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Stability Analysis Of Variable Structure Controlled Industrial Robotic Manipulator With Single Term Haar Wavelet Series Method

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Abstract

In this paper, stability analysis has been made using Neural Tool to validate the obtained errors from experimental work. A neural network prediction has been done by selecting appropriate factors which played vital role in increasing errors during continuous working of the robot. In NN prediction, two simulations were carried out, one for predicting variation from existing tested data and the other for finding out the unknown values of non-tested input values. From neural network analysis it has been observed that the neural network predictions very closely match with the variation obtained by experimental validation. Also the neural network predictions yield better results for non-tested input values and also it is very close to the actual values of variation obtained by experimental validation. The conclusion is that the proposed mathematical tool with variable structure control is stable and can be implemented to industrial robots for the robust control of positions.

Keywords: *Neural Network; Stability,; Variable Structure Control(VSC); Single Term Haar Wavelet Series (STHWS) ; Robot Manipulators; Manipulator Dynamics; Linear and Non linear Control; Singular and Non-Singular Systems, Trajectory Tracking.*

1. INTRODUCTION

High-precision mechanical devices such as robots currently perform a large number of industrial services, and commercial tasks around the world. Robots range from small robots capable of performing everyday tasks to large industrial robots bolted to the factory floor. Major applications which include Outer Space Applications, Welding and paint applications, radioactive material handling, under water research, and military uses (Ivanisevic I, and Lumelsky VJ, 2000; Hertling et al. 1996; Suzuki et al. 2001) (Nandhakumer, Selladurai, & Sekar,2009). In such critical operations, the manipulator follows a predefined trajectory. It is based on the design and control issues of the robot (Carmelo di Castri et al 2012).
Robot control issue mainly deals with keeping the dynamic response of the robot in accordance with some prescribed performance criterion which includes the non-linear and coupled characteristics of its dynamics. The dynamics of a robot can be described by a set of coupled non-linear equations in the form of gravitational torques, coriolis and centrifugal forces. The significance of these forces is dependent in the physical parameters of the robot, the load it carries and the speed at which the robot operates (Nandhakumar S. and Selladurai V, 2011). To reach the level of accuracy, compensation for the above mentioned parameter variations and disturbances, become much more critical. Hence the design of the control system becomes much more complex. The control problem consists of firstly obtaining dynamic models of the manipulator and secondly using these models to determine control laws or strategies to achieve the desired system response and system performance. (Lewis et al. 1993: Nandhakumar et al., 2010; Nandhakumer, Selladurai, & Sekar,2009, Ponalagusamy et al 2009: Thaer Alsultan et al 2018).
It is indeed true that a good number of researchers have studied the linear and non-linear problem for decades and many traditional and meta-heuristic techniques including artificial intelligence methods have been developed (Yu et al 2007). Neural Networks are capable of learning complex relationships in data. By mimicking the functions of the brain, they can discern patterns in data, and then extrapolate predictions when given new data. To obtain desired level of accuracy, NN could be trained on experimental data. (H.S.Chhatpar *et al 2003;* S.A. Kalogirou, 1999, Yu et al 2007). An NN is an information processing paradigm made up of a set of algebraic equations. The common type of neural network’s information-processing units (neurons) is organized in three groups, or layers: input, hidden and output (Lu et al 2015; Koker 2013; Ahmed et al 2016Ahmed et al 2016).

In this paper, singular system time invariant case robot arm has been taken for experimental purpose. An experiment has been carried out by using 2DOF pick and place. The experimental results demonstrated that the STHWS with Variable Structure control effectively controls the variations and achieves desired trajectories with in the projected accuracy. In order to analysis the stability of the robot, the NN predictions were made using Neural Tool 5.5 software developed by Palisade Corporation USA from obtained error values from the experimental work (Nandhakumar 2012)

In this NN prediction, four important parameters loads in grams, current in amps, voltages in volts, and speed in rpm are identified. The data of the mentioned parameters were collected during continuous operations of the robot at various trails. In NN prediction, two simulations have been carried out one is for predicting variations from existing tested data’s and the other is for finding out the unknown values of non- tested input values. From neural network analysis it has been observed that the neural network predictions very closely match with the variation obtained by experimental validation. Also neural network predictions yield better results for non-tested input values and also it very close to the actual values of variation obtained by experimental validation.

2. IMPLEMENTATION ON AN INDUSTRIAL ROBOT

The configuration of the robot is a pick and place, 2 DOF, rotation and linear model (RL), DC servo drive, pneumatic gripper with pay load of 1 kg-m with variable structure controller as shown in the figure 1. A suitable control law has designed by using variable structure control system discussed by Huang et al, (2004). Each movement of the robot has been measured by optical encoder during working. Trajectory of each joints are traced and compared with predefined path, if it goes out of control, mathematical block which is present control system calculates new torque with respect to new position. Computed new torque has compared with steady state torque and achieves the desired trajectories by varying the input torque. The total duration of one complete cycle is 51 seconds. (Nandhakumar et al 2013; Nandhakumar 2012).

Figure 1: Experimental Setup (2 DOF RL Manupulator)

3. NEURAL NETWORK SIMULATION

3.1 Joint 1

The Neural network simulation has been carried out individual joint separately. For joint 1, data set manager is used to define the obtained values of parameters. The parameters defined are load in grams, Voltage in Volts, Current in Amps, and Speed in rpm. Then, The NN was trained. The 'best net search' method is used for getting the best predictions. The results of training and testing results are shown in the Table 1 and 2.

Table 1 Joint 1 neural network simulation – training report

Testing	Values
% Bad Predictions (30% Tolerance)	0.7012%
Root Mean Square Error	0.000497
Mean Absolute Error	0.002017
Std. Deviation of Abs. Error	0.0003010

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Table 2 Joint 1 Neural network simulation – Testing report

Testing	Values
% Bad Predictions (30% Tolerance)	2.9714%
Root Mean Square Error	0.0005123
Mean Absolute Error	0.0003980
Std. Deviation of Abs. Error	0.0003105
R-Square value	0.9051

The performance of the neural network was determined based on the mean squared error (MSE) between the neural network's actual output and the desired output.
The differences between the network outputs and target are calculated through the mean squared error (MSE). From the table 1 and 2, it has been observed that the percentages of bad prediction values are very low in testing and increases in training. Since, the joint 1 is rotary motion; it reaches the set point immediately. Similarly MSE and Mean Absolute Error (MAE) are very less ($5x10^{-4}$). **R-square value** – The root mean square value is 0.9492. It indicates that that actual variations and neural network predictions are very close to each other.

After training and testing, NN predictions have been made for the existing data and for the new incomplete or unknown values of the above parameters. The variations which have been predicted are shown in the Table.3. The Table 3 shows the comparison between neural predicted values and the actual variations. From this table, it has been observed that the actual variations matches well with the neural network prediction values and the % of the errors is also within the acceptable level (5%). The Figure 2 shows the accuracy of the actual variation of joint 1. The neural network predictions very closely match with the actual variations.

Table 3 Joint 1 Neural Network Predictions

Load in Grams	**Joint 1**	
	Actual data	NN Predictions
750	0.0038	0.0039
850	0.0043	0.0045
950	0.0044	0.0045
1050	0.0045	0.0047
1150	0.0047	0.0049
1250	0.005	0.0052
1350	0.0059	0.0057
1450	0.0057	0.0059
1550	0.0057	0.0058
1650	0.0058	0.0059
1750	0.0058	0.0058
1950	0.0056	0.0057
2050	0.0056	0.0057

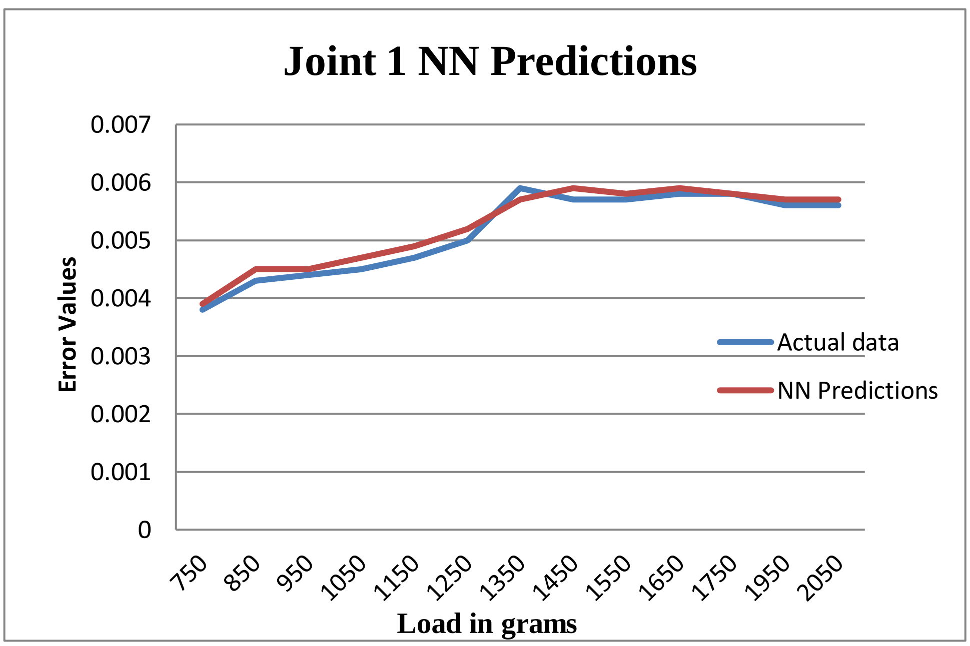

Figure 2 Joint 1 Neural network predictions

3.2 Joint 2

The same procedure is adopted to obtain values for neural network simulation. The results of training, testing, and predictions are presented in the table 4- 6 and figure 3.

Table 4 Joint 2 neural network simulation – training report

Testing	Values
% Bad Predictions (30% Tolerance)	2.7308%
Root Mean Square Error	0.0005161
Mean Absolute Error	0.0003850
Std. Deviation of Abs. Error	0.0003437

Table 5 Joint 2 neural network simulation – testing report

Testing	Values
% Bad Predictions (30% Tolerance)	4.6923%
Root Mean Square Error	0.0005788
Mean Absolute Error	0.0004397
Std. Deviation of Abs. Error	0.0003764
R-Square value	0.8971

From the table 4 and 5, it has been observed that the percentages of bad prediction values are high when compared to the joint 1, because the joint 2 is in linear motion. Due to the linear motion, joint 2 takes few seconds to reach the set point. But this % of bad prediction is also within the tolerance limits (30%). Neural network yields better results during training.. Similarly MSE and Mean Absolute Error (MAE) are very less ($5x10^{-4}$). **R-square value** – The root mean square value is 0.8971. It indicates that that actual variations and neural network predictions are very close to each other.

Table 6 Joint 2 Neural Network Predictions

Load in Grams	**Joint 2**	
	Actual data	NN Predictions
750	0.046	0.049

850	0.048	0.0516
950	0.051	0.0532
1050	0.057	0.0581
1150	0.085	0.0849
1250	0.086	0.0877
1350	0.088	0.088
1450	0.09	0.0891
1550	0.093	0.092
1650	0.095	0.0945
1750	0.096	0.0957
1950	0.097	0.0978
2050	0.098	0.0984

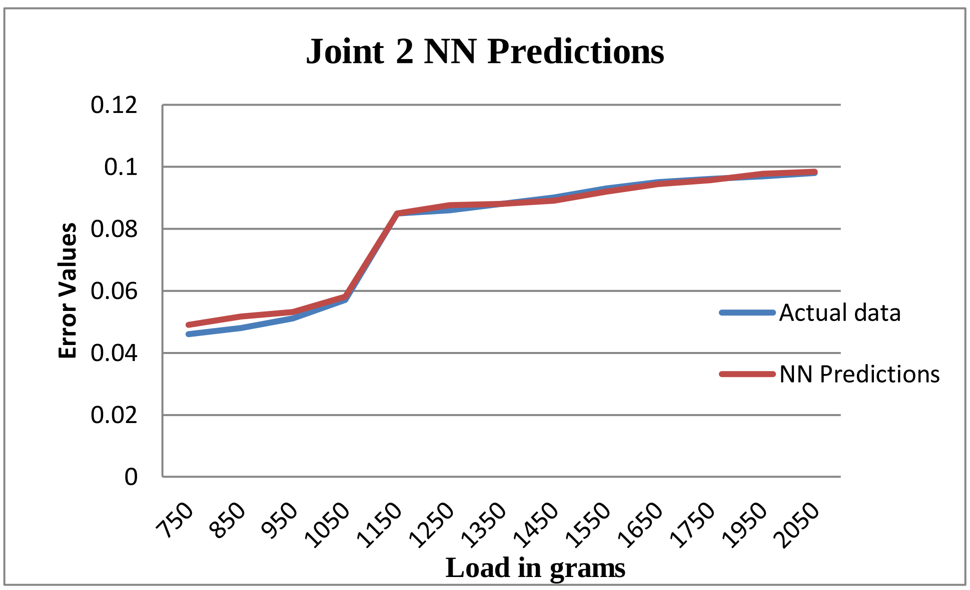

Figure 3 Joint 2 Neural network predictions

After training and testing, predictions have been made for existing data as shown in Table 6. The Table 6 shows the comparison between neural predicted values with the actual variations. From this table, it has been observed that the actual variations matches well with the neural network prediction values and the % of the errors are also within the acceptable levels. The Fig 4 shows that the accuracy of the actual variation of joint 2. The neural network predictions very closely match with the actual variations.

3.3 Neural network prediction of unknown values

The neural network predictions have been made to find out the unknown values of variations for non-tested input parameters. The different values of the input parameters like load, voltages, current and speed have been taken and are presented in Tables 7 & 8 for neural network predictions.

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Each individual joint non-tested input parameter is simulated separately and presented in the following tables.

Table.7 neural network prediction values of non-tested inputs of joint 1

Load in gms	Voltage in Volts	Current in Amps	Speed in rpm	Tag Used	Prediction
700	10.11	1.07	420	predict	0.0049
825	10.21	1.10	420	predict	0.0050
875	10.12	1.20	420	predict	0.0052
1025	10.21	1.20	420	predict	0.0055
1125	10.22	1.13	420	predict	0.0056
1300	10.15	1.12	425	predict	0.0058
1325	10.22	1.28	425	predict	0.0059
1400	10.12	1.24	425	predict	0.0062
1550	10.24	1.18	450	predict	0.0063
1675	10.25	1.21	450	predict	0.0060
1850	10.21	1.24	460	predict	0.0064
1925	10.22	1.26	460	predict	0.0066
2025	10.15	1.27	465	predict	0.0067

Table 8 neural network prediction values of non-tested inputs of joint 2

Load in gms	Voltage in Volts	Current in Amps	Speed in rpm	Tag Used	Prediction
725	10.21	1.07	460	predict	0.0501
850	10.12	1.08	462	predict	0.0534
975	10.22	1.07	465	predict	0.0563
1025	10.24	1.10	465	predict	0.0598
1150	10.12	1.11	465	predict	0.0777
1275	10.22	1.08	465	predict	0.0879
1350	10.24	1.15	452	predict	0.0891
1425	10.23	1.18	452	predict	0.0923
1775	10.25	1.20	445	predict	0.0944
1850	10.21	1.45	442	predict	0.0961
1900	10.20	1.24	438	predict	0.0965
2025	10.19	1.25	435	predict	0.0997

4 RESULTS AND DISCUSSIONS

The experiment has been carried out using 2 degrees of freedom, pick and place RL manipulator. Figure 2& 3 shows the prediction chart for joint 1 & 2. From Figures it has been observed that the neural network predicted values closely fit with the actual variations are obtained from experimental values. It can also be seen that if load increases the actual and neural network variations also increase.

Table 7 shows the predicted values of variation of the non-tested input parameters of joint 1. The predicted values closely match with the actual variation obtained by experimental validation as shown in the table 3.

Table.8 shows the neural network predicted values of non-tested input parameters of joint 2. The predicted values are yields some errors as compared to the joint 1. This is because of linear motion of the robot. From this analysis it has been observed that neural network prediction closely matches with the variation obtained by experimental validation as shown in the table 6.

5 CONCLUSIONS

In view of analyzing the stability of the proposed STHWS method with variable structure control system, the neural network prediction has been made by using Neural Tool 5.5 software from the obtained error values or variations from the experimental work,. In this neural network prediction, two simulations have carried out, one for predicting variation from existing tested data's and the other for finding out the unknown values of non-tested input values. From neural network analysis it has been observed that the neural network predictions very closely match with the variation obtained by experimental validation. Also neural network predictions yield better results for non-tested input values and also it very close to the actual values of variation obtained by experimental validation. From neural network simulations, it has been evidenced that the proposed mathematical tool called STHWS method minimizes the errors occurring during the various working conditions of the robot. It also yields better results when compared with the earlier studies in this field of study (Mendes et al 2002).

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