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Emerging Advances in Integrated Technology

An Investigative Study on Impact of Frequency Dynamics in Load Modeling

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Abstract: Load modeling plays a significant impact in assessing power system stability margin, control, and protection. Frequency in the power system is desired to be kept constant, but in a real sense, it is not constant as loads continually change with time. In much literature, frequency dynamics are ignored in the formulation of load models for the basic assumption that it does not affect the models. In this paper, the composite load model was formulated with Voltage-Frequency Dependency (V-FD) on real and reactive powers and applied to estimate the load model. 2- Area network 4-machines Kundur test network was used for testing the developed model. The model was trained with measurements from a low voltage distribution network supplying the Electrical Engineering department at Ahmadu Bello University, Zaria. Both training and testing data were captured under normal system operation (dynamics). To evaluate the V-FD model performance, Voltage-Dependent (VD) model was examined on the same measured data. The work makes use of the Feed Forward Neural Network (FFNN) as a nonlinear estimator. Results obtained indicate that including frequency dynamics in modeling active power reduces the accuracy of the model. While in modeling reactive power the model performance improves. Hence, it can be said that including frequency dynamics in load modeling depends on the intended application of the model.

Keywords: Feed forward neural network, load modeling, measurement-based approach, composite load, V-FD

1. Introduction

Studies of load modeling are significant in the sense that, power system operators require knowledge of the system dynamics under small and large disturbance (faults operating) conditions. This is for decision making with regards to system stability margin and subsequently, control and or protection. Recently, different types of loads are continuously invented which necessitate more research on the load dependency on voltage and frequency fluctuations [1-3]. If a load model did not represent the actual system load, the result of the analysis, controller design, or protective action will contain errors, thereby leading to improper decision making by system operators. In many simulation studies, loads are model as static components; this assumption is actually an approximation. Nowadays, some researchers are replacing the static models with dynamic models so that it will be closer to the real system Dynamics[4]. However, modeling Distribution Network (DN) as a dynamic model alone does not have any physical meaning since loads in any DN is jointly a static and a dynamic component. For this reason, composite load models are considered more appropriate [5, 6]. The composite load model is an amalgamation of static and dynamic load models, static loads represent a portion of loads that are not time-dependent, their characteristics are fixed such as resistive loads. On the other hand; dynamic loads are time-dependent and are largely represented by Induction Motors (IMs) [7].

Two different approaches of load modeling were established in numerous literature; component-based and measurement-based methods [8-11]. Component-based load modeling requires knowledge of individual loads, acquisition of relationship between the voltage and or frequency dependency on real and reactive power of each component, and then cumulate the results for all the components connected to the network. Due to the complexity of

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distribution systems, this method is practically not viable, unlike the measurement-based method, which employs the use of measurement instruments to capture the voltage/ frequency dependency on the real (active) and reactive powers expended by the load [4]. The measurement-based is easier and more accurate method since high-resolution measurement devices such as Smart Meter (SM), Power and Harmonic Analyzer (PHA), Frequency Disturbances Recorder (FDR), Phasor Measurement Unit (PMU), etc. are commercially available [12-14].

In Jahromi and Ameli[5], a measurement-based load model using the Genetic Algorithm (GA) was applied to optimally estimates load model indices. The researchers generated simulation data from digsilent software and implement a composite load model in the work, the work also makes use of standard IEEE 39 bus for testing. A noble result was obtained by minimizing errors between measured data and simulated outputs. Saviozzi, Massucco, and Silvestro[11], concentrated on load prediction and load modeling with the aid of Artificial Neural Networks (ANNs) for the execution of advanced functionalities for Distribution Management System (DMS), field measurement was used to carry out the proposed work in which a reasonable agreement was established between measured and estimated model. Zheng *et al.*, [1] Proposed a Recurrent Neural Network (RNN) based approach with measured data in Active Distribution Network (ADN). The performance of the technique was assessed with detailed simulation in PSCAD and with Feed Forward Neural Network (FFNN). RNN is confirmed to outperform most of the techniques used for dynamic load modeling. Though, with a large change in Operating Condition (OC) much from the initial condition, it does not execute very well. Hence an effective searching for the OC is required for generalization. Sharafi and Jalili [9], Described identification of low-frequency dynamics based on PMU data. The model of the system was identified using a transfer function to extract the model from input-output data. In their studies, disturbance such as fault was not considered, only the slow changes caused by load connection and disconnection and Static Var Compensator (SVC) encompassed the system dynamics. In the work of Zhang et *al.*,[15] a composite model structure was considered in estimating electromagnetic and electromechanical parameters of an ambient signal. However, the approach cannot work for large disturbance, and when there is a vast nonlinearity in the system. Contrary to the preceding works, Han [8] present an unbalanced fault data for load modeling, the work formulates a composite load model with separate equations that represent each phase for three different fault conditions considered. The result of the work reduced prediction error for the load model parameters estimation drastically.

In this work, a composite load model for secondary distribution feeder using concurrent measurement data of PHA and FDR for development of load models based Voltage Dependency (VD) and Voltage-Frequency Dependency (V-FD) were formulated. This idea is targeting on the best model among the two models. FFNN as nonlinear estimation approach was used to trained and estimate the model with 4-layers and 40-neuron in each layer. The contribution of this work is a V-FD on active and reactive powers investigation. Contrary to the recent literature, frequency is assumed constant and therefore ignored. With the recent invention of new types of loads, the transformation of DN from passive to active, frequency dynamics need to be investigated very well. The remaining of the article is structured as follows: section 2 brought about problem formulation and a brief on FFNN. In section 3 case studies are presented. Results and discussion are provided in section 4 while conclusions are presented in section 5.

2. Voltage Frequency-Dependent Model

In white-box modeling, systems are modeled from first principles. This is possible if the system is not very complex in which the mathematical relationships can be easily extracted. For gray box modeling, some information about the systems is known only the unknowns are searched. While in the case of black-box modeling (data-driven Models), everything of the systems is unknown only the input-output data is required to extract the model [16]. These are the three ways a load model can be formulated.

2.1 Mathematical Representation

The main interest of this work is in estimating a composite load model that represents relationships between voltage and frequency as inputs and power (active and reactive) as outputs. The composite load model can be described as a mixture of static and dynamic models as presented in Fig. 1.

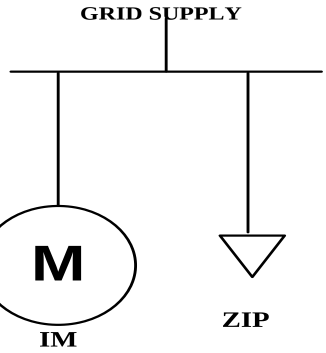


Fig. 1 - Composite load

The static part can be represented by constant impedance, constant current and constant Power (ZIP) model as follows:

$$P_s = P_n\left(\propto_z\left[\frac{V}{V_n}\right]^2 + \propto_i\left[\frac{V}{V_n}\right] + \propto_p\right) \quad (1)$$

$$Q_s = Q_n\left(\beta_z\left[\frac{V}{V_n}\right]^2 + \beta_i\left[\frac{V}{V_n}\right] + \beta_p\right) \quad (2)$$

where: P_s and Q_s are active and reactive powers of static model respectively. P_n *and* Q_n are active and reactive powers of the load at stipulated voltage V_n while V is a phase voltage. $\propto_z$,$\propto_i$, $\propto_p$, are quantities of ZIP components of the active power of the whole static load respectively. At the same time, β_z, β_i, β_p are quantities of ZIP components of reactive power of the entire static load respectively[8, 17].

Similarly, the dynamic part of the active and reactive P_m and Q_m can be represented by the equivalent d-q axes IM equations [8]:

$$P_m = v_{ds}i_{ds} + v_{qs}i_{qs} \quad (3)$$

$$Q_m = v_{qs}i_{ds} - v_{ds}i_{qs} \quad (4)$$

Then, the composite model will be

$$P_c = P_s + P_m \quad (5)$$

$$Q_c = Q_s + Q_m \quad (6)$$

Equations (5) and (6) represent the active and reactive component of the composite load model for voltage dependent model respectively.
The frequency dependency on the load can be derived by multiplying equation (5) and equation (6) with the frequency factor of equation (7).

$$f_{factor} = (1 + \propto \Delta f) \quad (7)$$

This yield equations (8) and (9) as composite load model representation

$$P_c = (P_n\left(\propto_z\left[\frac{V}{V_n}\right]^2 + \propto_i\left[\frac{V}{V_n}\right] + \propto_p\right) + [v_{ds}i_{ds} + v_{qs}i_{qs}])(1 + \propto \Delta f) \quad (8)$$

$$Q_c = (Q_n\left(\beta_z\left[\frac{V}{V_n}\right]^2 + \beta_i\left[\frac{V}{V_n}\right] + \beta_p\right) + [v_{qs}i_{ds} - v_{ds}i_{qs}])(1 + \propto \Delta f) \quad (9)$$

Where: Δf is a frequency deviation from nominal and $\propto$ is the sensitivity parameter of the frequency.
Generally, the process of load modeling is an optimization problem with the sole objective of minimizing the error between measured power, active and reactive ($P_{measured}$ and $Q_{measure}$), and the simulated (estimated) power, active and reactive (P_e *and* Q_e)[18]. In this case, the error measurement is evaluated by Mean Square Error (MSE) as given in equation (10).

$$MSE = \frac{\sum_{i=1}^{N}(error)^2}{N} \quad (10)$$

$$error = measured - simulated \quad (11)$$

where: N is the total sampled data. The whole process can be abridged as in Fig. 2.

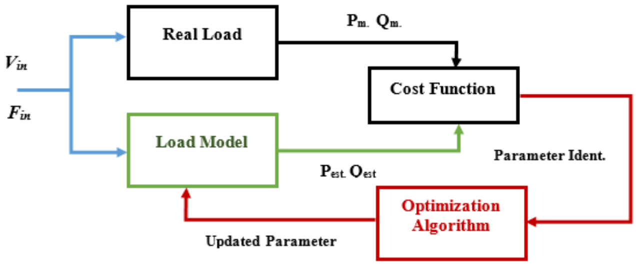


Fig. 2 - The procedure of load modeling and identification

Performance of the model can also be evaluated by measures of percentage fitness; this index can be expressed as:

$$\%fit = \frac{\sum(error)^2}{\sum(measured - average\ measured)^2} \quad (12)$$

2.2 Feed Forward Neural Network (FFNN)

Power systems are known to be dynamic and highly nonlinear, therefore, to capture its actual dynamics it has to be formulated in a nonlinear form. Although, the linearized system makes the model valid but only for small variations. Generally, Neural Networks (NNs) are brain-based imitation systems that are constructed on a mathematical model to process information [19]. NNs learn by experience from the fast information fed with and try to mimic how the human brain performs a particular task [20]. The model of FFNN happens to be a nonlinear network that maps from a group of the input variable(s) to a group of the output variable(s) structured by a vector W of modifiable parameters. Fig. 3 shows a basic FFNN configuration. FFNN knowledge acquisition is by calculating the error response of the NN for a given sample, transmitting the error back through the NN while adjusting the weight vectors trying to minimize the error. FFNN is known to be very great which qualifies them to handle a lot of complicated problems in a different area of applications [21]. FFNN describes a function as:

$$y = f(x, w) \quad (13)$$

This function studies the value of the vectors w that yield in the greatest function approximation. It has three layers: the input, middle also known as hidden and output layers. The middle layer may be of one layer (called Shallow network) or more than one number of layers (called deep networks). From Fig. 3 we can build N direct combinations of the input set $x_i \ldots x_D$ in form of:

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} . x_i + w_{jo}^{(1)} \quad (14)$$

Where $j = 1 \ldots N$ and the superscript (1) in Equation (14) indicates the matching parameters that are in the layer number one of the network. $w_{ji}^{(1)}$ and $w_{jo}^{(1)}$ are the weights and biases respectively. The quantity a_j is the activation, which can be transformed using a differentiable, nonlinear activation function. The nonlinear activation functions can either be sigmoid, logistic, rectified linear unit (ReLu), or tanh and many other functions[20].

A quantity z_j of equation (15) is known as a hidden unit and δ is the logistic sigmoid. Following equation (14) these values are again linearly combined to give output unit activations a_k of equation (16).

$$z_j = \delta(a_j) \quad (15)$$

$$a_k = \sum_{j=1}^{N} w_{kj}^{(2)} . z_j + w_{ko}^{(2)} \quad (16)$$

Where $k = 1, \ldots, K$, and K is the total number of outputs, $w_{kj}^{(2)}$ and $w_{K0}^{(2)}$ are the weights and biases. This transformation matches to layer number two of the network. Lastly, the output functions converted using a suitable triggering function to give a set of network outputs y_k as follows [22]:

$$y_k = \delta(a_k) \quad (17)$$

$$y_k(x, w) = \delta\left(\sum_{j=1}^{N} w_{1j}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(l)} . x + w_{jo}^{(l)}\right) + w_{K0}^{(2)}\right) \quad (18)$$

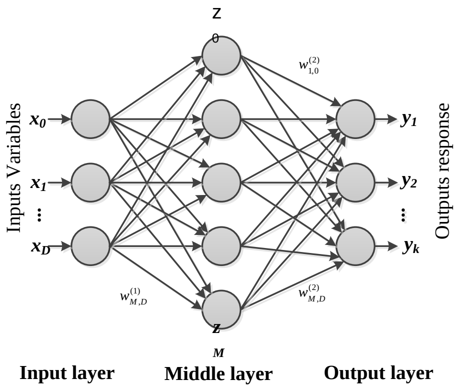


Fig. 3 - feed-forward neural network

3 Case Study

3.1 Actual System

Data from 0.415kV/ 50Hz line supplying our department was obtained using PHA to capture data of voltage magnitudes, active and reactive powers. For the inability of PHA in frequency measurements, we deployed FDR to give the corresponding frequency dynamics. Fig. 4 and Fig. 5 illustrate the Measurement setup. In the data selection, we try to choose an interval in which the frequency variation satisfied the requirement of the Nigerian Electricity Regulatory Commission (NERC) which is between 49.75Hz to 50.25Hz [23, 24]. The line was feeding some IMs, Incandescent Lamps (ILs) Compact Fluorescent Lamps (CFLs), Personal Computers (PCs) Air Conditioners (ACs), Heaters, etc.

Fig.4 - PHA measurements Setup

Fig.5 - FDR measurements setup

3.2 Test System

The proposed work was tested with data generated from 2-area 4- machine Kundur test system. The network is rated 60Hz. A composite load was connected to the load bus of area 2 (L2) and simulated to obtain different data of interest. Fig. 6 shows a single line drawing of the famous 2-area 4-machine test system.

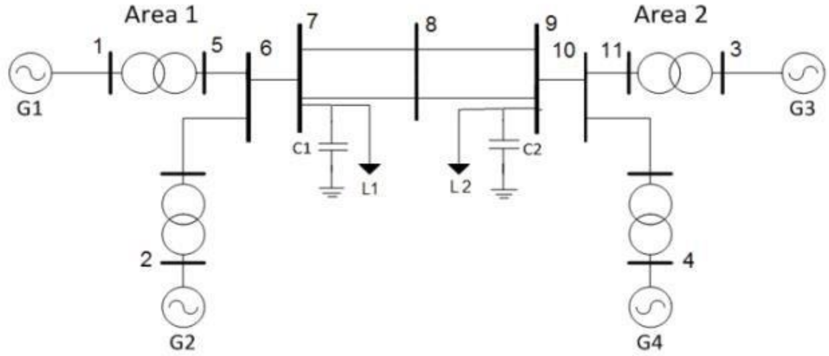


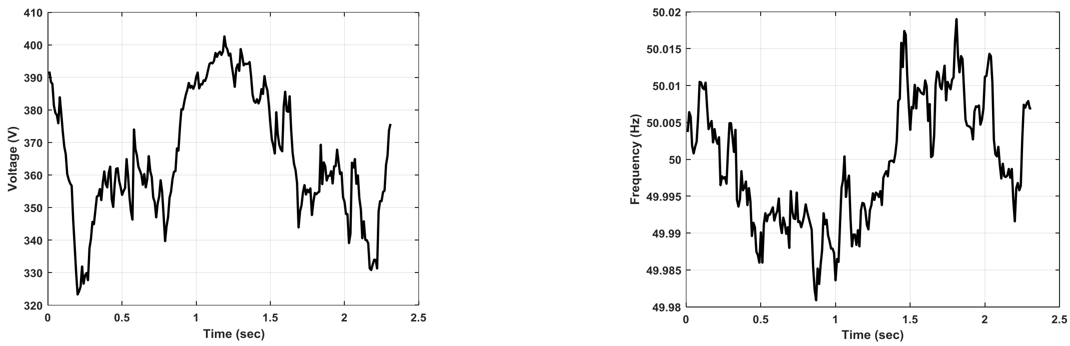
Fig. 6 - 2 –Area 4- Machine Kundur test system

4 Results and Discussions

Following data capturing and simulations studies carried out in Matlab (system identification and machine learning toolboxes), the following results were obtained:

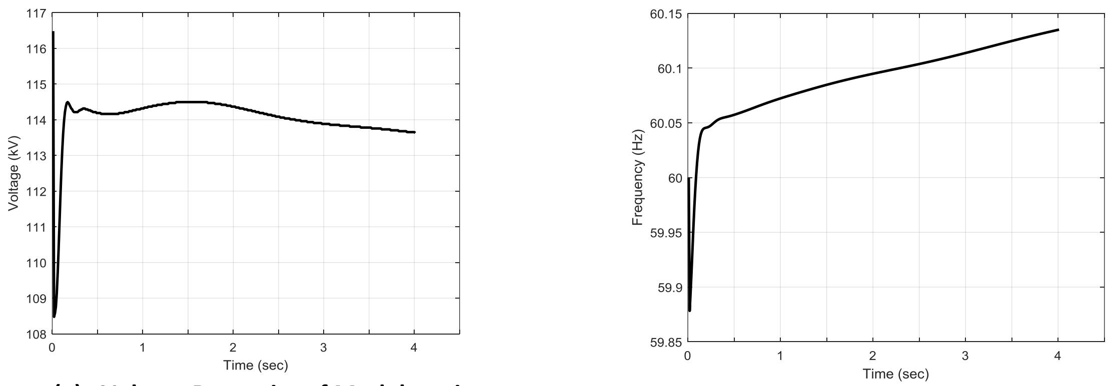
4.1 Measured Parameters

The measurements obtained indicate significant dynamics and nonlinearity between different parameters of interest, as seen in Fig. 7 (a) and (b). Input voltage dynamics and frequency dynamics of the training data respectively. While Fig. 8 (a) and (b) provides the input voltage and frequency dynamics of the testing set.



(a) Voltage dynamics of trained Model **(b) Frequency dynamic of the trained model**

Fig.7 - Input measurements used in model training

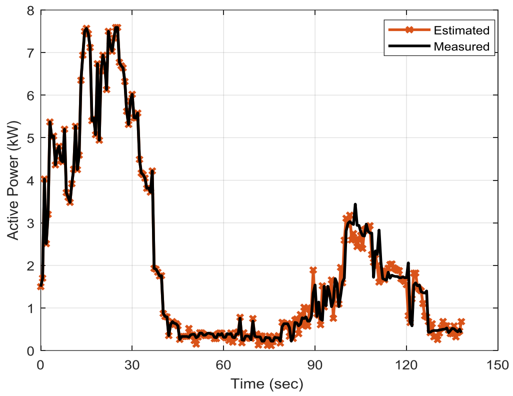


(a) Voltage Dynamics of Model testing **(b) Frequency Dynamic of Model testing**

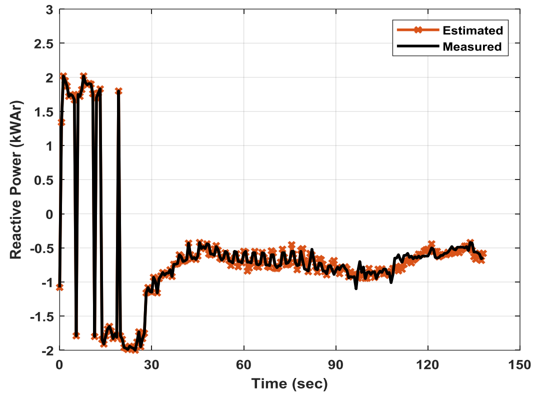
Fig.8 - Input measurements used in model testing

4.2 Training Results

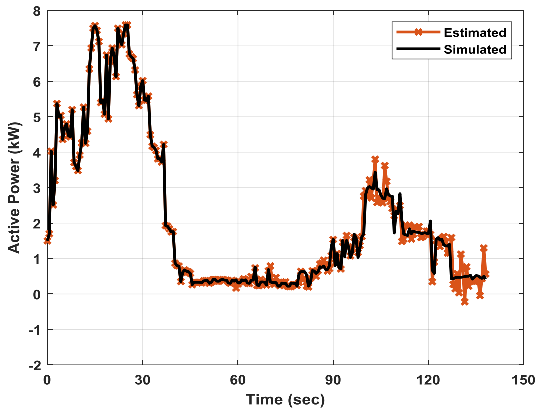
FFNN with 4- layers and 40 neurons in each layer was designed and trained using the Levenberg-Marquardt backpropagation algorithm. Fig.9 (a),(b),(c), and (d) shows how the model was able to follow the training data set. It can be observed from the figures as well as Table 1 and Table 2 that, VD model performs better in active power with 14.7% error reduction and 0.66% fitness improvement as compared with V-FD. While V-FD model performance was better in reactive power with 15.8% error reduction and 0.53% fitness improvement.



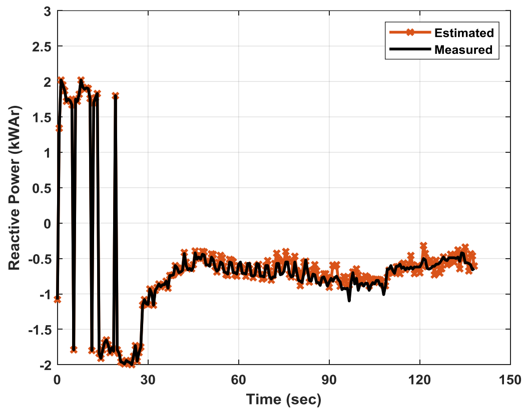
(a) Active power response VD model



(b) Reactive power response VD model



(c) Active power response V-FD model



(d) Reactive power response V-FD model

Fig. 9 - Active and reactive power responses of VD and V-FD models of training

Table 1 - Performance comparison of VD and V-FD models for the active power of training set

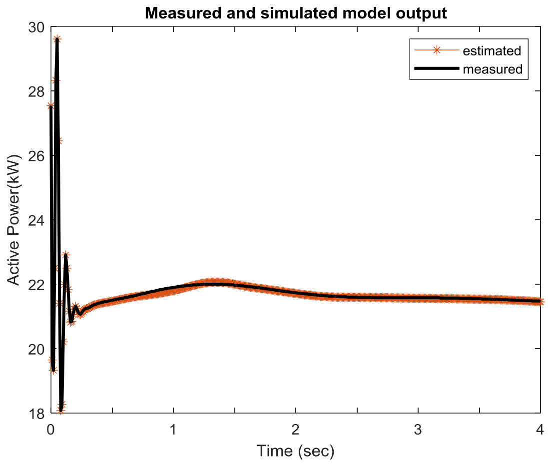
Model	MSE	% Fitness
VD	2.9×10^{-2}	92.1
V-FD	3.4×10^{-2}	91.5

Table 2 - Performance comparison of VD and V-FD models for reactive power of training set

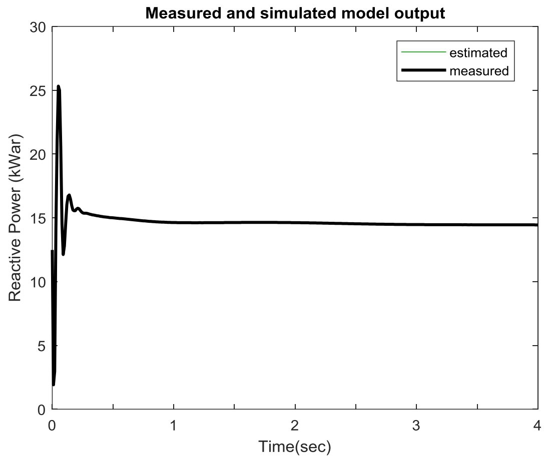
Model	MSE	% Fitness
VD	1.9×10^{-3}	94.8
V-FD	1.6×10^{-3}	95.3

4.3 Testing Results

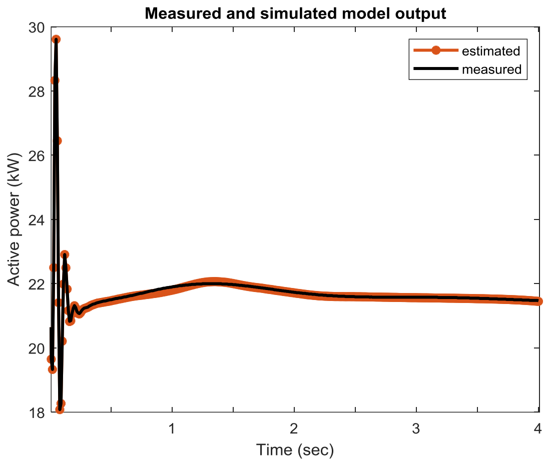
In an attempt to assess the validity of the trained model, new data generated from the 2-area 4 machine Kundur test network was presented to the model for testing. Fig. 10 (a), (b), (c) and (d) show the fitness of the models. Also, Table 3 and 4 provides a performance comparison of the testing data. It can be seen that the VD model is better than the V-FD model in the active power with a 15.4% error reduction and 0.2% fitness improvement. While reverse is the case for reactive power as the V-FD model wins the VD model with a 20% error reduction and 0.7% fitness improvement. The validity of the model was confirmed as the training data suggest the same with testing data.



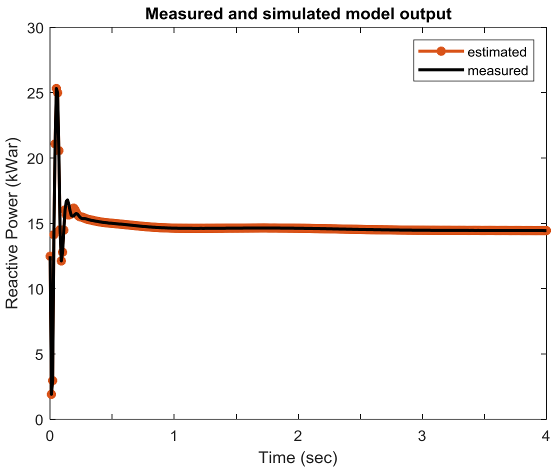
(a) Active power response VD model



(b) Reactive power response VD model



(c) Active power response V -FD model



(d) Reactive power response V-FD model

Fig. 10 - Active and reactive power responses of VD and V-FD testing models

Table 3 - Performance comparison of VD and V-FD models for the active power of the testing set

Model	MSE	% Fitness
VD	1.1 x10^{-5}	99.7
V-FD	1.3 x10^{-5}	99.5

Table 4 - Performance comparison of VD and V-FD models for reactive power of the testing set

Model	MSE	% Fitness
VD	2.0 x 10^{-5}	99.0
V-FD	1.6x10^{-5}	99.7

5 Conclusion

In this paper, power dependency on frequency dynamics was investigated. The results indicate that the VD model is better in active power formulation while the V-FD model is better in reactive power formulation. And therefore, the inclusion of frequency dynamics in load modeling depends on the intended application of the model. In the future, the performance of the models will be tested using other deep learning topologies and also, under different fault conditions for active distribution network. Additionally, frequency influence can also be checked under higher frequency dynamics.

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