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Modeling of Inverter of Photovoltaic System in Transient Condition Using Nonlinear System Identification

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Abstract: In this paper, modeling of one type of grid connected single phase inverter commercially available in Thailand is carried out. An inverter of a grid-connected photovoltaic system has been tested and its model determined. The inverter operates in transient conditions and its modeling is done using nonlinear system identification approach with Hammerstein Wiener Model. The models in transient conditions which compose of power step up and step down condition have been experimented. The results comparison on modeling of transient condition using Hammerstein-Wiener Model has been analyzed by system identification process.. The accuracy of waveform from the system identification between experimental and validate data in both transient conditions are 91.75%, 85.99% respectively. The mathematical model being the representation of the system can be analyzed and provide characteristics on controllability, stability, power quality, power flow in such condition.

Key words: Grid-connected Inverter, system identification, Transient condition, Hammerstein-Wiener

INTRODUCTION

Photovoltaic systems are now increasing particularly the distributed generating system known as PV grid connected system. Grid interconnection of PV systems is accomplished through the inverter, which converts dc power generated from PV modules to ac power used for ordinary power supply to electric equipments. Inverter technology is the key technology to have reliable and safety grid interconnection operation of PV system. Inverter system is therefore very important for grid- connected PV systems. An inverter as a power conditioner of a photovoltaic system consists of power electronic switching components, complex control systems and nonlinear behaviors (Chi, Kong Tse, 2004). To study the behavior of inverters, the operating conditions of PV based inverter in any condition such steady state condition, transient condition, and fault condition is studied. There are some efforts to model the inverter but it is only done in steady state condition (Middlebrook, R.D. and S. Cuk, 1977; Sedlacek, R., 1998; Araujo, R.E., 2002; Maksimovic, D., 2001; Cho, H.I., 2009; Dalibor Biolek, Onbilgin, 2007). In practical operation, inverter has change the operating condition due to variation of condition such irradiances, temperatures, load or grid impedance variation. Consequently, the behavior of inverter is mainly considered in steady state with slowly change condition upon the load and weather conditions. However, sometime the condition suddenly change i.e. load change or input change. In these conditions, PV based inverter operate in transient condition and average power increase or decrease upon the disturbance to Photovoltaic system. In order to understand the behavior of PV based inverter, modeling and simulation of photovoltaic based inverter systems is the one of essential tools for analysis, operation and impacts of inverters on the power systems.

There are two major approaches for modeling power electronics based system such analytical and experimental approaches. There are several analytical method to study transient model of PV based inverter system, follow as PSCAP/EMTDC, dynamic stability (Farid Katiraei, 2008; Li Wang and Ying-Hao Lin, 2008; Seul-Ki Kim, 2009; Saccomando, G., J. Svensson, 2001; Kassmi, A., 2007; Chen, C., 2010), these analytic methods need to know information of system. However, power electronics systems are usually composed of commercial converters and because of confidentiality of manufacturers, the system designer does not know the necessary information of product for parameterize the models. With this reason system identification is

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implemented for analyze the behavior of inverter without prior information (Sjoberg, J. and etc., 1995). System identification of power converter in steady state condition based on a black box approach is achieved (Choi, J.Y., 1998; Arnedo, L., 2008). The block oriented models (Hatanaka, T., 2003) such a Hammerstein (Alonge, F., 2007) and a Wiener (Wigren, T., 2003) for power converter model is executed. In transient condition, black-Box modeling of converters based on transient response analysis is presented (Valdivia, V., 2010; Valdivia, V., 2010). Because of advantage of Hammerstein model and Wiener model, combination of both model by enabling combination of a system, sensors and actuators in to one model is combined (Guo, F. and G. Bretthauer, 2003). The Hammerstein-Wiener model is the most effective for model the complex nonlinear system (Patcharaprakiti, N., 2010). This model has been attempted to model a photovoltaic grid connected inverter of system in steady state condition but still not in transient condition (Patcharaprakiti, N., 2009). In this paper, modeling of a single phase inverter of photovoltaic systems in transient condition by using nonlinear system identification with Hammerstein-Wiener model is initiated.

II. System Model:

A. Transient Condition:

An electrical transient is a temporary excess of voltage and/or current in an electrical circuit which has been disturbed. Transients are short duration events, typically lasting from a few thousandths of a second (milliseconds) to billionths of a second (nanoseconds), and they are found in all types of electrical, data, and communications circuits. In case of photovoltaic system, the operating condition in transient can be occurred by irradiance change, cloud effect, sudden load change and fault effect. A temporary component of current and voltage has been changed and waveform increase suddenly. Transient condition may occurs overvoltage, undervoltage or waveform distortion and these phenomena can affect to the power system. In order to understand the behavior and analysis, transient condition is simulated. The studied transient in this paper is composed of load/source step up and step down condition. The step up operating condition of inverter is increased from low power and then system sudden energized high power to load. In opposite, step down operating condition, the inverter is decreased high power to low power. Then the model of photovoltaic system based inverter is experimented and model by system identification based on Hammerstein-Wiener is estimated.

B. Hammerstein-Wiener Model:

A Hammerstein and Wiener model developed from a Hammerstein model and a Wiener model, shown in Fig 1. The nonlinear blocks contain the nonlinear functions and the linear block is an output error (OE) polynomial model.

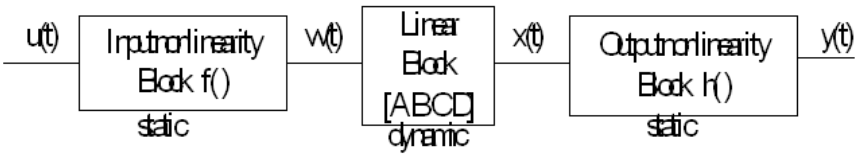


Fig. 1: Structure of Hammerstein-Weiner Model.

The following general equation describes the Hammerstein-Wiener structure are follow equations (1)

$$\left.\begin{aligned} w(t) &= f(u(t)) \\ x(t) &= \sum_{i}^{nu} \frac{B_i(q)}{F_i(q)} w(t-n_k) \\ y(t) &= h(x(t)) \end{aligned}\right\} \tag{1}$$

which u(t) and y(t) are the inputs and outputs for the system. w(t) and x(t) are internal variables that define the input and output of the linear block. In linear block, there are polynomials B and F contain the time-shift operator q, essentially the z-transform which be expanded as in equation (2). u_i is the i^{th} input, *mn* is the total number of inputs.

$$\begin{aligned} B(q) &= b_1 + b_2 q^{-1} + \ldots\ldots + b_n q^{-b_n+1} \\ F(q) &= 1 + f_1 q^{-1} + \ldots\ldots + f_n q^{-f_n} \end{aligned} \qquad (2)$$

b_n and f_n are input coefficients. nk_i is the i^{th} input delay that characterizes the delay response time and e(t)

is the error signal. The order of the model is the sum of b_n and f_n. This should be minimum for the best model. The Hammerstein-Wiener Model compose of the input and output nonlinear block which contain nonlinear functions f(·) and h(·) that corresponding to the input and output nonlinearities. The both nonlinear blocks are implemented using nonlinearity estimators. Inside nonlinear block, five nonlinear estimator are composed of deadzone, saturation, piecewise, sigmoidnet and wavenet (Lennart Ljung, 2009).

i) The dead zone function generates zero output within a specified region, called its dead zone or zero interval. The lower and upper limits of the dead zone are specified as the start of dead zone and end of dead zone parameters. Deadzone can define a nonlinear function y = f(x), where f is a function of *x*, It composes of three intervals as following in equation (3)

a<x<b	F(x) = 0	
x < a	F(x) = x – a	(3)
x ³ b	F(x) = x – b	

when x has value between a and b, then output of function equal to $F(x) = 0$ this zone is called as zero interval.

ii) Saturation saturation can define a nonlinear function y = f(x), where f is a function of x, It composes of three interval as the following characteristics in equation (4)

$$\left.\begin{array}{ll} x > a & f(x) = a \\ a < x < b & f(x) = x \\ x \leq b & f(x) = b \end{array}\right\} \qquad (4)$$

The function is determined between a and b values and always call this interval as Linear Interval

iii) Piecewise linear function (pwlinear) is define as a nonlinear function, y=f(x) where f is a piecewise-linear (affine) function of x and there are n breakpoints (x_k,y_k) which k=1,...,n. y_k = f(x_k). f is linearly interpolated between the breakpoints. y and x are scalars.

iv) Sigmoid network (SN) activation function or sigmoid network nonlinear estimator combines the radial basis neural network function using a sigmoid as the activation function. This estimator is based on the following expansion:

$$y(u) = (u-r)PL + \sum_{i}^{n} a_i f((u-r)Qb_i - c_i) + d \qquad (5)$$

when u is input and y is output. r is the the regressor. Q is a nonlinear subspace and P a linear subspace. L is a linear coefficient. d is an output offset. b is a dilation coefficient., c a translation coefficient and a an output coefficient. f is the sigmoid function, given by the following equation:

$$f(z) = \frac{1}{e^{-z} + 1} \qquad (6)$$

v) Wavelet network (WN) activation function. The term wavenet is used to describe wavelet networks. A wavenet estimator is a nonlinear function by combination of a wavelet theory and neural networks. Wavelet networks are feed-forward neural networks using wavelet as an activation function, based on the following expansion in equation (7)

$$y = (u-r)PL + \sum_{i}^{n} as_i * f(bs(u-r)Q + cs)$$
$$+\sum_{i}^{n} aw_i * g(bw_i(u-r)Q + cw_i) + d \qquad (7)$$

u and y are input and output functions. Q and P are a nonlinear subspace and a linear subspace. L is a linear coefficient. d is output offset. as and aw are a scaling coefficient and a wavelet coefficient. bs and bw are a scaling dilation coefficient and a wavelet dilation coefficient. cs and cw are scaling translation and wavelet translation coefficients. The scaling function f (.) and the wavelet function g(.) are both radial functions, and can be written as equation (8)

$$f(u) = \exp(-0.5 * u' * u)$$
$$g(u) = (\dim(u) - u' * u) * \exp(-0.5 * u' * u) \qquad (8)$$

In system identification process, the wavelet coefficient (a), dilation coefficient (b) and translation coefficient (c) are optimized during learning to obtain the best performance model.

III. Experiment:

In this work, we model one type of commercial grid connected single phase inverters, rating at 5,000 W. The experimental system composes of DC power supplies, a digital power meter, a digital oscilloscope, resistive (R), inductance (L) and capacitive (C) loads, a AC power system and a computer as shown in Figure 2. For system identification processes, waveforms are collected by an oscilloscope and transmitted to a computer to calculate power waveforms in single input and single output (SISO) type batch processing. In this experimental, testing is done when the inverter operates in transient conditions. The transient conditions are consisted of two cases follow as step up and step down transient condition. The step up transient condition is simulated by increase power output from 440 Watt to1,540 Watt and step down transient condition is determined by decrease power from 1,540 W to 440 W as shown in Table 1. After that, the data waveform of current and voltage is captured and transmitted to computer. Subsequently, power waveform data in each condition are divided in two groups. One group is used as data to estimate model, the second group is used to validate model. An inverter modeling using system identification approach is operated as shown in Fig. 3. The developed programming using the MATLAB software will check accuracy of model. This is done by selecting model structures and adjusting the model order of the linear terms and nonlinear estimators of nonlinear system identification.

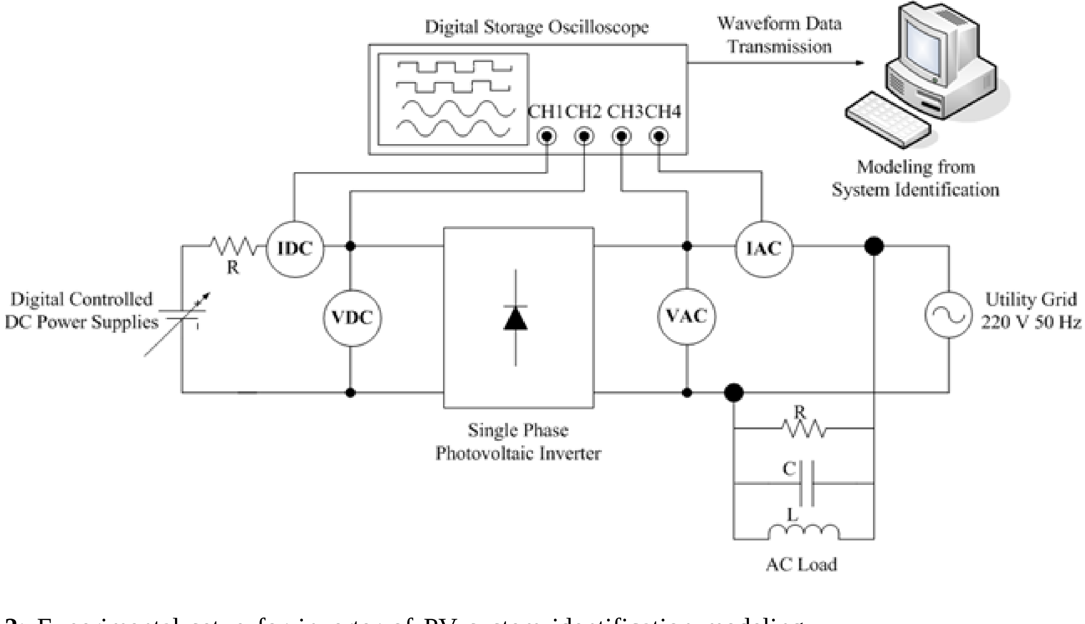


Fig. 2: Experimental setup for inverter of PV system identification modeling.

Table 1: An inverter operates in step up/down conditions

Electrical parameter	Step Up		Step Down	
AC Voltage output V)	220	220	220	220
AC Current output A)	7	2	2	7
AC Power output (W)	1540	440	440	1540

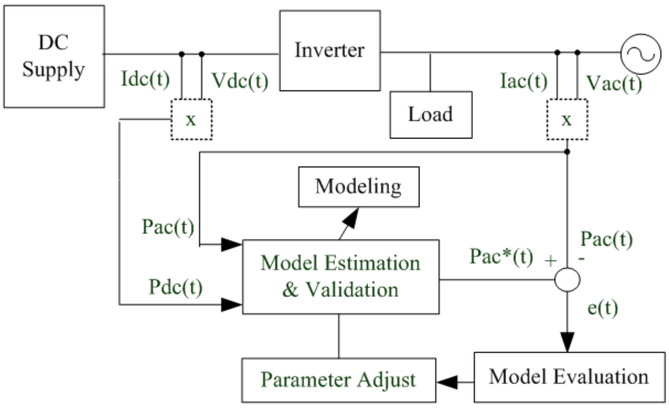


Fig. 3: An inverter modeling using system identification process.

The next stage, iterative simulation waveform and experimented have been compared until the best model performance is derived by results include a quantitative measure of the model quality in terms of goodness of fit to estimation data. The percentage of best fit accuracy is obtained from comparison between experimental waveform and simulation modeling waveform. Then, the accuracy of each case has been compared.

$$Best\ fit = 100 * (1 - norm(y^* - y) / norm(y - \bar{y})) \tag{9}$$

where y* is the simulated output, y is the measured output and $\bar{y}$ is the mean of output. FPE is Akaike Final Prediction Error for estimated model which the error calculation is defined as equation (10)

$$FPE = V\left(\frac{1+d/N}{1-d/N}\right) \tag{10}$$

where V is the loss function, d is the number of estimated parameters, and N is the number of estimation data. The loss function V is follow in equation (11) where θ_N represents the estimated parameters.

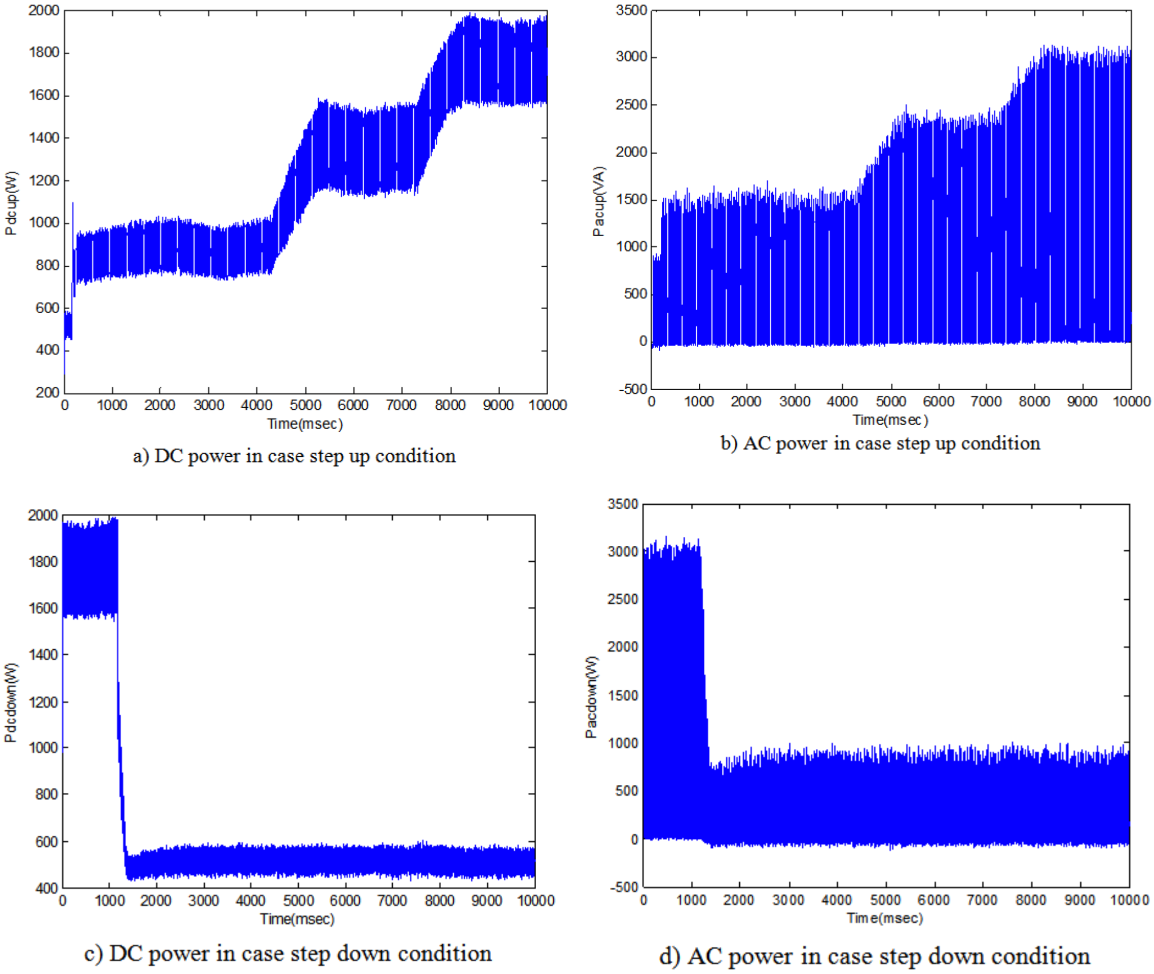
$$V = \det\left(\frac{1}{N}\sum_{1}^{N}\varepsilon\left(t,\theta_N\right)\left(\varepsilon\left(t,\theta_N\right)\right)^T\right) \tag{11}$$

Final Prediction Error (FPE) provides a measure of model quality by simulating the situation where the model is tested on a different data set. The Akaike Information Criterion (AIC) as shown in equation (12) is used to calculate a relative comparison of models with different structures.

$$AIC = \log V + \frac{2d}{N} \tag{12}$$

RESULT AND DISCUSSION

After implemented the experiment in the prior section, the result of experimental and modeling from system identification is illustrated. The DC voltage, DC current input waveform of transient step up condition have been captured and DC power input waveform is calculated by multiply voltage with current as shown in Fig. 4 a). The AC voltage and AC current is also collected and use to calculate the AC power output waveform as shown in Fig. 4 b). The DC and AC power are increased in 3 step. In case of transient step down, condition, the DC voltage, DC current input waveforms are also collected and compute the DC power waveform which shown in Fig 4 c). The AC power waveform in Fig 4 d) is calculated in the same manner. The trend of step down waveform is sharply decreased from 1,540 W – 440 W in range 1,500 – 2,000 msec.



a) DC power in case step up condition

b) AC power in case step up condition

c) DC power in case step down condition

d) AC power in case step down condition

Fig. 4: DC/AC power waveform of step up and step down transient condition

In the next step, the power data waveforms are divided into two groups follow as estimate data and validate data. The system identification process is executed by selecting the type of model, type of nonlinear estimator and linear parameter determine. The Hammerstein-Wiener which appropriates for model the nonlinear and linear system is chosen for represent the model. The Hammerstein-Wiener composes of input nonlinear block, linear block and output nonlinear block which connecting in cascade. The nonlinear estimator deadzone, saturation, piecewise and wavenet are selected for nonlinear estimator in input and output nonlinear block whereas linear block is instead by the output error model. Next step output waveform is generated by system model and accuracy of waveform from model and experimental is compared. The maximum accuracy is obtained by system identification process. Finally, the model from power waveform of inverter in step up transient conditions can be obtained. The accuracy of the model is 91.75% as shown in Fig. 5. The model properties of transient step up nonlinear models are shown in Table 2.

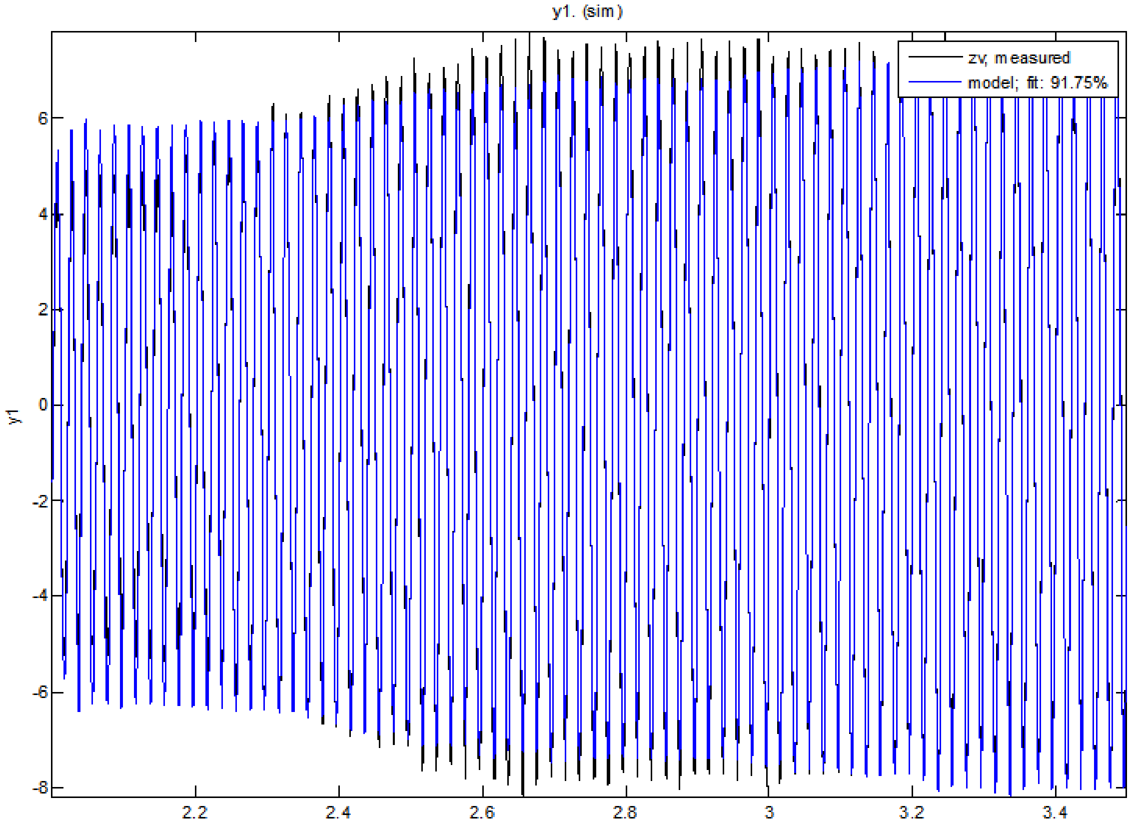


Fig. 5: Comparison of output waveform in step up transient condition from model and experimental

Table 2: Model properties of transient step up nonlinear models

Nonlinear		Linear			Model properties		
I/P	O/P	b_n	f_n	k_n	% fit	FPE	AIC
DZ	DZ	3	4	2	91.75	3,230	7.40
PW	PW	4	4	5	87.20	4,720	8.38
ST	ST	4	3	2	83.46	3,256	11.34
SN	SN	3	5	5	83.85	4,238	8.43
WN	WN	4	5	2	84.57	2,980	9.52

From table 2, the properties of nonlinear model, all of estimators can estimate the output waveform of model closely to the experimental data but the best estimator is deadzone with lowest pole and zero and 91.75% accuracy. The model analysis of inverter in step up transient condition is described by properties of an input nonlinear block and output nonlinear block. Input deadzone estimator is the range of [1,339.8 1,360.9] and output deazone [-1,185.0 -1,159.8]. In order to analyze model, the nonlinear tool can analyze in input/output block but for linear tool, linearization need to be done before using linear tool analysis, consist of mathematical equation and graphical tool such as bode plot, step response, frequency response, nyquist plot, and Nicole plot as shown in Fig 6.

In the same manner, the accuracy of waveform from the system identification in step down transient conditions is obtained as shown in Fig 7. The model properties of transient step down nonlinear models are shown in Table 3. In case of step down nonlinear models, the piecewise linear is the most suitable estimator for the nonlinear part of the model with low order but high accuracy 85.59%. Nonlinear estimator of the transient step down model is piecewise linear with 10 units.

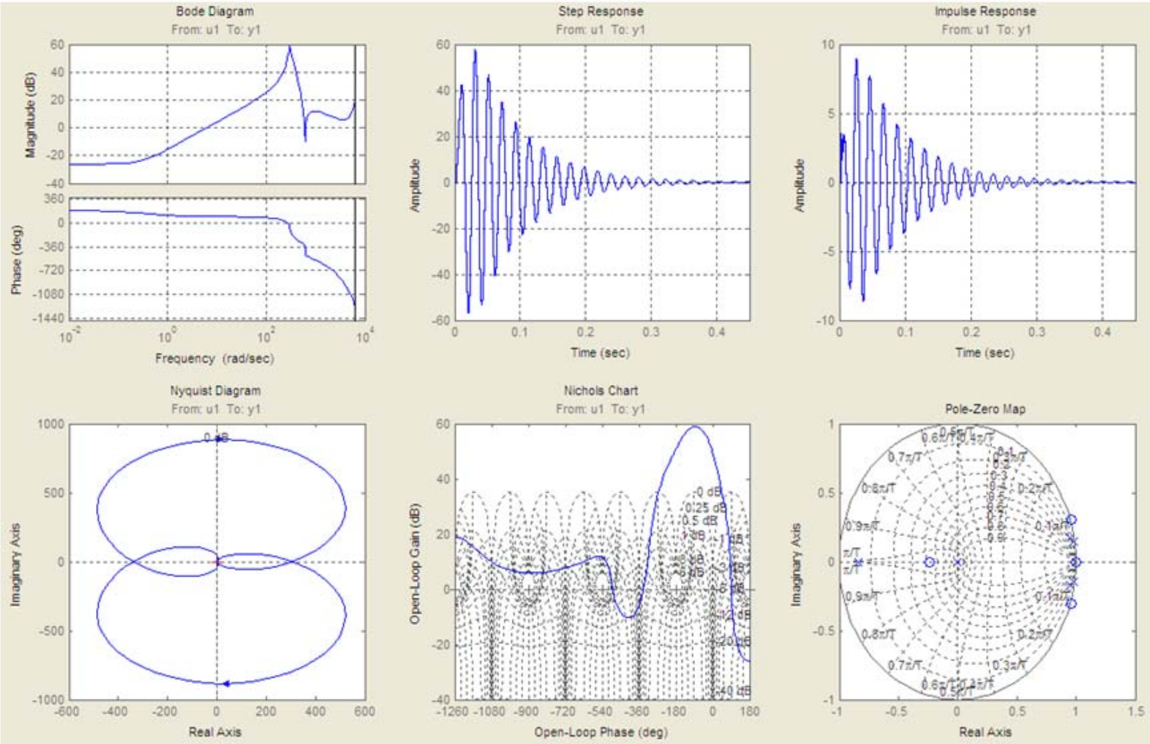


Fig. 6: Graphical tool for linear system analysis

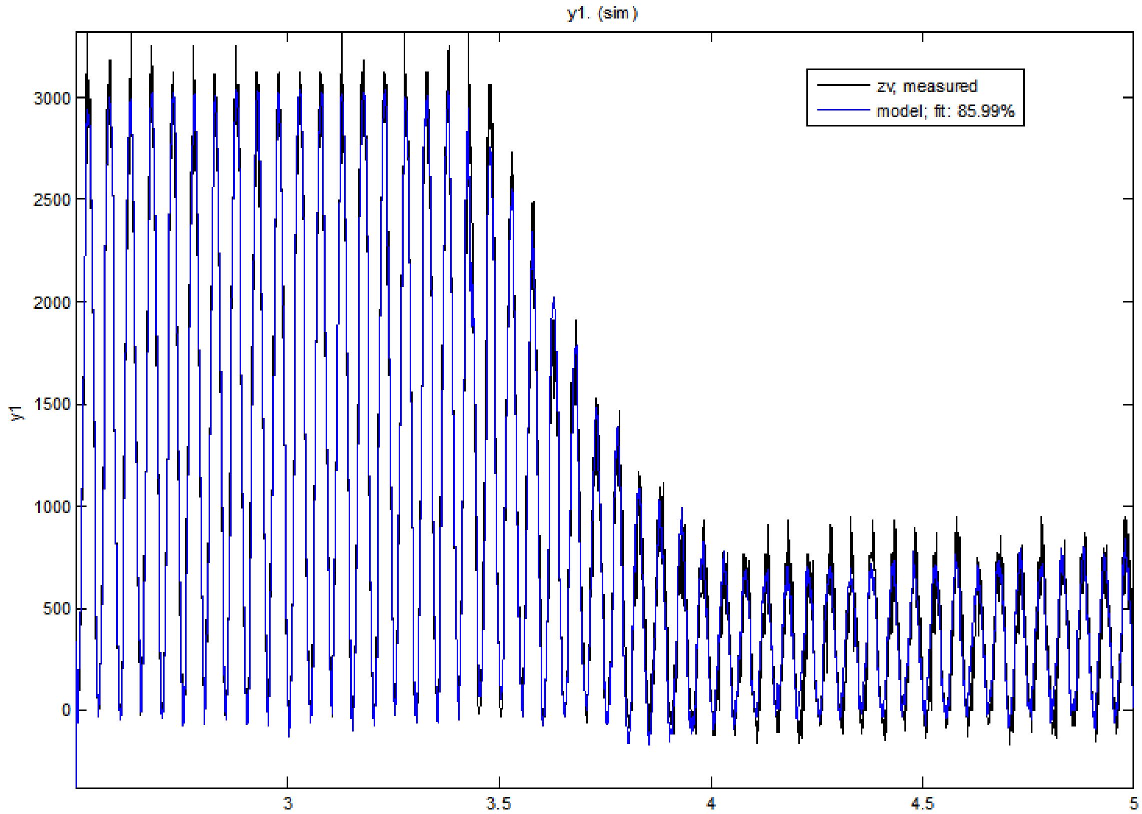


Fig. 7: Comparison of output waveform in step down transient condition from model and experimental

Table 3: Model properties of transient step down nonlinear models

Nonlinear		Linear			Model properties		
I/P	O/P	b_n	f_n	k_n	% fit	FPE	AIC
DZ	DZ	4	5	5	85.12	9,718	9.18
PW	PW	3	4	3	85.99	3,233	10.0
ST	ST	3	5	5	81.29	3,049	11.23
SN	SN	4	4	1	81.17	4,426	8.28
WN	WN	4	5	4	82.45	3,325	9.25

The mathematical model being the representation of the system can be analyzed and provide characteristics on controllability, stability, power quality, power flow in such condition. The step down transient condition of PV based inverter is shown to be an example of utilization of model, bode plot and stability is selected for analysis. The bode plot analysis of model is described the phase margin at 1,639 rad/sec is 0.7843 dB and gain margin at 89.30 rad/sec is -13.89 degree. One of the model utilization is stability analysis, for step down condition of inverter the model has 2 zeros and 4 poles as shown in Fig 8. The stability threshold for pole values of discrete-time is stable if the magnitude of the pole is less than 1. The fours poles are 0.9923 + 0.0575i, 0.9923 - 0.0575i, 0.7060 and -0.1213. Theirs magnitude are 0.9940, 0.9940, 0.7060 and 0.1213 which less than 1.

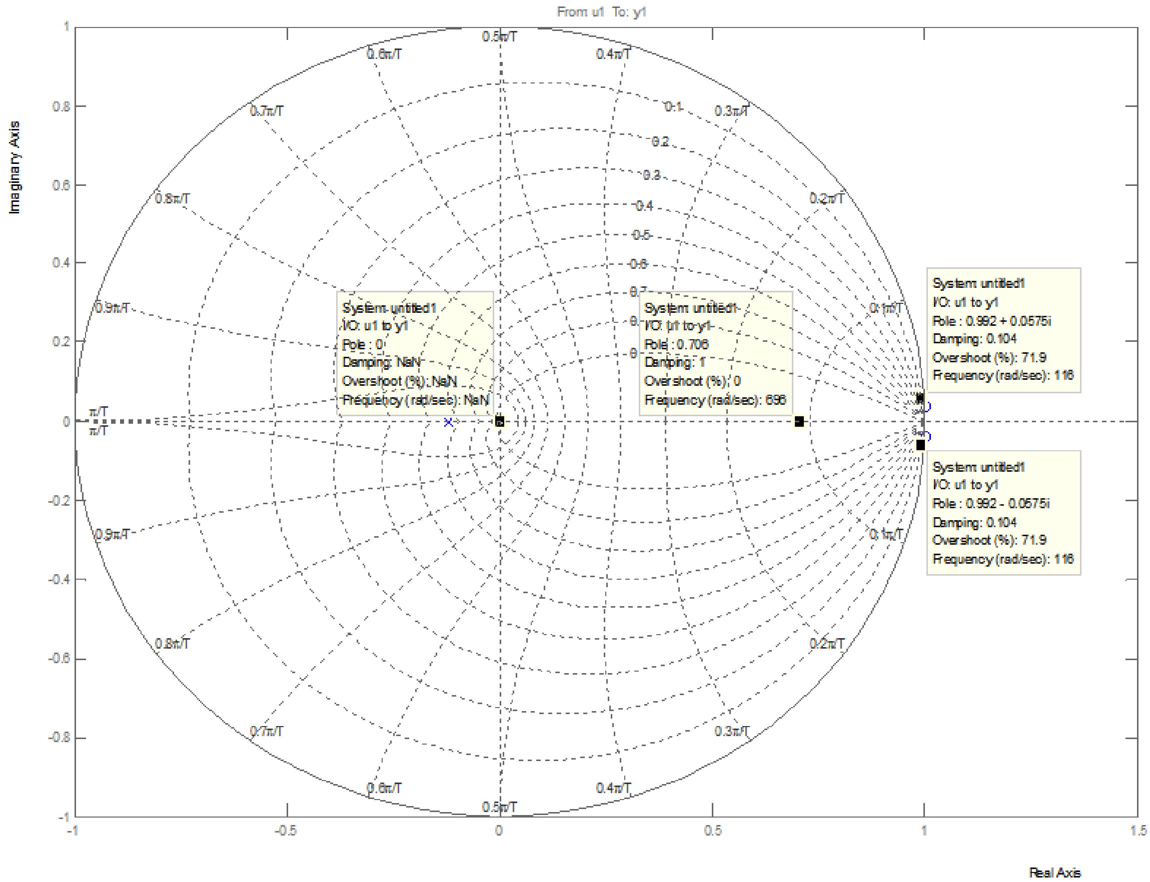


Fig. 8: Graphical tool for linear system analysis

V. Conclusion:

In this paper, modeling single phase grid connected inverter is carried out. The inverter operates in power step up and step down condition transient conditions and its model is done by nonlinear system identification approach via Hammerstein-Wiener Model. The accuracy of waveform from the system identification between experimental and validate data in step up and step down transient conditions are 91.79%, 89.59% respectively. The results from the model are shown that the system identification has a capability to follow the system even through it change operating condition. This potential of system identification for modeling is utilized for system control like model predictive control.

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