Nonlinear Model Identification for Inverter of AMB-Flywheel System

Yong He, Kenzo Nonami

***Abstract*—This study focuses on the modeling of the power electronic inverter of an active magnetic bearing flywheel (AMB-flywheel) energy storage system using a Hammerstein-Wiener (HW) nonlinear identification model. In order to verify the effect of the HW modeling, we use two standard nonlinear models (saturation and deadzone models) and compare their functioning with that of the estimated model of HW. Our simulation results show that the HW system identification model can realize the output target with 97% accuracy for saturation and deadzone characteristics. The power electronic inverter system uses a three-phase inverter connected to the induction motor of AMB-flywheel system. We evaluate the inverter based on using a nonlinear HW type identification mathematical model, and we present the nonlinear simulation results in this paper.**

***Index Terms*—Nonlinear system identification, Hammerstein-Wiener, AMB-flywheel, Inverter**

I. INTRODUCTION

ENERGY storage in electric vehicles (EVs) is currently accomplished using chemical batteries; most commonly used battery is the Li-ion Battery [1-2]. The flywheel energy storage system has been considered an alternative technology for EV power supply. By virtue of their facilitating high ratational dynamics, durability, and relatively high efficiency, active magnetic bearing flywheel (AMB-flywheel) energy storage systems are well suited for use as energy storage systems to improve the quality of electric power delivered to the EV.

When used in EVs, the AMB-flywheel energy-storage system, which can be delivered and charged to large power values via an appropriate power converter system, is limited only by the rating of the motor/generator. In this configuration, the design of charging circuit of the AMB-flywheel is constrained mainly by the energy storage system efficiency. The performance of the AMB-flywheel energy storage system is directly affected by the quality of its power supply system.

From the current literature, it can be observed that the linear time-invariant models, which are currently used standardized theories of the approximation and linearization method of linear systems, are similar to those used to analyze the power supply inverter circuit. The typical modeling methods comprise the switching state-space averaging method, circuit-average method, the average large-signal model and the generalized state-space averaging method [3].

In general power electronic systems include a high-order, strong nonlinearity, and high-frequency characteristics; hence, the approximation and linearization method cannot accurately express the dynamic behavior of the circuit between operation cycles. Thus, the estimation of an accurate nonlinear model by directly using the relationship between the input and output data, not only in theory, but also in practical application, control theory will be of immense value in improving the efficiency of power electronic systems. We call this nonlinear black box system identification model of the system [4].

In control engineering, system identification has been extensively studied for several decades, and has been proposed a variety of different identification methods. All the methods proposed embark on the same goal of improving and enhancing systems design by obtaining an improved mathematical model. System identification using the Hammerstein-wiener (HW) model has been the focus of active research for many years. In this study, we propose the application of the HW model is proposed to the AMB-Flywheel charging inverter system.

The paper is organized as follows. Section 2 describes the main components of the AMB-Flywheel energy storage system. An analysis of the nonlinear characteristics of the HW model is presented in Section3. Section 4 explains the mathematical models of the deadzone and saturation functions and the nonlinear system identification approach of the power supply inverter system. Experimental results and comparative performance evaluations are provided in Section 5. Further, we discuss the strengths, limitations and potential applications of the proposed design.

II. AMB-FLYWHEEL ENERGY STORAGE SYSTEM

An AMB-Flywheel energy storage system (FESS), is an electronic and mechanical device that stores electrical energy as the kinetic energy of the flywheel and provides electric power supply to connected electronic equipment such as the motor of an EV. The energy storage system is one of the most critical components in the development of energy-efficient EVs.

Fig.1 shows the EV-FESS assembly. The figure shows the

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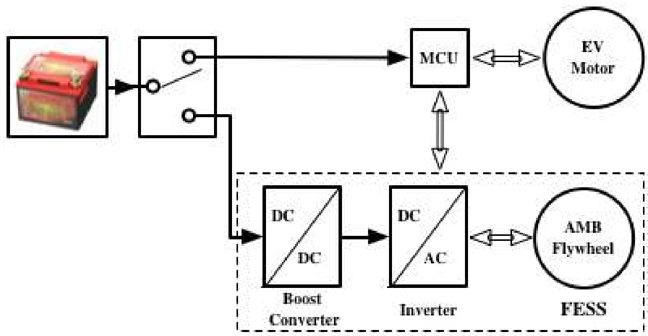

Fig. 1. AMB-FESS for EV Architecture

scale-modeled version of the laboratory test EV bench. The test EV bench has a modular structure that enables the study of different charge/discharge unit (CDU) topologies.

In this system, the electrical energy received from the DC input of the battery to the EV motor is switched to providing power from the battery to the FESS. After charging the FESS, the FESS begins supplying electric energy from the flywheel to the load.

An induction motor is used as the motor for AMB-Flywheel. A three-phase power electronic inverter system that includes exhibits strong nonlinear behavior is connected with the induction motor; therefore, in this study, we use nonlinear system identification for the AMB-Flywheel power converter system. The flywheel is directly coupled to 2.2KVA induction motor with 2 pole pairs. As the energy stored in the inertial storage system is directly proportional to the square speed of the wheel, it is not meaningful to consider lowering the speed. There are four main parts in the bench: DC battery, motor control unit (MCU), charging and discharging unit (CDU), AMB-flywheel.

III. Hammerstein-Wiener Model

The system identification model constitutes a number of linear and nonlinear blocks connected in various cascading and parallel combinations representing systems such as the Wiener model, Hammerstein model, Wiener-Hammerstein model and Hammerstein-Wiener model [5-6].

In this section, we introduce a nonlinear system identification method called the Hammerstein-Wiener model (HW), which is combination of the Wiener and Hammerstein models. In the HW model, the nonlinear block is static, and it follows or is followed by a linear system.

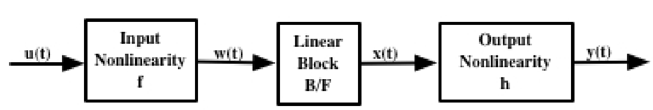

Fig. 2. Hammerstein-Wiener model structure

The structure of the Hammerstein model comprises a linear component following a nonlinear component. In contrast, the Wiener model structure has a linear component preceding a nonlinear component. These two schemes are combined together as one model, the HW model [7]. The nonlinear blocks are assumed to account for the static nonlinearities in the system, while the linear block account for the rest of the dynamics of the system. Fig.2 shows the Hammerstein-Wiener structure as well as the symbols for the subsystems and the signal names used in this paper.

A. Linear Subsystem

In the linear block, the signal $x(t) = (B/F)w(t)$ denotes a linear transfer function. The signal $x(t)$ has dimensions identical to that of $y(t)$. The polynomials B and F contain the time-shift operator q, which is essentially the z-transform that can be expanded as in the following equations.

$$B(q) = b_1 + b_2 q^{-1} + \cdots + b_n q^{-bn+1} \tag{1}$$

$$F(q) = 1 + f_1 q^{-1} + \cdots + f_n q^{-fn} \tag{2}$$

B. Nonlinear Subsystem

Nonlinear models are used extensively in various system domains. They allow the representation of physical processes over a wider range of operating points than the linear model. The HW model is composed of the input and output nonlinear blocks containing nonlinear functions $f(\cdot)$ and $H(\cdot)$ respectively, corresponding to the input and output nonlinearities. Both nonlinear blocks are implemented using nonlinearity estimators. Within this structure, $u(t)$ and $y(t)$ denote the input and output signals of the HW block structure respectively. In general, the intermediate variables $w(t)$ and $x(t)$ are not measurable.

The intermediate output $w(t) = f(u(t))$ is a nonlinear function transforming input data $u(t)$. The function $w(t)$ has dimensions identical to those of $u(t)$. The final output $y(t) = h(x(t))$ is a nonlinear function that maps the output of the nonlinear block.

The details regarding the estimation of the inverter's nonlinear functions and the linear component of the HW-Block-oriented model are covered in the next section prototype system under consideration.

IV. NONLINEAR IDENTIFICATION MODEL

The charging unit inverter of the AMB-flywheel system exhibits strong nonlinear characteristics. In order to verify the effect of the HW identification algorithm for the nonlinear deadzone and saturation models, we use designed simulations. The nonlinear block contains a simple nonlinear estimator with deadzone or saturation functions.

A. Examples of nonlinear model Estimation

This section presents a mathematical model for the deadzone function, which indicates a static input-output relationship. The lower and upper limits of the deadzone are specified as the start and end of points of the deadzone parameters. The deadzone can define a nonlinear function $y = f(x)$, where f is a function of x. The following equations define the output of this function.

$$\left.\begin{array}{ll} x \le a & f(x) = x - a \\ a < x < b & f(x) = 0 \\ x \ge b & f(x) = x - b \end{array}\right\} \quad (3)$$

Here, x denotes the input value, $f(x)$ denotes the output value, and a and b are breakpoints; consequently, the output interval of the function equal to $f(x) = 0$ this zone is called as zero interval.

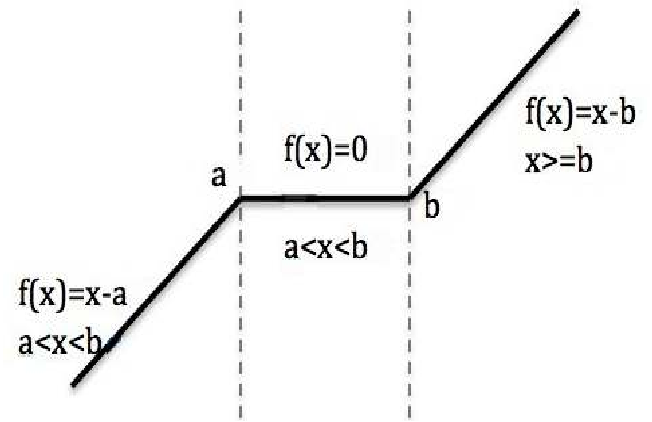

Fig. 3. Deadzone function

The saturation function generates an output signal with upper and lower limits. When the input signal value is between the upper and lower limits, the output signal is identical to the source signal. If the input signal exceeds the limit range, it will automatically be limited to the upper or lower limits. The following equations define the output of this function.

$$f(x) = \begin{cases} a & \text{if} \quad x > a \\ b & \text{if} \quad x < b \\ a = b & \text{if} \quad a = b \\ x & \quad a < x < b \end{cases} \quad (4)$$

Here, x denotes the input while $f(x)$ denotes the output.

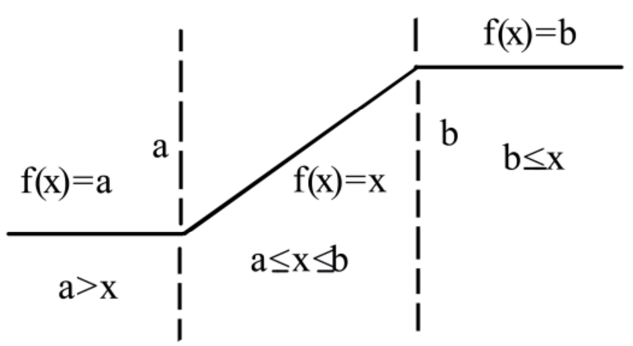

Fig. 4. Saturation function

Inverter modeling is performed by selecting the model structures and adjusting the model order of the linear terms and the nonlinear estimators of HW system identification model. In order to obtain the models of the saturation and deadzone functions. Batch processing is performed as shown in Fig.5. In the process, the output of the inverter is estimated, and the output signals are constructed from the saturation and deadzone nonlinear models.

The implementation of the process has been developed by programming using the MATLAB software in order to compare the accuracy between the actual nonlinear model and the identification model. In the simulation, a chirp signal is used as input data and the data are divided in two groups. One group is used as data to estimate the training model whereas the other group is used as input signal for the selected standard nonlinear models. The identification accuracy of each case has been observed. A comparison of the results for both cases is carried out following the system identification process shown in Fig. 5.

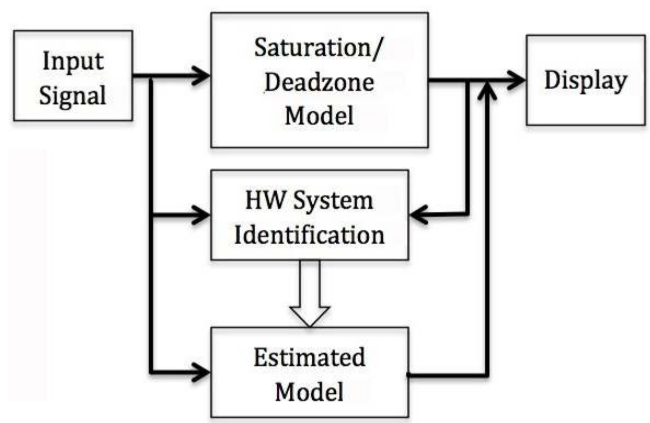

Fig. 5. Block diagram of comparison approach

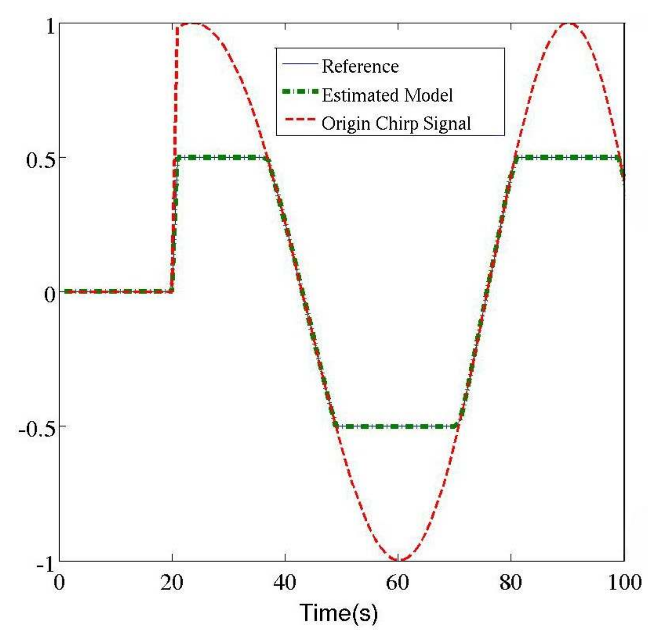

Fig. 6. Comparison of estimated model and reference model: saturation model

In the figure, the solid line indicates the reference signal; the dash-dot denotes the output of the estimated model while the dashed style line indicates the original chirp signal.

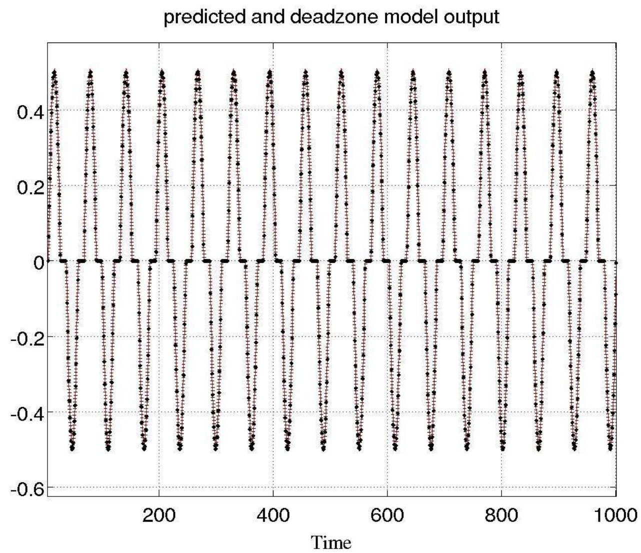

Fig.7. Outputs for predicted and selected deadzone models

The plots in Fig.7 show the predicted output and selected deadzone model output. The predicted model output is obtained from the validation data of selected model, whose output is plotted as indicated by the dotted line.

In both the abovementioned, the percentage of the output variations in the two standard nonlinear models (saturation and deadzone models) are accurately reproduced by our actual model; this percentage value is more than 97%, and this indicates the accuracy of our model.

B. *Modeling Inverter of AMB-Flywheel system*

The system used in this study is the AMB-flywheel charging inverter system. The plant system consists of DC power supply, AC power system, a power analyzer AMB-flywheel loads and a computer as shown in Fig.8.

The two steps required in modeling the inverter based on system identification are described as follows:

--First, preparing data for identification of models though the experimental system. In order to obtain the models, a laboratory setup is assembled, and it consists of a type of commercial grid connected to three-phase inverters. In the system identification process, both voltage and current values are measured by a power analyzer and transmitted to a computer, and subsequently, the power is calculated using the voltage and current waveform data to estimate the inverter model.

--Second, loading of data into the Matlab system identification toolbox. The first part of the input-output signal produced by the HW model system can be considered as a signal equivalently produced by two nonlinear static systems placed around a dynamic linear system. These models are difficult to identify due to the presence of two nonlinear systems. Usually, a nonlinear estimation procedure is necessary to estimate the parameters of the different parts of the HW model. These nonlinear estimation procedures need accurate starting values to converge quickly and/or reliably to a global minimum.

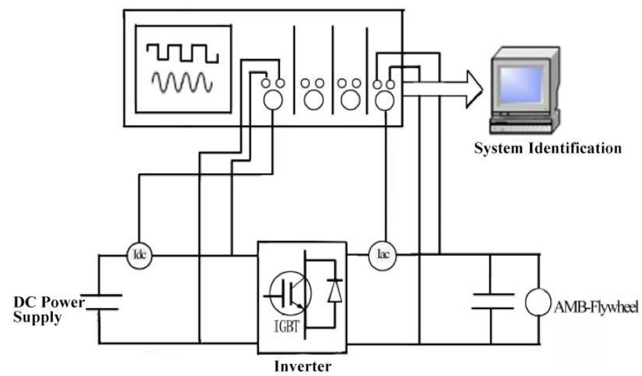

Fig. 8. Schematic of experimental setup for inverter modeling

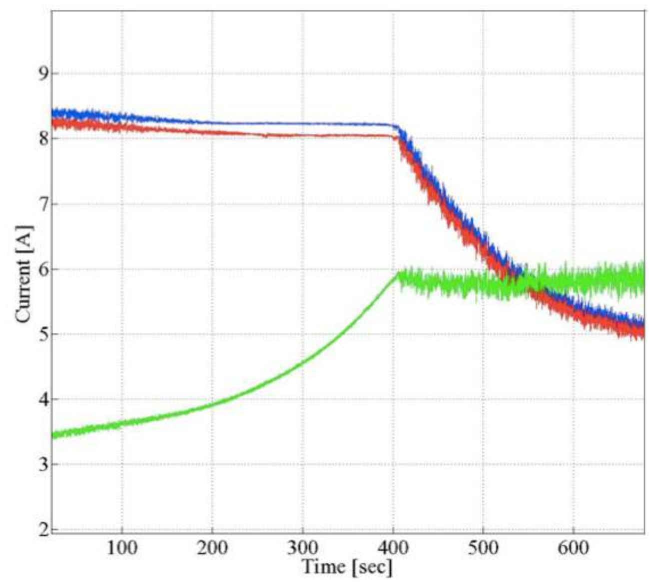

Fig. 9. Current waveform of inverter system

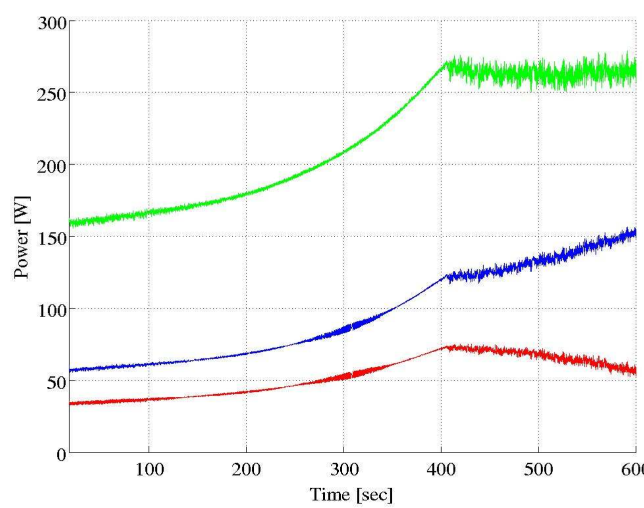

Fig.10. Power waveform of inverter system

In Fig.10, the green line indicates the DC power (P_{dc}), and blue and red line indicates AC power (P_a , P_b). The total active power of the three-phase three-wire system can be calculated as $P_{tol} = P_a + P_b$.

To illustrate the performance of the modeling in identifying the AMB-Flywheel power electronic converter system, data collection for the input-output testing of the plant was carried using the power analyzer. The power waveform data is used as data to estimate the actual model or training model.

For each of the input signals, both the static nonlinearities were modeled using saturation and deadzone functions. The breakpoints were chosen automatically for equal support. Fig.11 shows the result for the linear block section of the identified HW model result. Fig.12 shows the identification result for the output nonlinear function h(w) of the measured HW system. Fig.13 shows the identification result for the input nonlinear signal f (u) of the measured HW system.

Fig.14 describes the predicted output from the inverter model in comparison with the test set data. The linear model component is presented in equation (5). The linear block represents the embedded linear model in the HW model. The linear component of the HW-Block-oriented model is given by two polynomials show below.

$$y(t) = \left[\frac{B(q)}{F(q)}\right]u(t) + e(t) \tag{5}$$

$$B(q) = 0.3022 - 0.4751\ q^{-1}$$

$$F(q) = 1 - 0.6955\ q^{-1} + 0.0565\ q^{-2} - 0.0281\ q^{-3}$$

The percentage of best-fit accuracy is obtained from comparison between the experimental waveform and the simulation modeling waveform, and it can be calculated using Equation (6). The identified model is observed to show a goodness of fit rating of 0.9755.

$$fit = 100 \times (1 - norm(\breve{y} - y) / norm(y - \overline{y})) \tag{6}$$

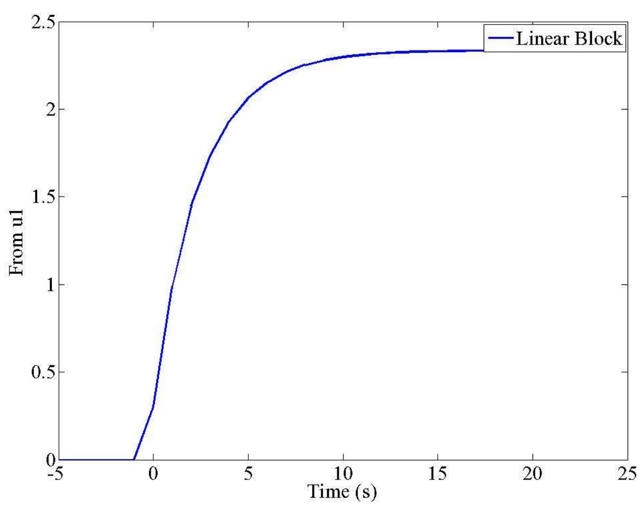

Fig. 11. Identification result for linear block section of measured Hammerstein-Wiener (HW) model

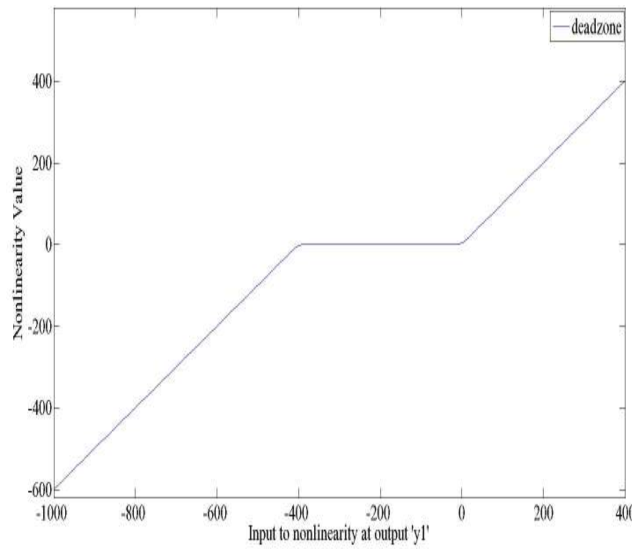

Fig. 12. Result for nonlinear output block

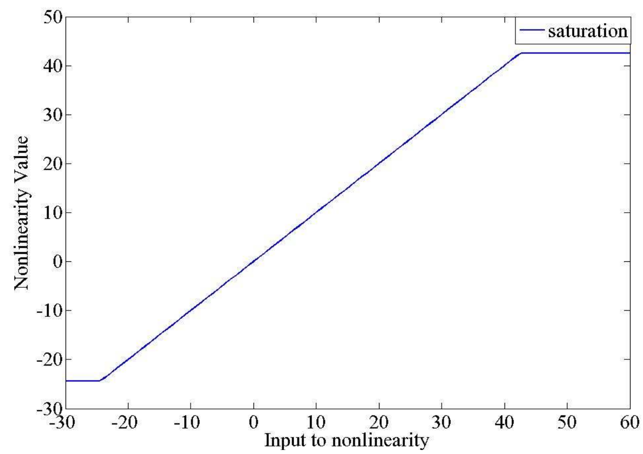

Fig. 13. Result for nonlinear input block

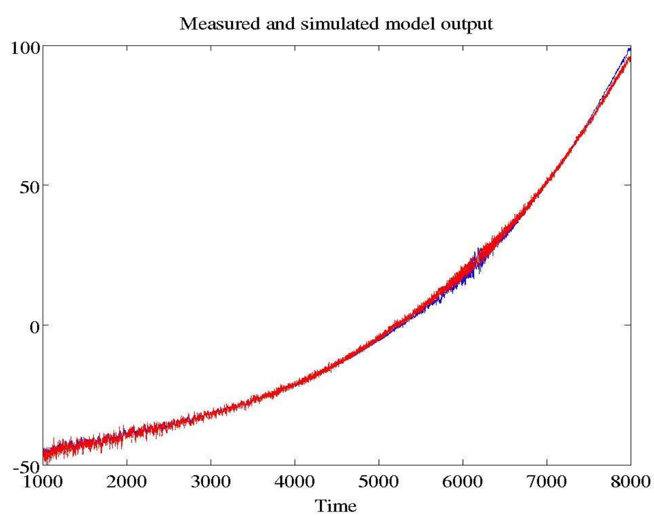

Fig. 14. Identification result for inverter system

In Fig.14, the red line represents the identified model and the blue line represents the true values on each of these plots. Using the model selection criteria, the following results were obtained: Best Fit， 97.55%; Loss Function, 1.073; Final Prediction

Error (FPE), 1.087. Based on the smallest value criteria of FPE and a best fit value of 97.55%, this model can be considered as an acceptable model of the inverter system.

V. CONCLUSION

In this study, charge/discharge unit is used in flywheel energy storage system, and this proposed system can boost and generate a desired output voltage efficiently when low voltage of power supply is introduced. We modeled one type of three-phase inverter, which was connected to the induction motor of an AMB-flywheel, was carried out, and the modeling was carried out using nonlinear system identification approach comprising the HW model. The comparison of the results of the saturation and deadzone models show that the differences between the known model and the estimated model are within 10%. The percentage accuracy of the HW system identification exhibits a high value for saturation and deadzone models. The result illustrates that HW algorithm has good performance for the nonlinear identification of the three-phase inverter in the AMB-flywheel energy storage system.

REFERENCES

[1] J. Mierlo, P. Bossche, G. Maggetto, "Models of energy sources for EV and HEV: fuel cells, batteries, ultracapacitors, flywheels and engine-generators", Journal of Power Sources, Vol. 128, 2004, pp. 76–89.

[2] B. Wang, G. Venkataramanan, "Dynamic Voltage Restorer Utilizing a Matrix Converter and Flywheel Energy Storage", Industry Applications Conference, 2007. 42nd IAS Annual Meeting. Conference Record of the 2007 IEEE, Volume, Issue, 23-27 Sept. 2007, pp. 208–215.

[3] H. X. Li, "Identification of Hammerstein models using genetic algorithms", Proc. lEE Control Theory Appl., Vol. 146, No. 6, 1999, pp. 499- 504.

[4] D. S. Bayard, "An algorithm for statespace frequency domain identification without windowing distortions," IEEE Trans. Auto. *Contr.,* Vol. 39, No.9, 1994, pp. 1880-5.

[5] T.Patikirikorala, L. Wang, A. Colman, "Hammerstein-Wiener nonlinear model based predictive control for relative QoS performance and resource management of softeare systems", Control Engineering Practice, Vol. 20, 2012, pp.49-61

[6] S. J. Norquay, A. Palazogulu, J. A. Romangnoli "Application of Wiener model predictive control (WMPC) to an industrial c2-splitter", Journal of Process Control. Vol. 9, 1999, pp. 461-473.

[7] E. W. Bai, "A Blind Approach to the Hammerstein-Wiener Model Identification", Automatica, Vol. 38, No. 6, 2002, pp. 967–979.

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