Artificial Neural Network Based Duty Cycle Estimation for Maximum Power Point Tracking in Photovoltaic Systems

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***Abstract*— According to a nonlinear current-voltage characteristic of Photovoltaics (PV) we need to track maximum power output of PV generation units instantly. The aim of this paper is to introduce a non-complicated method for tracking the maximum Power Point without any previous knowledge of the physical parameters linked with a Grid-Connected photovoltaic (PV) system using artificial neural networks (ANN) modelling. The ANN is trained in various conditions of PV Output Voltage and PV Output Current to forecast the Duty Cycle of DC-DC boost converter as the MPPT device. The proposed technique is implemented in Matlab/Simulink and compared with the conventional method of incremental conductance. Simulation results show a good performance of the ANN based MPPT controller. MPPT techniques that properly detect the global MPP has been widely investigated in the literature. They include hill climbing (HC), incremental conductance (IncCond), perturb-and-observe (P&O), and fuzzy logic controller (FLC). As the best of our knowledge estimation of the duty cycle of the DC-DC boost converter by Artificial Neural Network and using it in place of the whole MPPT controller and using Voltage and current has not been done so far in the literature.**

Keywords—Photovoltaic (PV); MPPT; Artificial Neural Network; Duty Cycle; DC-DC Boost Converter

I. Introduction

RENEWABLE energy sources of energy, e.g. photovoltaic (PV), play an important role in electric power generation, and are becoming essential nowadays as a result of inaccessibility and environmental influences of fossil fuels. In a very close future, more than 45 percent of necessary energy in the world will be produced by PV arrays [1-2]. On the other hand, one of the biggest obstacles towards the high-volume growth of solar electricity is low-energy conversion efficiency of PV panels [3-5]. Furthermore, the nonlinear current - voltage (I-V) and Power-voltage (P-V) characteristics of Photovoltaic systems makes their output power always varying with weather conditions, i.e., solar radiation, atmospheric temperature and also the load connected [6, 7]. So as to keep effective procedure of producing energy, a Maximum Power Point Tracking (MPPT) system which has rapid reaction and can exploit the largest power from the PV arrays becomes vital. By means of MPPT the cost of energy generated by PV panels is reduced [8]. Plenty of methods have been using artificial intelligence techniques for MPPT of PV systems in recent years [9-10]. The usefulness of Neuro-fuzzy structures for the MPPT control and the forecast of maximum power generation of PV systems in partly shaded situations was discussed in [12]. A joint radial-basis-functions (RBF) and backprop network, which used the solar irradiance as Input signal to estimate the effects of random cloud movement on the electrical parameters of the MPPT and the variables of the inverter was proposed by Giraud and Salameh in [13].

Similarly, tracking the maximum power by implementing microcomputer with a lookup table was suggested in [14]. There are some additional widely used methods like incremental conductance method (IncCond) [15] and the hill climbing method (HC). These techniques are widely applied in the MPPT controllers because of their clarity and easy application. However, to the best of our knowledge estimation of the duty cycle of the DC-DC boost converter by Artificial Neural Network and using it in place of the whole MPPT controller and using Voltage and current has not been done so far in the literature. The objective of this study is to bridge this gap. In this work, the attention will be focused on simulation assessment study between Incremental Conductance Technique and ANN, considering the panel output current and voltage variation in order to better performance in actual changing irradiance conditions.

II. Configuration of the Proposed System

The formation of the proposed system consists of the PV array, Artificial Neural Network MPPT, DC-DC boost converter and 3level bridge inverter as shown in Fig. 1.

Solar irradiance (E) in W/m2 and the cell temperature (Tc) in degree Celsius are the inputs for the PV array, where the actual voltage and current expressed in V_{dc} and I_{dc}. The coordinates of the city of Miami in the USA were used in HOMER[1] Software, 25°78 N latitude and 80°22 W longitude, to obtain hourly solar radiation values. Hourly average values of

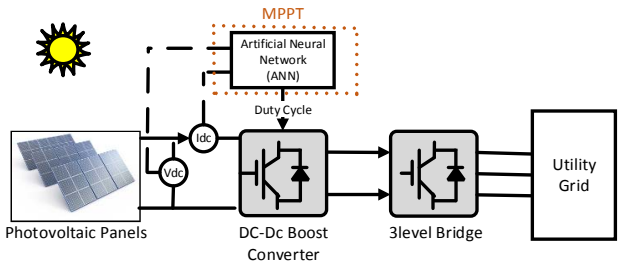

Fig. 1. Configuration of proposed system

[1] Hybrid Optimization Model for Electric Renewables

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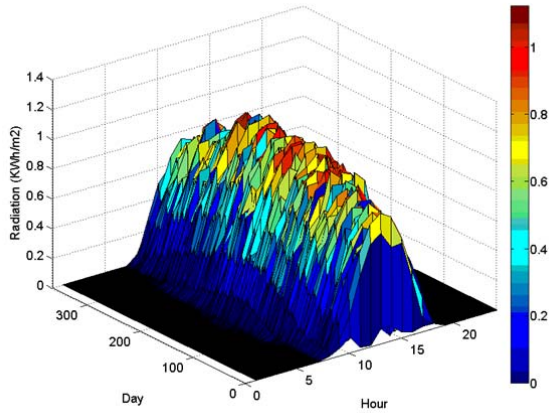

Fig. 2. Hourly solar irradiation

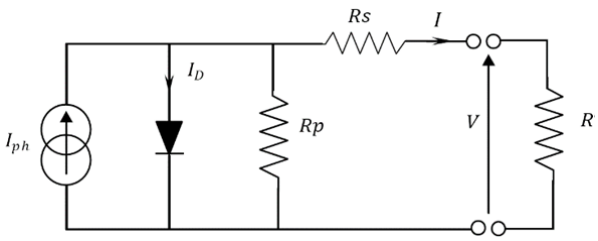

Fig. 3. The equivalent circuit of a photovoltaic array

solar data are shown in Fig. 2. In this study the temperature was considered constant at 25℃.

The MPPT is based on a DC-DC boost converter with an insulated gate bipolar transistor (IGBT) power switch. The duty cycle of this converter is obtained by artificial neural network (ANN) which is trained using V_{dc} and I_{dc}.

A. PV array characteristics

The Fig. 3 illustrates the equivalent circuit of the PV cell where I_{ph} is current source of the PV array, largely depends on the insolation and cells temperature. R_{sh} is an equivalent shunt resistance, R_s is an equivalent series resistance, I and V are the output current and output voltage of the PV array. Generally, for uncomplicatedness R_{sh} and R_s are considered to be open circuit and short circuit, respectively. The shortened mathematical model of the output current and voltage is given as:

$$I = n_p I_{ph} - n_p I_{rs}(e^{\frac{q}{pkn_s}\times\frac{V}{T}} - 1) \quad (1)$$

Where

I_{rs} : Cell reverse saturation current

q : Electronic charge

k : Boltzmann's constant ($1.38\times10^{-23}\ J/°K$)

T : Cell surface temperature ($°K$)

p : Cell ideality factor (p =1~5)

n_p : Number of solar cells in parallel

n_s : Number of solar cells in series

The current source of PV array, I_{ph} varied according to solar irradiation and cell temperature, is given by:

$$I_{ph} = (I_{sc} + K_1(T - T_r))\lambda / 100 \quad (2)$$

Where:

T_r : Reference temperature

I_{sc} : Short circuit current at reference temperature and solar irradiation;

K_I : Short circuit current temperature coefficient at reference temperature and solar irradiation;

λ : Solar radiation, irradiation, or insulation (W/m^2).

In this study we are going to develop an artificial neural network based MPPT controller for the PV arrays. In the incremental conductance method, which is used to generate training data for the Artificial Neural Network in this study, the controller senses incremental variations in current and voltage array to foresee the consequence of a voltage alteration. This method involves more calculation in the controller, but changing conditions can be tracked more quickly than perturb and observe method (P&O). Similar to the P&O algorithm, it may produce swaying in output power.

In this paper, a 100-kW PV array of 330 SunPower modules (SPR-305) is used for a Matlab simulation model. The array involves 66 parallel strings of 5 series-connected modules connected in parallel (66*5*305.2 W= 100.7 kW) [16]. The electrical specification of the mentioned module on standard test condition (STC) is shown in Table 1. I - V and P - V curves of single module at 25℃ for different irradiance is illustrated in Fig. 4.

B. Neural Network Architecture

Lately, the use of ANN has entered various scientific areas as an approximation technique because of the very good pattern recognition capability [17]. A three-layer neural network can fairly perfectly estimate any nonlinear function to a random accuracy. A three layer feedforward backpropagation ANN is used: an input, a hidden and an output layer to guess Duty Cycle of DC-DC boost converter. The input layer consists of a two dimensional vector, one is the DC output Voltage of PV modules and the other is the PV current, output layer is one dimensional vector consisting of Duty cycles. The training procedure needs a set of samples of appropriate network behavior inputs and target outputs.

TABLE I. SPECIFICATION OF SPR-305 PV MODULE ON STANDARD TEST CONDITIONS1000 W/M^2, 25℃

Maximum power	305W
Open circuit voltage	64.2 V
Short circuit current	5.96 A
Voltage at maximum power point	54.7 V
Current at maximum power point	5.58 A

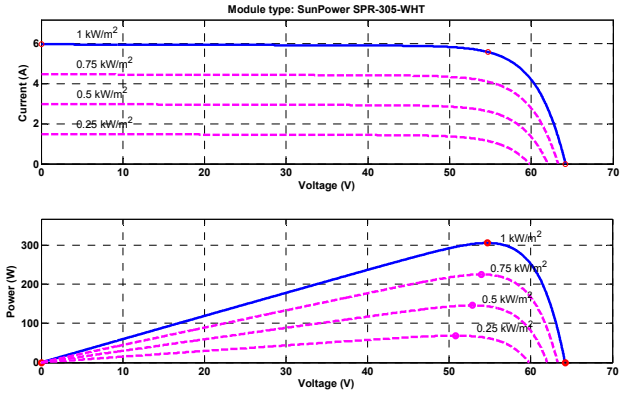

Fig. 4. I-V and P-V curves of single module at 25℃ for different irradiance

The procedure of training a neural network includes modification of the weights and biases of the network to enhance network performance. Throughout the training, the connection weights are modified until the best fit is attained for the input–output patterns based on the minimum errors.

The default performance function for feedforward networks is mean square error (MSE) which is the average squared error between the outputs, a, and the target outputs t. It is shown as [16]:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad (3)$$

Another performance function for neural networks is the mean absolute percentage error (MAPE), which is a measure of exactness of the method specifically in trend estimation. It typically articulates accuracy as a percentage, and is well-defined by the formula:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - a_i}{a_i}\right| \quad (4)$$

TABLE II. TRAINING PARAMETER VALUES

Number of Hidden Layers	26
Epochs between displays	5
Learning rate	0.001
Maximum number of epochs to train	1000
Performance goal	0

In this paper, we used MAPE as the evaluation factor of our approximation. Training parameter values of the proposed network are tabulated in Table II.

IV. RESULTS AND DISCUSSIONS

In this study, quite a lot of inhomogeneous irradiance distributions are utilized to test the operation of the proposed scheme. In order to generate data that can be used as training sets of Artificial Neural Network we run the Simulink model with hourly average irradiance of the first 42 weeks of the year from 7 am in the morning to 5 pm in the evening. As the control system uses a sampling time of 100 microseconds for voltage and current controllers, simulation of each day produces 20000 inputs of Voltage, Current and Duty Cycle which are big enough for training the network. In the simulation we used a time step of 0.1 for each hour and ran the simulation for 42 seconds. The simulation results for extracting the training data is shown in Fig. 5. The simulation was run by using the irradiance data of the last 10 weeks of the year to calculate the testing data of the neural network which are depicted in Fig. 6. As it can be seen from figures 5 and 6 stated maximum power of 100.7 kW is obtained at times of a 1000 W/m^2 irradiance and generally power is tracking the irradiance, which means that the incremental conductance method can produce a reliable set of training and testing data. In the next step the acquired data are used to simulate the neural network to train and then approximate the duty cycle of the MPPT.

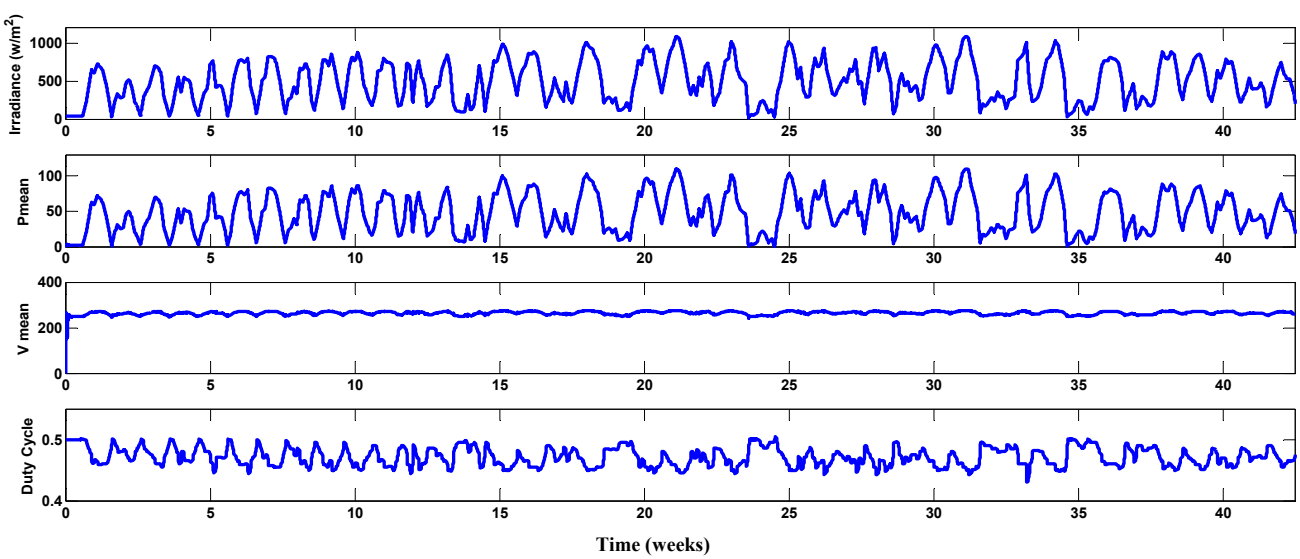

Fig. 5. Irradiance, output voltage, output current duty cycle and generated power of PV system for the first 42 weeks of the year (Training Data)

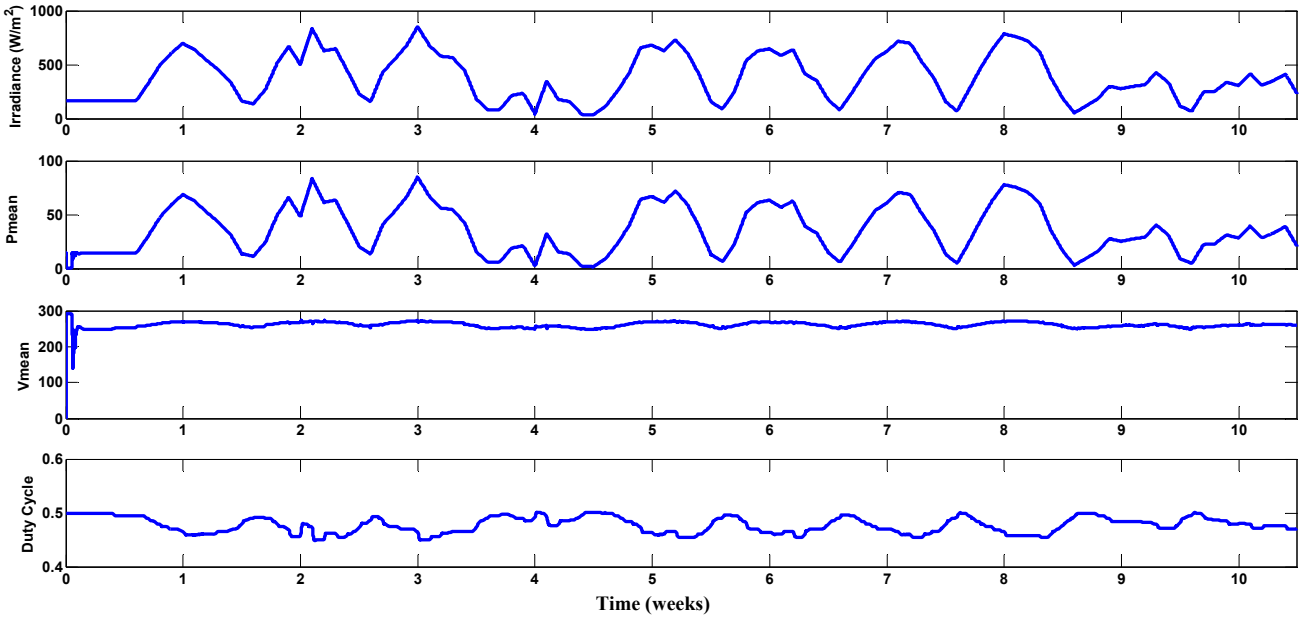

Fig. 6. Irradiance, output voltage, output current duty cycle and generated power of PV system for the last 10 weeks of the year (Testing Data)

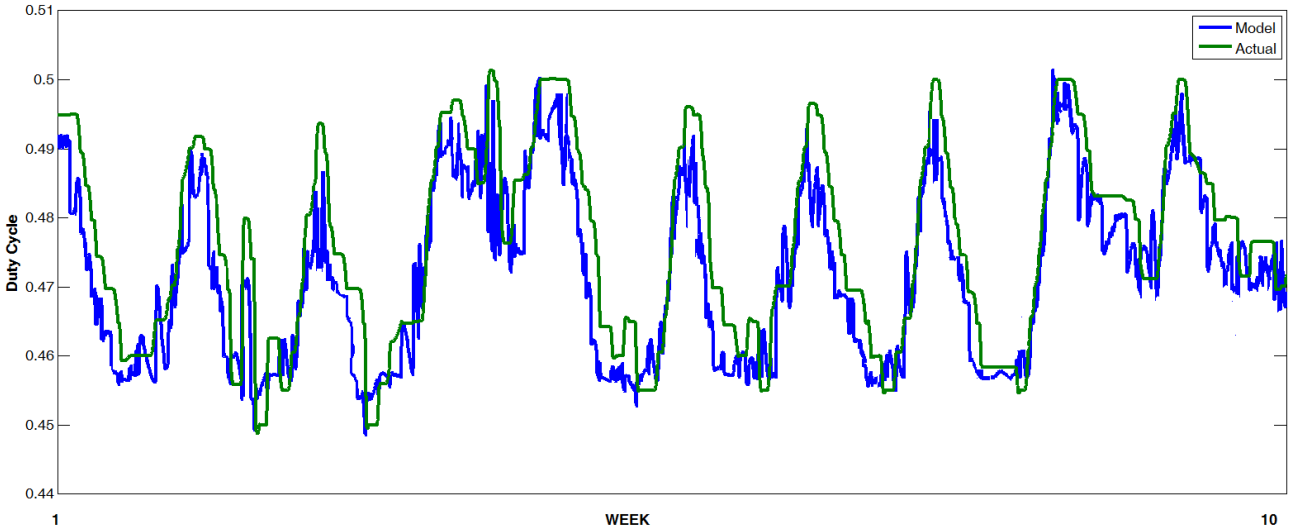

Fig. 7. Results of estimated duty cycle values compared to actual values

Fig. 7 shows the estimated (blue line) and actual (green line) values of the Duty Cycle ratio. Undoubtedly considering the mean absolute percentage error of 1.49% the results approved the effectiveness of the proposed technique.

The main advantages of the proposed MPPT method is that the system needs less computational work because of no necessity for awareness of internal MPPT system parameters and the system offers a compressed solution for this multivariable problem.

IV. Conclusion

The productivity of the suggested Artificial Neural Network structures for the MPPT control and the forecast of Duty Cycle of DC-DC boost converter has been presented. Since the duty cycle is directly achieved by using ANN, the proposed system does not need complicated processes and cutting-edge power electronic control units. The results how that the ANN is sufficiently accurate and can identify the duty cycle under different solar irradiance.

REFERENCES

[1] Fangrui Liu; Shanxu Duan; Fei Liu; Bangyin Liu; Yong Kang, "A Variable Step Size INC MPPT Method for PV Systems," *Industrial Electronics, IEEE Transactions on* , vol.55, no.7, pp.2622,2628, July 2008

[2] Salmani, M.A.; Anzalchi, A.; Salmani, S., "Virtual Power Plant: New Solution for Managing Distributed Generations in Decentralized Power Systems," *Management and Service Science (MASS), 2010 International Conference on* , vol., no., pp.1,6, 24-26 Aug. 2010.

[3] A. Anzalchi, B. Mozafari, "Winnd-PV-Grid Connected Hybrid Renewable System in Kish Island",International Review on Modelling and Simulations (I.RE.MO.S.), Vol 4, No 6, December 2011.

[4] Berrera, M.; Dolara, A.; Faranda, R.; Leva, S., "Experimental test of seven widely-adopted MPPT algorithms," *PowerTech, 2009 IEEE Bucharest* , vol., no., pp.1,8, June 28 2009-July 2 2009

[5] Sreekanth, S.; Raglend, I.J., "A comparitive and analytical study of various incremental algorithms applied in solar cell," *Computing, Electronics and Electrical Technologies (ICCEET), 2012 International Conference on* , vol., no., pp.452,456, 21-22 March 2012

[6] Ahmed, E.M.; Shoyama, M., "Modified adaptive variable step-size MPPT based-on single current sensor," *TENCON 2010 - 2010 IEEE Region 10 Conference* , vol., no., pp.1235,1240, 21-24 Nov. 2010

[7] Weidong Xiao; Dunford, W.G., "A modified adaptive hill climbing MPPT method for photovoltaic power systems," *Power Electronics Specialists Conference, 2004. PESC 04. 2004 IEEE 35th Annual* , vol.3, no., pp.1957,1963 Vol.3, 20-25 June 2004

[8] Chia Seet Chin; Yit Kwong Chin; Bih Lii Chua; Kiring, A.; Teo, K.T.K., "Fuzzy Logic Based MPPT for PV Array under Partially Shaded Conditions," *Advanced Computer Science Applications and Technologies (ACSAT), 2012 International Conference on* , vol., no., pp.133,138, 26-28 Nov. 2012.

[9] Boztepe, M.; Guinjoan, F.; Velasco-Quesada, G.; Silvestre, S.; Chouder, A.; Karatepe, E., "Global MPPT Scheme for Photovoltaic String Inverters Based on Restricted Voltage Window Search Algorithm," *Industrial Electronics, IEEE Transactions on* , vol.61, no.7, pp.3302,3312, July 2014

[10] Ocran, Theodore Amissah; Cao, Junyi; Cao, Binggang; Sun, Xinghua, "Artificial neural network maximum power point tracker for solar electric vehicle," *Tsinghua Science and Technology* , vol.10, no.2, pp.204,208, April 2005

[11] Bendib, B.; Krim, F.; Belmili, H.; Almi, M.F.; Bolouma, S., "An intelligent MPPT approach based on neural-network voltage estimator and fuzzy controller, applied to a stand-alone PV system," *Industrial Electronics (ISIE), 2014 IEEE 23rd International Symposium on* , vol., no., pp.404,409, 1-4 June 2014

[12] Syafaruddin; Karatepe, E.; Hiyama, T., "Artificial neural network-polar coordinated fuzzy controller based maximum power point tracking control under partially shaded conditions," *Renewable Power Generation, IET* , vol.3, no.2, pp.239,253, June 2009

[13] Giraud, F.; Salameh, Z.M., "Analysis of the effects of a passing cloud on a grid-interactive photovoltaic system with battery storage using neural networks," *Energy Conversion, IEEE Transactions on* , vol.14, no.4, pp.1572,1577, Dec 1999

[14] Guan-Chyun Hsieh; Hung-I Hsieh; Cheng-Yuan Tsai; Chi-Hao Wang, "Photovoltaic Power-Increment-Aided Incremental-Conductance MPPT With Two-Phased Tracking," *Power Electronics, IEEE Transactions on* , vol.28, no.6, pp.2895,2911, June 2013

[15] Villalva, M.G.; Gazoli, J.R.; Filho, E.R., "Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays," *Power Electronics, IEEE Transactions on* , vol.24, no.5, pp.1198,1208, May 2009

[16] "SimPowerSystem User's Guide Version 5", MATLAB Manual Periodicals and Conference Proceedings

[17] Jian Liang; Ng, Simon K.K.; Kendall, G.; Cheng, John W.M., "Load Signature Study—Part I: Basic Concept, Structure, and Methodology," *Power Delivery, IEEE Transactions on* , vol.25, no.2, pp.551,560, April 2010