Modeling of Induction Heating Inverter Using System Identification

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Abstract. In this paper, Auto Regressive eXogenous input (ARX), Auto Regressive Moving Average eXogenous input (ARMAX), Output error and BJ models of class D voltage-source half-bridge series-resonant inverter used for induction heating are identified and studied based on prior knowledge and measured data from PSIM simulation Environment. The output data are generated by applying Pseudo-Random-Binary-sequence (PRBS) as an input through the inverter MOSFET gate in the PSIM software. PRBS signal is generated using standard components such as flip-flops or XOR gates to approximate the white noise in the PSIM software. The generated output and input data are loaded in the MATLAB to identify the unknown system parameters of induction heating inverter by using MATLAB system identification toolbox. Estimation of models with pre-selected structures can be performed using system identification toolbox. To validate the models and their limitations, the fitness properties of the models based on percentage best fit and their resonant frequencies are examined.

Keywords: System identification · Induction heating inverter · PRBS

1 Introduction

Recently a class D voltage-source half-bridge series-resonant inverter has become very popular and become more and more widely used in various applications, especially in the applications where small-size electric appliances are required as a main purpose. They are, for example; electronic ballasts, induction heaters and induction cookers, etc. Depending on the position of the load with respect to the elements of the resonant circuit, the converters of class D may be divided into series resonant converters, parallel resonant converters, and series–parallel (hybrid) converters [1]. The characteristics of the induction heating converter must be identified as much as possible accurately to control the efficient transfer of energy from the source. There are many simple analytical methods to obtain the mathematical model of a converter. However, to have a

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good understanding on the correct behavior of the converter, it is necessary to utilize advanced technique to achieve accurate model that resemble the converter. In [2], a PSpice software is used to obtain a simple mathematical model for the series-parallel resonant topology with a capacitor as output filter. A generalized state space averaging model for LCL resonant inductive power transfer is constructed to transform the nonlinear model into a linear approximation model [3]. In this work, the authors mainly consider the running frequency and load parameter uncertainty to detached the uncertain system model from the system model by using the linear fractional transformation method. A good review of analytical methods for IH can be found in [4].

System identification can be used in a wide range of applications, including mechanical engineering, biology, physiology, meteorology, economics, and model-based control design [5]. Among different system identification technique, least square method is probably the most popular and numerically simple, in which error is appropriately defined. However, the least square method suffers if the model order is not sufficiently high and cause accuracy problems if the noise level increases [6]. Moreover, if the model structure is not linear in the parameters, this approach may be invalid [7]. To identify the parameters in nonlinear model structure, the modern optimization techniques such as genetic algorithm and particle swarm optimization algorithms seem to be a more hopeful approach and provide a powerful means. [8] proposed a methodology to find optimal system parameters and optimal control parameters using adaptive particle swarm optimization for nonlinear system. In [9], an overview of the basic principles and results and the problem areas in the practical side of how to approach and solve a real problem have been extensively studied. Nonlinear system on-line identification via dynamic neural networks is studied in [10]. The main contribution of the paper is that the passivity approach is applied to access several new stable properties of neuro identification.

The main concern of the paper is to obtain the linear discrete model of medium frequency induction heating by using system identification technique. This paper is organized as follows. Section 2 proposes a family of different linear model formulations and identification. In Sect. 3, a Class D voltage-source half-bridge series-resonant inverter PSIM data measurement results are presented. Section 4 reports model validation and comparison. Finally, the paper is concluded in Sect. 5.

2 Linear Model Formulation and Identification

The two most common techniques to estimate models that represent linear time-invariant systems are nonparametric estimation and parametric estimation. In this paper, the nonparametric estimation approach has been proposed to obtain the models. Consider the general stochastic model shown in Eq. (1).

$$y(t) = q^{-k}G\left(q^{-1},\theta\right)u(t) + H\left(q^{-1},\theta\right)e(t) \tag{1}$$

Where $u(t)$, $y(t)$, $e(t)$, $G(q^{-1},\theta)$, $H(q^{-1},\theta)$, θ are the input, output, zero-mean white noise (the disturbance of the system), transfer function of the deterministic part of the system, transfer function of the stochastic part of the system, the set of model parameters respectively. $G(q^{-1}, \theta)$, $H(q^{-1}, \theta)$ are rational polynomials as defined by the following equations [11].

$$G\left(q^{-1}, \theta\right) = \frac{B(q, \theta)}{A(q, \theta)F(q, \theta)} \tag{2a}$$

$$H\left(q^{-1}, \theta\right) = \frac{C(q, \theta)}{A(q, \theta)D(q, \theta)} \tag{2b}$$

In this section, discrete linear system model formulations are introduced from the general stochastic model by Setting one or more of $A(q, \theta)$, $C(q, \theta)$, $D(q, \theta)$, and $F(q, \theta)$ equal to one. The ARX model of a system is given by setting $C(q)$, $D(q)$, and $F(q)$ equal to one.

$$A(q)y(t) = B(q)u(t) + e(t) \tag{3}$$

The e(t), residual or equation error, is used to account for the fitting error. The major drawback of the ARX model is lack of adequate freedom in describing the properties of disturbance term. An important properties of the equation error as moving average of the white noise is described in ARMAX model. When $D(q, \theta)$, and $F(q, \theta)$ equal to one.

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \tag{4}$$

The output error model and Box-Jenkins (BJ) model structures in a more compact form are shown in Eqs. (5) and (6) respectively.

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

$$y(t) = \frac{B(q)}{F(q)}u(t) + \frac{C(q)}{D(q)}e(t) \tag{6}$$

The issue of system identification technique has been addressed by many authors in several books and survey articles where many different identification methodologies have been exploited. For instance, the authors of [12] obtained the ARX model for billet induction heating process with the help of Matlab system identification toolbox and the result shows the model has high prediction accuracy. In [13], on-line parameter estimation method has been proposed to obtain the model of a 3-phase induction heating. The approach uses PSIM simulation and experimental results to study its impedance matrix for control application.

3 Data Measurement

In practice, most often test signals are added to the inputs of the system to move the output up and down around a working point. For theoretical analysis purpose, white noise is used as test input in system identification since white noise has autocorrelation that is impulse response function at the origin and a wide (theoretically infinite) frequency range. It can therefore excite the process over a wide frequency range. In practice, it is impossible to generate a pure white noise so that we need to approximate the white noise signals by PRBS. This type of noise has a periodic autocorrelation function and it can be easily generated by using a feedback shift register. The different properties of PRBS including its autocorrelation, its realizations and its similarities with white noise is clearly explained in the literature [5]. In this work, we generate PRBS signal using standard components such as flip-flops and XOR gates to approximate the white noise in the PSIM software. This type of signal, $u(t)$, has a periodic autocorrelation function and given by (7).

$$\phi_{uu}(\tau) = \frac{1}{T}\int_{0}^{T} u(\lambda)u(\tau+\lambda)d\lambda \tag{7}$$

Pseudo random binary signal was generated by a shift register with 4 stages shown in the Fig. 1. The maximum length of the signal (maximum period) sequence is $N = 2^n - 1 = 15$, where n is the number of D flip flop used in the circuit. As follows from the figure shown in the Fig. 1, the clock frequency of PRBS is $\frac{1}{\Delta} = 100$ kHz. As we know, PRBS is a deterministic signal and its autocorrelation function can resemble the autocorrelation function of a white random noise if the length of signal is large. From Eq. (7), the autocorrelation of PRBS has been found in Eq. (8).

$$\phi_{uu}(\tau) = \begin{cases} 1, & for\ \tau = 0, T, 2T, 3T, 4T\ldots \\ \frac{-1}{15\Delta} & elsewhere \end{cases} \tag{8}$$

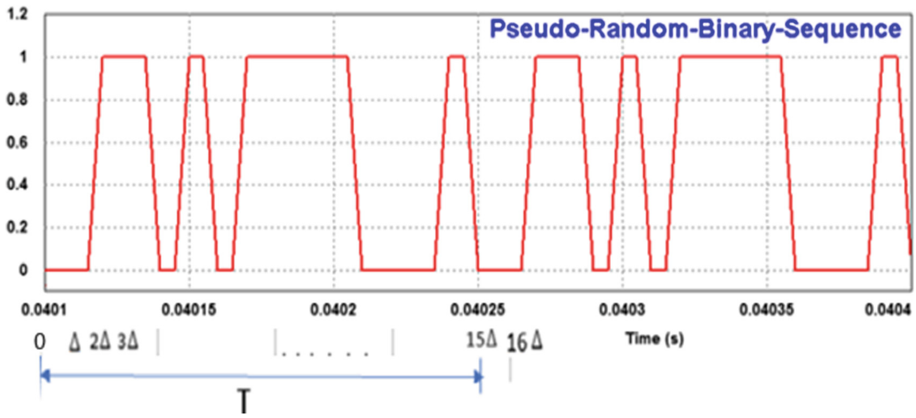

Fig. 1. PRBS waveform

In this paper, a Class D voltage-source half-bridge series-resonant inverter topology shown in Fig. 2 has been proposed to identify the model of induction heating converter by collecting a time varying data in PSIM simulation software. The converter is excited by Pseudo-Random-Binary-Sequence (PRBS) input in the gate of MOSFET and a valuable data is obtained by measuring the output current through the load. L_{eq}, R_{eq}, C_r are the equivalent load inductance, equivalent load resistance and resonant capacitor respectively. For simulation purpose, the load parameters are taken from [14]. Table 1 gives a summary of the PSIM simulation parameters. A total of 20,000 input/output data pairs were collected with a clock frequency of 100 kHz and transferred to MATLAB to estimate a linear discrete model of the system from the measured data. As shown in Fig. 2, the inverter is excited by a 4-stage PRBS at the gate side of the MOSFET and output current data is observed through the load.

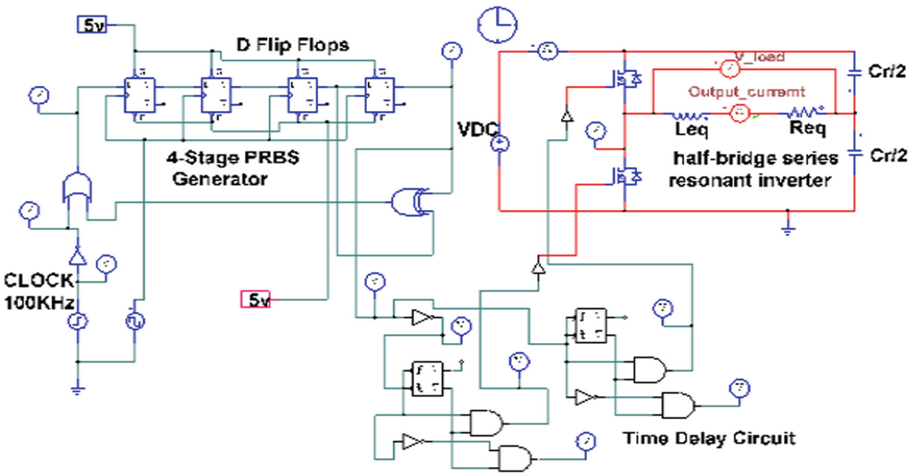

Fig. 2. The complete induction heating PSIM mode

Table 1. PSIM simulation parameters

V_{DC}	L_{eq}	C_r	R_{eq}	Flip-flop clock frequency
198 V	82.4 μH	0.3024 μF	3.55 Ω	100 kHz

4 Model Comparison and Validation

In this section, different models are computed and compared with validation data with the help of MATLAB system identification tool. The measured data is stored in a MATLAB file. We selected the first 13,000 data points for model estimation and the rest for model validation. The system identification toolbox can also be used to obtain a model with a prescribed structure. The discrete form of ARX model is identified and given in Eqs. (9a) and (9b). As stated before ARX model lacks in describing the

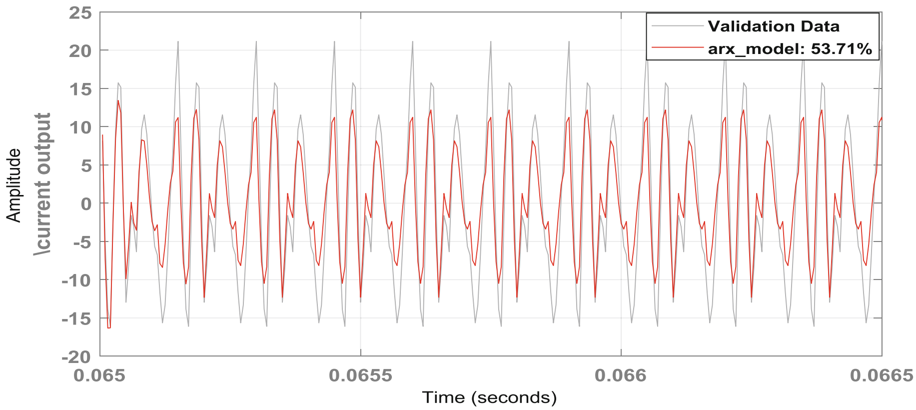

Fig. 3. ARX model simulated response vs. validation data output

properties of disturbance, the data fit is only 53.71 shown in Fig. 3. This reveals that the information in the measured data has not adequately captured by the estimated ARX model. In other word, the model is not rich enough to explain all the information in the measured data of induction heating. By increasing the order of the system, we can get an accurate ARX model that fits the data. However, this increases the complexity of the system. Accordingly, there is a need for improving the fitness value with minimum system order and complexity. Therefore, based on the collected data, the discrete form of ARMAX model is obtained as (10a, 10b and 10c).

$$A(z) = 1 - 1.1328z^{-1} + 0.7323z^{-2} \tag{9a}$$

$$B(z) = 6.946z^{-1} - 6.77z^{-2} \tag{9b}$$

$$A(z) = 1 - 1.422z^{-1} + 0.7602z^{-2} \tag{10a}$$

$$B(z) = 8.334z^{-1} - 8.366z^{-2} \tag{10b}$$

$$C(z) = 1 - 0.7716z^{-1} - 0.2176z^{-2} \tag{10c}$$

Similarly, the discrete form of output error model and BJ model have been found to be in Eqs. (11a and 11b) and (12a, 12b, 12c and 12d) respectively.

$$F(z) = 1 - 1.409z^{-1} + 0.7488z^{-2} \tag{11a}$$

$$B(z) = 9.188z^{-1} - 9.329z^{-2} \tag{11b}$$

$$F(z) = 1 - 1.432z^{-1} + 0.7688z^{-2} \tag{12a}$$

$$B(z) = 8.599z^{-1} - 8.631z^{-2} \tag{12b}$$

$$C(z) = 1 - 0.4554z^{-1} - 0.5293z^{-2} \tag{12c}$$

$$D(z) = 1 - 1.076z^{-1} - 0.5244z^{-2} \tag{12d}$$

Figures 4, 5 and 6 illustrate the model validation using validation data for different models by assuming the order of the system is the same as ARX model. As one can see from figures, the estimated model of ARMAX, Output error and BJ model are fitting the validation data set more than ARX model. It has been found that the ARMAX,

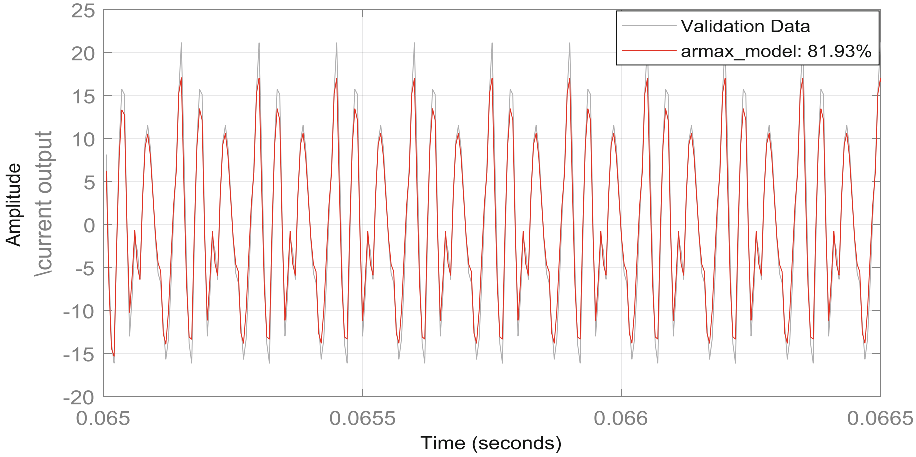

Fig. 4. ARMAX model simulated response vs validation data output

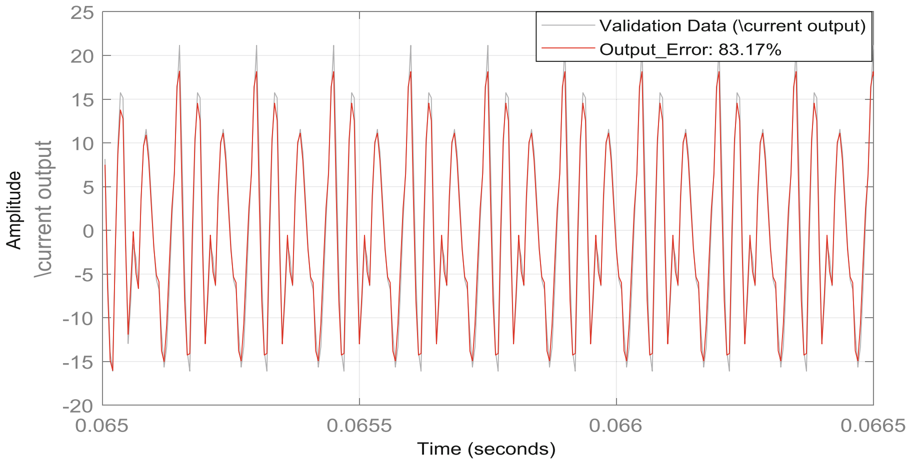

Fig. 5. Output error model simulated response vs validation data output

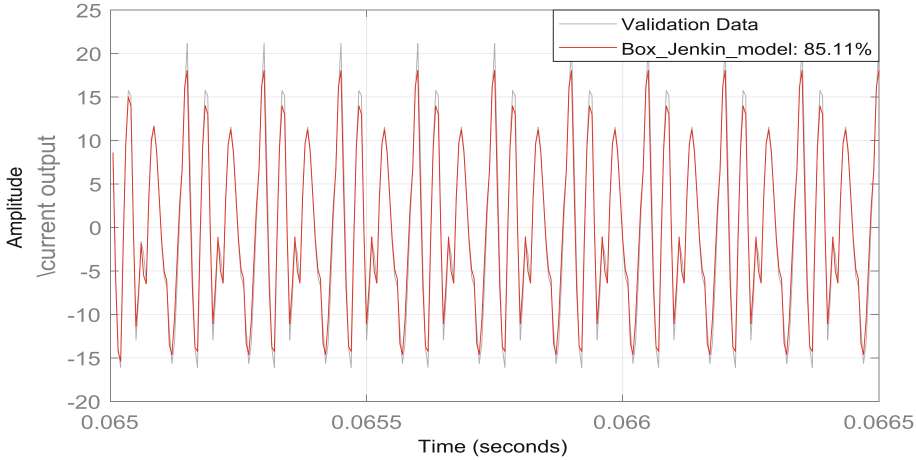

Fig. 6. BJ model simulated response vs validation data output

Output error and BJ model fits to measured data are identified as 81.93%, 83.17%, 85.11% respectively. It can be observed here that the validation agreement is very good, and the models are rich enough to explain most of the information in the measured data of induction heating.

To evaluate the estimated models' quality in frequency domain, we simulate the bode plot and observe the behavior of the models near to the resonance frequency of the induction heating. The simulation result is depicted in Fig. 7. The simulation result shows that the estimated models are very close to each other near to working frequency

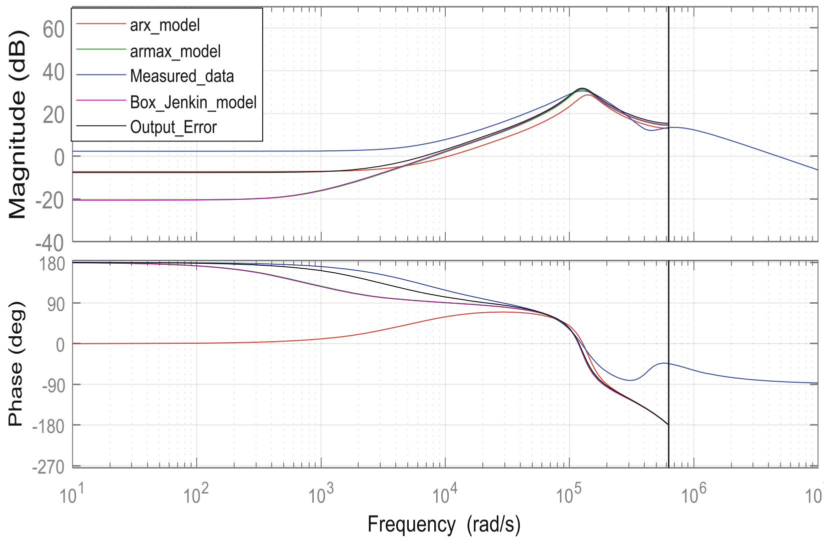

Fig. 7. Bode plot of estimated models

of the inverter, and there is also a clear difference between the measured data and models while moving away from the resonant frequency.

As can be seen from Table 2 and Fig. 7, ARMAX, output error and Box-Jenkins models give a peak magnitude very close to the load resonant frequency (20.3 kHz). Whereas, ARX model shows a peak magnitude away from load resonant frequency. The ARX-model is not so good due to the bias caused by the non-white equation error noise. It is valuable to note that the maximum energy transferred from the source to the induction heating load is at the resonance frequency. Therefore, from the above result suggests ARMAX output error and Box-Jenkins models captures most of the frequency band width of the inverter around the resonance frequency.

Table 2. Response of the models at resonance frequency

Estimated models	Approximated resonance frequency (Hz)	Magnitude (dB)
BJ output error	20,212	31.8
Output error	20,212	31.7
ARMAX	20,053	31.3
ARX	22,600	28.7

5 Conclusion

This paper described the application of model identification technique for medium frequency class D series-resonant inverter used for induction heating based on measured data from PSIM simulation environment. A second order ARX, ARMAX, output error and Box-Jenkins models are obtained, and the result is compared with validation data. ARX model shows a 11.33% deviation in resonance frequency from the measured data. This suggests ARX model is not rich enough to explain all the information in the measured data of induction heating. By increasing the order of the system, we might improve ARX model that fits the data. However, this increases the complexity of the system. From bode plot simulation result, it has been noticed that ARMAX shows a 1.22% deviation in resonance frequency, whereas output error and Box-Jenkins models show a 0.43% deviation in resonance frequency from the measured data. This indicates that these models describe the characteristics of the induction heating with acceptable value very close to the working frequency of the converter.

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