# EM–SS-Wavelets for Characterization of High-Speed Generators in Distributed Generation

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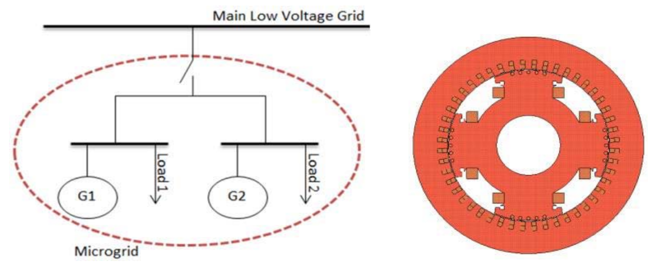
**An electromagnetic–state space–wavelet neural network modeling environment is presented and used for the characterization of high-speed synchronous generators during out-of-phase operation in distributed generation (DG) of a microgrid. This mode of operation may result in stresses in the network or the failure of the high-speed generators. The approach is validated, by comparing simulation results with test data, and its effectiveness is established in terms of accuracy and fast response. In addition, it is demonstrated in a case study involving two DG units in a microgrid that the stresses and damages are minimized in an out-of-phase DG unit when connected to the grid through an inverter.**

***Index Terms*— Finite-element (FE) analysis, high-speed generators, microgrid, state space (SS) models, wavelet neural networks (WNNs).**

## I. INTRODUCTION

DISTRIBUTED generation (DG) is the employment of relatively small-scale power generating devices, which may or may not operate on renewable resources, to produce electricity close to the end users. In DG networks (Fig. 1) the addition of an out-of-phase generator during islanding mode could disturb the system and result in high currents in the machine windings and high transients in the microgrid load system [1]. Accurate determination of system voltage and current values is very important for the design of protection systems and high-speed generators used in this mode of operation. Although electromagnetic–state space (EM–SS) modules are very accurate, it requires extensive computational time [2]. Accordingly, a wavelet neural network (WNN) is proposed and used, due to its fast and accurate response, with an EM–SS module. The WNN is trained offline using nonlinear finite-element (FE)-based EM–SS solutions. The importance of the proposed approach is that it models both ac and dc (electronic converters) loads and it captures the effects of space harmonics due to machine complex geometry, magnetic saturation due to material nonlinearities, and time harmonics due to load switching electronics. This EM–SS–WNN technique showed both accurate results and very fast responses. Accordingly, the modeling environment presented in this paper could be the basis of a framework for the online characterization of large smart grids during fault conditions.




(a) (b)

Fig. 1. (a) Microgrid. (b) 90 kVA high-speed generator.

## II. MODELING APPROACH

The EM–SS–WNN modeling environment presented in this paper consists of two modules. The first utilizes an indirectly coupled EM–SS approach used to accurately predict the performance characteristics of high-speed synchronous generators in microgrids (Fig. 1) and to generate database needed to train the second module, made up of WNN. The first module is outlined in Fig. 2, where offline generated FE magnetic field solutions are used to compute the high-speed ac generators winding inductance family of curves, function of load,

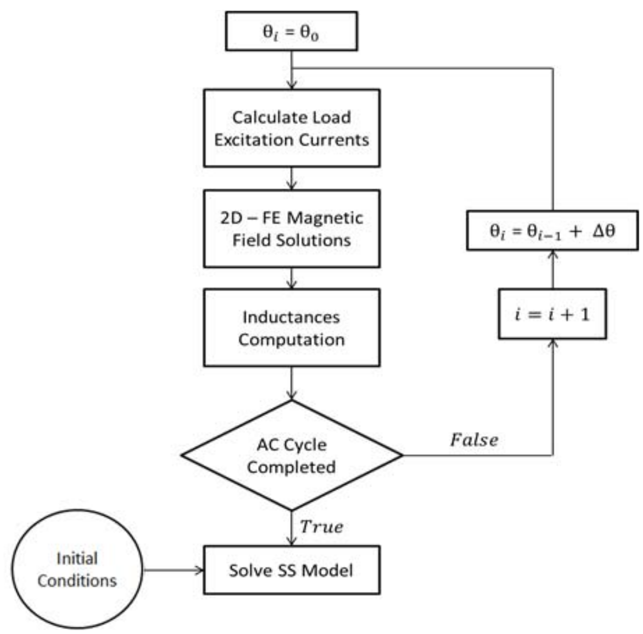



Fig. 2. Flowchart of the EM–SS module.

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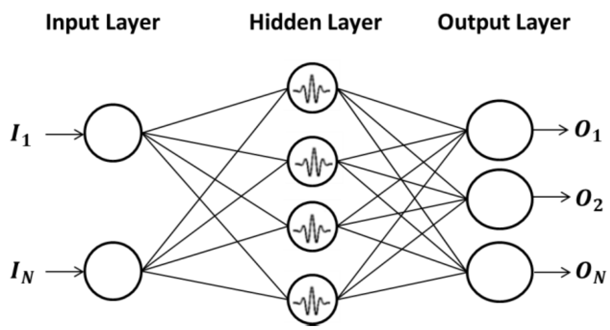


Fig. 3. WNN structure.

and rotor position [3]. This process is iterative and is repeated to cover a full ac cycle of each load condition under consideration. It is to be noted that the rotor step movements are chosen such that the rotor $d$-axis moves alternatively between a stator middle of a slot and middle of a tooth positions to account for slotting effects. The computed family of curves is integrated into the SS model of an N-generator microgrid (1), where $i$ denotes generator $i$, $s$ and $r$ denote stator and rotor quantities, respectively, $V$ denotes its voltage vector, $I$ denotes its current vector, and $R$ and $L$ matrices denote its resistances and inductances, respectively.

Accordingly, (1) is used to accurately predict the performance characteristics of a microgrid and to generate database needed to train the second module, made up of WNN. The WNN used in this paper is made of one hidden layer feedforward neural network

$$
\begin{aligned}
\begin{bmatrix} V^1 \\ V^2 \\ \vdots \\ V^n \end{bmatrix}
&= \begin{bmatrix}
(R_{ss}^1 + R_{eq}) & 0 & R_{eq} & 0 & \dots & R_{eq} & 0 \\
0 & R_{rr}^1 & 0 & 0 & \dots & 0 & 0 \\
R_{eq} & 0 & (R_{ss}^2 + R_{eq}) & 0 & \dots & R_{eq} & 0 \\
0 & 0 & 0 & R_{rr}^2 & \dots & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
R_{eq} & 0 & R_{eq} & 0 & \dots & (R_{ss}^n + R_{eq}) & 0 \\
0 & 0 & 0 & 0 & \dots & 0 & R_{rr}^n
\end{bmatrix}
\begin{bmatrix} I^1 \\ I^2 \\ \vdots \\ I^n \end{bmatrix} \\
&+ \frac{d}{dt}\left\{\begin{bmatrix}
(L_{ss}^1 + L_{eq}) & L_{sr}^1 & L_{eq} & 0 & \dots & L_{eq} & 0 \\
L_{rs}^1 & L_{rr}^1 & 0 & 0 & \dots & 0 & 0 \\
L_{eq} & 0 & (L_{ss}^2 + L_{eq}) & L_{sr}^2 & \dots & L_{eq} & 0 \\
0 & 0 & L_{rs}^2 & L_{rr}^2 & \dots & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \ddots & 0 & \vdots \\
L_{eq} & 0 & L_{eq} & 0 & \dots & (L_{ss}^n + L_{eq}) & L_{sr}^n \\
0 & 0 & 0 & 0 & \dots & L_{rs}^n & L_{rr}^n
\end{bmatrix}
\begin{bmatrix} I^1 \\ I^2 \\ \vdots \\ I^n \end{bmatrix}\right\}
\end{aligned} \tag{1}
$$

as shown in Fig. 3, with an activation function drawn from an orthonormal wavelet family [4].

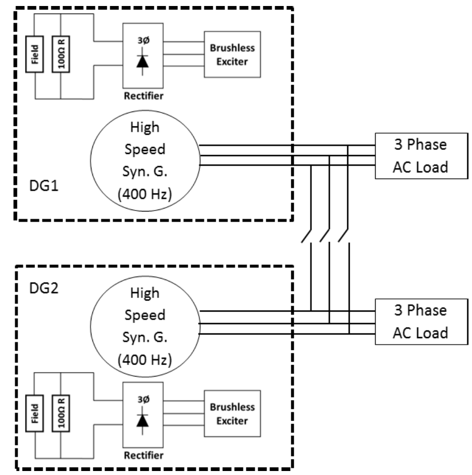


Fig. 4. Block diagram of microgrid.

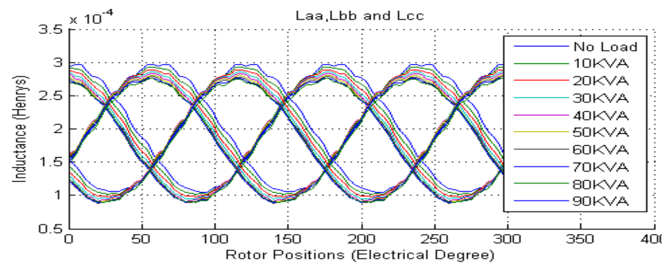


Fig. 5. Generator inductance family of curves.

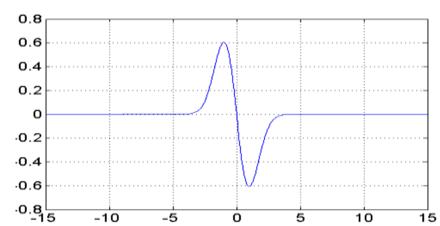

Fig. 6. Gaussian derivative wavelet function.

## III. EM–SS–WNN Experimental Verification

The approach is validated by comparing the simulation results with the test data of two out-of-phase generators in an islanding mode. This was caused by a fault condition that resulted in a phase shift $\alpha$ between the terminal voltages of the two generators. The EM–SS approach of Fig. 2 is used to model the paralleling of the two identical out-of-phase DG units in the microgrid of Fig. 4. The units are three-phase, 400 Hz, 208 V, 4-pole, and 90 kVA high-speed synchronous generators feeding 10 kVA ac loads. The application of the approach resulted in the inductance family of curves of Fig. 5. The application of the EM–SS module (Fig. 2) resulted in the current waveforms of the two generators, which are used to train the WNN. The WNN constructed to model the system consists of 12 networks connected in parallel. The Gaussian derivative function given is (2) and shown in Fig. 6 was used as the activation function of the hidden layer neurons of the WNN

$$\psi(u) = -ue^{-\frac{u^2}{2}}. \tag{2}$$

In contrast to traditional neural networks, which involve only weights and biases of neurons, the wavelet networks also

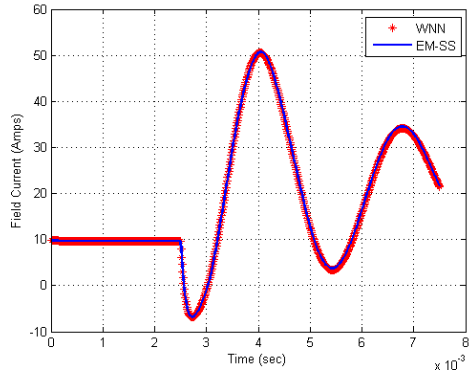


Fig. 7. Field current of DG2—from EM–SS and WNN for $\alpha = 60°$.

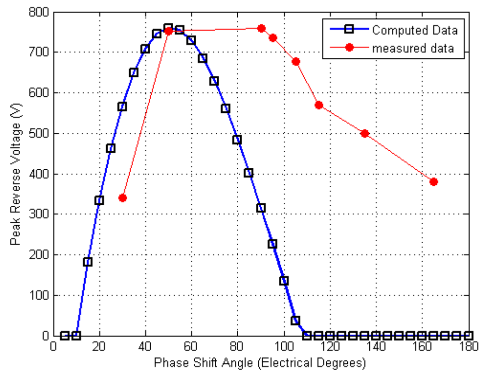


Fig. 8. DG2 reverse field peak voltage versus phase shift angle $\alpha$.

involve translation and dilation factors. That is, in order to match the type of the signal analyzed, a specific wavelet can be created by dilating and transforming the mother wavelet. This gives an advantage for WNN, as part of their training procedure involves training the WNN using different dilation factors and selecting appropriate ones based on the best performance of the network. In this paper, the WNN has two inputs: the phase shift angle $\alpha$ between DG1 and DG2 phase voltage waveforms and the instantaneous time of simulation. The WNN outputs are the 12 currents of DG1 and DG2 in Fig. 4: the three-stator phases, the field, and the two-rotor damper bar currents, per generator. It is noted that the gradient descent with momentum and adaptive learning rate backpropagation is used to update the weights and biases of the WNN. After setting up the training data offline, the WNN required 2.36 s of training using MATLAB traingdx function in the neural network toolbox. The field current of DG2 is given in Fig. 7 and shows the excellent agreement between EM–SS and WNN results. In addition, Fig. 7 shows a reversal of the field current (negative values) due to the out-of-phase or asynchronous operation that produced reverse voltage at the terminals of the generator brushless exciter (Fig. 4).

Next, in order to study the effects of the out-of-phase operation, the analysis was repeated for a range of phase shift angles, $\alpha = [0°–180°]$ in increments of 5°. Values of simulated peak reverse field voltages versus angle $\alpha$ are given, in Fig. 8, along with measured data. The excellent agreement of the maximum peak reverse voltage value is demonstrated in Table I for $\alpha = 60°$. However, as shown in Fig. 8, some simulation and measured peak reverse values are occurring at

TABLE I
GENERATOR #2 PEAK REVERSE FIELD VOLTAGES

| DG2 | Computed | Measured | Difference |
|---|---|---|---|
| Phase Shift $\alpha = 60^0$ | 720 V | 740 V | 2.7% |

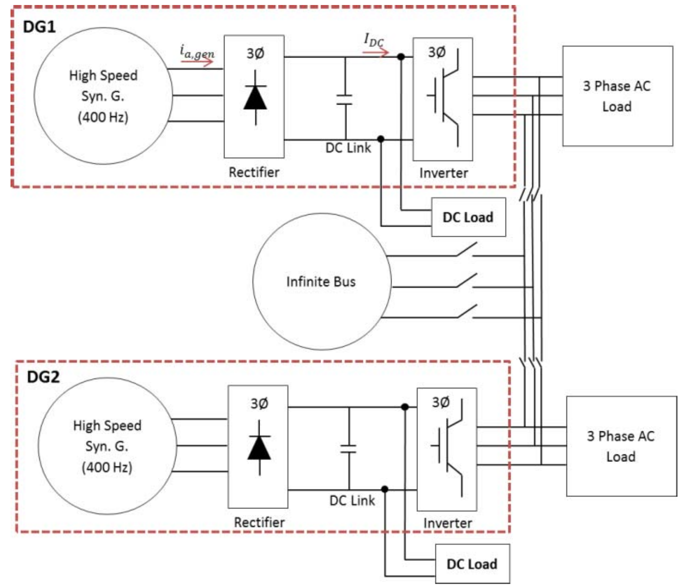


Fig. 9. Block diagram of microgrid–infinite bus system.

different phase angles, $\alpha$. It is the case as the FE–SS model uses inductances obtained for 10 kVA load condition. The method can be further improved if one updates the inductance values at each time step based on the instantaneous values of the machine currents. In spite of that, the results demonstrate the validity of the proposed EM–SS–WNN approach in predicting maximum peak reverse field peak voltage, which could cause the failure of the brushless exciter rectifier bridge diodes, if not properly sized.

## IV. CASE STUDY OF MICROGRID ISLANDING MODE

Most of the faults on a utility network are temporary. Therefore, the automatic reclosing provides significant advantages in terms of reduced outage time and reduced operational costs [5]. However, after certain faults, such as a line-to-ground fault, and during the auto-reclose open time, the microgrid operates in an islanding mode and a DG unit can accelerate or decelerate, so that reclosure occurs when the utility and the DG terminal voltages are out-of-phase. Such a situation can cause serious damage to the generating units and other equipments connected to the network due to overvoltages and currents, and significant mechanical torques on DG units' shafts. In this paper, the effectiveness of the EM–SS–WNN approach is shown as it is used to demonstrate that the stresses and damage to a DG unit can be reduced if connected to the grid through an inverter during an out-of-phase reclosure of a microgrid [6], [7].

Consider the microgrid in Fig. 9, where the two high-speed synchronous generators DG1 and DG2 are feeding combined 10 kVA ac and dc loads through an assembly of electronic converters. The EM–SS approach was applied and resulted in the performance characteristics of the system, which are used to train a WNN. The model simulated a

TABLE II

BRUSHLESS EXCITER MAXIMUM PEAK REVERSE FIELD VOLTAGES

| DG2 | Without Inverter | With Inverter |
|---|---|---|
| Reverse Voltage | 760 V | 0 V |

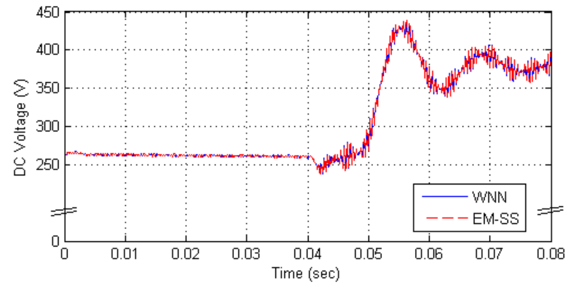


Fig. 10. DC link voltage of DG1 for $\alpha = 130°$.

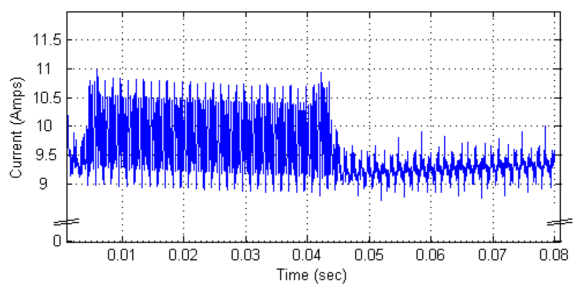


Fig. 11. Field current of DG1.

scenario, where the microgrid is in an islanding mode at $t = 0$ s, and auto-reclosure commences at $t = 0.04$ s. The WNN constructed to model the system has the instantaneous simulation time and the phase shift angle $\alpha$, between the microgrid and infinite bus phase voltages, as inputs and produces the dc link voltages as outputs. The dc link voltage of DG #1 (Fig. 10) shows the excellent agreement of results as obtained from EM–SS and WNN. The high voltage values after $t = 0.04$ s are due to negative reverse currents flowing back into the DG system after the commencement of the out-of-phase operation of the microgrid. The maximum peak reverse voltage of the DG unit brushless exciter is given in Table II. As shown, no reverse voltage exists when the DG unit is connected through an inverter. However, in this case and as shown in Fig. 10, high voltage values exist at the terminals of the dc link that could cause the failure of the inverter's flyback diodes, if not properly protected. In this paper, a control scheme is implemented, where the DG unit is isolated, once a dc link voltage exceeds a preset value [6], [7]. This is clearly shown in Fig. 11 where the DG1 field current value increases at $t = 0.4$ s due to the out-of-phase auto-reclosure of the microgrid. Next, it drops back to the no-load value operating condition following the commencement of the protection scheme that isolates the generator. Accordingly, it is demonstrated that the proposed EM–SS–WNN modeling approach can be used effectively to characterize the microgrids and to study the effects of stresses on DG units.

In addition, the effectiveness of the proposed EM–SS–WNN approach in terms of its fast response is demonstrated,

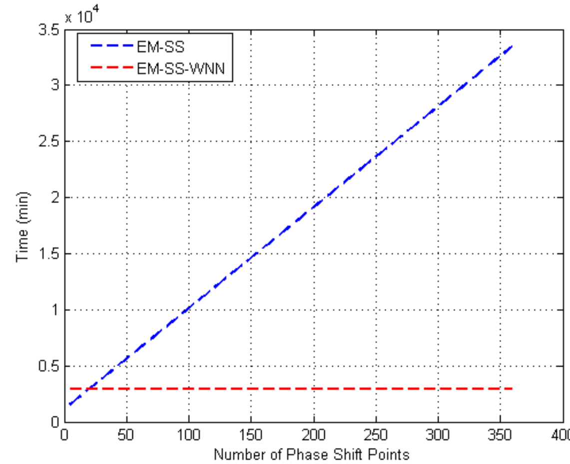


Fig. 12. Time comparison between EM–SS and EM–SS–WNN.

in Fig. 12, by comparing computational time needed to characterize the microgrid of Fig. 9 using EM–SS with and without the WNN module. In this case, the WNN training required 3.53 s. As can be appreciated, from Fig. 12, the use of WNN can result in up to 90% reduction in computational time.

## V. CONCLUSION

An EM–SS–WNN modeling approach was presented and used for the characterization of high-speed synchronous generators feeding ac and dc loads during islanding and out-of-phase operation in the microgrids. The approach is based on the use of offline nonlinear FE field solutions and was validated, by comparing the simulation results with test data. In addition, the effectiveness of the approach was established in terms of accuracy and fast response. It was also verified in a case study that stresses and subsequent damage to a DG unit can be reduced if connected to the grid through an inverter during an out-of-phase reclosure of a microgrid. Accordingly, it was demonstrated that the proposed modeling environment could form the basis of a framework for online characterization of DG in large smart grids during normal and fault operating conditions.

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