A Deep-Learning Approach to Load Modeling in Modern Power Distribution System

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ABSTRACT: Modern Power Distribution Networks (MPDNs) are no longer passive, because Distributed Generations (DGs) are integrated in them to enhance system reliability and power quality. For this reason, load modeling has to be updated to capture the new dynamics of active DN. This paper presents a composite load modeling for a grid-connected photovoltaic (PV) distribution network using Levenberg-Marquardt algorithm in deep learning feed forward neural network approach. Load modeling is a process of constructing a relationship between input excitation(s) and its output response(s); it can be used for simulation studies, stability analysis, and or control/protection design. A grid-connected PV distribution network was model in Matlab/Simulink and generates data for training and model estimation. The estimated model was tested and validated using laboratory experimental test bed. Results of the model exhibit a good fitness of 99.8% and 97.2% in active and reactive power models respectively during training. While, 97.84% and 94.65% respectively were obtained during testing. The estimation error were found to be 0.0025 and 0.0049 for active and reactive powers respectively with 0.0473 and 0.0701 corresponding errors in models respectively during training. While, 97.84% and 94.65% respectively were obtained during testing. The estimation errors were found to be 0.0025 and 0.0049 for active and reactive powers respectively with 0.0473 and 0.0701 corresponding errors in testing.

Key words: Grid-connected PV, deep learning FFNN, Load modeling, composite load, Error minimization

1. INTRODUCTION

Load modeling and identification is a science of developing a mathematical relationship between load excitation (voltage/frequency) and load response (active and reactive power consumed) of a typical load Bus of interest [1]. Power systems consist of three different branches; Generators, lines, and loads. Diverse models of generators are searched with a high level of precision, likewise transmission lines, but due to varied nature of power system loads, time and different disturbances affecting distribution lines as well as innovation of new types of loads, Load Models (LMs) need to be search and formulated for more understanding and accuracy [2-4]. In power system stability studies, simulation, monitoring, control, and protection exact LMs are required. If the load model failed to represent the actual behavior of the loads the intended application of the model will certainly unperformed, thereby leading to unexpected behavior of the system[5-7]. There are two available approaches used in handling load modeling of a power system; component-based which requires a deep understanding of individual loads connected to a load Bus of interest, formulate and aggregate the models. The second approach is measurements based which make use of measurement sensor to extract data. The measurement-based is easier than the component-based because Distribution Networks (DNs) are now becoming more complex than ever before, so component-based will be difficult in such a situation. Additionally, advanced measurement devices are readily available nowadays. Loads can be classified as static, dynamic and a combination of the two (i.e. composite)[8, 9]. A static load is one with fixed characteristics such as lightings and resistive loads, they are normally represented by constant impedance, constant current, and constant power (ZIP). While a dynamic load has a varying characteristic, it is normally represented by Induction Motor (IM). The composite load model combines the two and it is often more realistic in DN representations. Details of these classifications can be obtained in [3]. In this paper, a composite load based measurement approach is chosen for the reasons outlined above. A search for the best NARX candidate to handle the nonlinearity and dynamic nature of loads in active DN was carried out with data generated from a model of a North American Distribution network connected with PV. In validating the work, a laboratory equivalent network was set up and obtains data which was used for validation. In recent works, Zhang, Lu [10] investigate load modeling accuracy based on an ambient signal generated by PMU, the authors realized that results of ambient signals-based load modeling are more sensitive to PMU data errors for the least disturbance issue of the signal. Measurements error of PMU data were acquired through experiments and the impact of those errors are analyzed on the load model. The results suggested that unintentional errors have more impact on the

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The precision of models. The work concludes that PMU measurements are capable of producing a good model. In the work of Massucco, Mosaico [11], a Markov chain technique was used to accurately established a load model, based on large data available with the recently advanced metering infrastructure. The fact that loads is dynamic and depends on-time duration of day and year a large data can
give more information on the load dynamics which recent
literature did not address. A clustering technique was applied
to the data and later load models were developed. The results
of the model were validated through experiment and comparison
with dynamical Clustering and k-Means to ascertain the accuracy
and computational time. Alahmed and Almuhaini [12],
presents results of a residential load composition based on the
top to down and bottom to up
approaches of a case study of SCADA system of the eastern
province in Saudi Arabian Power Company. Details of the
residential load data were captured for the whole year and
consumptions based summer and winter periods were
analyzed for hourly and daily periods. The objective of this
paper is to model Grid-PV and develop a Load model based
Grid-PV as the DN are transforming from passive to active
so the load modeling needs to follow the trend. In addition,
a practical setup was made to authenticate the model
accuracy. This paper is organized as follows: section two
brought step-by-step methods followed in actualizing the
aim of the paper; in section three results and discussion are
provided while conclusions are drawn in section four.

2. METHODOLOGY

To achieve the aim of this work, a step by step process
was carried out as indicated in figure 1. Load modeling
follows a sequence of experimental design and measurements,
model selection, model estimation, and model validation. The process is iterative in the sense that
several training/estimation, model selection, and even data
regeneration had to be done to have a generalized acceptable
model of interest. Figure 1 indicates a flowchart used for
the load model.

a. Experimental Design and Data Collection

Model of grid distribution network with 50kW solar-based
DG incorporated was developed in MATLAB/Simulink. The grid includes two 25-kV feeders, loads, a
grounding transformer, and an equivalent 10-kV distribution
system. To transform the load bus to composite, an
induction motor, and static load were connected in parallel
in addition to a DG connected to the bus. By doing so, the
DN is transformed from passive to active and from static
load to a composite load. The Simulink model can be seen in
Figure 2. Voltage disturbance was created and cleared
during the simulation, and samples of 1000 measurements
were generated from the Simulink model within 10-step
time window at a sampling time of 0.01 sec. The data were
stored in excel files ready for model selection and training.

b. Model Selection

In model selection, emphasis is given to which
algorithm/model structure will give an accurate result based
on the data presented to the network. In a nonlinear
situation, the choice is directed by behavior and structural
aspect of the system[13]. Since power systems loads are
known to be nonlinear and our focus in this paper is on
active distribution network operating under disturbance
conditions, deep learning NN based on Feed Forward
(FFNN) was selected. NN is a brain-based mathematical
model that learns from experience rather than programming.
It is very capable of mapping the nonlinear relationship
between input and output of a classic DN.

c. Model Estimation

With input-output data at hand, the target is to estimate a
model of the load $P_m$ and $Q_m$ that describes the actual output
more closely. In this case, the measured input is voltage
magnitude $V_m$ and the outputs are real power $P_m$
and reactive power $Q_m$. The objective functions are:
The accuracy of the estimation is measured by percentage fitness and error minimization of the model. Equations (3) and (4) described the measure of error that is targeted to be zero.

\[
J_{min} = \frac{1}{N} \sum (P_m - P_e(\theta))^2
\]  

(1)

\[
J_{min} = \frac{1}{N} \sum (Q_m - Q_e(\theta))^2
\]  

(2)

The performance of the model can also be evaluated by measures of percentage fitness. This index can be express as:

\[
MSE = \frac{\sum_{i=1}^{N}(error)^2}{N}
\]  

(3)

\[
error = measured - estimated
\]  

(4)

The unknown relationship between the input and the output of equations (6) and equation (7) can be derived from the system response. A difficulty of estimation/training is in obtaining the correct regressors, algorithm, neurons, delays, layers, and type of network configuration in case of deep learning NN modeling. FFNN was designed with five layers of 40 neurons in each layer, train, and estimated using the Levenberg-Marquardt algorithm. This was achieved through training/retraining and searching until an acceptable error is obtained.

\[
P = f(V)
\]  

(6)

\[
Q = f(V)
\]  

(7)

where: P and Q are active and reactive powers consume by the load as a result of a dynamic input voltage (V).

d. Model Validation

The acceptability of a model depends on how well the model is when presented a different data of equivalent dynamics. The work was validated through the experimental setup using gadgets of Elettronica Vaneta (Power simulator) synchronized with 15kW PV supply to form an equivalent Grid-connected PV (Active DN) as illustrated in Figures 3 and 4.
In this case, the synchronous generator serves as the grid supply while the white cable in figure 4 is the PV supply to the synchronization panel. A composite load consisting of Resistive, inductive, and an induction motor was connected to the output of the panel and applied different load switching to emulate a real DN. Data were generated, retrieved and presented to the deep FFNN for testing/validation.

3. RESULTS AND DISCUSSIONS

Performance of the proposed FFNN based load model for representing the dynamic behaviors of Grid-connected PV distribution network is presented and evaluated using simulated data and experimental data.

a. Result of the Training

The voltage dynamic obtained from simulation is depicted in Figure 5; it was used as input in training the model. It can be seen that voltage disturbance happens at 0.5 sec and recovered at 1sec, leading to a corresponding response in the active and reactive powers of the system as indicated in figures 6 and 7. After recovery, the system continues to fluctuate up to the 10 seconds of the recording. These dynamics are due to the natural fluctuation of the system.

![Fig. 5. Voltage Dynamics of Grid-connected PV for Training](image)

![Fig. 6. Active Power Response for grid-connected PV for Training](image)

It can be observed that the trained model has fitted the measured values very closely in both Active and reactive powers response. This is an indication that good learning has been achieved by the FFNN model. Table 1 summarized the numerical performance of the training in terms of MSE and % fitness. From the table, it is clear that the active power response is more accurate than the reactive power by 2.61% fitness and 48.98% error reduction. This is because the non-linearity between the input and output power is more in the reactive data than that of active. This indicates that, the voltage dependency on real power is clearer. The active power is seen to be greater than the reactive, this is solidly depends on the nature of the load connected to the system.

Table 1

| Power       | MSE    | Fitness (%) |
|-------------|--------|-------------|
| Active Power| 0.0025 | 99.8        |
| Reactive Power| 0.0049 | 97.2        |

b. Results of Testing/Validation

To verify the good performance of the trained model a new data based on the experimental setup was presented to the trained model and performance responses were given in figures 8, 9, and 10. The dynamics of the data, in this case, change faster than that of the Simulink data generated, and therefore the accuracy is less. However, good and acceptable results were obtained as seen in Table 2.

Table 2

| Power       | MSE    | Fitness (%) |
|-------------|--------|-------------|
| Active Power| 0.0473 | 97.84       |
| Reactive Power| 0.0701 | 94.65       |
4. CONCLUSIONS

The contribution of this work lays on the development of Model considering penetration of grid-PV DNs. The work, focus on composite load modeling using deep learning approach for a grid-connected PV distribution network. Modern distribution networks are said to be active rather than passive, such that DGs are connected to them for power quality enhancement. The model developed exhibits a very good performance as the mean squared errors are very close to zeros. In testing the performance of the model, the mean squared errors obtained are higher than those obtained in training indicating that the experimental data dynamics and nonlinearity are also higher. In both training and testing, the active power model performs better than the reactive power model. This shows that the voltage dependency is more on the active power component of the load. To this extent, it can be said that the Grid-connected PV load model based on deep FFNN has been developed, tested, and validated.

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