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# A Simulation and Experimental Study on Identification of an Electromechanical System

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**Abstract—The current applications in electromechanical energy conversion demand highly accurate speed and position control. For this purpose, a better understanding of the motion characteristics and dynamic behavior of electromechanical systems including nonlinear effects is needed. In this paper, a suitable model of Permanent Magnet Direct Current (PMDC) motor rotating in two directions is developed for identification purposes. Model is parameterized and identified via simulation and using real experimental data. Linear and nonlinear models for the system are built for identification, and the effective nonlinearities in the system, which are Coulomb friction and dead zone, are integrated into the nonlinear model. A Weiner- Hammerstein nonlinear system description is used for identification of the model. MATLAB is selected as the investigating tool, and a simulation model is used to observe the error between the simulated and estimated outputs. Identification of the linear and nonlinear system models using experimental data is performed using the least squares (LS) and recursive least squares (RLS) methods. Performance of the model and identification method with the real time experiments are presented numerically and graphically, revealing the advantages of the proposed nonlinear identification approach.**

**Keywords—Nonlinear system identification, Wiener-Hammerstein model, Nonlinear PMDC motor.**

## I. INTRODUCTION

Electromechanical systems (EMS) play an essential role in fulfilling the needs of modern technological applications. The electrical energy supplied to these systems is transformed into mechanical energy with an efficiency of 60 per cent by electric drives [1]. The requirements in today's technology for EMS quality are becoming more and more demanding. In addition, the range of technological tasks that need these systems broadens every year. This results in an increasing necessity for more advanced modeling, identification and control strategies for these systems. Many applications need a sufficiently concise and accurate description of the dynamics of these systems. This is especially true in automatic control applications. Dynamic models describing the electromechanical system in use can be developed using principles of physics. However, models constructed in this way may be difficult to derive due to lack of sufficient knowledge or uncertainties in system dynamics.

An alternative way of building models is by system identification. In system identification, the aim is to find estimation for the selected dynamic model structure using observed input and output data. Principles of physics are not directly used to develop a model, but knowledge about the system behavior maintains its importance. Such knowledge is of great value for setting up identification experiments to generate the required measurements, for deciding upon the type of models to be used, and for determining the quality and validity of the estimated models. System identification often yields compact accurate models that are suitable for fast on-line applications and for model-based predictive control.

In today's world of high technology, DC electric drives (DCED) are still important elements of technological processes for various applications in modern industry [1]. The main advantages of using DC motors in such applications are ease of control for speed and position, wide range of operation, and ability to follow a set speed or position under load. Having these capabilities, these systems have been extensively used in many industrial applications [2]. However, when a DC motor rotates at relatively low speeds and in both directions, or when it works in a wide range of operation where high precision control is needed, the nonlinear effects on system behavior become far from negligible and may lead to intolerable modeling errors and poor control performance [3].

The objective of this research is to present the results of a recent simulation and experimental study on identification of a DC motor with load. First, a PMDC motor model is developed with a single-input-single-output (SISO) structure, taking into consideration the Coulomb friction and Dead Zone nonlinearities. Then, the nonlinear model is selected and built with a Wiener-Hammerstein structure for the identification procedure. Root-mean-square-error method is used to compute the error criterion and check the model matching.

## II. NONLINEAR SYSTEM IDENTIFICATION

### A. General Concepts

System modeling and identification involve the effort to describe the dynamic behavior of a given real system by a model selected within a set of approximate models [4, 5]. It constitutes a diverse and established field in both science and engineering for analysis and control of systems. The identification of a plant or system is an approximation of its model from its input/output data to find a suitable model structure and for determining the best suitable mathematical model [6]. Each operation of system identification has to determine a model of a dynamic system, so the executing of the identification for each process consists of a series of basic steps. Some of them may be hidden or selected without the user being aware of his choice. Clearly, this can result in poor or suboptimal results [4, 5]. In each session the following actions should be taken:

1. **Collecting information about the system (Data record):** the observed data from input/output of the system to obtain its information, an excitation that optimizes the goal within the operation constraints must be generated. The

quality of the final results can depend heavily on the collected data.

2. **Model structure to represent the system:** collecting the conditions and the nature of the models is important to look for a suitable model. The choice of the model should be carefully handled to contain all of the possible mathematical models, which are considered to be useful to represent the system. There is a wide variety of possibilities, as:

- Parametric and nonparametric models.
- Linear models and nonlinear models.
- Linear-in-the-parameters and nonlinear-in-the-parameters.

3. **Criterion to select a particular model in the set (goodness of fit):** the observed data and a model set have to be used to select the optimal model based on the performance of the models when the measured data are applied on them.

4. **Validating the selected model:** when an optimal model is reached, it must be tested whether this model is good enough (test of the validity of the model). The best model gives the smallest error or describes the system within the specified error bounds, which is preferred.

A model may not be as suitable as required. In this case, one should go back and repeat the steps. Nonlinear system identification is a useful tool especially with the systems that contain some degrees of nonlinearities. In this case a suitable system identification method and a suitable model structure to face these difficult problems of nonlinearities should be selected.

### *B. Nonlinear Models for Identification*

For studying the behavior of nonlinear systems, it is possible to use linear models to approximate their behavior. These linear models are easy to study, to understand and to build, but in this case the approximate models will be adequate for a range of input and out of this range they may lose their validity. Hence, nonlinear modeling is preferred for many applications.

The process of mathematical modeling consists of some steps that have been discussed in the previous section. In selecting a suitable model for system identification, it needs to be decided whether a parametric or nonparametric model is more suitable.

The system with a parametric model is described using a finite number of parameters, which are also called characteristic quantities. It is possible to build this type of a model using a set of mathematical equations and this approach is especially useful with linear models or when using linear identification. In system identification, in order to use the algorithms of parameter estimation, a parametric nonlinear model structure is needed. Depending on the dynamic behavior of the plant and the type and hardness of the nonlinearity, one of several parametric models may be preferred. The most common structures are Wiener, Hammerstein, and NARMAX model structures. Combinations of Wiener and Hammerstein models, which are the Wiener-Hammerstein and Hammerstein-Wiener models, are also used to represent nonlinear systems in relatively simpler forms with cascaded linear and nonlinear subsystems [7, 8].

The system with nonparametric model is described using measurements of a system function at infinitely many number of points. When there exists no parametric model structure that can describe the nonlinear system, a nonparametric algorithm is proposed for recovering the characteristic from input/output observations, which are the data of the whole system. The infinite Volterra Series model is a commonly used nonparametric model structure for nonlinear systems [8].

### *C. Wiener-Hammerstein Model Structure*

The structure of the class of Linear-Nonlinear-Linear (LNL) models, which consist of a static nonlinear block sandwiched between two linear dynamic systems, is called Weiner-Hammerstein structure, which is shown in Figure 2.1. The static nonlinearity of the subsystem due to Dead Zone, frictions, saturation, or if the sensor have some characteristics of nonlinearity.

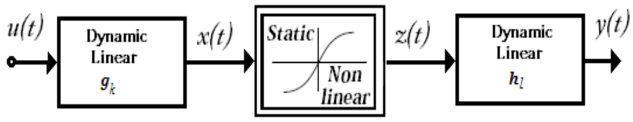


**Figure 2.1.** Cascaded LNL (Wiener-Hammerstein) model block diagram.

Wiener-Hammerstein model is a useful tool in many applications, such as modeling electromechanical systems. These models are popular because they have a suitable block representation, and are easy to implement than other nonlinear models (such as neural networks and Volterra models). This structure provides a simple parametrization for the cascaded linear and nonlinear models.

## III. IDENTIFICATION OF WIENER-HAMMERSTEIN MODEL

### *A. Model Parameterization*

Identification of cascade models has been widely discussed, where they consist of special and simple formulations and these models are widely useful in a variety of fields. The nonlinear characteristics of the Wiener-Hammerstein model from nonparametric approaches are estimated from input and output data. In direct consequence, classification of Linear Nonlinear (LN, also known as Weiner systems), Nonlinear-Linear (NL, also known as Hammerstein systems) and LNL models can be developed. Once this structure determination has been made, any of the standard methods can be used to estimate the appropriate parameters [8].

It is proposed to identify the structure of the class of LNL models according to Figure 2.1, where the first linear block denotes FIR filter, the static nonlinear block denotes polynomial expansion and the second linear block denotes ARX structure. For the first filter the output $x(t)$ of it can written as:

$$x(t) = \sum_{k=0}^{N_g - 1} g_k . u(t-k) \tag{3.1}$$

where $g_k$ are the impulse response series coefficients. Assuming a specific polynomial structure for the nonlinearity, $z(t)$ is given by:

$$z(t) = \sum_{p=1}^{P} \lambda_p . x^p(t) \tag{3.2}$$

assuming that the nonlinearity has no memory and can be modeled sufficiently well by a truncated Taylor series of p[th] order [9]. Substituting (3.1) into (3.2) gives:

$$\begin{aligned} z(t) &= \sum_{p=1}^{P} \lambda_p \cdot \left( \sum_{k=0}^{N_g-1} g_k u(t-k) \right)^p \\ &= \sum_{p=1}^{P} \lambda_p \cdot \left( \sum_{k_1=0}^{N_g-1} \cdots \sum_{k_p=0}^{N_g-1} g_{k_1} \cdots g_{k_p} \cdot \prod_{q=1}^{p} u\left(t-k_q\right) \right) \end{aligned} \tag{3.3}$$

Finally, for the second filter the output is given by:

$$A\left(q^{-1}\right) y(t) = \sum_{l=0}^{N_h-1} h_l \cdot z(t-l) \tag{3.4}$$

If we put (3.3) inside of (3.4) and re-arrange all of the signal components, the total output of the LNL system is obtained as:

$$A\left(q^{-1}\right) y(t) = \sum_{p=1}^{P} \lambda_p \cdot \left( \sum_{l=0}^{N_h-1} h_l \cdot \left[ \sum_{k_1=0}^{N_g-1} \cdots \sum_{k_p=0}^{N_g-1} g_{k_1} \cdots g_{k_p} \times \prod_{q=1}^{p} u\left(t-l-k_q\right) \right] \right) \tag{3.5}$$

*B. Least-squares Identification of Wiener-Hammerstein Model*

Least square method (LSM) is an accurate method in identification for estimation of unknown parameters of the system by defining an objective function; the objective function would repeat the algorithm for all points of data until it reaches its minimum. At the minimum of the objective function, the values of the parameters describe the real structure of the system. Then, the criterion of this method has a unique solution. The linear regression of the estimated output can be written as:

$$y(t) = \varphi^T(t)\theta \tag{3.6}$$

where $\varphi^T(t)$ is regression vector at time (t), and $\theta$ is vector used to parametrize models.

$$\begin{aligned} \varphi^T(t) = [&-y(t-1), -y(t-2), \ldots, -y\left(t-n_a\right), u(k), \ldots \\ &\ldots, u\left(k-l-k_q\right), \ldots, u^2(k), \ldots, u^2\left(k-l-k_q\right), \ldots, u^p(k), \ldots \\ &\ldots, u^p\left(k-l-k_q\right), \ldots, u(k)u(k), u(k)u(k-1), \ldots \\ &\ldots, u(k)u\left(k-l-k_q\right), \ldots, u\left(k-l-k_q\right)u\left(k-l-k_q\right)] \end{aligned}$$

$$\theta = [a_1, a_2, \ldots, a_{n_a}, s_1, s_2, \ldots, s_{k-l-k_q}, \ldots, s_{n_s}]$$

The prediction error of linear regression is:

$$\varepsilon(t,\theta) = y(t) - \varphi^T(t)\theta \tag{3.7}$$

and the criterion function resulting from:

$$\varepsilon_F(t,\theta) = L(q)\varepsilon(t,\theta) \tag{3.8}$$

$$V_N\left(\theta, Z^N\right) = \frac{1}{N}\sum_{t=1}^{N} l\left(\varepsilon_F(t,\theta)\right) = \frac{1}{N}\sum_{t=1}^{N} l\left(\varepsilon_F(t,\theta)\right)$$

with $\left(L(q)=1\right)$ and $l(q)=\frac{1}{2}\varepsilon^2$ is:

$$V_N\left(\theta, Z^N\right) = \frac{1}{N}\sum_{t=1}^{N} \frac{1}{2}\left[y(t) - \varphi^T(t)\theta\right]^2 \tag{3.9}$$

The best fit for the parameter estimates can be obtained by minimizing this quadratic criterion as follows:

$$\begin{aligned} \theta_N^{LS} &= \operatorname{argmin} V_N\left(\theta, Z^N\right) \\ &= \left[\frac{1}{N}\sum_{t=1}^{N} \varphi(t)\varphi^T(t)\right]^{-1} \frac{1}{N}\sum_{t=1}^{N} \varphi(t)y(t) \end{aligned} \tag{3.10}$$

*Recursive Least-squares Algorithm:*

Recursive Least-squares is the most common recursive identification and parameter estimation method available, due to its simplicity, ease of application, and accuracy [4, 5]. The algorithm of the Recursive version of the identification method described above is given in the following:

- Select a forgetting factor $\lambda$ , $0< \lambda \leq 1$ is introduced.
- Choose initial value of the matrix p.
- Data set (input/output) of the plant is placed in the vector $\varphi$ .
- The minimization criterion is:

$$V_N(\theta, N) = \frac{1}{2}\sum_{t=1}^{N} \lambda^{N-t}\left[y(t) - \varphi^T(t)\theta(t)\right]^2$$

- For minimization of $V_N(\theta, N)$ over $\theta$ , apply the following:

$$p(t) = \frac{1}{\lambda} p(t-1)\left[I_p - \frac{\varphi(t)\varphi^T(t)p(t-1)}{\lambda + \varphi^T(t)p(t-1)\varphi(t)}\right]$$

$$\theta(t) = \theta(t-1) + p(t)\varphi(t)\varepsilon(t)$$

## IV. ELECTROMECHANICAL SYSTEM WITH PMDC MOTOR

In current research the Permanent Magnet DC (PMDC) motor is considered, which is illustrated in Figure 4.1. It is aimed to built the suitable model of it with taking into account its nonlinearities with a control point of view.

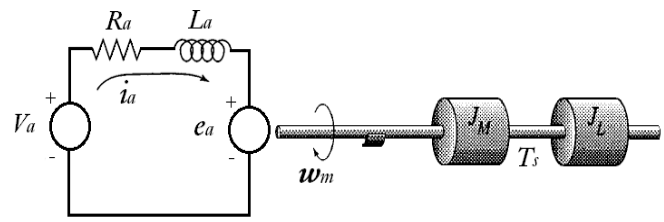


**Figure 4.1** A schematic diagram of the PMDC motor.

*A. Linear System Dynamics*

The model of the plant is developed taking into account the fact that this model is subject to control, and this step is important for the control applications. The model of the PMDC motor to be built relies on the equations that describe its electrical and mechanical sides. For the mechanical side equations which are suitable for the system that consists of a two-mass structure are derived [10].

First the linear model of PMDC is studied and then the nonlinearities of it such as Dead Zone and Coulomb Friction and their effects on the whole plant are taken into consideration in order to know where these effects should appear in the model. For the electrical side according to Kirchhoff's laws, it is possible to write the equation as follows [3]:

$$v_a = R_a i_a + L_a i_a + e_a \tag{4.1}$$

$$e_a = K_m \omega_m \tag{4.2}$$

$$T_m = K_m i_a \tag{4.3}$$

where $v_a$ is the armature voltage which is applied to the motor, $R_a$ and $L_a$ are the armature coil resistance and inductance respectively, $i_a$ is the armature current through the motor, $e_a$ is the back electromotive force (emf), $K_m$ is the motor constant, $T_m$ is the torque generated by the motor.

Also the equations that describe the mechanical side using Newton's laws of motion are [3]:

$$J_m\left(\frac{d\omega_m}{dt}\right) = -B_m\omega_m - T_s + T_m \tag{4.4}$$

$$J_L\left(\frac{d\omega_L}{dt}\right) = -B_L\omega_L + T_s - T_d \tag{4.5}$$

$$T_s = K_s\left(\theta_m - \theta_L\right) + B_s\left(\omega_m - \omega_L\right) \tag{4.6}$$

with

$$\frac{d\theta_m}{dt} = \omega_m, \frac{d\theta_L}{dt} = \omega_L$$

where $J_m$ is the rotor moment of inertia, $B_m$ is the motor viscous friction, $T_s$ is the shaft torque, $J_L$ is the total load moment of inertia, $B_L$ is the load viscous friction coefficient, $T_d$ is the disturbance torque, $K_s$ is the shaft elasticity, and $B_s$ is the shaft inner damping coefficient. $\theta_m$, $\theta_L$ are the motor and load angular displacements, and $\omega_m$, $\omega_L$ are the motor and load angular velocities, respectively.

*B. Nonlinearities in System Mechanics*

The PMDC motor to be controlled has to work with high volume demand and a high quality of its performance. In this case, it is necessary to take into account all natural effects such as the effect of connection between the electrical and mechanical sides, the connection with loads, and the motor rotation in two directions. The linear model described above with its electrical and mechanical sides is capable of fulfilling the performance requirements when the mechanical system rotates in one direction. However, if the system speed output has zero crossings, the dead-zone and Coulomb friction nonlinearities cannot be neglected [3, 11]. Consequently, the linear model will be insufficient in representing the system behavior accurately for this case.

These connection effects appear as nonlinear functions and characteristics. For example the Coulomb friction effects appear if there is a physical interface of the connection between two surfaces. The friction and its model are discussed in literatures [3, 11, 12]. The general model of the Coulomb friction with the viscous friction is given as [3]:

$$T_f(\omega) = \alpha_0 sgn(\omega) + \alpha_1 e^{-\alpha_2|\omega|} sgn(\omega) \tag{4.7}$$

where $\alpha_i > 0, i = 0,1,2$ and $\alpha_i \in R$ . The signum function in the equation is defined as [13]:

$$sgn(\omega) = \begin{cases} 1 & \omega > 0 \\ 0 & \omega = 0 \\ -1 & \omega < 0 \end{cases} \tag{4.8}$$

Nonlinearity of the Dead Zone region also is a common effect in the PMDC, which appears in many practical systems. In an electromechanical system without a gearbox, dead-zone is caused either by the Coulomb friction force from of the drive's rotor, or it appears when the motor rotates in two directions with very low speeds. The description of Dead Zone is given in literature [11], and for an input $v(t)$ the output $w(t)$ :

$$w(t) = D(v(t)) = \begin{cases} m_r\left(v(t) - b_r\right) & v(t) \geq b_r \\ 0 & b_l < v(t) < b_r \\ m_l\left(v(t) - b_l\right) & v(t) \leq b_l \end{cases} \tag{4.9}$$

The model generally assumes that the dead-zone has equal and constant rates of change with respect to input in positive and negative regions, i.e. $m_r = m_l = m$ . The parameters $b_r$ , $b_l$ , and $m$ are not known, but their signs are as follows: $b_r > 0, b_l < 0, m > 0$. Nonlinearities (Coulomb friction and Dead Zone) are graphically described in Figure 4.2.

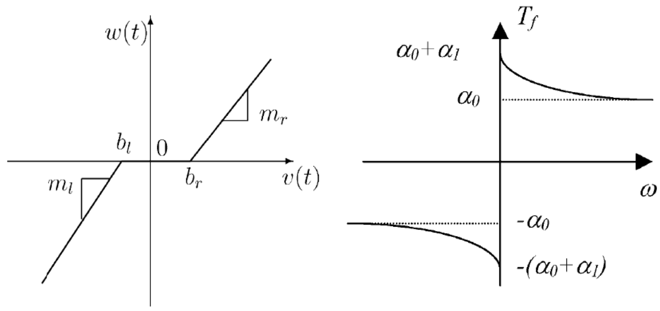


**Figure 4.2** Nonlinearities of the Dead-Zone and Friction

Integrating the nonlinear Coulomb friction and dead-zone models into the system, the general system model covers the linear and nonlinear system characteristics. The equations of system dynamics with the speed dependent friction are as follows:

$$J_m\left(\frac{d\omega_m}{dt}\right) = -B_m\omega_m - T_s + T_m - T_f\left(\omega_m\right) \tag{4.10}$$

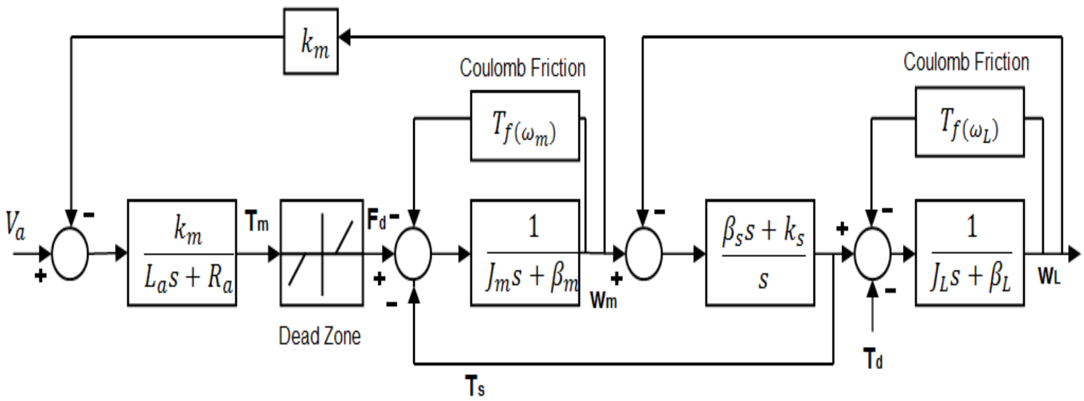


**Figure 4.3**. Block Diagram of the System Model

$$J_L\left(\frac{d\omega_L}{dt}\right)=-B_L\omega_L+T_s-T_d-T_f\left(\omega_L\right) \qquad (4.11)$$

The block diagram of the system model with linear and nonlinear components is given in Figure 4.3.

## V. Simulations and Experiments

### A. Simulation Model and Results

The PMDC motor model developed using the equations presented above is built as a simulation model in Simulink Matlab. The input signal, which is designed to be sufficiently rich and exciting, is given in Figure 5.1.

From the results of the study on the real plant, it is found that the effect of the nonlinearities is small especially in the connection between the motor and the load; where there is no gear to introduce a significant friction effect. So, the friction on the output side of the nonlinear model is ignored and the difference between the previous model and this model without friction effects is studied. It is verified that this model is suitable to be represented by a Weiner-Hammerstein structure. Comparing the results for these models (with friction on the output and without fiction on the output) the error is observed to be around 3.341e-006.The Simulink model for the PMDC motor with its nonlinearities is simulated to get the data for identification. Then these data are used with the algorithm of LSM that is coded using an M-file in MATLAB to obtain the identified linear and nonlinear model responses.

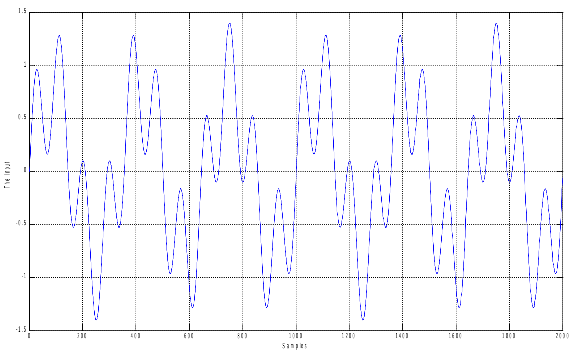

**Figure 5.1.** Input signal for simulation using Simulink

For identification, a FIR filter model is used for the first block of Weiner-Hammerstein structure. This filter has the structure that is suitable for the proposed model structure.

$$x(t)=B\left(q^{-1}\right)u(t)=b_1u(t-1) \qquad (5.1)$$

The nonlinear block has a polynomial structure of second degree as follows:

$$z(t)=\lambda_1x(t)+\lambda_2x^2(t) \qquad (5.2)$$

If we assume that $\lambda_1=1$ then the previous equation becomes:

$$z(t)=x(t)+\lambda_2x^2(t) \qquad (5.3)$$

Substituting (5.1) into (5.3) gives:

$$z(t)=b_1u(t-1)+\lambda_2b_{1^2}u^2(t-1) \qquad (5.4)$$

The second linear block has an Autoregressive with Exogenous input (ARX) structure given by the following:

$$A\left(q^{-1}\right)y(t)=D\left(q^{-1}\right)z(t) \qquad (5.5)$$

which can also be written in open form with the selected orders as:

$$\begin{aligned}&\left[1+a_1q^{-1}+a_2q^{-2}+a_3q^{-3}+a_4q^{-4}\right]y(t)\\&=\left[d_0+d_1q^{-1}+d_2q^{-2}\right]z(t)\end{aligned} \qquad (5.6)$$

Substituting (5.4) into (5.6) gives:

$$\begin{aligned}&\left[1+a_1q^{-1}+a_2q^{-2}+a_3q^{-3}+a_4q^{-4}\right]y(t)\\&=\left[d_0+d_1q^{-1}+d_2q^{-2}\right]\left[b_1u(t-1)+\lambda_2b_{1^2}u^2(t-1)\right]\end{aligned} \qquad (5.7)$$

$$\begin{aligned}&\left[1+a_1q^{-1}+a_2q^{-2}+a_3q^{-3}+a_4q^{-4}\right]y(t)\\&=d_0b_1u(t-1)+d_0\lambda_2b_{1^2}u^2(t-1)+d_1b_1u(t-2)\\&+d_1\lambda_2b_{1^2}u^2(t-2)+d_2b_1u(t-3)+d_2\lambda_2b_{1^2}u^2(t-3)\end{aligned} \qquad (5.8)$$

The last equation (5.8) of the output can be written in linear regression form as following:

$$y(t) = \varphi^T(t)\theta \tag{5.9}$$

where:

$$\varphi(t) = [-y(t-1), -y(t-2), -y(t-3), -y(t-4), u(t-1), u(t-2), u(t-3), u^2(t-1), u^2(t-2), u^2(t-3)]^T \tag{5.10}$$

$$\theta = [a1, a2, a3, a4, s1, s2, s3, s4, s5, s6] \tag{5.11}$$

For linear identification we selected the following:

$$\varphi(t) = [-y(t-1), -y(t-2), -y(t-3), -y(t-4), u(t-1), u(t-2), u(t-3), u(t-4)]^T \tag{5.12}$$

$$\theta = [a1, a2, a3, a4, b1, b2, b3, b4] \tag{5.13}$$

The results for linear and proposed nonlinear identification tests together with the simulated model output variation are illustrated around selected critical time intervals by the graphs in Figures 5.2 and 5.3.

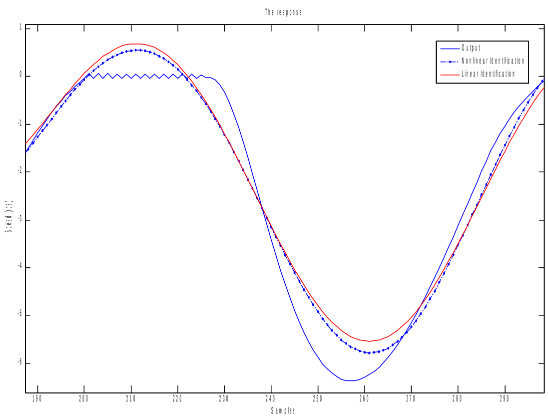

**Figure 5.2.** Output responses for simulated system (I). Solid blue: model output, solid red: linear identified model output, dotted blue: nonlinear identified model output.

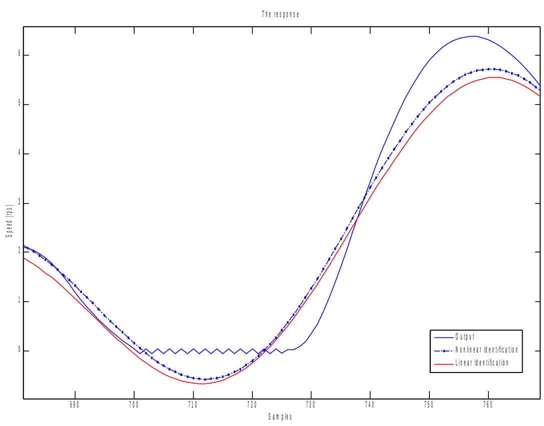

**Figure 5.3.** Output responses for simulated system (II). Solid blue: model output, solid red: linear identified model output, dotted blue: nonlinear identified model output.

### B. *Experimental results*

Experimental set-up is shown schematically in Figure 5.4. Two signal generators are used to supply input signal to the armature, which generate sinusoids of different amplitudes and frequencies. The two signals are added to combine as a persistently exciting signal for identification [4]. The signals are adjusted for low speed bidirectional operation, which permits examination of the system nonlinearities. The motor transmits motion via a shaft that carries various transducers together with a tacho-generator for speed measurement.

Input-output data for identification of the electromechanical system are acquired using the experimental setup in Figure 5.4. The test signal is selected to be, as given in Figure 5.5, for persistence of excitation. The results of the experiments, performed using the setup, are illustrated by the graphs in Figures 5.6 and 5.7.

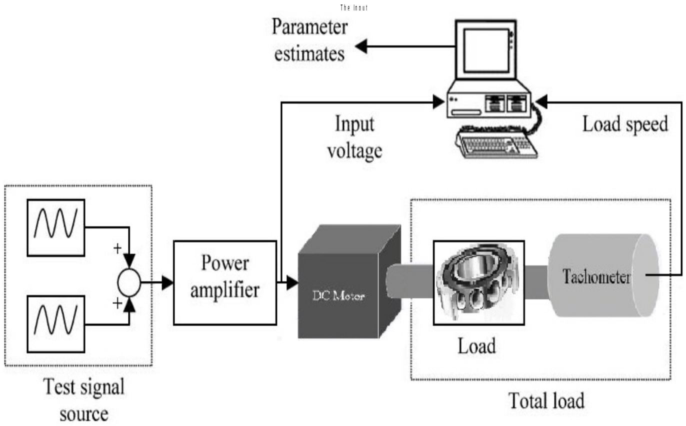


**Figure 5.4.** Experimental Setup for nonlinear identification.

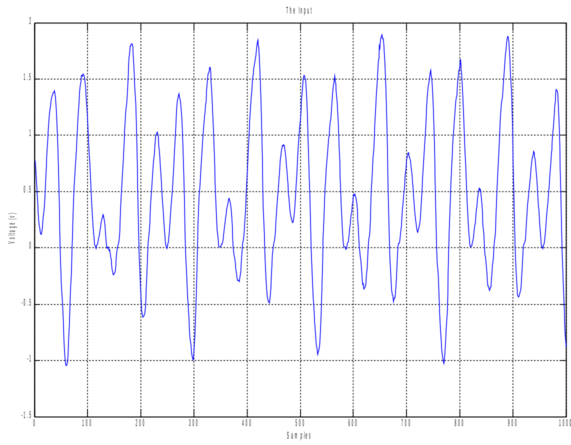

**Figure 5.5.** Input signal for identification via experiments.

### C. *Model Verification*

Mean square error (MSE) is a commonly used error criterion for model testing purposes [4, 5, 8]. The criterion is given by:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(y(t) - \hat{y}(t)\right)^2 \tag{5.14}$$

where $\hat{y}(t)$ is the predicted output of the identified model and N is the number of samples used in the identification process. MSE values for the linear and nonlinear identification simulations are calculated for two different input signals and tabulated in Table 1. Also the MSE values for the linear and nonlinear identification experimental set-up are calculated for two different input signals and tabulated in Table 2.

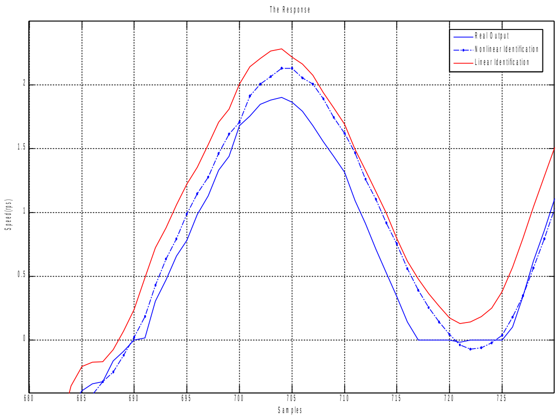

**Figure 5.6.** Output responses for real system (I). Solid blue: real system output, solid red: linear identified model output, dotted blue: nonlinear identified model output.

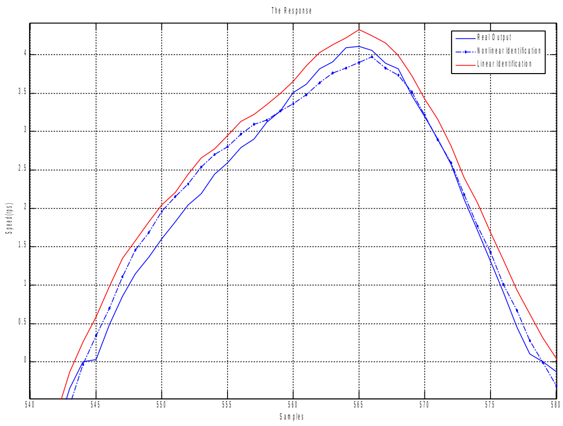

**Figure 5.7.** Output responses for real system (II). Solid blue: real system output, solid red: linear identified model output, dotted blue: nonlinear identified model output.

Table 1. MSE values for nonlinear and linear identification via simulation

| | MSE, nonlinear identification | MSE, linear identification |
|---|---|---|
| Identification | 2.559e-005 | 0.0005634 |
| Model Verification | 4.063e-006 | 0.002264 |

Table 2. MSE values for nonlinear and linear identification via experiment

| | MSE, nonlinear identification | MSE, linear identification |
|---|---|---|
| Identification | 0.004573 | 0.1105 |
| Model Verification | 0.06834 | 0.1933 |

The results presented in Table 1 clearly show that the proposed nonlinear identification procedure gives a better result. MSE values in simulations prove that the identification results, in terms of the selected error criterion, definitely improved with the proposed nonlinear identification. The improvement can also be observed in Figures 5.2 and 5.3. These figures prove the necessity of using nonlinear identification for the systems which contain nonlinear characteristics, especially around the operating points close to nonlinearities as shown in the figures.

The results presented in Table 2 show that the proposed nonlinear identification procedure gives improved results experimentally as well. MSE values in experimental identification results prove that the identified model error, in terms of the selected error criterion, definitely improved with the proposed nonlinear identification. The improvement can also be observed in Figures 5.6 and 5.7.

## VI. CONCLUSION

This study applies the Wiener-Hammerstein model with the LNL structure for describing the PMDC motor dynamics. The nonlinear Dead zone and Coulomb friction effects are taken into account in the model of the PMDC motor. The proposed identification technique is based on developing a nonlinear model with static nonlinear and dynamic linear subsystems, which are cascaded in LNL order. The model structure permits parametrization of the model for identification. The LSM and RLS algorithms are used for testing the model in Simulink, MATLAB and in the experimental setup. A different set of data other than the identification data is used for model verification. The results are demonstrated using graphs and performance is presented using a common error criterion. These reveal that the proposed approach gives a better result in identification in comparison to the conventional linear approach, especially around the low speeds where the nonlinearities in the system are more effective. The identification error also seems to improve with the introduction of the Wiener-Hammerstein approach to identification. The results of this study have revealed that modeling a generally nonlinear electromechanical system with a Wiener-Hammerstein structure, parameterizing the model for identification, and obtaining an identified parametric nonlinear model covers the nonlinearities better than the linear approach. The future work of the study will be on the identification of electromechanical systems with hard nonlinearities that cannot be modeled or identified with a linear approach.

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