Identification of Hammerstein-Weiner System for Normal and Shading Operation of Photovoltaic System

Mohd Najib Mohd Hussain, Ahmad Maliki Omar, Pais Saidin, Ahmad Asri Abd Samat, and Zakaria Hussain

***Abstract*—This paper present an identification of model system performance for Photovoltaic (PV) System under normal and shading operating condition in UiTM Pulau Pinang, Malaysia of 2.4 kW systems. A system identification approach was implemented by employing a Hammerstein-Weiner (HW) model as model structure. The approach concerned on the estimation of the photovoltaic system basis of observed data. The nonlinearity input and output are taken from irradiance and dc output current data of the real system severally. These data were used in Hammerstein-Weiner model to generate a black-box model structure which provides a flexible parameterization for nonlinear models. The best fit nonlinear model when using data from normal operating condition is when HW model incorporate with piecewise linear as the input channel and wavelet network estimators as output channel. For normal operation of PV system, the percentage of best fit was 96.51% by means of b_n = 1, f_n = 3, and k_n = 2 of the linear model order. While the percentage best fit model generate considering shading effect was 86.32% with b_n = 1, f_n = 3, and k_n = 1 of the linear model order. The modelling is implemented using system identification toolbox of Matlab software package.**

***Index Terms*—Photovoltaic system, nonlinear hammerstein-weiner, shading, system identification.**

I. Introduction

Nowadays, installations of photovoltaic system incorporate with power electronics converter are growing tremendously. There are many [1-3] of topologies, techniques and approaches exist in developing architectural of photovoltaic system constructed with the converters to harvest maximum power point energy either during normal or shading condition. The system level examine is complex and difficult to analyse for real systems. Even it is inappropriate to investigate or simulate the performance of the system that already installed in an expensive basis.

Therefore, a model of the PV system representing the real environment is needed. The model should be as simple as possible to demonstrate the real system in order to explain the behaviours of the system. In addition, the model can be further enhanced as a design controller for the system. Traditional modelling of the PV system with the converter has been published in [4-7]. However, the system designer did not usually consider all the essentials data parameter to summarize the real models. Thus, the system identification approach is required to resolve the necessity.

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To solve a problem or evaluate the system, the model is reliant to adequate data information about the system. The forms of data are required to be interpreted before any analysis and decision can be made. From the real data information, the model can be created efficiently. The term system identification is referring to the derivation of a relevant description from the observed data and the resultant system description is called as a model. Methodically, the system identification is deals with the problem of constructing the mathematical models of dynamic systems to describe the underlying mechanism of the observed data of the system.

System Identification Approach

System identification approach is the important tool for technical areas which all physical systems are nonlinear operating routine and it is good to epitomize the nonlinear model to describe the real system. Practically most of the systems are nonlinear and the output is a nonlinear function of the input variables. However, a linear model is often sufficient to accurately describe the system dynamics, which is normally by fitting the system from trial fit linear models. The ddynamics models in system identification approach are mathematical relationships between the system's inputs *u(t)* and outputs *y(t)*. These relationships are used to compute the current output from previous inputs and outputs. The general equation of nonlinear model for discrete time is shown as below. The model in function *f* is a nonlinear model which including nonlinear components representing arbitrary nonlinearities of the systems.

$$y(t) = f(u(t-1), y(t-1), u(t-2), y(t-2), \ldots.) \quad (1)$$

There are quite number of nonlinear models can be used, such as Autoregressive Exogenous model (NARXM), Hammerstein model (HM), Weiner model (WM) and Hammerstein-Wiener model (HWM). Among them, the Hammerstein-Weiner model has been proved to be good descriptions as nonlinear dynamic systems [5]. Estimating Hammerstein-Wiener models requires uniformly sampled time-domain data. The data are consists of single-input and single-output (SISO) channels.

The aims of system identification are to obtain the best suitable mathematical model or transfer function of the real system between the exact data of inputs and outputs. The best fitting model can be helpful for gaining a better understanding on the real system and also useful to predict or simulate system behaviour, moreover to act as control technique for design and analysis of controllers which based on models of real systems [8].

The approach is implemented in Fig. 1 which shows how to observe the dynamic system from measuring the input and output data of the real system. The PV system is constructed and implemented for data collections purposes. The input-output data is recorded for the full dynamicity of the real-time system. The measured data are divided into several set of training and testing/validating of the identified model. Nonlinear system identification is selected since the system operates in nonlinear ranges. Furthermore, the model is estimated with experimental data, hence validated. Once the proper model has been selected, estimated and validated, the model can then carried out for future intended applications.

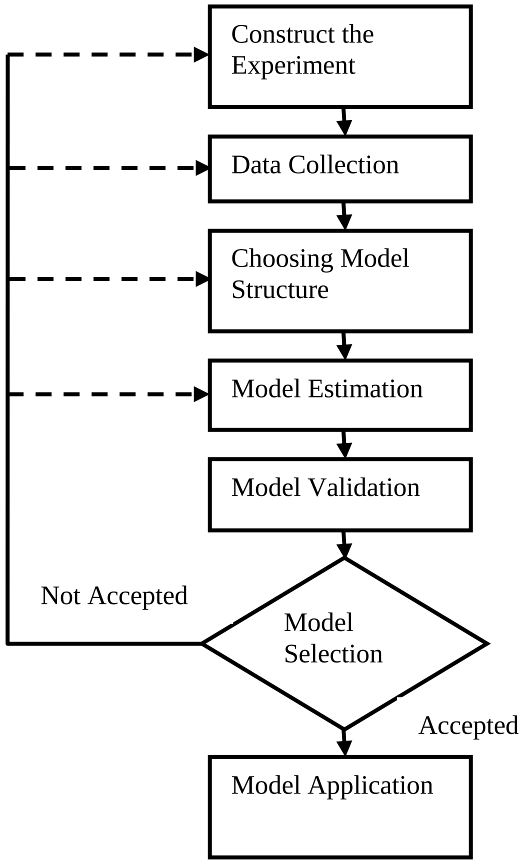

Fig. 1. Process of System Identification using HW method

A. Nonlinear Hammerstein-Weiner Model (NLHW)

Hammerstein-Weiner models were described as dynamic systems using one or two static nonlinear blocks in series with a linear block. The linear block is a discrete transfer function and represents the dynamic component of the model. In this paper, this structure is chosen as the best fitting model for nonlinear real-time ranges. Fig. 2 shows the structure of NLHW which represents the dynamic system using input and output static nonlinear blocks in between dynamic linear blocks which is distorted by static nonlinearities [5]. Hammerstein-Weiner structure is then used to capture the physical nonlinear effects in the system that will affect the input and output of the linear system.

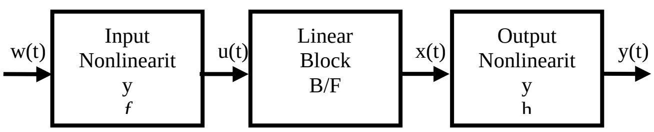

Fig 2. Structure of Hammerstein-Weiner Model

The applications of NLHW model depend on its inputs. If the output of a system depends nonlinearly on its inputs, it can be decompose the input-output relationship into two or more interconnected elements. This system is preferred because they have a convenient block representation, transparent relationship to linear systems, and easier to be implement than heavy-duty nonlinear models. In this paper, it is present an algorithm to identify Single-Input Single-Output (SISO) HW systems.

II. Model Identification in MATLAB

A. Analysis of PV System under Normal Operating

The data collections were taken for PV array of 2.45 kW_p systems for a 2 parallel by 7 series string combinations. The input and output data severally referred to irradiance (W/m^2) and DC output current (A) which illustrate in Fig. 3. For selection of nonlinear Hammerstein-Weiner model structure, the estimation [9] of the model gives the results as specified in Table I. The first two peak waveform represents the training set of data while the last two peak waveform corresponds to validation set of data out of 1000.

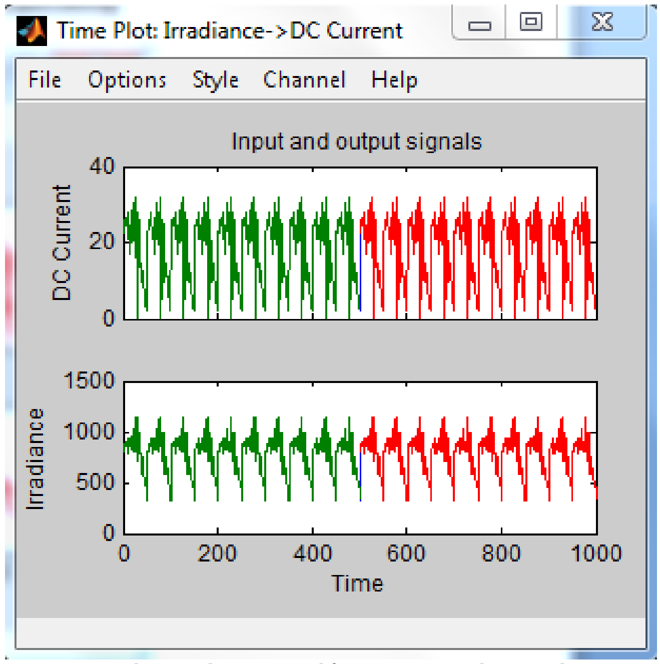

Fig. 3. Input and output data measured for PV system under normal operating

From the estimation of nonlinear input and output channel together with varying of linear order for trial and error methods, the system identification tool GUI will produces an accurate best fit to the data. From Table 1, it visualises that the model nlhw11 give the best fit of 96.51% and less Final Prediction Error (FPE) [10] and Loss Function. Using the Hammerstein-Wiener model, and the Adaptive Gauss-Netwon algorithm for system identification, the orders of the middle linear block were chosen to be for both lateral and longitudinal commands as of $b_n = 1$, $f_n = 3$, and $k_n = 2$. It shows that the Hammerstein-Wiener model is given a better estimation in the transient and the sudden changes in the steady-state and that can be clear in Fig. 4. The quality of the model after using the Hammerstein-Wiener model with the preferred parameter between the original output and estimated output for the Normal Operating model is approximately same.

TABLE I: MODEL PROPERTIES OF NONLINEAR MODELS UNDER NORMAL OPERATION

Model	Nonlinear		Linear			Model Properties			Algorithm/Search Method
	Input Channel	Output Channel	b_n	f_n	k_n	% Fit	FPE	Loss Fcn	
nlhw1	Piecewise Linear	Piecewise Linear	2	3	1	61.91	12.58	10.38	Auto
nlhw2	Sigmoid	Piecewise Linear	2	3	1	60.89	13.81	10.94	Auto
nlhw3	Wavelet network	Piecewise Linear	2	3	1	47.5	39.32	19.72	Auto
nlhw4	Wavelet network	Sigmoid	2	3	1	30.21	72.69	34.84	Auto
nlhw5	Wavelet network	Wavelet network	2	3	1	84.68	12.67	1.679	Auto
nlhw6	Wavelet network	Wavelet network	2	3	1	80.14	21.29	2.821	Gauss-Newton (gn)
nlhw7	Wavelet network	Wavelet network	2	3	1	93.62	2.194	0.291	Adaptive Gauss-Newton (gna)
nlhw8	Wavelet network	Wavelet network	2	3	1	84.68	12.67	1.679	Levenberg-Marquardt (lm)
nlhw9	Wavelet network	Wavelet network	2	3	1	80.9	19.69	2.068	Trust-Region Reflective Newton
nlhw10	Wavelet network	Wavelet network	1	3	1	95.42	0.666	0.15	Adaptive Gauss-Newton (gna)
nlhw11	Wavelet network	Wavelet network	1	3	2	96.51	0.35	0.087	Adaptive Gauss-Newton (gna)

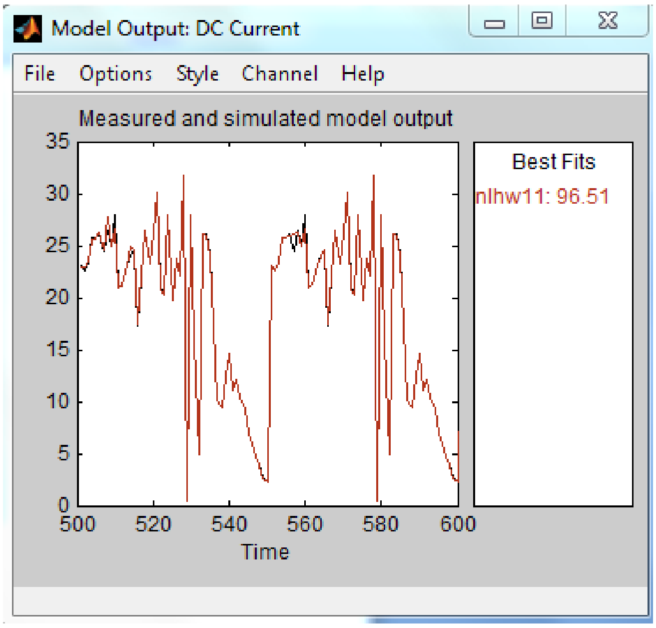

Fig. 4. Original output (Black) and estimated output (Brown) for the same input signal

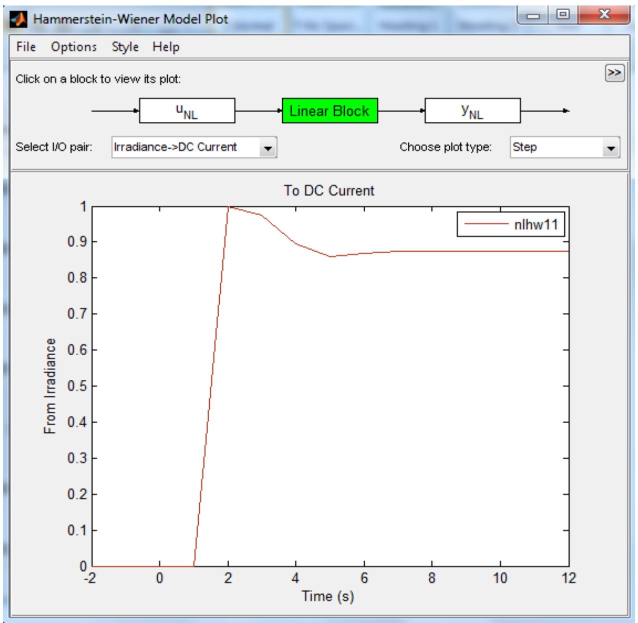

Fig. 5. Linear transfer function of Step Plot type

Fig. 5 illustrate displays the linear transfer function of step plot type for the model which significantly describe as a stable system. While the response of the system execute from small signal LTI model is almost identified as shown in Fig. 6.

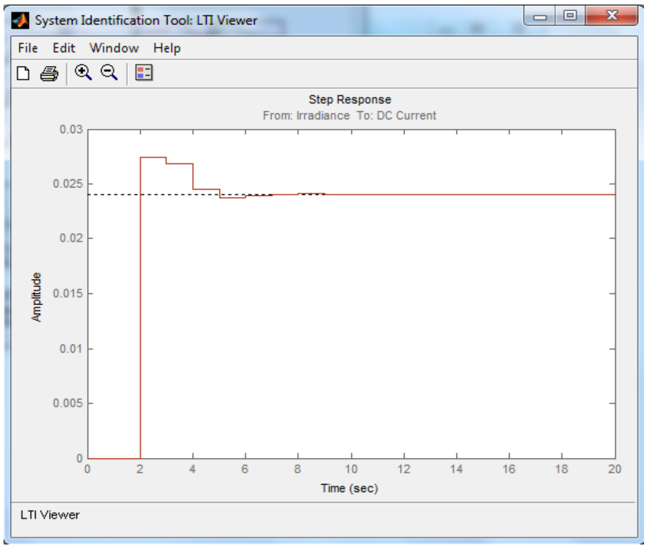

Fig. 6. Step response from LTI Viewer

The transfer function representing block as shown in Fig. 2 from input "u1" to output 'y1' for normal operating condition is given as;

$$TF = \frac{z}{z^3 + 0.02566 * z^2 + 0.08104 * z + 0.03689} \quad (2)$$

B. Analysis of PV System under Shading Operating

For the similar PV array of 2.45 W_p systems, the PV array structure are arrange to be partially shading. The shading data information for irradiance (W/m^2) and DC output current (A) are simplified in Fig. 7. It is seen that the DC current are decrease due to shading effect and purposely affected to the performance PV array [6]. These illustrations are used to analyses the response of partially shaded PV array. The model properties for this effect are demonstrated in Table II.

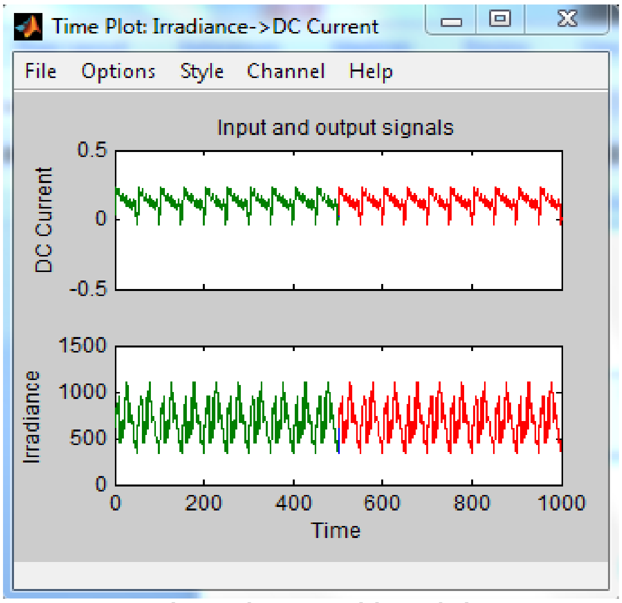

Fig. 7. Input and output data measured during shading operation

The model output of the DC current which give the best fit to the original model is shown in Fig. 8. The best percentage fit is 86.32% for the model of nlhw9, using the Trust-Region Reflective Newton algorithm for system identification. The orders of the middle linear block was chosen to be for both lateral and longitudinal commands as bn = 1, fn = 3, and k_n = 1.

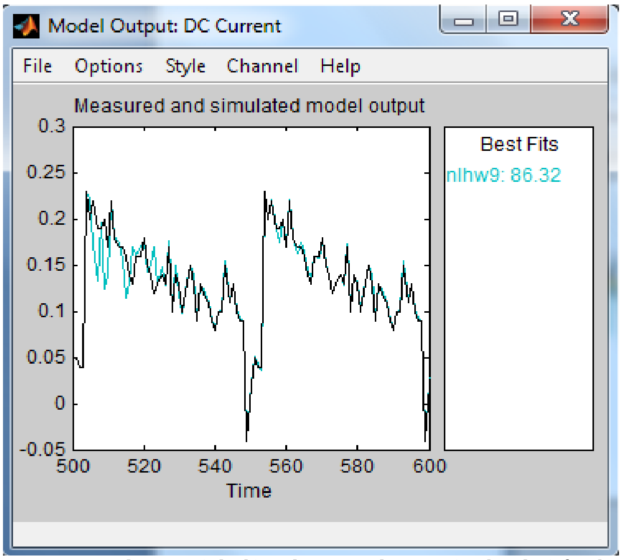

Fig. 8. Original output (Black) and estimated output (Light Blue) for the same input signal

The HW model plot of the linear transfer function is shows in Fig. 9. The response of the system during shading effect is represent in Fig. 10 from small signal LTI viewer.

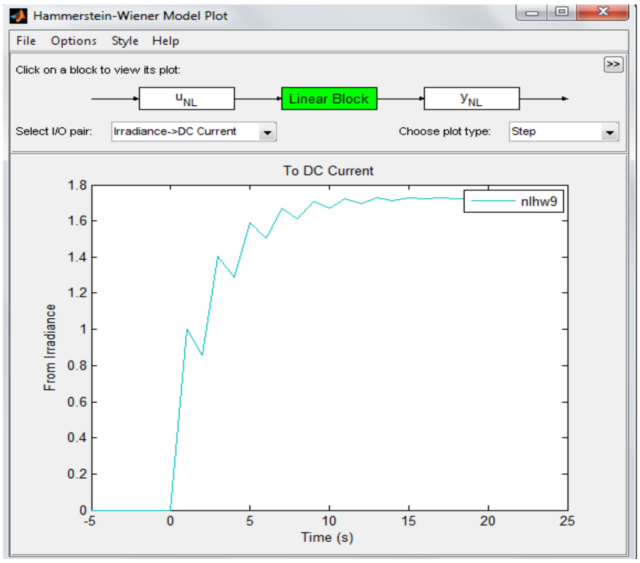

Fig. 9. Linear transfer function of Step Plot type

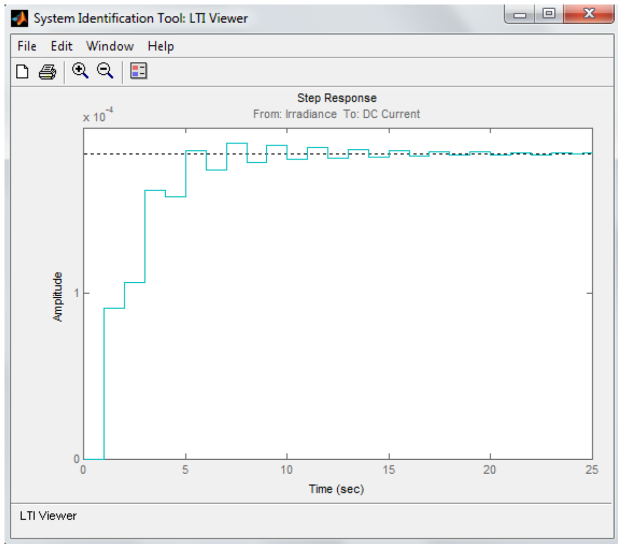

Fig. 10. Step Response for shading operation

TABLE II: MODEL PROPERTIES OF NONLINEAR MODELS UNDER NORMAL OPERATION

Model	Nonlinear		Linear			Model Properties			Algorithm/Search Method
	Input Channel	Output Channel	b_n	f_n	k_n	% Fit	FPE	Loss Fcn	
nlhw1	Piecewise Linear	Piecewise Linear	2	3	1	41.88	0.001	0.001	Auto
nlhw2	Sigmoid	Piecewise Linear	2	3	1	35.69	0.001	0.001	Auto
nlhw3	Wavelet network	Piecewise Linear	2	3	1	13.87	0.004	0.002	Auto
nlhw4	Wavelet network	Sigmoid	2	3	1	27.78	0.003	0.001	Auto
nlhw5	Wavelet network	Wavelet network	2	3	1	42.46	0.002	0.001	Auto
nlhw6	Wavelet network	Wavelet network	2	3	1	75.55	0.001	0.0002	Adaptive Gauss-Newton (gna)
nlhw7	Wavelet network	Wavelet network	2	3	1	75.88	0.001	0.0002	Levenberg-Marquardt (lm)
nlhw8	Wavelet network	Wavelet network	2	3	1	75.92	0.001	0.0002	Trust-Region Reflective Newton
nlhw9	Wavelet network	Wavelet network	1	3	1	86.32	0.0002	0.0001	Trust-Region Reflective Newton
nlhw10	Wavelet network	Wavelet network	1	3	2	60.3	0.002	0.0004	Trust-Region Reflective Newton

The model obtained in both conditions can be additionally used to analyse the characteristics of the system such as the controllability, stability, power quality and power flow in developing PV system in order to harvest maximum power to the users. The Transfer function from input "u1" to output "y1" of shading operation for PV system model for single-input single-output (SISO) are specified as follows;

$$TF = \frac{z^2}{z^3 + 0.144 * z^2 - 0.5278 * z - 0.03807} \qquad (3)$$

III. Conclusion

Nonlinear Hammerstein-Weiner (NLHW) model is able to provide an accurate description and prediction for a real system of PV system. Under normal and shading conditions it may have a nonlinear behavior operation. There were three nonlinear estimators for inputs and outputs have been studied, i.e. Piecewise-Linear, Sigmoid and Wavelet-Network. From the trial and error methods, NLHW model will contribute the highest percentage fitting with low FPE and loss function. Meanwhile the scalar nonlinearity estimators for input and output nonlinearities are identify as piecewise linear and wavelet network severally. The step response results from the system identification tool for both conditions shows a good oscillatory reaction to the final steady value. The percentage of best fit can give better percentage if the multiple input data; in example temperatures are also considered. The algorithm method and linear order value selected from the project can be furthered investigated to be as a model based design to control a power electronics converter for a PV system. The system under normal and shading operation of photovoltaic system are estimated and analyzed using system identification approach.

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