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

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An Electromagnetic-State Space-Wavelet Neural Network, EM-SS-WNN, modeling environment is presented and used for characterization of high-speed synchronous generators during out of phase operation in Microgrids. 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 to test data, in a case study involving two out of phase high-speed generators. In addition, the effectiveness of the EM-SS-WNN approach is demonstrated in terms of accuracy and fast response.

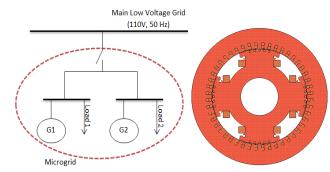
Index Terms-Wavelet Neural Networks, Finite Element Analysis, State Space Models, Microgrid High Speed Generators.

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, 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 EM-SS modules are very accurate, it requires extensive computational time [2]. Accordingly, a WNN is proposed and used with an EM-SS module due to its fast and accurate response. The WNN is trained offline using nonlinear Finite Element based EM-SS solutions. The importance of this technique is that 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 work could be the basis of a framework for online characterization of large smart grids during fault conditions.

II. THE MODELING APPROACH

The EM–SS–WNN modeling environment presented is this work consists of two modules. The first utilizes an indirectly coupled EM-SS approach used to model high-speed synchronous generators in Microgrids, as feeding AC and DC loads, Fig. 1. The module is outlined in Fig. 2, where offline FE magnetic field solutions are used to compute the generators inductance family of curves, function of load and rotor position, Fig. 3. These family of curves are integrated into the state space model of an N-generator Microgrid, equation (1), where, *i* denotes generator *i*, V represents its voltage vector, I represents its current vector, and R and L are matrices representing its resistances and inductances, respectively. In addition, *s* and *r* denote stator and rotor quantities. Accordingly, equation (1) is used to accurately predict the performance characteristics of a Microgrid and to generate a database needed to train the second module, made up of a Wavelet Neural Network (WNN). The WNN used in this work is made of one hidden layer feedforward neural network, Fig. 4, with an activation function drawn from an orthonormal wavelet family [3].





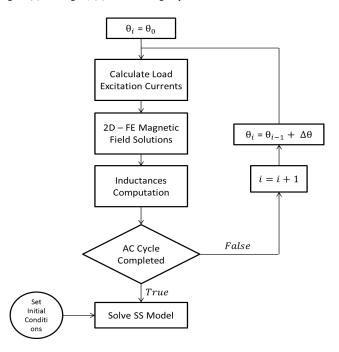


Fig. 2. Flowchart of the EM-SS Module

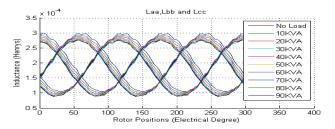


Fig. 3. Generator Inductance Family of Curves

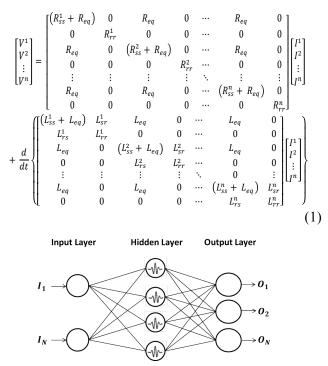


Fig. 4. The WNN Structure

III. APPLICATION AND RESULTS

The developed EM-SS-WNN approach is used to model the Microgrid of Fig. 1 during islanding mode. This is resulted from a fault causing a phase shift α between the terminal voltages of the two generators. The approach is validated, by comparing simulation results to test data in a case study of two identical 3-phase, 400Hz, 208V, 4-pole, 90kVA high-speed synchronous generators paralleled while out of phase and feeding 10kVA loads, Fig. 1. The WNN constructed to model the system consists of 12 networks connected in parallel. The inputs to these networks are the phase shift angle α and the instantaneous time of simulation. The outputs are the 12 currents of the two generators, G1 and G2 of Fig. 1: six phase, two field, and four damper bars currents. The field current of Gen #2, Fig. 5, shows the agreement of results as obtained from the EM-SS module and from WNN. The negative current due to out of phase operation produces a reverse voltage at the terminals of the generator brushless exciter. The results of peak reverse field voltage vs. phase shift angle α are given in Fig. 6 and Table 1 along with measured data. These values, which demonstrate the accuracy of the WNN, are important for sizing the excitation system diodes and generator's protection system. Furthermore, the fast response of the

proposed approach is demonstrated in Fig. 7 by comparing computational time needed to characterize the Microgrid using the EM–SS module with and without WNN. As shown in Fig. 7, the use of WNN resulted in 90% reduction in computational time. As such, 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.

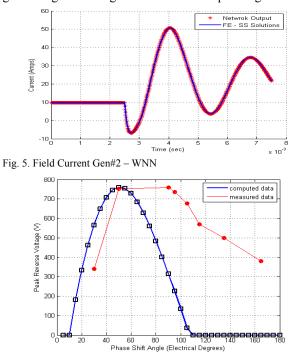


Fig. 6. Gen. #2 Reverse Field Peak Voltage

	TABLE 1			
GENERATOR #2 PEAK REVE			E FIELD VOLTAGES	
	60° Phase Shift	Computed	Measured	
	Reverse Voltage	720 V	740 V	

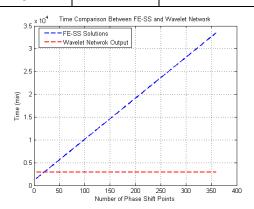


Fig. 7. Time Comparison between EM-SS and EM-SS-WNN

IV. REFERENCES

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