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System Identification of Clamping Force Controller for Secondary Pulley of Electro Mechanical Dual Acting Pulley Continously Variable Transmission (EMDAP CVT)

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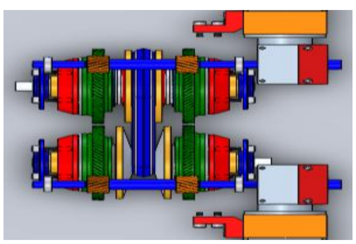
Graphical abstract



Abstract

This paper investigates the performance of clamping force at the secondary pulley actuator of Electro-mechanical Dual Acting Pulley Continuously Variable Transmission (EMDAP CVT) using an identification technique for development of intelligent control. The implementation details are described and the experimental studies conducted in this research are analyzed. To investigate the dynamic response of the system, step input was applied to the EMDAP CVT and clamping forced was measured. The modeling of the system was developed using the Genetic Algorithm (GA). The validation and verification of the obtained model were evaluated using mean squared error (MSE) and correlation test. The performance of the nonlinear approach was compared and discussed based on MSE value. The predictive ability of the model was further observed with unseen data. The result shows that, Nonlinear ARX (NARX) model converges to an optimum solution faster with increasing of model order and the obtained dynamic model also described the system well.

Keywords: System identification; nonlinear identification; continuously variable transmission, clamping force

1.0 INTRODUCTION

Drive-train Research Group (DRG) of Universiti Teknologi Malaysia (UTM) has designed and developed an Electro-mechanical Dual Acting Pulley Continuously Variable Transmission (EMDAP CVT) system which adopts power-screw mechanism to overcome hydraulic power loss when maintaining a constant transmission ratio, and two movable pulley sheaves on each of its pulley shaft to eliminate belt misalignment. Axial movements of both primary (input) and secondary (output) movable pulley sheaves are electro-mechanically controlled by direct current (DC) motors that turn power screw mechanism and shift the movable V-pulley sheaves axially. The axial movements of pulley sheaves change the effective pulley-belt contact radii and consequently changing the transmission ratio.

EMDAP CVT uses V-belt as its ratio variator and electro-mechanical actuation system (EM actuation system) to actuate the movement of the dual pulley sheaves simultaneously during the event of changing ratio. Since the last prototype, The EM actuation system in EMDAP CVT uses 2 DC motors to actuate the axial movement of the primary and secondary pulley respectively during the process of changing ratio. These movements change the radius of the V-belt on the primary and secondary pulleys simultaneously hence changing the ratio accordingly.

Synchronization in changing of the pulley axially movement is very important in the process of changing ratio but the controllers become complicated because the motors depend on each other. (DRG) found out this complication, hence, they improve the EMDAP CVT with new design which primary motor focus on changing ratio while the secondary controller focus on controlling clamping force at the secondary pulley only in order to provide sufficient clamping force on the V-belt in preventing excessive slip and excessive clamp. Furthermore, in long term applications the slippage can leads to life span reduction and damage the belt [1].

The first work related with the EMDAP-CVT was done by Sugeng Ariyono [2]. In his research, Ariyono controlled the engine speed for the vehicle with EMDAP-CVT system. His work focused on developing an intelligent control system using adaptive artificial neural network (AANN) method that provide appropriate CVT ratio. The research then continued by Bambang Supriyo [3,4] who focused on designing and developing EMDAP CVT ratio controllers in time domain analysis based on several algorithms. The current research on EMDAP CVT is continued by Izahari Izmi [6] who came out with new design concept on the changing ratio for primary motor and proposed an independent controller at the secondary motor as shown in figure 1. The current problems with the secondary pulley of the EMDAP CVT, it is nonlinear and a complex system. Using system identification method, it is possible to obtain the transfer function of secondary pulley of the EMDAP CVT system.

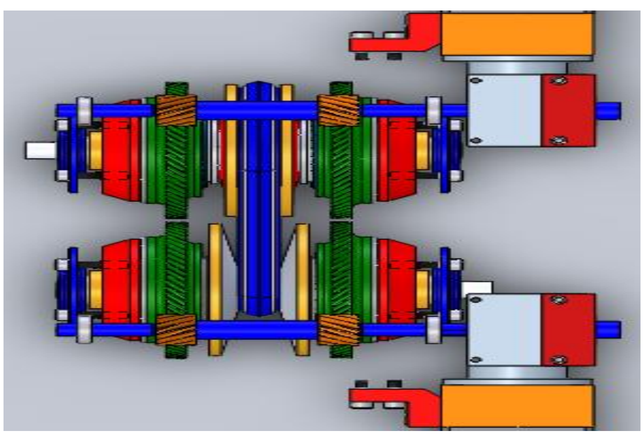


Figure 1 The existing EMDAP CVT (Drivetrain Research Group of UTM, 2011).

Pesgens et al. (2005) [7] developed a new ratio controller for a metal pushing V-belt CVT with a hydraulic clamping system. Using the dynamic models of the variator and hydraulics, and compensator constraints, a set point feedforward and a linearizing feedback controller were implemented. The feedback controller was a PID controller with a conditional anti-windup protection. The total ratio controller guaranteed that at least one of the pressure set points was always minimal with respect to its constraints, while the other was raised above the minimum level to enable shifting.

Yang, Liu and Zhao (2010) [8] has performed dynamic performance optimization of CVT speed ratio control valve based on genetic algorithm (GA). The speed ratio control valve with optimal associated performance index used in CVT electro-hydraulic control system is developed by optimal design. They found an associated performance index considering the response time, overshoot and saving energy, and then four structural parameters are selected to adjust for deriving the optimal associated performance index. The optimization problem is solved by the classic genetic algorithm with necessary constraints.

Nowadays, system identification techniques have become potential candidates for control application. The major aim of the system identification is to locate approximate or accurate models of dynamics systems based on the observed input and output data. A number of researchers have applied techniques to solve the problem related to system identification [9,10,11,12]. The purpose of this study is to develop a model characterizing the system using system identification techniques. Finally, the validity of the obtained model was investigated using mean squared error (MSE) and correlation tests.

2.0 EXPERIMENTAL

In this paper, the input-output data of the system were first acquired through experimental studies using National Instruments (NI) data acquisition system. To provide the experimental data, the DC motor is given full voltage to actuate the axial movement of the secondary pulley and the clamping force response was then investigated. The experimental arrangement developed for this study was established as shown in figure 2.

Figure 2 Experimental setup

A force sensor is place in between the pulley sheaves to sense the clamping force as shown in figure 3. The sensor can measure force that applied to it up to 40K lbs and the output of the sensor is 1.8583 mV/V. The signal from the force sensor is amplified to 10 times to enlarge the scale of measuring the force.

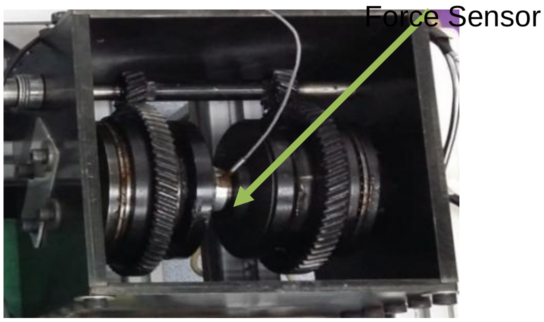


Figure 3 Force sensor placed in between two moveable sheaves pulley

The experimental measurement is measured and analyzed with the aid of NI acquisition system integrated to computer and engineering software (Matlab/ Simulink). Figure 4 shows the input and output data acquired from the experimental test. The output data has been plotted in terms of Clamping Force versus time as shown in figure 5.

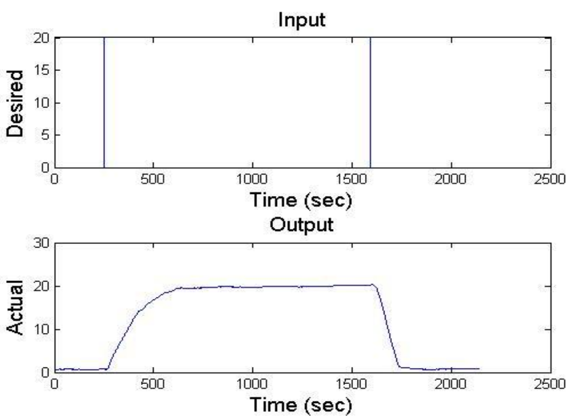


Figure 4 Experimental input and output data

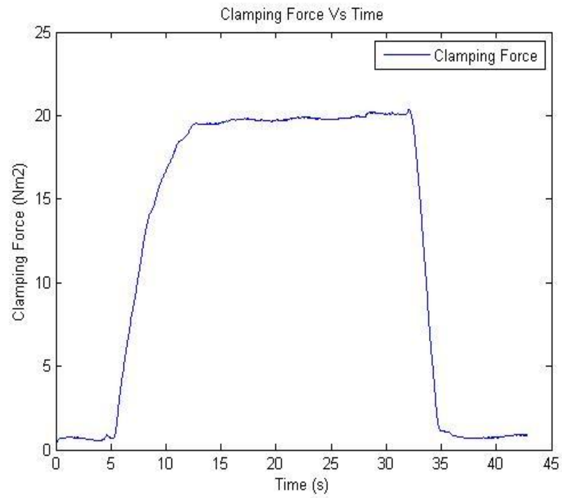


Figure 5 Clamping force versus time

3.0 MODEL STRUCTURE

There are a lot of model structures that available to assist in modeling of a system. Non-linear autoregressive moving average model with exogenous input (NARMAX) is the most renowned for non-linear models (Ljung L., 1999) [13]. It is obvious from the literature that if the plant's input and output data are obtainable, the NARMAX model is an appropriate option with standard back-propagation learning algorithms for modeling non-linear systems. Mathematically the model is given by Eq. (1) [14].

$$\hat{y} = f(u(t-1),\dots,u(t-n_u),y(t-1),\dots,y(t-n_y),e(t-1,\dots,e(t-ne)) \quad (1)$$

where $\hat{y}$ represents the output vector determined by the past values of the system input vector, output vector and noise. n_u, n_y and n_e represent model orders. $f()$ represent the system mapping, which can be constructed through non-parametric method with a suitable learning algorithm. If the model is acceptable to identify the system without noise term incorporated or the noise is considered as additive term at output, the model can be represented in the NARX form (Ljung L. 1999) [13]. The NARX model is used as a model structure for this research. Mathematically the model in (1) can be written in discrete form as in Eq. (2) [15];

$$y = f(u(k-1),\dots,u(k-n_u),y(k-1),\dots,y(k-n_y)) + e(t) \quad (2)$$

4.0 GENETIC ALGORITHM (GA)

Most Genetic Algorithm (GA) methods have at least the following in common: populations of chromosomes, selection according to fitness, crossover to produce new offspring, and random mutation of new offspring [16]. Solutions in GA are encoded as chromosomes which are strings of numbers or characters that represent the values or parameters of the solution to the problem. The chromosomes are commonly encoded as strings of binary, real-valued, integer, octal, or hexadecimal numbers [17]. Each of these types of numbers has their own advantages and disadvantages when used for certain data types or for searching for solutions to certain problems. In this study, real-valued numbers string was selected as the chromosome encoding for the population of potential solutions.

The set of potential solutions to the problem is represented as a population of chromosomes. Initially, a random population is created, which represents different points in the search space of potential solutions [18, 19, 20]. A fitness function assigns a score (fitness) to each chromosome in the current population, which will determine its survival into the next generation. The fitness of a chromosome depends on how well that chromosome can solve the problem at hand [19]. The selection of chromosomes is done on the current population based on the fitness values – chromosomes with higher fitness are more likely to be selected than those with low fitness values. Selected chromosomes are then included in the next generation of population.

Next the population undergoes the crossover (also called recombination) genetic operator, which selects chromosomes from the population to produce off-springs. Using random selection or any of the previously mentioned selection methods, two parent chromosomes are chosen for crossover operation. Using single-point, two-point, or N-point crossover, parts of the gene string in each parent chromosome are swapped to produce two new offspring, which are included in the next generation of population. The process is repeated a number of times, usually according to some user-specified proportional value of the current population.

Random chromosomes from the surviving population are selected for mutation, where some random part of the chromosome's gene is arbitrarily changed. This genetic operation may or may not yield superior offspring, but it ensures that solutions are not trapped in local extrema. Mutation is performed according to some degree of probability, usually very small, so that the GA does not approximate a random search [17].

The process of selection, crossover, and mutation are then repeated on the surviving population, until some terminating criteria is reached, i.e. a maximum number of generations, a minimum change in population fitness, etc. The resulting final population is then considered to be the set of solutions that best solves the problem at hand. The best individual chromosome (the chromosome with the highest fitness value) in the final population is usually determined to be the optimal solution to the problem.

5.0 MODEL VALIDATION

The procedures that considered for sensing the sufficiency or fitted model are called Model validity tests. It is necessary to validate whether the model is sufficient to represent the system or not after obtaining the model for the system. The principles of model validation are:

i. Compare model simulation or prediction with real data in time domain.
ii. Compare estimated model's frequency response and spectral analysis result in frequency domain.
iii. Perform statistical test prediction errors.

There are a lot of validation tests that are existing in the literature, some of which are mean squared error, correlation test, model predicted output and one step-ahead prediction [15]. The mean squared error and correlation test are used to validate the model in this research.

5.1 Mean Squared Error (MSE) Test

MSE is one of the most common methods used for validations purposes. The MSE is different between the real output $y(n)$ of the system and the predicted output output $\hat{y}(n)$ produced from the input to the system and the optimised parameters as shown in Eq. (3).

$$mse = \frac{1}{N}\sum_{t}^{N}(y(t) - \hat{y}(n))^2 \qquad (3)$$

5.2 Correlation Test

Correlation test is the usual statistical method to validating identified non-linear models which is more convincing for model validation than others method [15]. It has been shown that a suitable prediction through different data sets is produced only if the model is unbiased. The prediction error sequence $e(t)$ should be uncorrelated with all linear and non-linear combinations of past inputs and outputs (unbiased)

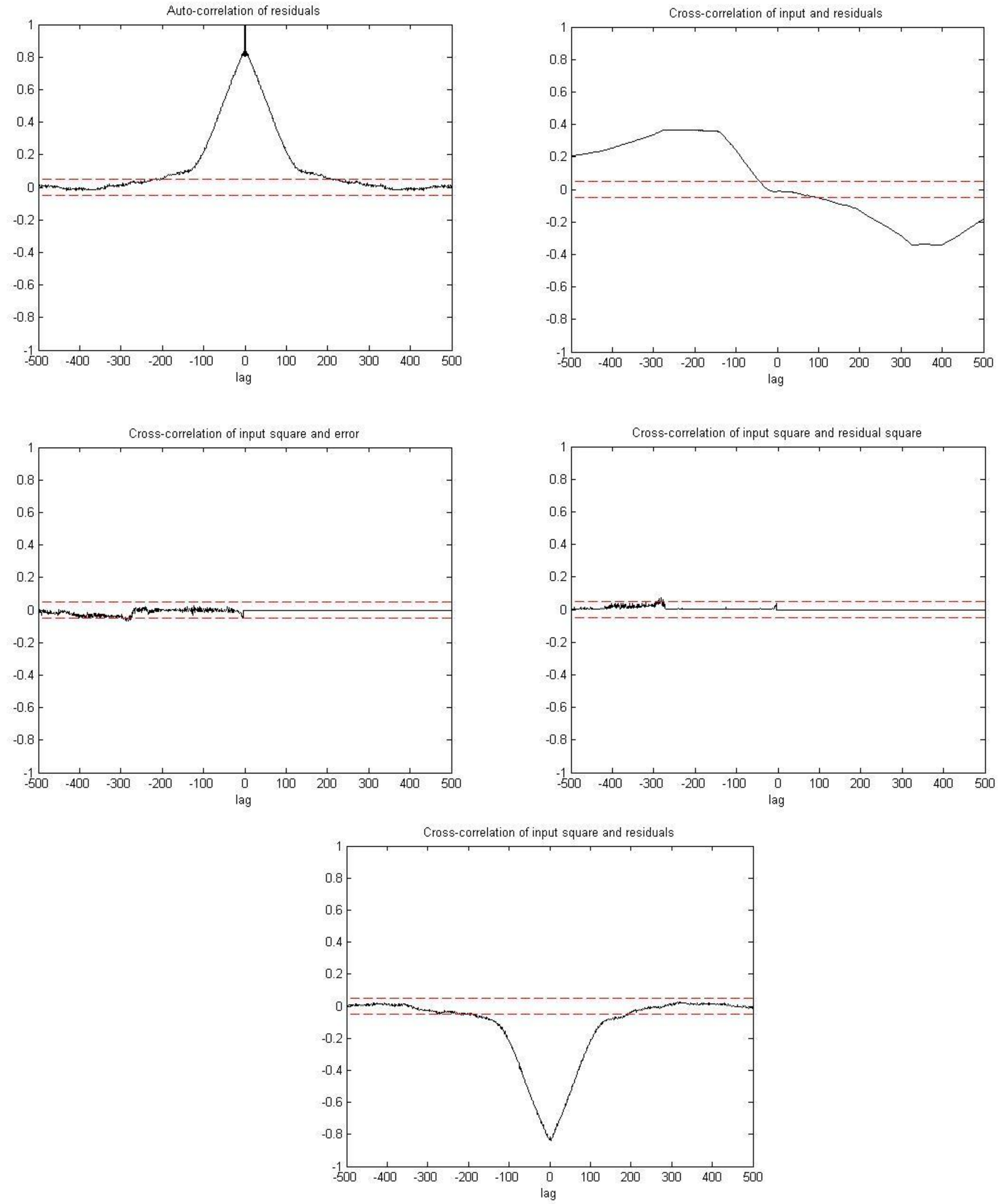


Figure 6 Correlation tests. (a) Auto-correlation of residuals, (b) cross-correlation of input square and error, (c) cross-correlation of input and residuals, (d) cross-correlation of input square and residual square, (e) cross-correlation of input square and residuals.

when the model structure and the estimated parameters are correct. This will hold if and only if the following conditions are satisfied, Eq. (4)-(8) (Billings and Voon, 1986) [21]:

$$\emptyset_{ee}(\tau) = E[e(t-\tau)e(t)] = \delta(t) \quad (4)$$
$$\emptyset_{ue}(\tau) = E[u(t-\tau)e(t)] = 0, \quad \forall\tau \quad (5)$$
$$\emptyset_{u^2e}(\tau) = E[(u^2(t-\tau) - u^2(t))e(t)] = 0, \forall\tau \quad (6)$$
$$\emptyset_{u^2e^2}(\tau) = E[(u^2(t-\tau) - u^2(t))e^2(t)] = 0, \quad \forall\tau \quad (7)$$
$$\emptyset_{(e)(eu)}(\tau) = E[e(t)e(t-1-\tau)u(t-1-\tau)] = 0,\ \tau \geq 0 \quad (8)$$

where $\emptyset_{ue}(\tau)$ indicates the cross-correlation function between $u(t)$ and $e(t), eu(\tau) = e(t+1)$, $\delta(t)$ is an impulse function.

The model is considered as satisfactory if the correlation test lay within 95% confidence limits, which is defined as $1.96/\sqrt{N}$, where N is the data length. Autocorrelation of the error also will never be as an ideal delta function but will be considered as sufficient if the autocorrelation plot enters the 95% confidence limits before lag one [15].

6.0 RESULTS AND DISCUSSION

Results of the nonlinear ARX (NARX) model have been validated with a range of test including input/output mapping, mean-squared error and correlation tests. It is observed that the modeling method have performed very well in approximating the system response.

6.1 Nonlinear Identification

The data set, comprising 2140 data points was divided into two sets of 1070 data points. The model was trained using the first data set, and validated using the whole set. For nonlinear identification, Nonlinear ARX (NARX) model was used as the model structure. The model was tested with several different orders. The best result for the nonlinear identification was achieved with an order 3. The models reached the MSE value of 0.00016. Figure 7 represents the complexity level of model output before and after tune over the MSE value. The blue circle represents complexity before tuned meanwhile the green star represents complexity after getting tuned. It is shown that the complexity of the model getting better after tuned.

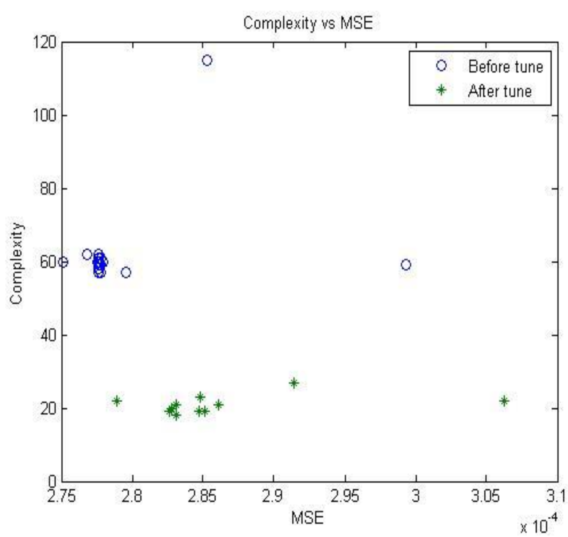


Figure 7 Complexity of model output before and after tune versus MSE value

The models of the EMDAP CVT system thus developed and validated will be used as the transfer function of the system in subsequent investigations for the development of the control strategies in the future. Figure 8(a) shows output model data obtained from the system identification. The blue line indicates the system output obtained from the experimental test, meanwhile the green line indicates the model output data obtained from the nonlinear identification. Meanwhile, figure 8(b) shows a closer look of the model.

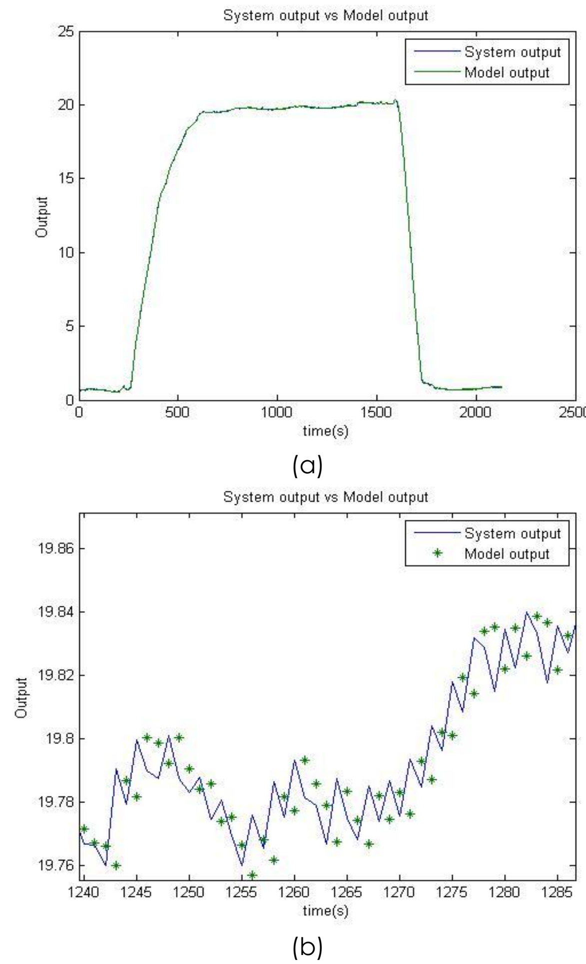


Figure 8 System output (Actual) and model output (prediction) for nonlinear identification

Figure 9 shows the error between the real system model and output model response. The result clearly indicates the good output tracking performance of the nonlinear identification process with respect to the linear approach. To determine the model effectiveness, correlation tests were carried out. Figure 6 shows the result for the correlation tests. The results were found out to be within 95% confidence level thus confirmed the accuracy of the obtained results.

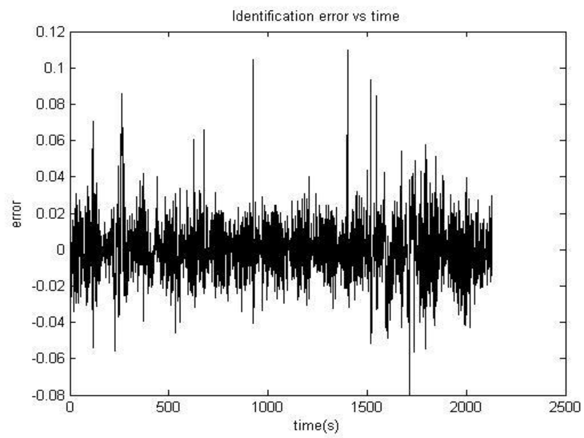


Figure 9 Identification errors for nonlinear model

6.2 Discussion

The Mean Square Error (MSE) values for the nonlinear identification experiment were calculated for different model orders and summarized in Table 1.

Table 1 MSE value for nonlinear identification

Model order	1	2	3	4
Nonlinear	0.00023	0.00020	0.00016	-

From the validation tests, it is observed that different modeling methods considered in this study have performed sufficiently well. Comparing the MSE value in Table 1, it is showed that the nonlinear identification method have performed better with the increasing of model order. From the result, it is noted that by having more (nonlinear) flexibility can improve the model fidelity.

The results are numerically and graphically demonstrated. For nonlinear identification, nonlinear ARX model with 3rd order shows the best fit with MSE value 0.00016. The identification error and the convergence properties of the estimates also seemed to improve with introduction of the nonlinear approach. The outlined identification method assumes the system to be linear. However, the system obtained is nonlinear. The nonlinearities of the system are caused by the actuators and CVT geometry [13].

7.0 CONCLUSION

Results of various modeling methods have been validated with a range of test including input/output mapping, mean-squared error and correlation tests. The modeling method that used is observed to be performed very well in approximating the system response.

The models of the system thus developed and validated will be used as the transfer function of the system in subsequent investigations for the development of the control strategies in the future.

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