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Model Parameter Calibration in Power Systems

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Abstract

In power systems, accurate device modeling is crucial for grid reliability, availability, and resiliency. Many critical tasks such as planning or even realtime operation decisions rely on accurate modeling. This research presents an approach for model parameter calibration in power system models using deep learning. Existing calibration methods are based on mathematical approaches that suffer from being ill-posed and thus may have multiple solutions. We are trying to solve this problem by applying a deep learning architecture that is trained to estimate model parameters from simulated Phasor Measurement Unit (PMU) data. The data recorded after system disturbances proved to have valuable information to verify power system devices. A quantitative evaluation of the system results is provided. Results showed high accuracy in estimating model parameters of 0.017 MSE on the testing dataset. We also provide that the proposed system has scalability under the same topology. We consider these promising results to be the basis for further exploration and development of additional tools for parameter calibration.

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Chapter 1

Introduction

Power system models are used to represent the dynamic behavior of components of power systems, such as generators, transformers, and loads. In addition, these models promote the study of large power system networks and contribute to decisions affecting long-term planning, short-term planning and even in real-time operations. Inaccurate models that result in the power system being either overestimated or underestimated and the effects could be disastrous [1]. For example, the Western System Coordinating Council (WSCC) system can not avoid a blackout event in August 1996, because of the expected simulation forecast a stable situation, in fact, the system collapsed within minutes [2]. After this blackout event, North American Electric Reliability Corporation (NERC) and the Western Electricity Coordinating Council (WECC) in North America implemented a number of policies and standards to guide the power industry in periodic validation of power grid models and calibration of poor parameters with a view to building sufficient confidence in model quality [3]. The simulated models must therefore be verified to ensure that they can accurately estimate the actual network performance.

Through growing additions of renewable energy sources, smart loads, and mid-size generators, power generation is now facing substantial changes in its power grid. The current power grid is becoming more complex and stochastic, which could invalidate conventional studies and pose significant operational challenges. Recent criteria are therefore becoming more steady to certify precise modeling. Standards of the NERC

Reliability MOD include the provision of power flow and dynamic models for all operating systems. In particular, models with capacities greater than 20 MVA as a single unit and 75 MVA as a plant facility are required to be validated every five years. Whereas the Western Electricity Coordinating Council (WECC) lowered the model validation threshold to 10 MVA as an individual unit and 20 MVA as a plant facility to be validated every five years [4].

Stage tests are the most commonly used methodology for validation and calibration of power plant models. The staged test takes the generator offline and applies a set of simple and well-defined producers. This approach is costly as during the testing process the measured generators are no longer able to produce the energy for the revenue. Also, with more renewable energy sources and mid-size generators added to the grid the staged test becomes an unpractical solution to meet NERC standards [5]. The 2016 WECC REMTF workshop showed that there are no dynamic models for 94 plants with a generating capacity of 5.2 GW and 54 plants with a generating capacity of 2.8 GW are modeled with inappropriate dynamic models. Power grids are therefore more than ever in need of accurate, reliable and scalable models/modeling tools.

Mathematical disturbance-based approaches were implemented in the last few years. These methods use dynamic disturbance recording data, such as Phasor Measurement Units (PMUs). The models can be tested by these methods without the need to take the system offline, thereby allowing for more regular testing than the 5- or 10-year duration needed by NERC and WECC standards. For example, Western Interconnection has 10 to 15 disturbance events every year, allowing for more frequent identification of abnormal plant activity and model adjustments.

Disturbance-based tests are more cost-effective, timely, and scalable than staged tests. However, the current methods are ill-posed and may suffer from instability or lack a unique solution. According to the latest NERC guidelines on the validation of power plant models, the existing disturbance-based testing tools are imperfect, and grid operators should exercise engineering judgment when using numerical curve fitting methods.

In this research, and given the urgent need for reliable, scalable and less time-consuming model validation and calibration methods, we are introducing a methodology for calibrating power systems based on disturbance data from PMUs using machine learning algorithms. **Our main contribution in this thesis is to evaluate the usability of machine learning algorithms in power systems calibration from simulated data.**

We estimate two types of generator model parameters: GENCLS and GENROU using a deep neural network trained offline from simulated disturbance events. The main advantage of the proposed approach is the ability to provide a well-posed solution that is trained with minimal pre-processing of data and therefore relies less on expert judgment. We validated the effectiveness of the proposed method by using IEEE 14-bus and using IEEE 39-bus.

Chapter 2

Related Work

2.1. Practice Methods

Several methods have been used to validate the power system model and perform parameter calibration, as summarized in Table I. Performing these methods may require taking out generators offline from normal operations and using sophisticated data acquisition/processing tools. These actions are not desirable because of its high implementation cost [3] and they are mandatory to prevent blackouts like the one that happened in 2003 in the USA [4]. Up to our knowledge, there is no existing solution to address this problem efficiently.

Method	On-line/off-line Time to do	Advantage	Disadvantage
Staged test	Off-line, Commission/scheduled test	Very simple Time efficient	Very expensive (it cost 15,000-35,000 per generator per test in USA)
Disturbance-based test	On-line, Via disturbance	Can provide high-quality data Real-time	The collected data need to be processed effectively

Table I. Existing Methods For Power System Validation And Calibration

The two most common methods are *staged test* and *disturbance-based test*. In the first method, the generator is required to be taken offline from the normal operation. As a result, this method is costly since the tested generators are no longer able to produce electricity for the revenue.

The second method is the disturbance-based power plant model verification using dynamic disturbance recording data such as Phasor Measurement Units (PMUs). PMUs are one of the most important measuring devices in the future of power systems [6] that been recently deployed across many nation’s bulk power electric systems, providing more extensive grid-related measurements. PMUs perform continuous high-speed monitoring that records plant’s response to actual transmission levels grid disturbances, such as generator faults, losses or breaker operations. Using PMU data device model validation can be done without the need to take the device offline.

2.1.1. Staged Test

The most common method of validation and calibration of power plant models is the staged test. It requires the device to be taken offline for 2 or 3 days from normal operation. The testing equipment is connected to the offline generator and a series of required tests (generator test, exciter test, governor test, and reactive power test) are performed to determine the desired model parameters using mathematical techniques. The staged test validation method is well known, but it has a high upfront cost (e.g., $15,000-$35,000 per generator per test in the U.S.) and time-consuming, making it an unpractical model testing method according to the requirements of the recent standard from NERC and WECC [3].

In the last two decades, PMUs have been established and implemented over North America. Researchers found the optimal position for installing PMUs for online model verification is at the interconnection point of a large power plant [7]. Disturbance-based methods have been proposed as a low-cost alternative to staged tests since they allow device models to be verified online without taking the generator offline. In addition, the data collected by PMU is realistic and describes the operating range for each element in a precise comparison with the stand-alone testing of individual machines. The key idea is to inject PMU measurements into the bus terminal of the power plant during dynamic simulation so that the response of the model can be compared to the actual PMU measurements [8]. As a result, disturbance-based methods are more scalable and reliable in comparison with staged test methods.

2.1.2. Disturbance-Based Test

The second method is the disturbance based on PMU. Disturbance in the power system is a sudden change or a sequence of changes in one or more of the parameters of the system, or in one or more of the operating quantities [9]. It has two types: small disturbance type where the dynamic power system could be linearized. And a large disturbance where the power system cannot be linearized for the purpose analysis.

PMUs typically measure grid conditions at least 30 times per second, 100 times faster than the 2 to 4 seconds reporting rate typically corresponding to Supervisory Control and Data Acquisition (SCADA) systems [10]. PMU is well synchronized with the global positioning system clock (GPS) and it can capture continuously the dynamic response of power system and abnormal condition then it can be used and applied as online validation tools. Meanwhile, a validating system based on this method is recommended by NASPI.

Previous work showed the feasibility of estimating dynamic states using PMUs data. In [11], authors compared and examined the four commonly used algorithms for state estimation: Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Ensemble Kalman Filter (ENKF), and Particle Filter (PF). The statistical performance for each algorithm is compared using a two-area-four-machine test system and Monte Carlo methods. Finally, the authors suggested some recommendations on how to select the state estimation algorithm based on the studied problem.

In [12], the authors investigated the estimation of synchronous generator states and parameters related to angular stability using PMU data. The proposed method uses the finite difference technique and least-squares method to evaluate differential equations governing the synchronous machine using a time window of PMU measurements.

These validation techniques still have problems and gaps to represent the real-time performance of the power system based on the latest NERC guideline on power plant validation. The principal difficulty is related to (1) the fact that while the numerical model represents a well-defined mapping from input parameters to the outputs, the inverse problem often presents itself as an ill-posed problem that often yields multiple solutions for the same model performance. The solutions can be plagued with problems of non-identifiability, non-uniqueness, and instability; (2) The accuracy and effectiveness of the process heavily rely on expert's judgment about the system such as parameter sanity check and parameter sensitivity evaluation; (3) Manual search for the optimal solution via methods such as the least-squares method of all parameters when the number of parameter increases can become tedious and convergence becomes slow. Often, only one or two machines in the plant will go under such tests and the results will be assumed valid to represent all the machines in the plant! Hence, there is a strong need to develop and improve the model parameter tuning and model validation process to reduce cost and improve the reliability and robustness of the models.

The main issue that faces this approach and software tools is having multiple solutions that may exist for the same model performance after performing the calibration procedure, so identifying the true parameter set is somehow difficult. In addition, although such a method can provide a unique solution calculated by the least square method for a particular event, the derived set of parameters may not be the same for other events. So, it is strongly recommended by NERC guidelines not to rely solely on numerical curve fitting methods without engineering judgment.

Using PMU data to validate and calibrate a particular model on the power system network will improve the reliability of the power system. Its main benefits come from that the data collected by PMU are realistic and describes the operating range for each element accurately comparing to the stand-alone testing of the individual machine. As a result, this may enhance asset utilization once a good model has been developed. Based on modeling the PMU data, an equipment misoperation or failure could be expected, so a maintenance plan could be established to prevent the failure.

At the same time, the disturbance based model is more economical cost-effective, timely, and accurate than validation methods that take a generator offline for the performance of the staged test. Validation is done online without stopping operations to conduct testing, it also satisfies the requirements of NERC Reliability Standards MOD-26, MOD-27, MOD-32, and MOD-33 to verify generator responses during system disturbances.

Disturbance-based methods have been proposed to solve the non-uniqueness problems [13]. These methods mainly depend on more than one disturbance for model calibration. The idea is to find the optimum solution that fits the different disturbance events applied to the same model. Even though multiple events will help to reduce the number of multiple solutions, there is no guarantee that these methods will find an optimal solution. In addition, if the disturbance events happened in a long period of time, the characteristic of the power system model might change, which will lower the reliability of the optimal solution. In fact, NERC is working now on developing a guideline on how to use and choose multiple events for model verification and calibration.

2.1.3. Machine Learning-Based Methods

Disturbance based method has its challenges due to the limited number of measurement tools, as well as its security systems may be affected by the attacker who wants to disturb the power network. As a result, the data provided from PMUs need to be accurate since it may affect the stability assessment of the power system.

Recently, some of the machine learning techniques have been used to address many problems in power systems. Research presented in [14] and [15] uses ML for fault detection and power stability issues. In the last few years, many support vector machines (SVM) methods have been used to predict transient stability with success compared to other methods such as decision tree and rule-based methods [16]. All of these methods and classifiers rely on pre-processing and accurate instant disturbance information. In [17], the authors proposed a deep neural network, the input of which is a heatmap representation of PMU measurements, to predict the stability of the power system. There is no known machine learning-based approach for model calibration. In [18], the author uses disturbance information and a machine learning technique called Random Forest (RF) for model validation. Their research involves a single error classification and multiple error classification for model validation. However, the solution proposed in this research is applied only to the validation of the model without giving a precise correction.

2.2. Algorithms and Tools

PMUs have been developed and adopted across the world, using disturbance based model has become accepted due to its benefit compared to perform the offline staged test. Currently, a lot of research suggests optimum locations for PMUs to be installed at the point of interconnection at a large power plant to apply online model verification. In the industry. The model validation approach of using measured data by PMUs in time domain simulations has been widely adopted by software vendors, such as GE PSLF, SIEMENS PTI PSSE, PowerWorld Simulator and TSAT [3].

Recently, phasor measurement units (PMUs) involved in many power systems applications, In [19], a tool that uses PMU data at the generator terminals to validate the models without taking them offline was presented, which consist of two main steps process, starting with deciding whether the model is valid and then calibrate the model parameters when it is required. In the validation process, simulation output waveforms are compared against the PMU measured data. If the simulation results indicate a reasonable match with measured waveforms then the model parameters used in dynamic simulations accurately represent the generator performance during the actual disturbance.

Several algorithms and tools are reported to provide calibration of power system models using PMU measurement data. Integrated methodology and software tool suites were presented to systematically validate the stability models. One of these is the advanced Kalman Filter Algorithm used to identify/calibrate problematic model parameters using online PMU measurements. This tool is introduced to validate as well as calibrate models based on the Kalman Trajectory Sensitivity Analysis Method [20]. This developed prototype demonstrates excellent performance in identifying and calibrating bad parameters of a realistic hydropower plant against multiple system events. The PMU-based approach using online measurements without interfering with the operation of generators provides a low-cost alternative to meet NERC standards. This PMU-based approach can effectively reduce the frequency of costly staged generator tests.

Another calibration identification algorithm has been developed in [21], to calibrate parameters of individual components using PMU measurement data from staged tests. A model reduction that is used to reduce the complexity of a power system model and calibration approach using phasor measurement unit (PMU) data were presented. An on-line parameter identification algorithm is developed to calibrate generator parameters in the reduced model using PMU measurements. Applying disturbance in the close area, the PMU measurements were observed to use. PMU implementation makes the on-line calibration possible. To make full use of dynamic data transmitted by PMU. This can also be applied for tuning the parameters by playing back equipment testing data.

Many studies have been done to estimate the generator parameters. A dynamic state estimation method for synchronous generator parameter estimation using PMU data as described in [22]. PMU phasor data with disturbance was converted to three-phase sampled data to feed into the dynamic state estimation. It was used for better estimation accuracy. So, the comparison between the calibrated parameters and actual parameters to prove the effectiveness of this method.

Furthermore, PMU technologies and the Extended Kalman Filter (EKF) were introduced in [23], which have been used for sub-system model validation. It enables rigorous comparison of model simulation and recorded dynamics and facilitates identification of problematic model components. In this work, A four-machine modeled as classical models (GENCLS), and the two-area system is applied to illustrate the calibration process of the EKF-based model parameter. The EKF-based parameter calibration method is shown to have good convergence efficiency and to be robust in respect of significant initial parameter errors.

A Power Plant Parameter Derivation (PPPD) tool, developed by the Electric Power Research Institute (EPRI) [24]-[25], and a model calibration toolbox in MATLAB, developed by MathWorks [26]. Both of these two tools are developed based on linear or nonlinear curve fitting technique which has proved effective in the derivation of parameter sets corresponding to PMU measurements. It is reported, however, that for the same model performance, multiple solutions may exist, making it difficult to identify the true parameter set that works for different events. However, after starting the calibration procedure, multiple solutions may exist for the same model performance, which makes it difficult to identify the true parameter set. This is a common issue for all numerical curve fitting algorithms. Therefore, it was strongly recommended by NERC guidelines not to rely solely on numerical curve fitting methods without engineering expert judgment [3]. Although such methods can provide a unique solution for a certain system event calculated using the less square nonlinear method, the derived parameter sets may not be the optimum solution for other events.

In this research, we propose a data-driven machine learning approach to model calibration of power planet models using Convolution Neural Networks (CNNs). Our method does not suffer from multiple solutions as it is trained in a large number of simulated disturbance events that do not include multiple solutions for the same event and therefore rely less on expert judgment. We have shown the effectiveness of our method by comparing it with the mathematical approaches implemented in the PPPD tool.

2.3. Power System Model Validation vs Calibration Process

With the ever-increasing penetration of renewable energy, smart loads, energy storage and new consumer behavior, today's power grid is more dynamic and stochastic, which can invalidate conventional study assumptions and present significant operational challenges [13]. The key to maintaining stability and reliability of the power system is model validation and parameter calibration.

Models are the foundation of virtually all power system studies, validation of the power system model is an important procedure for maintaining system protection and reliability. validation and calibration will be used in the calculation of operating limits, planning studies for assessment of new generation and load growth, performance assessments of system integrity protection schemes [27]. If a particular model does not reflect the observed phenomena on the power system with fair accuracy, how can one have confidence in the studies derived from that model? The answer to this question is validation.

The eventual goal is to have a generator model that can reasonably predict the outcome of an event i.e. disturbance. In modeling a large power system, such as the eastern interconnection in North America, there are several categories of models that need to be developed: transmission system, generating units and loads.

Deploying PMU makes model validation can be applied in on-line models. The model validation procedure injects PMU measurements into the power plant terminal bus during the dynamic simulation so that the response of a model to real PMU measurements can be compared [8]–[28]. When model variations are detected, the incorrect parameters must be defined and calibrated. Several algorithms and tools currently used are reported to provide calibration functions in Section 2.2.

Our proposed approach, used in the estimation of generator model parameters, applies deep learning techniques to predict model parameters. In order to calibrate the power system model, it is only necessary to provide the disturbance event data to the trained convolutional neural networks for obtaining the accurately calibrated parameters. In general, model calibration is more complicated than model validation. In this thesis, we have shown that CNN can achieve a good model calibration performance.

After the prediction of the model parameters, the proposed approach enables the comparison of model simulation measurements and recorded real PMU measurements from previous events. When discrepancies are established between the measurements and simulation results, then we can tell the model is accurate or not.

There are some challenges in the validation and calibration process. Data availability, it is due to many factors that there is a lack of measurement data. Experimental testing is limited in that it involves component switching or part of the network, which is expensive. Therefore, modeling, analytics, and simulation techniques must be used to gain further insight into the dynamics of the system.

2.4. System Identification

Power generation systems with multiple input-output have a wide operating range and due to high order nonlinear dynamics cannot be entirely described by a fixed model. Since the parameters of conventional excitation and speed governor controllers are determined by the system model, which is linearized around rated operational point, the performances of the controllers at different operating points can be reduced [29].

The method of transferring from observable data to a mathematical model is a theoretical basis of science and engineering this method was called System Identification. System identification is a mathematical model to define and describe system action based on system input/output data. And the objective is then to find dynamical models from observed input and output signals. System Identification deals with the problem of building models of systems where there is insignificant prior knowledge and where system properties are known. The area of system identification begins and ends with real data. Data are required to build and to validate models.

The system identification procedure has four basic ingredients [30]:

1- Measure the input and output signals from your system in time or frequency domain. System identification uses the input and output signals you measure from a system to estimate the values of adjustable parameters in a given model structure. Obtaining a good model of your system depends on how well your measured data reflects the behavior of the system.

2- Select a model structure. Select a mathematical relationship between input and output variables that contains unknown parameters.
3- Apply an estimation method to estimate value for the adjustable parameters in the candidate model structure.
4- Validation and evaluate the estimated model to see if the model is adequate for your application needs. It can be evaluated the model quality by Comparing Model Response to Measured Response.

These main steps are shown in Figure 1, in the system identification process that can be considered as modeling from experimental data [31].

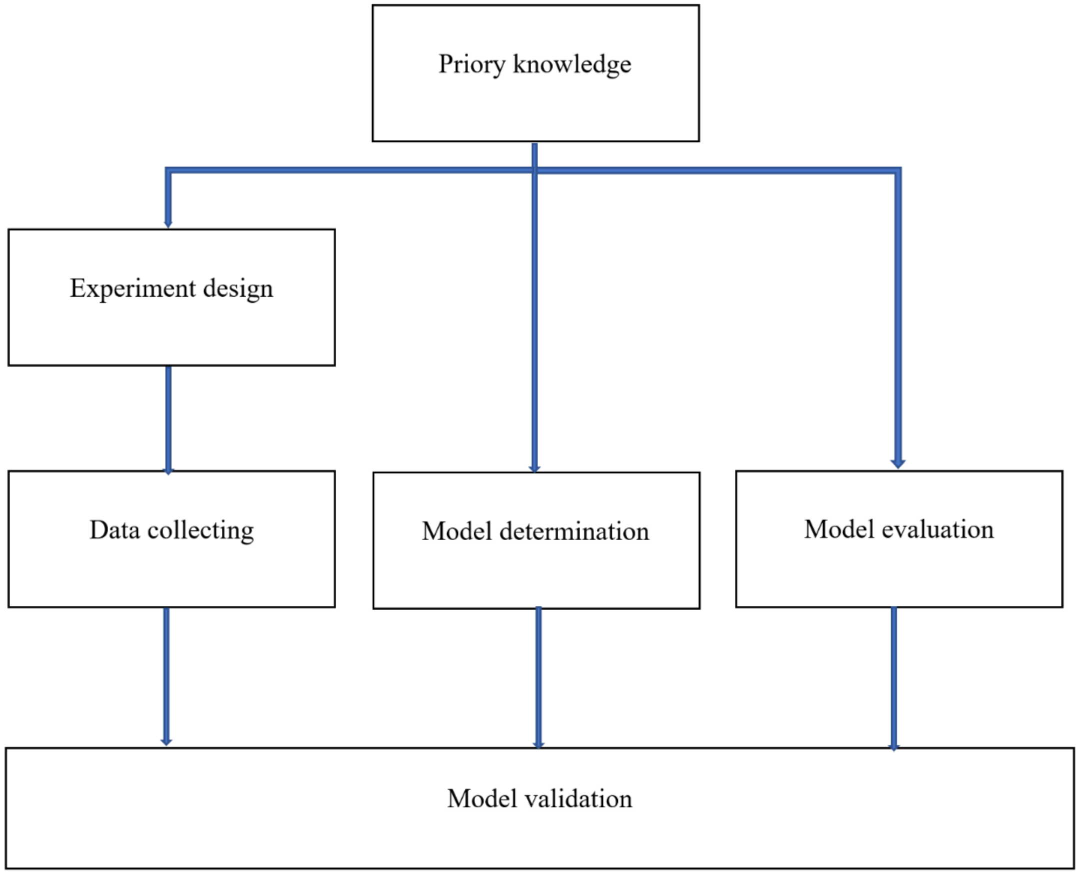

Fig. 1: Steps of system identification

Generally, the system's input and output at time t are denoted by $u(t)$ and $y(t)$ respectively [32]. Perhaps the most basic relationship between the input and output is the linear difference equation:

$$y(t) + a_1 y(t+1) + \cdots + a_n y(t-n) = b_1 u(t-1) + \cdots + b_m u(t-m) \tag{1}$$

In particular, because the data are always obtained by sampling, the system prefers to be represented in a discrete time. So the comparison of the observed data with discrete-time models becomes easier.

In equation (1) assuming the sampling interval to be a one-time unit. This is not essential but makes notation easier. A logical and practical way of looking at it is to see it as a way to evaluate the next output value given previous observations:

$$y(t) = -a_1 y(t-1) - \ldots - a_n y(t-n) + b_1 u(t-1) + \ldots + b_m u(t-m) \tag{2}$$

For more compact notation we introduce the vectors

$$\theta = [a_1, \ldots, a_n b_1, \ldots, b_m]^T \tag{3}$$

$$\varphi(t) = [-y(t-1) \ldots - y(t-n) u(t-1) \ldots u(t-m)]^T \tag{4}$$

With these four equations can be rewritten as:

$$\hat{y}(t|\theta) = \varphi^T(t)\theta \tag{5}$$

The system identification process can be explained as a model fitting to the experimental data recorded by giving appropriate values to the system parameters. Basically, there are two standard methods for system identification: parametric methods and nonparametric methods [33]. Parametric methods: The method by which the recorded data is matched to the estimated parameter vector. Nonparametric methods: The preferred method in the preliminary steps for estimating the structure of the system when there is no need for prior information about the model structure or where there is no prior information.

Many studies have been conducted using non-parametric and parametric methods, the most related work being the following. Chen et. al. [34] present nonlinear dynamical system analysis, identification, signal process, and fault diagnosis. In this work, Matlab was used to identify nonlinear dynamical system coefficients by truncation model and adopts a group of experiment input/output data to simulate, which obtaining nonlinear dynamical system 1 order and 2 order amplitude-frequency response.

Wang et. al. [35] presented a new dynamic neural network based on the Hopfield neural network was proposed to perform the nonlinear system identification. The Lyapunov's criterion is applied to derive the adaptive training laws of weighting factors of the Hopfield-based dynamic neural network. Kaur et, al. [36] presented analyses and compares the applicability of various system identification techniques for modal analysis of a multi-area power system. It was applied to PMU measurements of frequency and active power to find a linear multi-input multi-output dynamic model of the primary frequency control of the power system. The study was based on the Kundur two area power system simulated in Digsilent Powerfactory.

In the study [37], another method is used for the identification of inertia constant. A closed-loop micro perturbation method (MPM) is used to estimate the system equivalent inertia which is sensitive to turbine controllers and the changing operating conditions. In order to estimate the inertia constant, frequency and active power measurements are made using the phasor measurement unit at the transmission line at the point where the plant is connected to the system. To be able to perform identification with sufficient performance, the energy in the disturbance signal which is injected into the system during the identification process must be greater than the energy of the system noise which are the changes in load and operating conditions.

In [38], computer simulation in which the non-linear equations are used to create a mathematical model is done for a thermal power plant. With a fuzzy neural network identifier, it is tested whether the system can identify the transient conditions that occur in the system after any fault such as 3-phase short-circuit faults. The identifier predicts the action signals given at the plant input and follows terminal voltage or active power deviations. The delayed states of the plant inputs are also given as inputs to the identifier, while the other identifier inputs are speed, actual terminal voltage, and turbine power. The parameters of the identifier's membership function are updated each time.

Chapter 3
System and Methodology

This chapter describes the main system, including the methods used to generate training and testing data, as well as the proposed CNN architecture.

3.1. Main System

The main system, as shown in Figure 2, includes a deep neural network trained from the simulated dynamic response data of the power system for disturbances, and the output is the estimated model parameters. The system uses a deep CNN to map the dynamic response data of the system to the generator parameters. Deep learning is part of a machine learning family based on artificial neural networks that typically need a large amount of data to make it work. Thus, thousands of simulated disturbances are generated to train the proposed system on a wide range of model parameters and disturbances, as discussed in detail in the following section. To calibrate the power system model (we have two types of generator: GENROU and GENCLS), it is only necessary to provide the disturbance event data to the trained neural convolution network for obtaining the calibrated parameters.

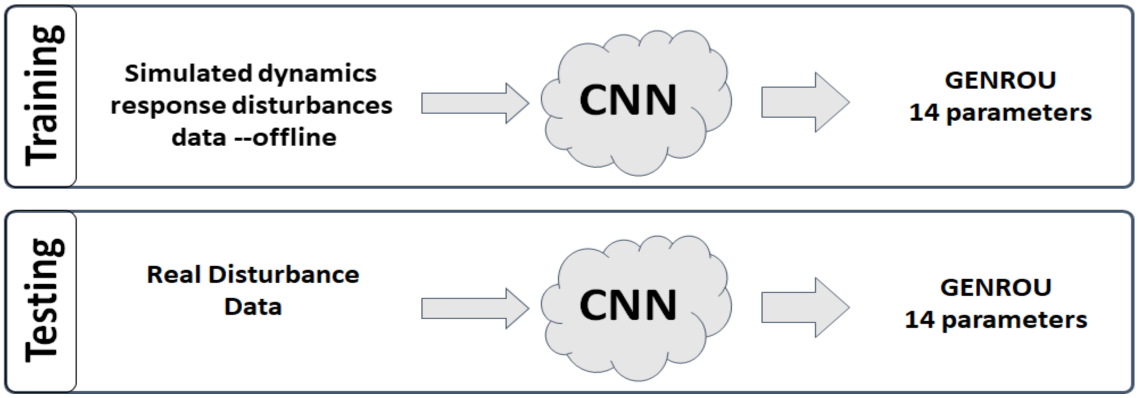

Fig. 2. The designed system to estimate generator parameters. The Convolutional Neural Network (CNN) takes as input the response data. Take GENROU as an example, the output of the CNN is the 14 estimated parameters.

3.2. Data Generation

We used three power systems: IEEE 14-Bus shown in Figure 3 and IEEE 39-Bus shown in Figure 4 to generate the system dynamics response data. For each generator in the bus systems used, the stability dynamics are modeled using the GENROU or GENCLS model. The transient stability of the system is simulated using the simulation package of the power system. Dynamic data is collected as GENROU model 14-parameters or GENCLSE model 2-parameters are simulated at different 100 MVA base values along with a random duration of three-phase bolt faults applied to system buses such that the system stability is maintained.

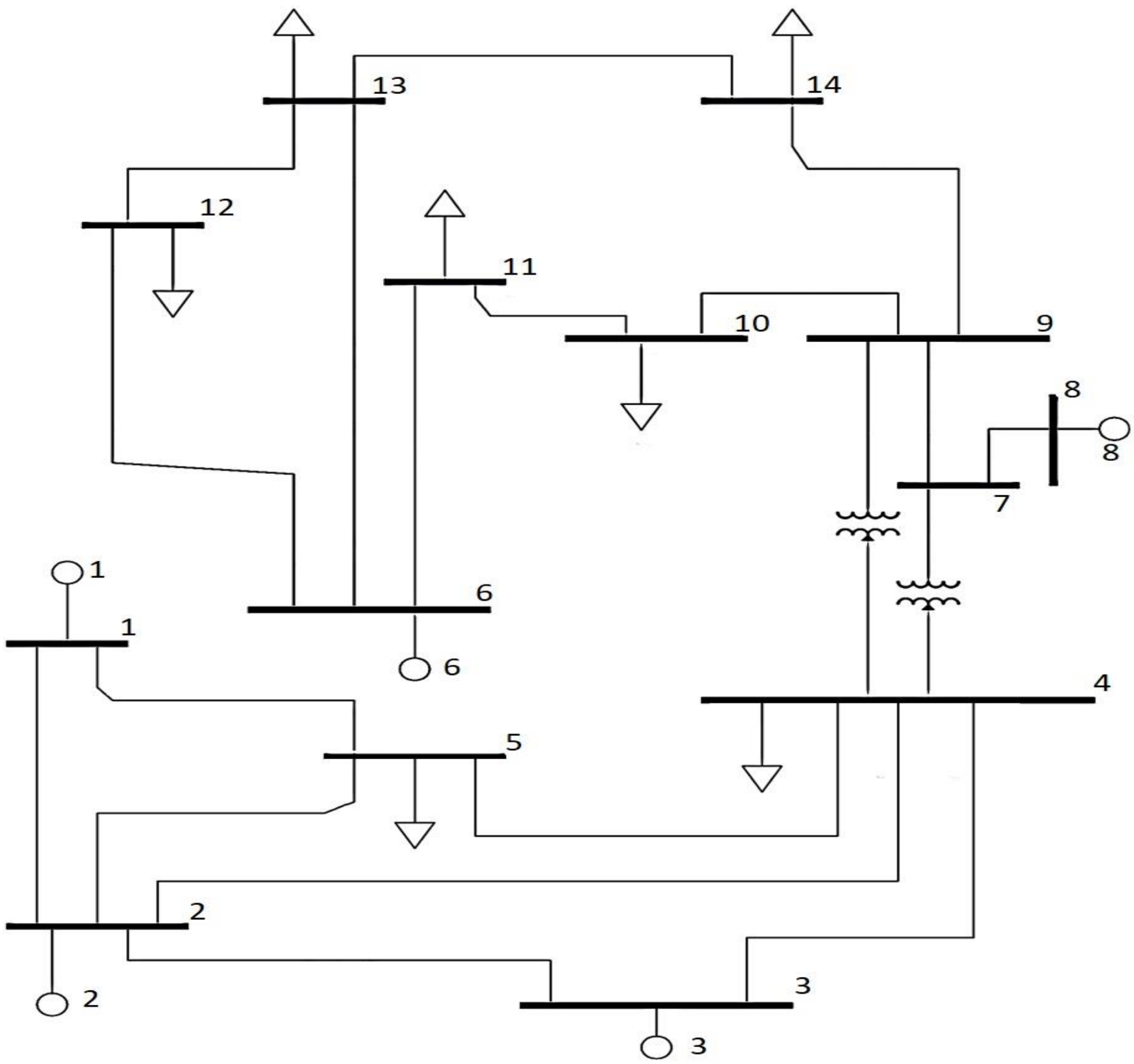

Fig. 3. IEEE 14-bus system.

At the beginning of the research, we only consider the classical generator model GENCLS in our system, which has two parameters H and D. After this, we use a more complicate generator called GENROU that has 14 parameters. We selected the GENROU not only because of its popularity but also because of its high complexity, which consists of 14 parameters. GENROU is a synchronous machine modeled through two circuits, representing the d and q axis. The summation of machine electrical torque obtained from the two circuits is used in the swing equation, establishing a link between the speed and the net torque acting on the machine.

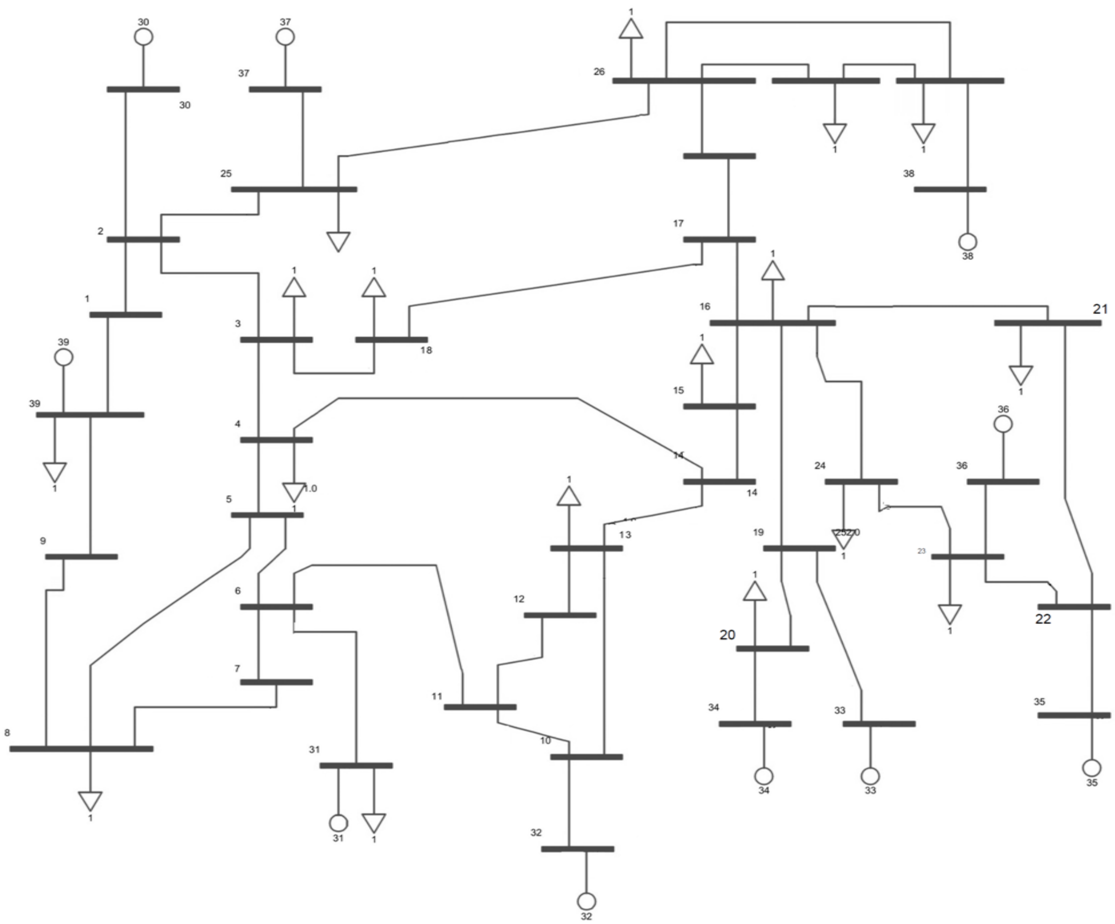

Fig. 4. IEEE 39-bus system.

To train an efficient system that can verify most of the combinations of the parameters, the dataset is chosen to cover most of the space of the model parameters. This is done by randomly adding a parameter combination to a dataset called *databank*. If the

Euclidean distance between the stored parameters in the *databank* and the new combination is greater than a given threshold, a combination of Random GENROU parameters is added to the *databank*. We randomly generated 60 K samples for this research, each of which has a Euclidean distance of 0.7 or more from the other *databank* parameter sets. The reason for not applying *databank* for GENCLS is that the possible combinations of GENCLS parameters are much less than GENROU parameters (2 parameters versus 14 parameters). GENCLS parameters and their ranges are shown in Table II. GENROU parameters and their ranges are shown in Table III.

Parameter	Low	High
H	1	10
D	1	8

Table II. The range of the parameters in GENCLS.

Parameter	Low	High	Parameter	Low	High
T'_{do}	2	10	Xq	0.4	2.4
T''_{do}	0.06667	0.2	X'_d	0.8	2.5
T'_{qo}	0.5	1.2	X'_q	0.4	2.4
T''_{qo}	0.1	0.2	X''_d	0.3	0.3
H	1	10	X_l	0.01	0.25
D	0	3	$S_{1.0}$	0.001	1
Xd	0.8	2.5	$S_{1.2}$	0.01	5

Table III. The range of the parameters in GENROU.

In order to build IEEE power systems and use the GENROU or GENCLS model, we chose the "Power System Simulator for Engineering" (PSSE) software to simulate data in different scenarios. This software is used to simulate electrical power transmission networks in steady-state conditions as well as in timescales of a few seconds to tens of seconds. Moreover, the software provides its own Python API, which allows easy communication with the simulator. By writing just a few lines of code, we were able to generate data as much as we need to train our CNN models.

3.3. Principal Component Analysis

Principal Component Analysis (PCA) simplifies the complexity of high-dimensional data by compressing correlated data without a significant loss of information. It obtains Principal Components that are uncorrelated by projecting physical variables into a low-dimensional subspace that retains most of the variances of the projected variables [39].

In the first experiment, we reduced the size of the used features by downsampling the PMU signal sampling rate from 60 to 10 samples per second. Each feature was downsampled independently by implementing a PCA for each feature. We used more than 200K samples to find the highest 10 principal components after projecting 60 samples into 10 PCA components. The mean reconstruction error achieved after PCA was 0.01%, thus we were able to reproduce the original data from the reduced dimensions.

3.4. Convolutional Neural Network Based Approach

This section describes a system to estimate the generator (GENROU or GENCLS) parameters. The system input is the dynamic response data of the power system for disturbances and the output is estimated values for parameters. The size of the output depends on the generator type. The system uses a deep machine learning technique to map the dynamic response data of the system to the generator parameters, see Figure 2.

The deep learning technique features a CNN consisting of two convolutional layers interleaved with maximum pooling operations, followed by two fully connected layers. See Figure 5 for more details. The input layer consists of time samples for PMU data recording the dynamic response of the power system to disturbances. These samples record the status of the system just before the occurrence of the disturbance and the system response after it. These responses include such as rotor angle, rotor speed, and voltages at different buses.

The first convolutional layer consists of 256 filters and employs a one-dimensional convolutional kernel with a size equal to one-fourth of the number of input samples. This allows filters to be applied and features to be compared across most input samples. The output of each filter is forced to have the same size as the input using the padding technique. Then it is followed by an element-wise rectified linear activation. A downsampling process by a factor of four is applied using a max-pooling layer to compress the features.

The second convolutional layer consists of 512 filters and employs a one-dimensional convolutional kernel of the same size as the number of input samples divided by four. This allows filters to be applied and features to be compared across multiple filter responses. The output of each filter is forced to have the same size as the input using the padding technique. Then it is followed by an element-wise rectified linear activation. A downsampling process by a factor of two is applied using a max-pooling layer.

The two fully connected layers consist of 1024 and 256 hidden neurons, respectively. The first layer is connected to the downsampled output of the second convolutional layer. The output of this layer is the input for the second fully connected layer. Each layer employs an element-wise rectified linear activation and followed by a dropout layer with a drop rate set to 0.2 to prevent overfitting.

The number of the output layer neurons is decided by the generator type. Take GENROU as an example, the output layer consists of 14 output neurons: one for each 14 GENROU parameter. The input of this layer is the output of the second fully connected layer, i.e., the one with 256 hidden neurons. This layer employs an element-wise rectified linear activation to allow an estimate of the GENROU model 14 parameters that are greater than or equal to zero.

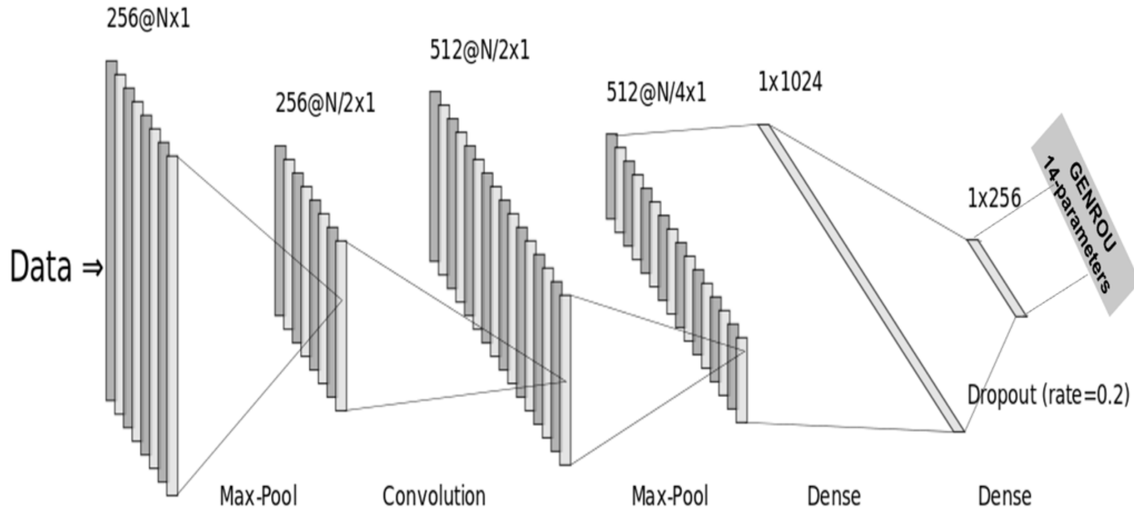

Fig. 5. The architecture of the CNN. Information flows from left to right. The first layer is the convolutional layer of 256 filters of size Nx1 followed by Max-Pooling layer of size 1xN/2x256. The third layer is the convolutional layer with 512 filters of size N/2x1. Then follows Max-Pooling layer with the size of 1xN/4x512. The output of Max-pooling is connected to Fully-connected layer of size 1024 which is further connected to Fully-connected layer of size 256. The last layer is the output layer of size 14 which gives the values of GENROU 14-parameters.

The CNN model is implemented using TensorFlow Python API (https://www.tensorflow.org/). TensorFlow is chosen due to the wide range of available functions and community support. All models are mainly trained and tested with TensorFlow on the UVM DeepGreen cluster, which is a new massively parallel cluster composed of over 70 GPUs capable of over 8 petaflops of mixed precision calculations based on the NVIDIA Tesla V100 architecture (https://www.uvm.edu/vacc).

3.5. Recurrent Neural Network Based Approach

In order to find the optimal deep learning architecture to calibrate the models in the power system, we build a different system that uses a deep learning algorithm called recurrent neural network (RNN). Specifically, the hidden unite of RNN is long short-term memory (LSTM) or gated recurrent units (GRU). LSTM is an artificial recurrent neural network (RNN) architecture used in the field of deep learning [40]. GRU is similar to LSTM with forget gates. There are two RNN architectures: one for LSTM in Figure 6 and the other for GRU in Figure 7.

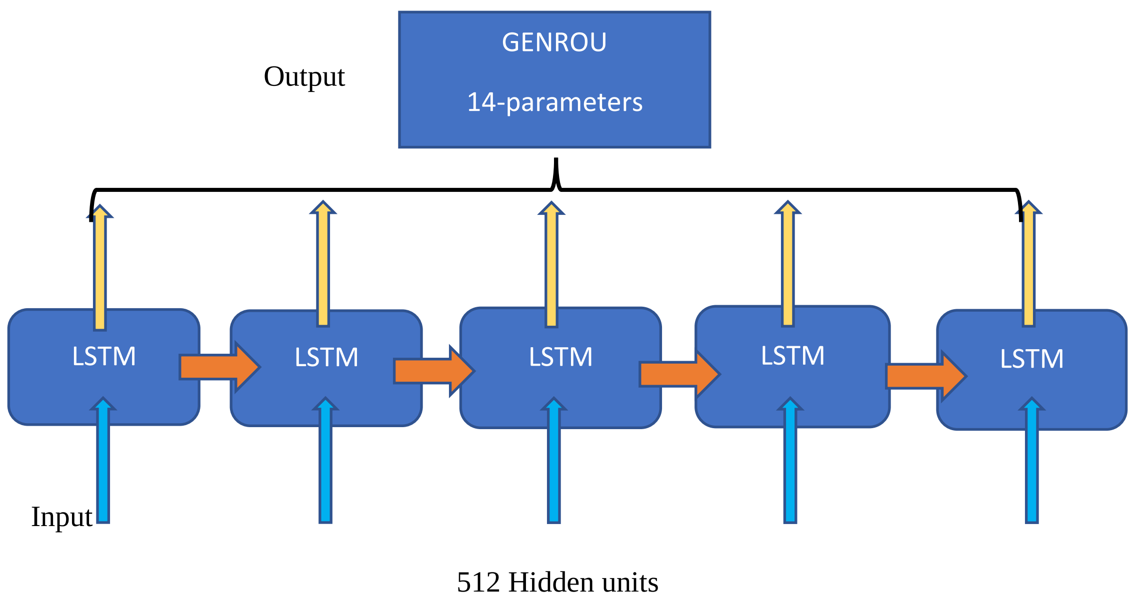

Fig. 6. The architecture of the LSTM.

The input layer consists of time samples for PMU data recording the dynamic response of the power system for disturbances. These samples record the status of the system just before the occurrence of the disturbance and the system response after it.

The hidden layer consists of 512 LSTM/GRU units. It processes data passing on information as it propagates forward. The difference between LSTM and GRU is that an LSTM cell has three gates (namely input, output and forget gates) whereas it has two gates (reset and update gates) only.

The output layer consists of 14 output neurons: one for each 14 GENROU parameter. The input of this layer is the output of the hidden layer. This layer employs an element-wise rectified linear activation to allow an estimate of the GENROU model 14 parameters that are greater than or equal to zero. All RNN models are mainly trained and tested with TensorFlow on the UVM DeepGreen cluster.

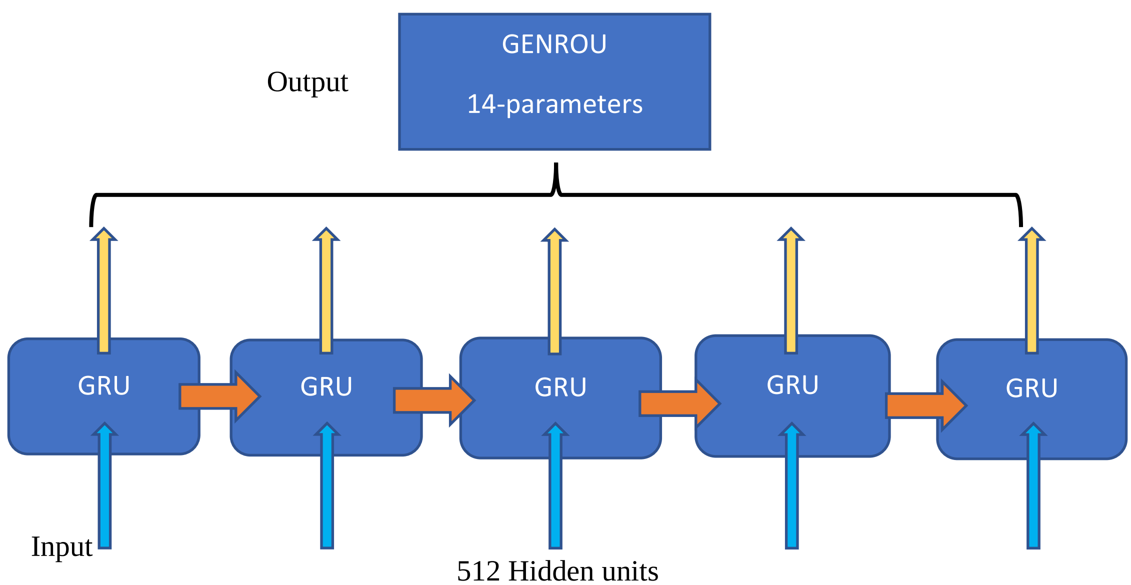

Fig. 7. The architecture of the GRU.

Chapter 4

Result

The proposed system was quantitatively evaluated to demonstrate the ability of the proposed CNN to estimate the model parameters from the recorded system response data. We did three main experiments to verify the accuracy, scalability, and reliability of the proposed system.

4.1. Accuracy

We train a CNN model by modeling a GENROU generator from the IEEE 14-bus system. All generators used in the 14-bus system are GENROU type. The proposed CNN in III-C was trained in such a way that for each set of 14 parameters in the database described in Section III-B, twelve different disturbances have been introduced on the IEEE 14-bus system with a random fault location and duration. The fault was applied to all buses except for bus #3 (where the generator model is connected). Each disturbance event lasts for 15 seconds. The fault starts at the beginning of the third second. Table II displays the 14 GENROU parameters low- and high-range used for calibration. Each event included eight measurements obtained from the bus directly connected to the generator with a sample rate of 60 samples per second. These measurements included rotor angle, real power, reactive power, field voltage, speed, field current, voltage&angle, and flow. The measurements were normalized and standardized by removing the mean and scaling variance to the unit. The length of the feature vector has been reduced from 81,000 to 13,500 using PCA described in section 3.4.

The dataset included 390K samples of simulated responses after removing the samples that caused system instability. The dataset is divided into training, validation and testing sets at a ratio of 60:20:20. The model has been trained for 100 epochs on the training set and validated on the validation dataset at each epoch. We found the best model in epoch# 88. The Mean Square Error (MSE) for the training set was 0.048, and the validation set was 0.016. The testing dataset contains events that have not been shown to the trained model. The total number of samples in the testing dataset is 19.5K samples. The Mean Square Error (MSE) for the testing set is 0.017. The experimental results summarized in Figure 8 shows that the proposed system is capable of accurately estimating the value of the model parameters. Having a very small MSE of 0.017 on the testing set indicates that the proposed training methodology of a very large-scale deep neural learning network is capable of finding a well-posed solution.

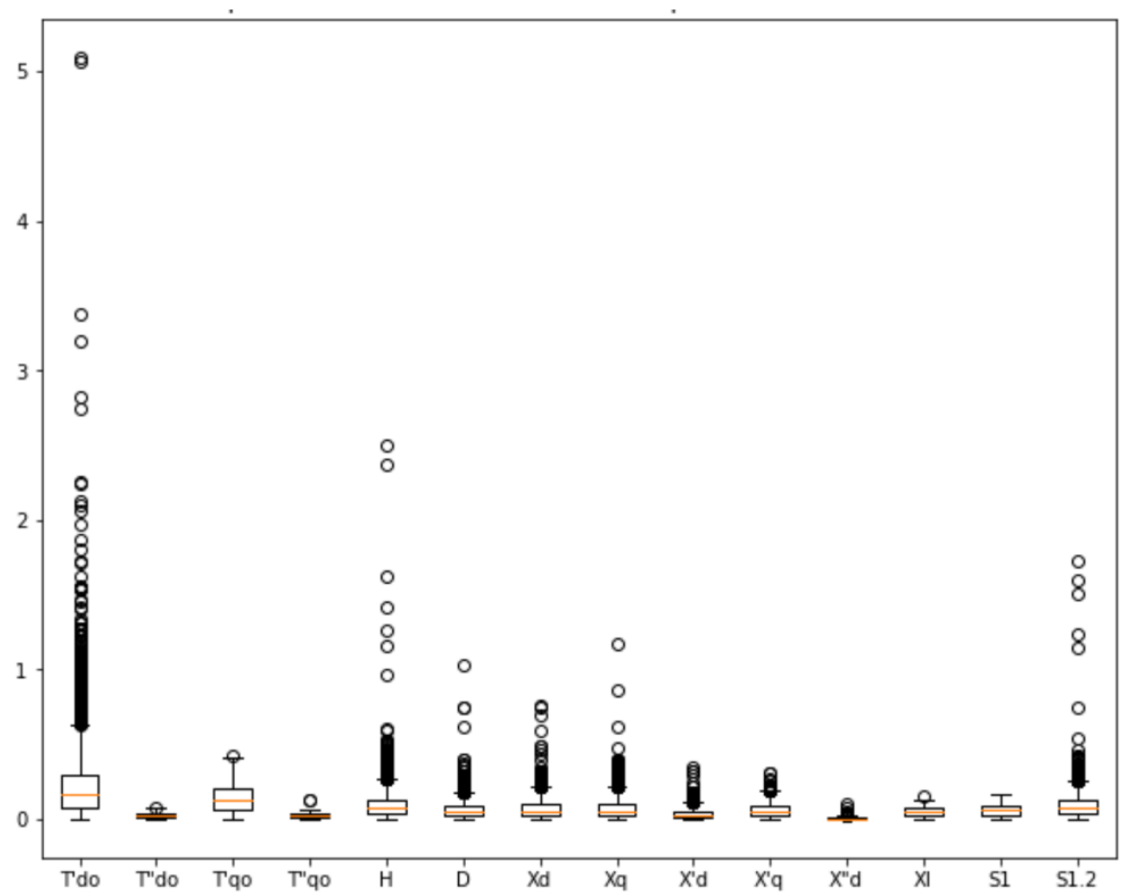

Fig. 8. Boxplot of absolute errors for the CNN experiment.

For comparing the performance of CNN and RNN, the RNN based models were trained by the same dataset described above. The best model of LSTM achieved an MSE of 0.026 on the testing data. The best model of GRU achieved an MSE of 0.0079 on the testing data. The experimental results of LSTM and GRU summarized in Figure 9, 10. show that the RNN based system is capable of accurately estimating the value of the GENROU model parameters in the IEEE 14-bus system.

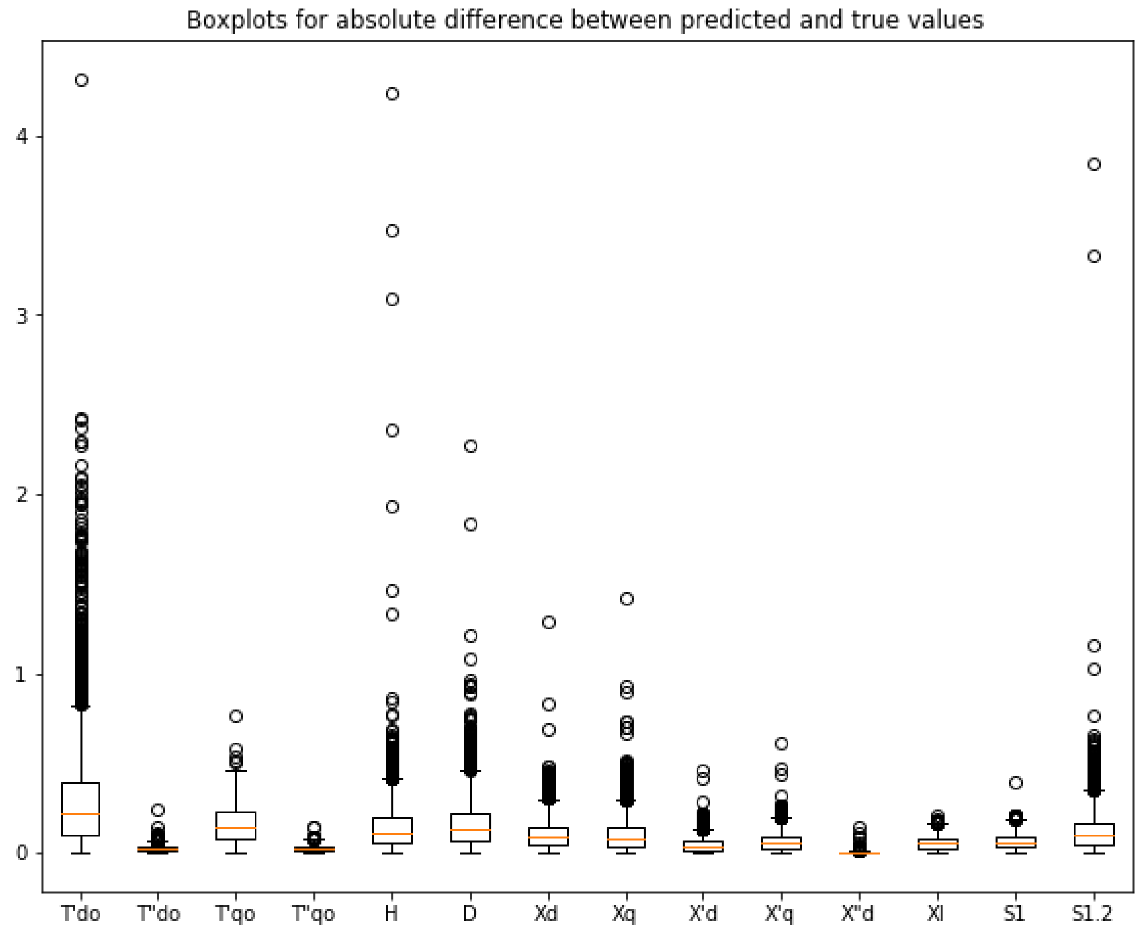

Fig. 9. Boxplot of absolute errors for the LSTM experiment.

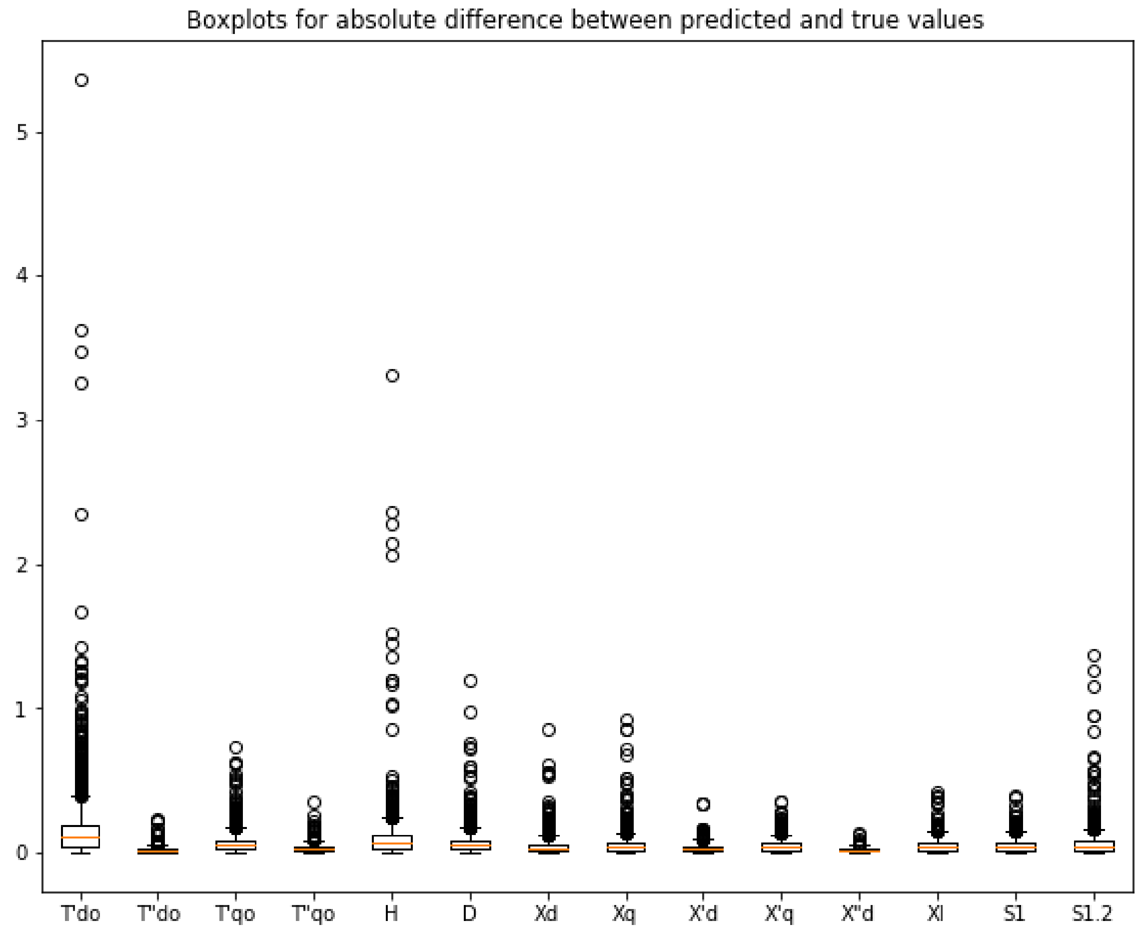

Fig. 10. Boxplot of absolute errors for the GRU experiment.

The results in Table IV showed that GRU achieved an MSE of 0.0079 which is much smaller than an MSE of 0.017 achieved by CNN. In this type of experiment, the performance of CNN, LSTM, and GRU is GRU > CNN > LSTM. However, the most appropriate model for the parameter calibration we have found is CNN. The RNN based model achieved a bad result when it calibrated the generator model in a large power system such as the IEEE 39-bus system. In the scalability testing, the validation error loss of the GRU model stopped decreasing after 5 epochs and maintain a big MSE of 0.9 (the

CNN model achieved a small MSE of 0.12 in the same experiment). The training processing of RNN is quite time-consuming, the training time of the RNN based model is more than 4 times of CNN. Overall, our proposed CNN is the most suitable model to do the calibration so far.

Model	Testing MSE	Training Time
CNN	0.017	525 seconds per epoch
LSTM	0.026	1915 seconds per epoch
GRU	0.0079	1789 seconds per epoch

Table IV. The testing results of CNN, LSTM, and GRU.

4.1.1. Data Comparison With PPPD

We also compared the proposed system with the PPPD tool in Figure 11 by providing ten random disturbance events from the testing dataset. The input data (ten random disturbance events) must include six features: electrical power, reactive power, terminal voltage, filed voltage, field current, and speed. The PPPD tool was able to calibrate the models with an MSE of 2.6. The proposed system was able to calibrate the models on the same disturbance events with a small MSE of 0.018. We noticed that the PPPD tool depends on the initial model parameters, and relativity achieved better results if the disturbance caused by a long fault duration.

Our method doesn't suffer from having multiple solutions as it is trained from a large number of simulated disturbance events that don't include multiple solutions for the same event and thus rely less on expert judgment. We showed the effectiveness of our method by comparing it to the mathematically based approaches implemented in the PPPD tool and we showed our method usability on one real example.

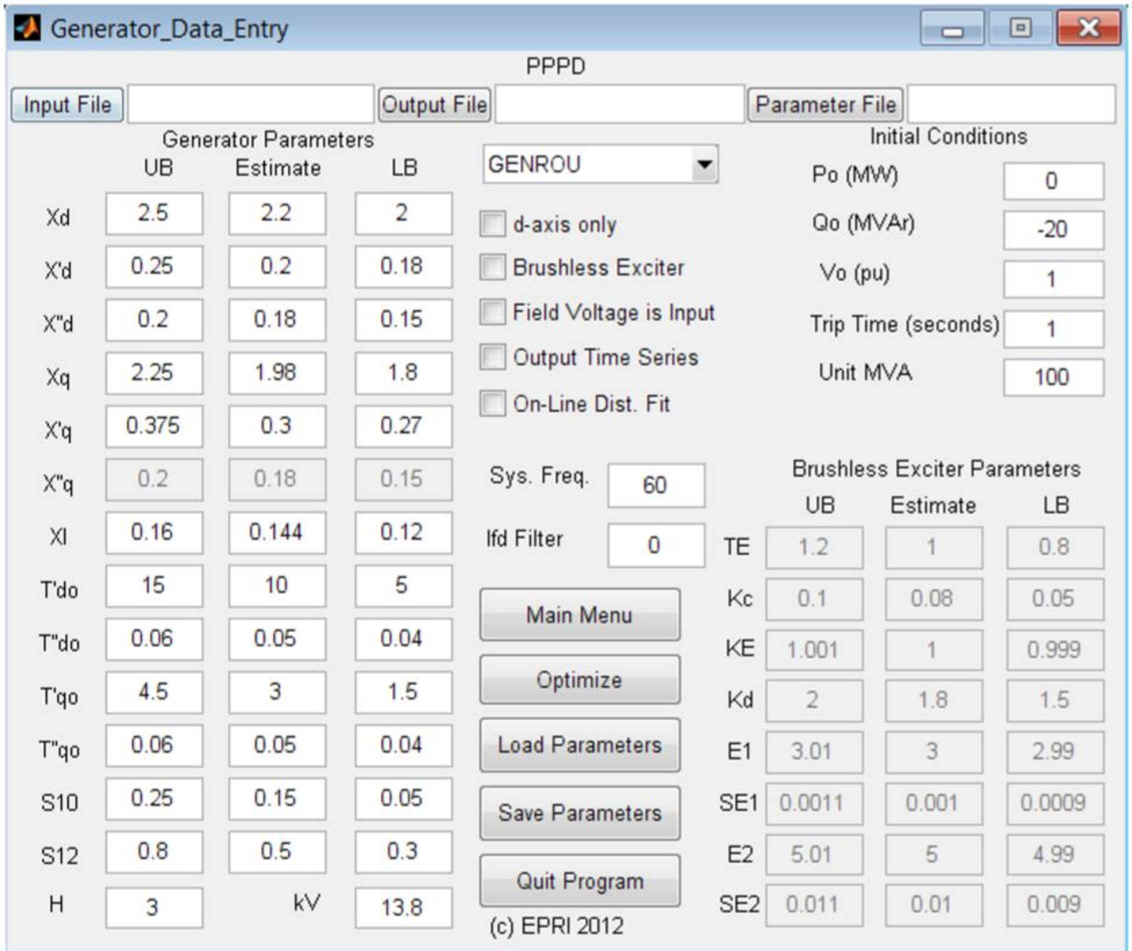

Fig. 11. PPPD Generator Data Entry Screen.

4.2. Scalability

To prove the scalability of the proposed system, we train a CNN model by modeling 10 GENCLS generators from the IEEE 39-bus system. All generators used in the 39-bus system are classical generator model "GENCLS". The dataset includes 60K records of simulated responses for the system described in subsection 3.1 for different disturbances. It is divided into training and testing sets at a ratio of 9 to 1. Each disturbance event lasts for 15 seconds by using random H and D values, as well as, different fault parameters. The ranges for H and D are shown in Table I. The range of H values is between 1 and 10, while the range for D values is between 1 and 8. Fault parameters include fault location and fault duration. The fault starts at the beginning of the third second. Each record includes 6 measurements obtained from the 39 buses with a sample rate of 120 per second. These measurements include real power, reactive power, speed, field current, frequency, and voltage for each of the buses in the system. The measurements were normalized and standardized by removing the mean and scaling variance to the unit. The sample rate has been reduced from 120 to 30 by downsampling. It will slice each feature vector and take every third element of the slice.

Cross-Validation is a method used to estimate the generalization of machine learning models. In this experiment, we especially applied K-Fold Cross-Validation. K is a parameter that refers to the number of groups that a given dataset is to be split into. There are 10 generators in the 39-bus system, the dataset is split into 10 groups (K = 10) base on these 10 generators. Each group represents the response data from the different generators.

For each unique group: 1. Take the group as a testing dataset; 2. Take the remaining groups as a training dataset and fit it into a model; 3. Evaluate it on the testing data and retain the evaluation results, see Figure 12.

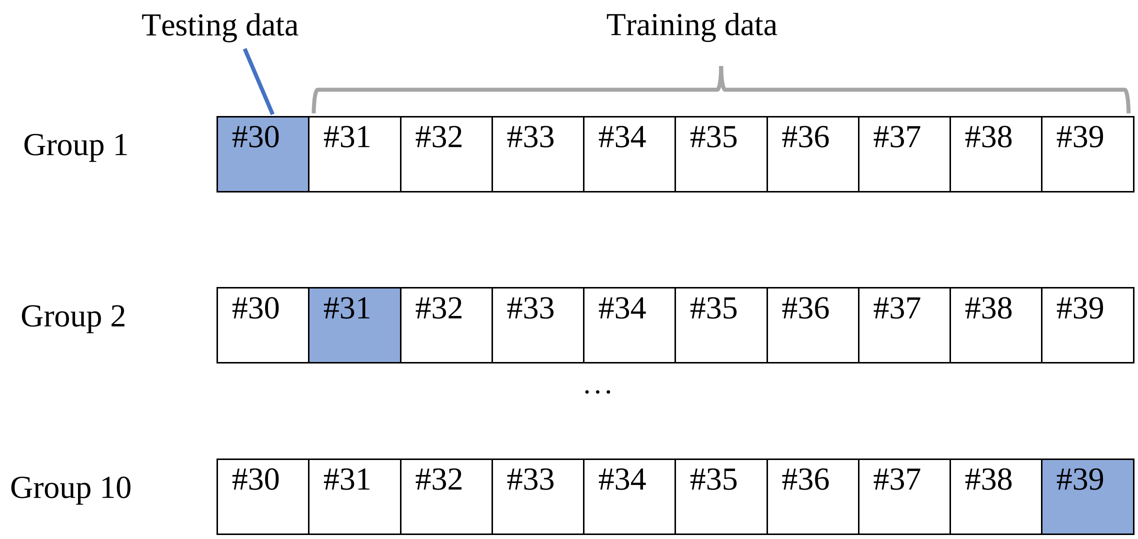

Fig. 12. Cross-Validation for 10 generators in the IEEE 39-bus system. For example, #30 means the generator connected to the Bus 30 in the power system.

The evaluation score summarized in Table V shows that the proposed system is scaling very well since it can model the generator that has never been shown to the trained system and achieve very high accuracy, the average of MSE is less than 0.05.

TABLE OF SCORES ON TEST DATASET

Generator	MSE	Generator	MSE
#30	0.008	#35	0.006
#31	0.02	#36	0.02
#32	0.008	#37	0.008
#33	0.007	#38	0.009
#34	0.0098	#39	0.43

TABLE V. IEEE 39-bus system with all GENCLS generators.

In order to further prove the scalability of the system, we replace the much more complicate generator model "GENROU" in the IEEE 39-bus system. This GENROU has 14 parameters and makes the model more difficult to estimate the well-posed solutions. The experiment is based on the same methodology as we introduced above. The CNN model was trained in such a way that for each set of 14 parameters in the *databank* described in Section 3.2. The dataset includes 60K records of simulated responses for different disturbances. The six measurements: real power, reactive power, speed, field current, frequency, and voltage were normalized and standardized by removing the mean and scaling variance to the unit. The sample rate has been reduced from 120 to 30 by downsampling.

The evaluation scores in Table VI give us the confidence to say that the model is scalable even we test it on the more complicate generator.

TABLE OF SCORES ON TEST DATASET

Generator	MSE	Generator	MSE
#30	0.11	#35	0.55
#31	0.16	#36	0.12
#32	0.11	#37	0.11
#33	0.11	#38	0.11
#34	0.13	#39	0.19

TABLE VI. IEEE 39-bus system with all GENROU generators.

The proposed method requires only one disturbance event to precisely calibrate the model parameters. The results shown in this research are still subject to improvements by providing more training data, bigger and ensemble models, and thus more reliable modeling. The results of the calibrated models can be verified by comparing the output of the calibrated models to the recorded PMU data.

Chapter 5

Conclusion and Future Work

In this thesis, a robust and fast estimation approach has been offered. The main contributions of the master's thesis can be summarized in the following two significant points:

1- An approach for model parameter calibration in power system models using deep learning was created.

2- A comparative study has been conducted between three architectures of deep learning, which are CNN, GRU, and LSTM. All of these are trained with row data. It has been found that CNN is more accurate and robust in parameter calibration and this decision has been reached through two types of generator models (GENROU and GENCLS).

This research illustrates a novel approach for dynamic model parameter calibration by using PMU disturbance measurements. The proposed approach has achieved very high accuracy in estimating parameters of different models in different systems trained from a massive amount of simulated data. The proposed system integrates deep leaning techniques with existing computational power system simulation tools to find the optimal solution for the parameter estimation problem. In this research, the proposed system showed a well-posed solution for parameter calibration comparing to mathematically based methods. It is important to help engineers in estimating the correct responses of power systems in real-time to enhance their stability and reliability.

Future work is going to investigate methods to improve these results in complex topology such as modeling the complicate type of generators in the big power system with more buses and using reinforcement learning to refine the results.

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