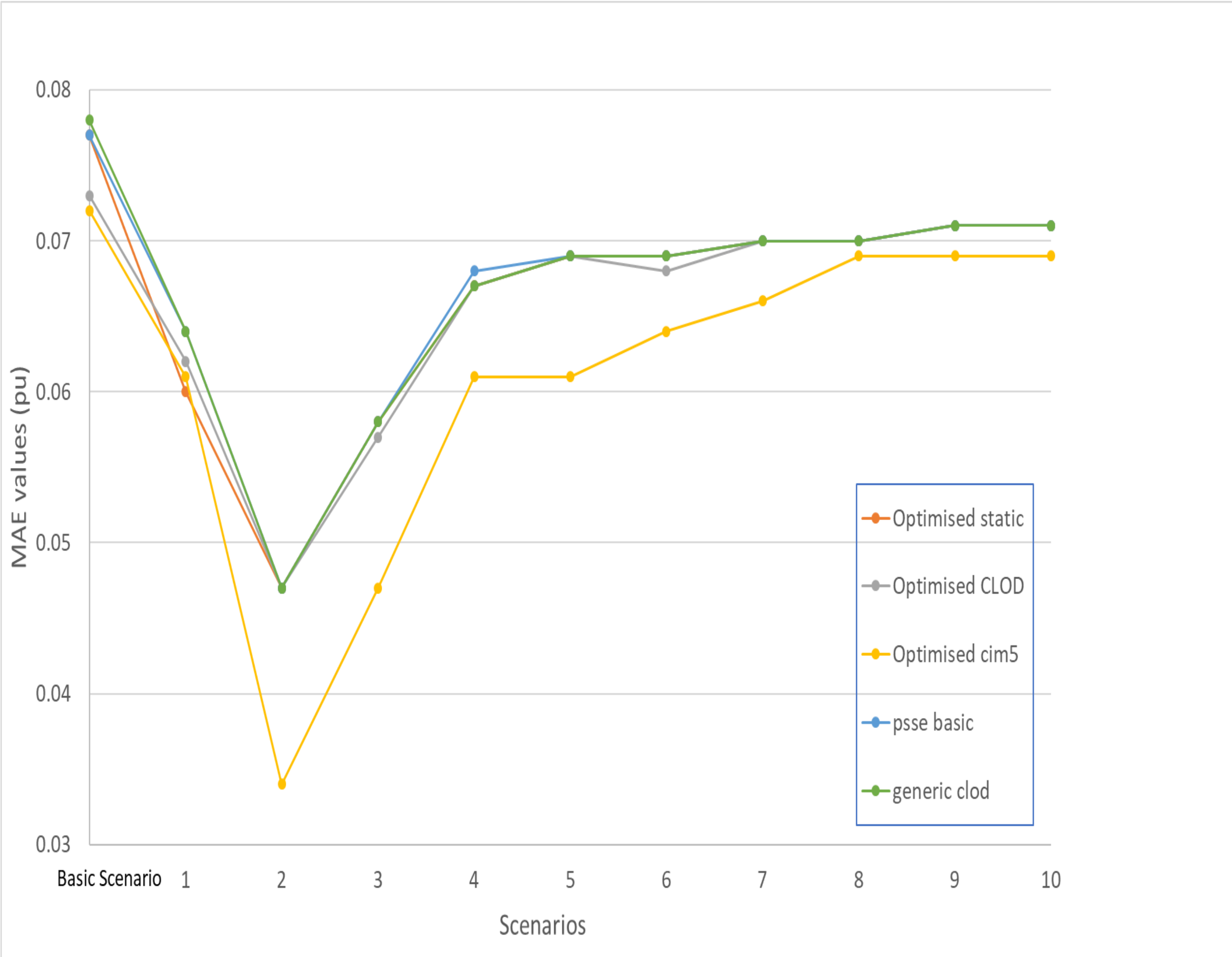
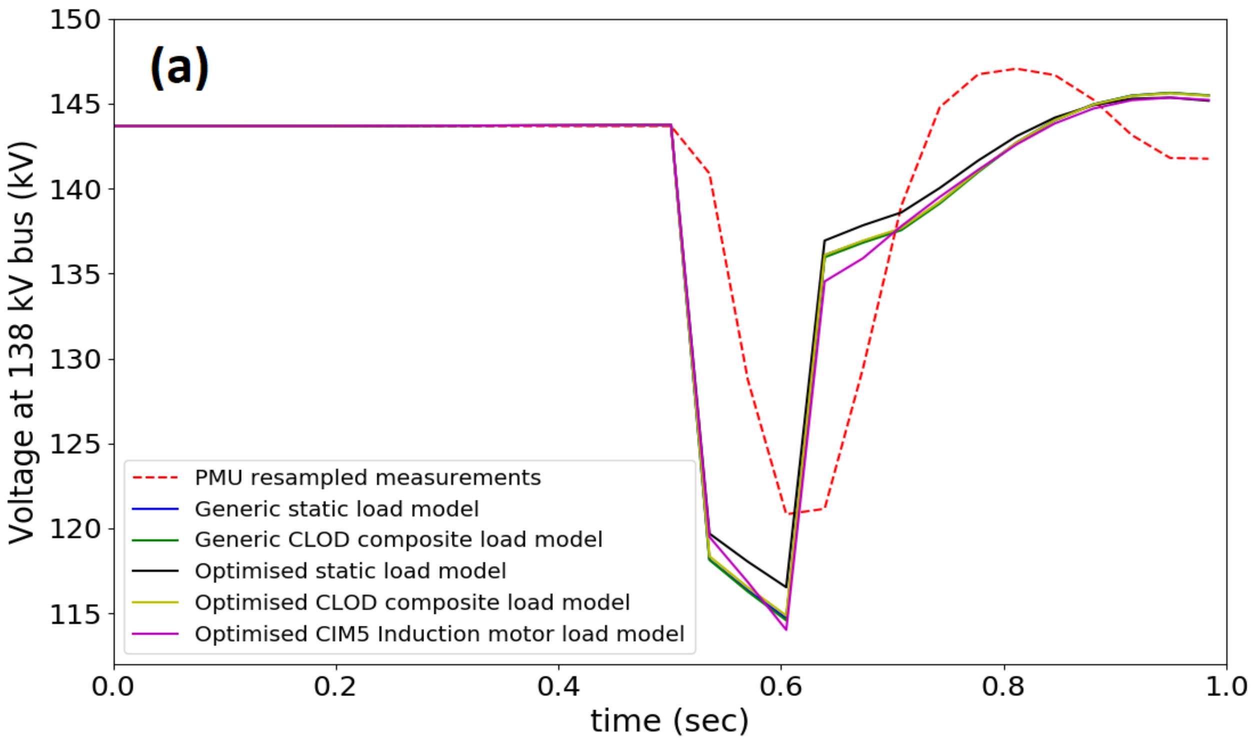
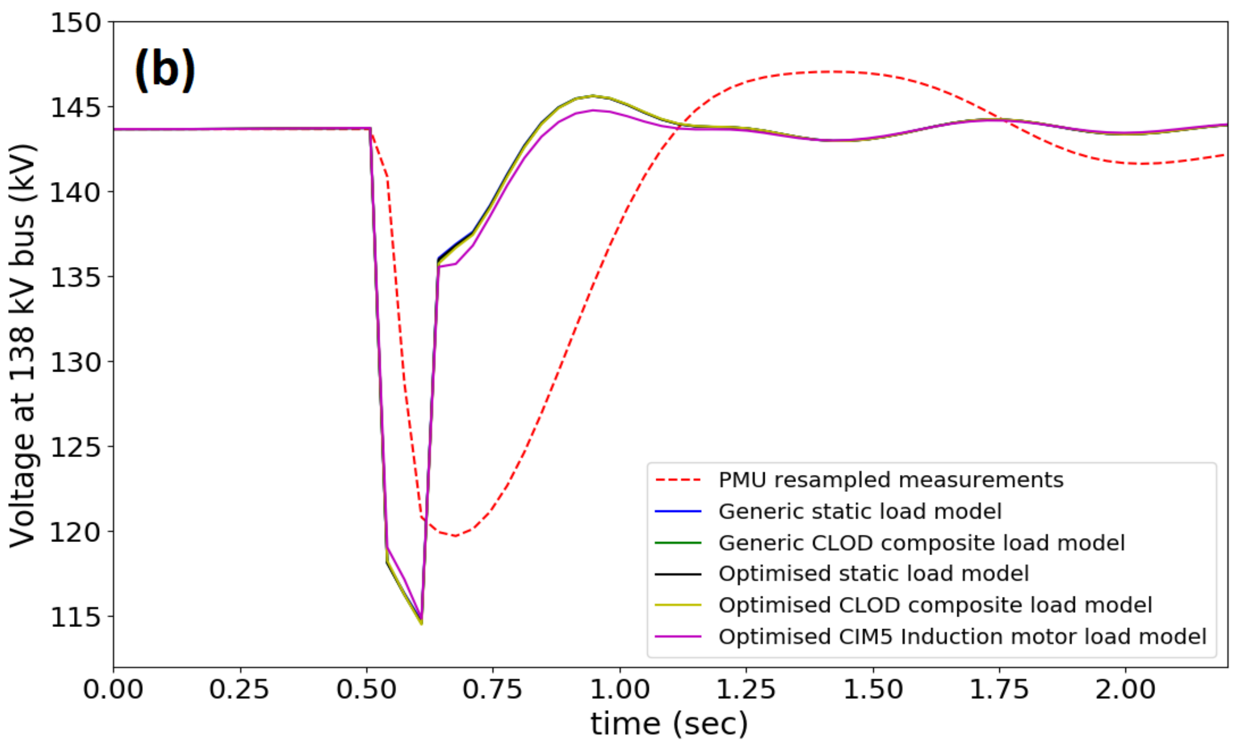


Figure 5.2: MAE pattern for five different loading conditions at generated scenarios.

As can be seen in Figure 5.2, 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. It can be observed that the induction motor load model has a slightly lower error in moderately delayed scenarios. In addition, MAE differences between generic CLOD or static models and that of optimized 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, Figure 5.3 can be investigated which depicts voltage responses for some of the discussed scenarios.

Figure 5.3 shows the simulated voltages for five different conditions of load modeling, namely, optimized static, optimized CLOD, optimized induction motor, generic static and generic CLOD along with their corresponding re-sampled measurements. Generic static model is considered as constant current for the active power and constant admittance for the reactive power. This generic static model is also the basic load model assumption for PSS/E when no specific model is selected. Four out of the ten scenarios including scenarios one, four, seven and ten are given in sub-figures (a), (b), (c) and (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, such as 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.


(a)
Voltage at 138 kV bus (kV)
time (sec)
PMU resampled measurements
Generic static load model
Generic CLOD composite load model
Optimised static load model
Optimised CLOD composite load model
Optimised CIM5 Induction motor load model


(b)
Voltage at 138 kV bus (kV)
time (sec)
PMU resampled measurements
Generic static load model
Generic CLOD composite load model
Optimised static load model
Optimised CLOD composite load model
Optimised CIM5 Induction motor load model

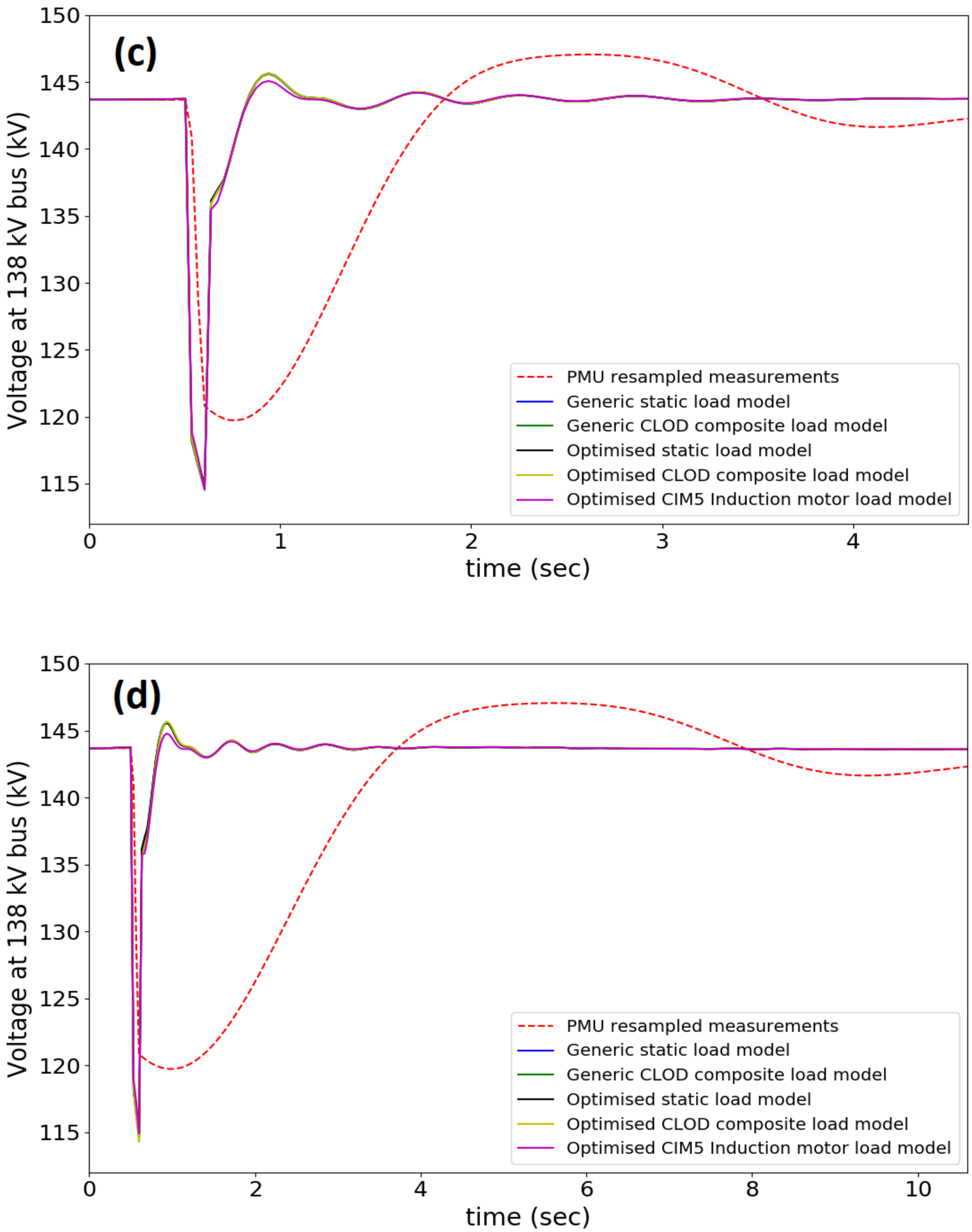


Figure 5.3: Voltage responses considering 5 different load presentation versus PMU resampled measurements; a. scenario 1; b. scenario 4; c. scenario 7; d. scenario 10.

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 5.3, the estimation of initial drop is almost same for all the models and it is closed to the initial drop of re-sampled measurements. Therefore, simulations are successful in predicting the drop independent of their load modeling 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 former perspective shows higher agreement in the 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 a signal to more or less delayed ones and thus, 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.

5.7 Discussion on the Second Scenario

As it can be seen from the MAE results illustrated in the Figure 5.4 , the second scenario has the lowest MAEs for all of the load models. There are two main reasons behind this higher similarity of simulations to the second scenario. First, the voltage response of the case-study is more similar to this scenario independent of the load model type being used. This is due to the off-line model building assumptions, such as the models for other components or switching conditions of lines. This can also be verified according to better performance of generic static model, no specific load model selected, in this scenario. Furthermore, it could be because of the possible mismatches between real-time operation and the re-simulated planning base-case. Another potential reason for this mismatch is the difference between simulation time steps and PMUs' sampling size. The PMUs installed in AIES measure the voltage every two cycles which is much slower than dynamic simulation steps. Hence, PMUs miss more detail of the system behavior in a very fast scenarios which all the recovery happens in a few cycles. As a result, measurements can distribute better when the event is longer. Thus, better matches with simulations are expected as illustrated in the Figure 5.4 for the second scenario. A possible misunderstanding is to expect better match for more delayed scenarios as the distribution of measurements become wider and wider. However, it should be noted that this is only one of the factors and the general response of the system based on the available models, as mentioned in the first reason, contributes more to the observed response.

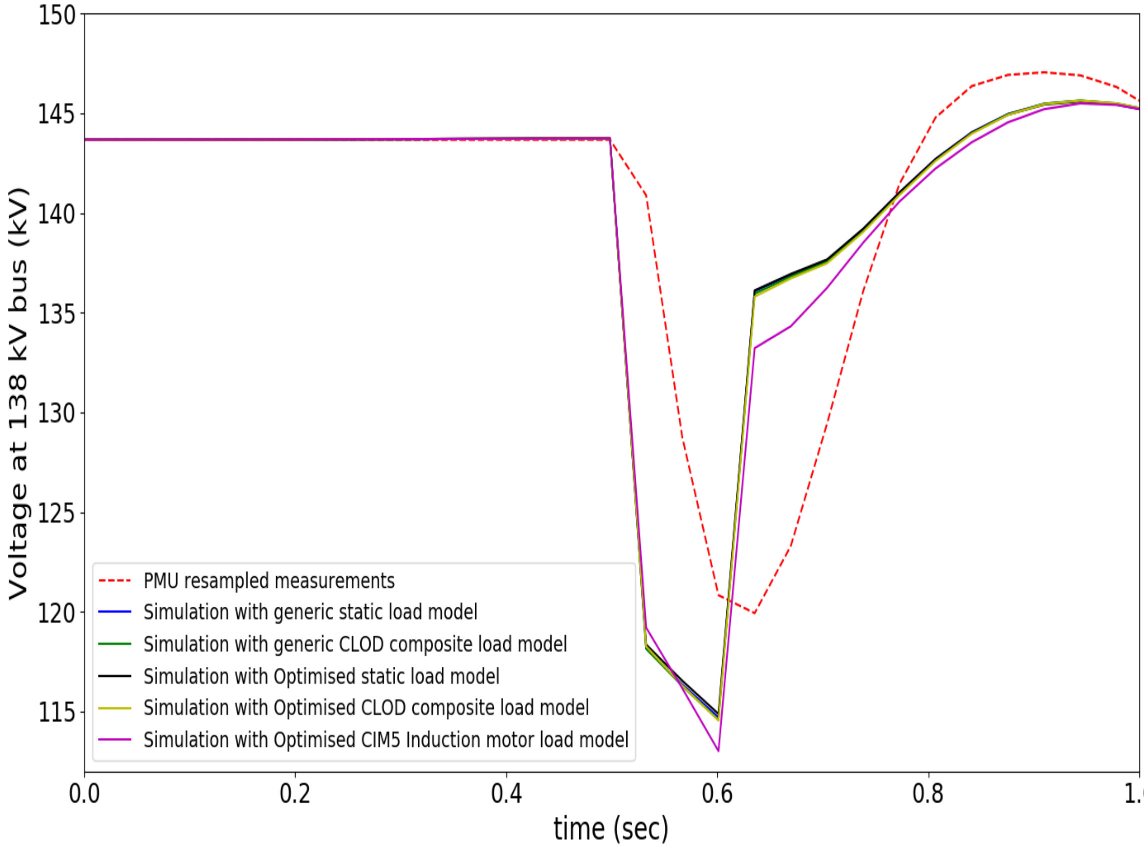


Figure 5.4: Voltage responses at scenario 2.

5.8 Performance of WECC Composite Load Model

The WECC CLM is a complex model, and thus, compared to other discussed models in this chapter, it is more difficult to implement. Although this model is very complex, it is available as an user-written model in some power system simulators (e.g., PSS/E) and can be considered for implementation in the industry-level practice. The three other load models respond similarly and performed relatively acceptable in less delayed scenarios, as discussed in the previous section. They fail to improve the response to better match with the more delayed scenarios. The WECC CLM has so much flexibility with 132 parameters available for user to control. Additionally, it can simulate the stall characteristics of single phase air conditioning loads. In following sections a brief investigation on the performance of this load model along with a comparison with other models is presented.

5.8.1 Major Assumption on WECC Composite Load Model Implementation

All the loads in the study area are replaced by the WECC CLM and same model parameters are considered for models in the same category. In contrast to other models, sensitivity analysis is not performed on this model, but available information in the literature are used to select the important parameters. M ost of the model parameters do not need to be changed for adjusting the model to different cases [1]. Non-stall and stall are considered as two main phases for this model. A very large time constant for motor stalling is considered in the non-stall phase which consequently prevents the model from transferring to the stalling mode. If operation in the stalling phase is required, it is necessary to tune stall voltage and reduce time constant accordingly. Given this, some parameters of the model never change and some can only once be adjusted for the specific case under study. Hence, different responses can be produced by changing of the key parameters. The key parameters selected for optimization are described in the next paragraph.

The parameters which control stalling characteristics are important as they can make a substantial difference in the voltage response. These parameters define if any stalling occurs in the system and how long it takes for recovery after entering the stall phase. Stall voltage and stalling time are among these parameters. If voltage drops below the stall voltage for at least the stalling time constant considered for single phase motors, then system goes into the stall condition. T_th defines the time that thermal relay trips the stalled motor and therefore has a significant effect on determining the recovery time. Fu_vr defines the percentage of motors capable of under voltage relay tripping and is important factor when it comes to voltage recovery. Th_1 and Th_2 define the first and second step of relay tripping time constant in the stall condition. Tripping voltages for other three phase motors are important as they can reduce the total load and thus change the voltage recovery time. Eventually, the percentage of different components in the WECC model, especially the percentage of motor D, are among the important parameters. These parameters are used for the optimization of WECC CLM in this thesis. Default parameters for the WECC CLM can be found in [1]. Parameters that are not considered for optimization are fixed to their recommended values as given in [1].

5.8.2 Optimization Results for the WECC Composite Load Model

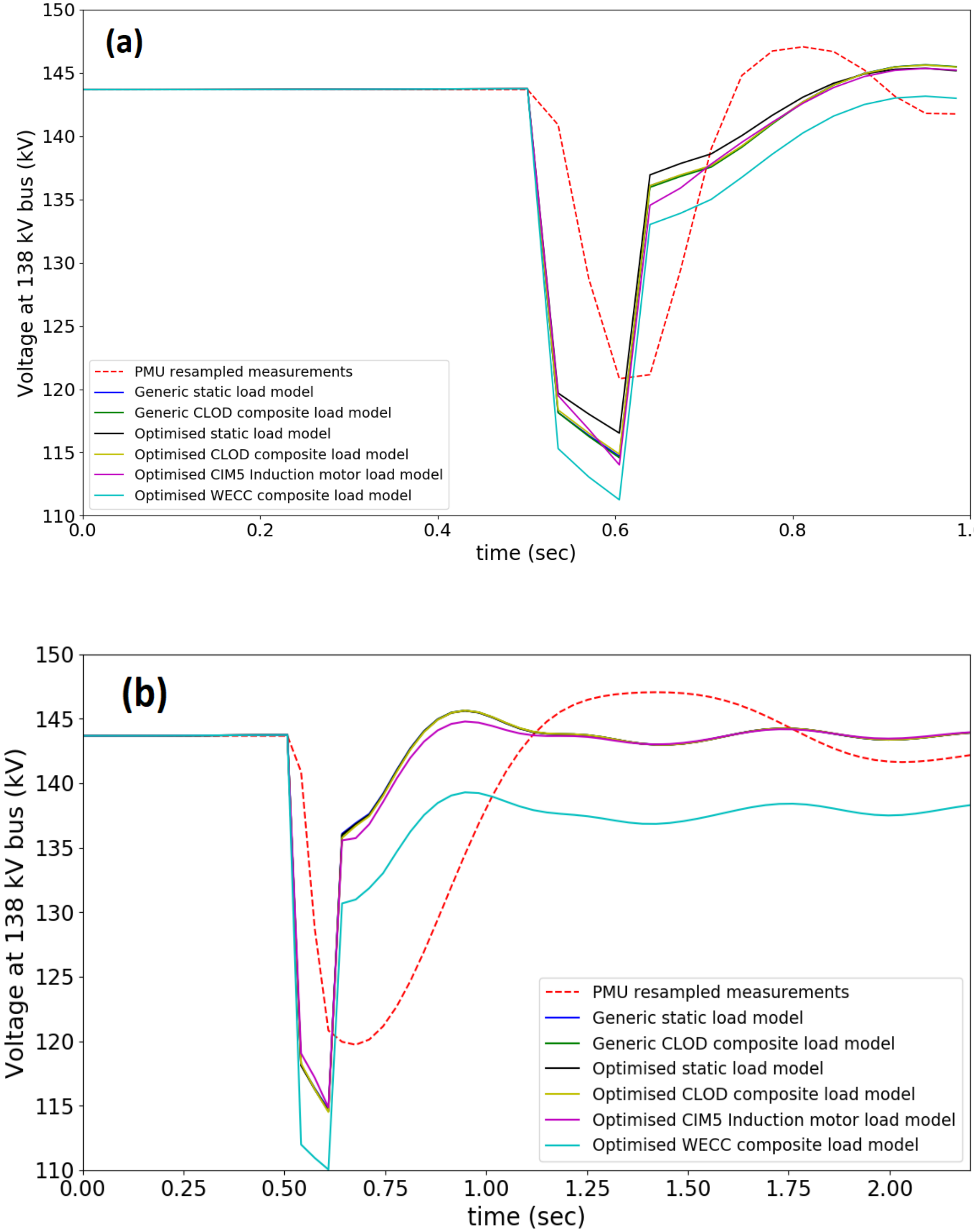
As the WECC CLM is more complex than other models, simulation time can significantly increase and it is not feasible to perform optimizations for all ten re-sampled scenarios. Hence, optimizations are performed for scenarios one, four, seven and ten. Investigating these scenarios is enough to perceive the general performance of the WECC CLM. These four scenarios cover a range of responses from very fast to more delayed recovery ones. Thus, responses in other scenarios cannot be unexpectedly different. Table 5.3 shows the MAE distribution of WECC CLM at these scenarios. Comparing these values with what is observed for other load models, it can be concluded that this load model can generally reduce the error for more delayed scenarios. As discussed earlier, MAE value itself is not meaningful. Hence, these voltage responses are visualized and compared with other load models in the next section.

Table 5.3: MAE results for optimization with WECC composite load model.

Scenario	MAE value
1	0.064
4	0.044
7	0.046
10	0.047

5.8.3 Voltage Responses with the WECC Composite Load Model

Figure 5.5 visualizes the voltage responses with different load models including the optimized WECC CLM for scenarios one, four, seven and ten. This figure illustrates that WECC CLM can better simulate the delay in voltage. Therefore, a better match for delayed scenarios can be observed. The best scenario to observe this better performance is the tenth scenario which the voltage response with the WECC CLM can clearly follow the delay more than the other models. WECC CLM is able to transfer into the stalling mode. Hence, it can keep the voltage at low values for a longer time. Performances of all the other models are similar and they fail to follow the delay characteristics of voltage responses.


(a)
Voltage at 138 kV bus (kV)
time (sec)
PMU resampled measurements
Generic static load model
Generic CLOD composite load model
Optimised static load model
Optimised CLOD composite load model
Optimised CIM5 Induction motor load model
Optimised WECC composite load model
(b)
Voltage at 138 kV bus (kV)
time (sec)
PMU resampled measurements
Generic static load model
Generic CLOD composite load model
Optimised static load model
Optimised CLOD composite load model
Optimised CIM5 Induction motor load model
Optimised WECC composite load model

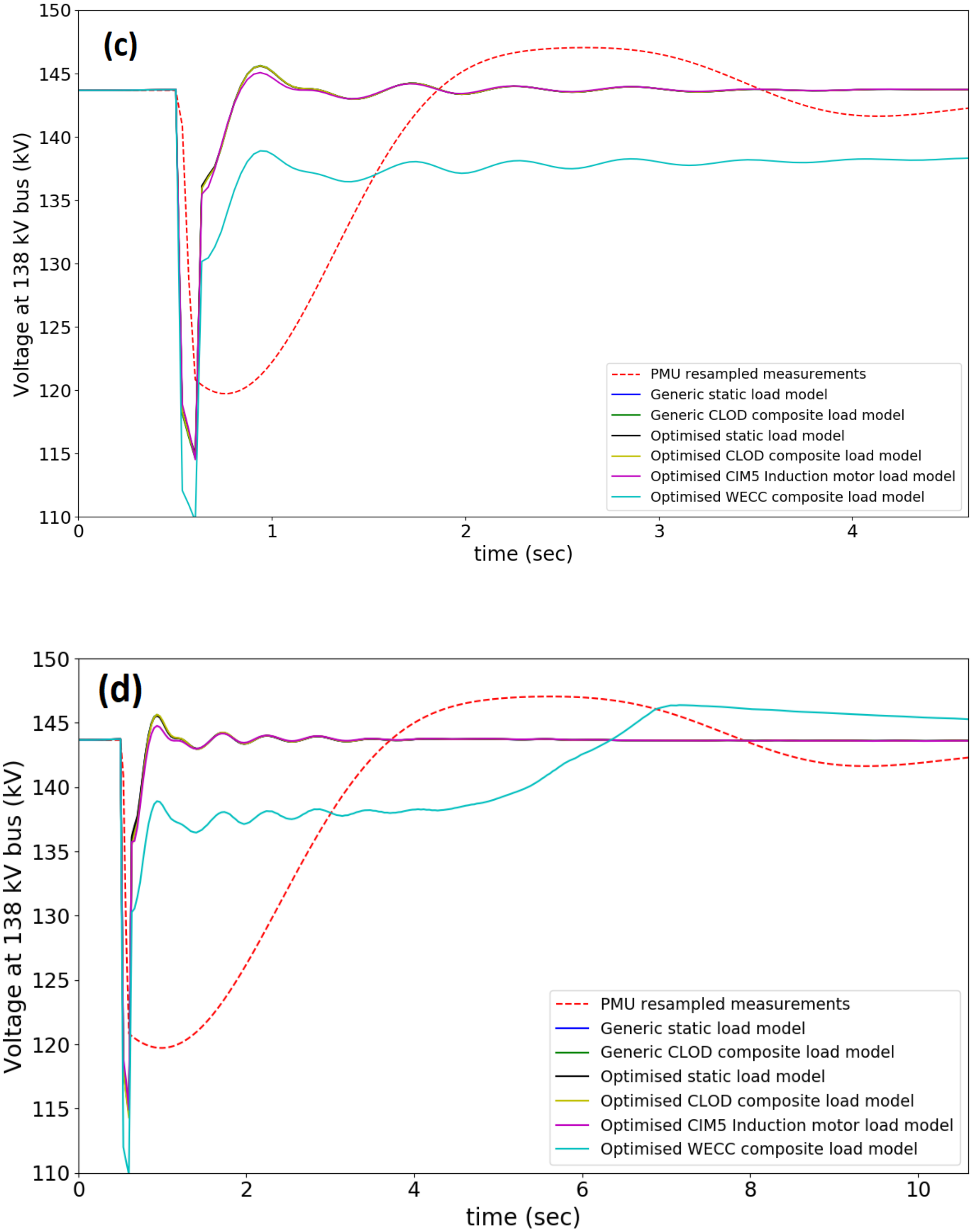


Figure 5.5: Voltage responses considering WECC CLM and other different load presentations versus PMU re-sampled measurements; a. scenario 1; b. scenario 4; c. scenario 7; d. scenario 10.

According to the presented simulation results in this section, this model can significantly perform better for more delayed scenarios in comparison with the other load models. Performance is similar to other models for fast recovery events, such as the first scenario. In the first scenarios, no delay is observed in the voltage behavior with the WECC CLM. This means that the model is operating in non-stall mode which is often called phase one for this model. Once PMU scenarios become more delayed, the WECC CLM transfers to the stalling mode and attempts to keep up the simulations with the delay. This is usually considered as phase two for the performance of the WECC CLM. The delay in the WECC CLM simulations can improve the response to better match with the PMU re-sampled measurements, but simulations are overly delayed for scenarios four and seven. The tenth scenario is the best representative for delayed scenarios and voltage simulation with the WECC CLM can follow the delay at this scenario. Response is still overly delayed by about one second, but it is significantly more successful to follow the delay compared to other models. In addition, The simulation based on the WECC CLM can better predict the peak value in the first voltage swing at the tenth scenario. The other difference between the performance of the WECC CLM and other models is in the amount of initial drop. More initial drop for the WECC CLM is observed for all of the scenarios. This higher initial drop is mainly due to more motor tripping ability of this model. WECC CLM is able to trip all three phase motors and the single phase air conditioner regarding the parameters related to the protection system.

The WECC CLM is more difficult to implement and optimize compared to other models. Thus, it is not recommended for industry-level purposes unless it is necessary, such as what is observed for delayed scenarios. It is important to understand the significance of compromising between model accuracy and complexity. The improvement that the WECC CLM brings into simulations is only substantial for delayed scenarios. Hence, Selecting this model for faster scenarios is not recommended according to implementation difficulties. Eventually, the choice of the WECC CLM is recommended for FIDVR types of events and as always depends on the study scope and engineer's point of interest.

5.9 Summary and Conclusions

In this chapter, a comprehensive investigation on the impact of 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 a fault event was selected and ten voltage scenarios were constructed according to the real-life PMU data. Complete sensitivity analysis was performed prior to optimization on the considered load models except the WECC CLM and sensitivity rankings are established. Wide area model identification was considered for load model parameter optimization in the study area. Optimizations are solved for each load model at generated scenarios using a combination of evolutionary optimizers and trust region least squares resulting in MAEs reported as a quantitative measure.

Simulation results considering different optimized or generic static, CLOD or induction motor load models do not show any significant differences in the voltage response at the monitored HV substation. These 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. The WECC CLM showed more dependency on the choice of parameters as it has two very different phases namely non-stall and stall. The WECC CLM operates in the non-stall phase in less delayed scenarios and no significant difference between its performance and other three load models is observed. However, the WECC CLM can substantially perform better in delayed scenarios as it can be observed in the tenth scenario making it a preferable choice to address the failure of other models in delayed recovery scenarios. The WECC CLM is not recommended for fast recovery scenarios as its performance is similar to other models but its implementation is more demanding.

Chapter 6

Summary and Conclusions

This thesis investigated the load modeling problem in power systems. The first chapter of the thesis presented the thesis motivations, literature review, thesis objectives and organization. A review of the technical background related to the work which was performed in the thesis was presented in Chapter 2. A general review of the load modeling literature was provided in Chapter 3. In this chapter, different load modeling techniques from validation or modeling perspectives were explained. Static and dynamic models were discussed and literature was reviewed with more emphasis on the dynamic models. Dynamic models were investigated in four categories, namely, general input-output, evolutionary optimization based, ANN-based and PMU measurement based methods. Finally, practical models that were mostly used by power system operators were discussed. In particular, applicability of the presented models to modeling the load in industrial applications were elaborated. Considering the presented review, it was argued that more research is necessary to connect the literature and industry-level practice. The ZIP and Exponential models have been the most popular candidates for static load modeling, while dynamic modeling experienced more variety of techniques. Moreover, ANN-based models seemed to be too complicated for most of technical load modeling practices. Models implemented in large-scale power system simulators, such as CLOD and the WECC CLM, were more popular for industry-level practice. In terms of the solution methods, evolutionary and least square methods were broadly utilized in the literature. The choice of solution method depends on the required level of accuracy and the way that a problem is modeled. In conclusion, a mechanism is necessary to understand which load model types and parameters better match an operating power system.

Following the presented review, a measurement-based load modeling approach was defined. The purpose of this section was to investigate how the choice of CLOD complex load model parameters impact the voltage simulation results. Firstly, a detail description on event detection process, off-line model building, and the approach used to apply this measurement-based technique to the Alberta's grid was provided. Models were considered for all the loads in the study area, instead of focusing on a single load. Thus, a wide-area simulation was designed by cross-referencing between the available SCADA and PMU data resources. This process to prepare the base-case and an event for simulations can be useful for other power system operators aiming to perform load model validation studies. Sensitivity analysis was implemented on the CLOD model and sensitivity rankings were established. GA and PSO were used to find the optimum parameters for the model. Lastly, quantitative and qualitative comparison between optimized and generic models were made.

The work in Chapter 4 showed that the simulated voltage responses considering the optimized model did not show significant improvements compared to the generic CLOD model. This revealed that choice of different parameters for CLOD cannot alter the general voltage response at high voltage substations. It should be noted that this response was in high voltage level and was greatly influenced by transients of other system elements as well. The mismatches between simulations and measurements were partly from the inevitable inequality between the modified off-line base case and the actual state of the grid prior to the event. Hence, all power system elements should be examined to find the perfect match, as loads may only have a minor contribution to this response. This method is general and can be applied to any large-scale power system. Results can substantially differ for different load structures and network topologies. Upon following the proposed process, power system operators can understand how much time and resources are reasonable to spend for transforming their load models from generic ones to optimized CLOD.

The work presented in the Chapter 5 aimed to draw a generalized conclusion by extending the scope of the study in Chapter 4 to other load models and under different scenarios for the observed voltage behavior. Power grids might observe different voltage recovery following a breaker event. This difference mainly depends on the type and amount of loads, climate zones and topologies. The idea behind creating PMU scenarios was to have a variety of potential voltage responses in large power systems. The performances of four different practical load models namely, IEEL static, CLOD, induction motor CIM5, and WECC CLM were investigated in these scenarios. A combination of GA and Least-squares methods were used for the optimization. Sensitivity analysis performed on the load models to reduce the number of parameters prior to optimizations. Finally, performances of the selected load models were compared in different scenarios. Several recommendations on the choice of load model and its parameters were provided based on the simulation results.

The IEEL static, CLOD and induction motor models were initially optimized for each of the scenarios in Chapter 5. Voltage responses considering the optimized parameters were visualized along with generic CLOD and generic static models. Comparing the voltage response of these load models did not show any significant difference between their performances. Although optimized models always performed better than the generic ones, no major differences between responses were observed. The induction motor model was able to marginally better simulate the moderately delayed scenarios. Acceptable performance for fast recovery responses was a common trend for all these three models. However, these three load models fail to resemble more delayed scenarios. The WECC CLM was considered as a potential mitigation for delayed scenarios. This model was optimized for four of the scenarios ranging from very fast ones to delayed recovery scenarios. Results showed that the WECC CLM could substantially change the voltage response for delayed scenarios. Simulations with the WECC CLM followed the delayed recovery in the response more than the other models. The tenth scenario clearly showed this difference between the performance of models. Furthermore, this comparison provided insight into the selection of model structures and parameters in different potential PMU scenarios. It is worth mentioning that the developed process in this thesis is mainly considered for off-line studies. Additionally, load compositions constantly change over time and hence, evaluating models for different events at different times of a year can help to improve the accuracy of models.

Several recommendations are made to finalize the referred observations in this thesis. The IEEL static model, CLOD complex model and induction motor model have very similar response characteristics. They can all predict fast recovery responses but fail to follow delayed recovery voltage responses. Induction motor load model is slightly more complex than the other two for implementation and can marginally perform better for moderately delayed scenarios. Therefore, it is recommended to use either the static or CLOD complex model for fast recovery voltage responses as the induction motor model is more difficult to implement. The WECC CLM is the better choice, among the considered models, for more delayed scenarios as it is observed in the tenth scenario. This model is complex and more difficult to implement, but can address the failure of other models in delayed voltage recovery events. Hence, the WECC CLM is only recommended for delayed voltage recovery events. In terms of parameter selection, the WECC CLM is very sensitive in contrast to other models. It is required to carefully tune and maybe optimize model parameters for the WECC CLM. Other models were not sensitive to the choice of parameters and only marginal improvements between their optimized and generic structures were observed. Thus, optimizing model parameters is recommended for the WECC CLM but not for the other three load models.

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Best regards,

Amir Saman Hoshyarzadeh

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Figure A.4: Copyright permission email from IEEE- page 4.