Depth Control of an Unmanned Underwater Remotely Operated Vehicle using Neural Network Predictive Control

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Abstract

This paper investigates the depth control of an unmanned underwater remotely operated vehicle (ROV) using neural network predictive control (NNPC). The NNPC is applied to control the depth of the ROV to improve the performances of system response in terms of overshoot. To assess the viability of the method, the system was simulated using MATLAB/Simulink by neural network predictive control toolbox. In this paper also investigates the number of data samples (1000, 5000 and 10,000) to train neural network. The simulation reveals that the NNPC has the better performance in terms of its response, but the execution time will be increased. The comparison between other controller such as conventional PI controller, Linear Quadratic Regulation (LQR) and fuzzy logic controller also covered in this paper where the main advantage of NNPC is the fastest system response on depth control.

Keywords: Depth control; Unmanned Underwater Remotely Operated Vehicle; Neural Network Predictive Control

1. Introduction

The neural network predictive control is considered as a basic type of model based predictive system which is the model is a trained neural network using neural network toolbox in MATLAB as shown in Fig. 1. It is consists of four components (i.e. the plant to be controlled, the desired performance of the plant, a neural network that models the plant, and an optimization process that determines the optimal inputs needed to produce the desired performance for the plant) [1]. The neural network predictive control normally optimizes the plant responses over a specified time horizon [2],[3]. The role of neural network model predictor, which uses the error e between the system output yp and the neural network model output ym, as neural network training signal. The nonlinear neural network model is to predict the future performance, determine the control signal u by minimizing cost function, J as in Equation (1) [4]. The steps of the neural network predictive algorithm as shown in Fig. 2.

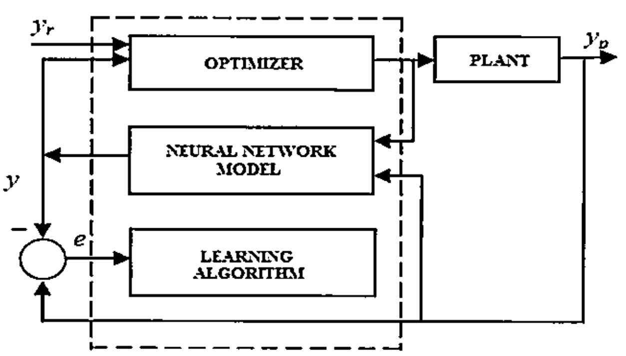

Fig. 1: Block diagram of neural network predictive control system [1]

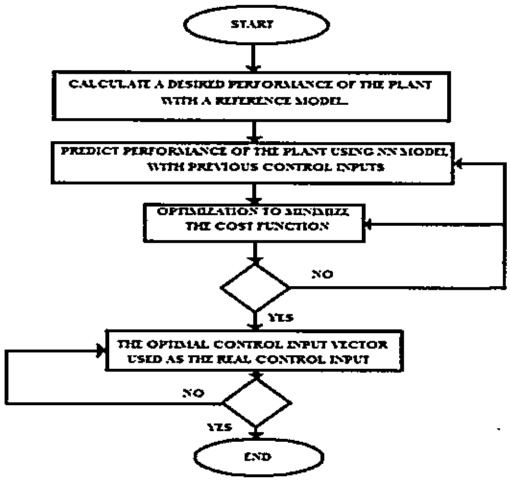

Fig. 2: steps of the neural network predictive algorithm

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$$J = \sum_{j=N_1}^{N_2}[y_r(k+H_p) - y_m(k+H_p)]^2 + \rho\sum_{j=1}^{N_u}[u(k+H_p-1) - u(k+H_p-2)]^2 \qquad (1)$$

where

N_1 is the minimum costing horizon

N_2 is the maximum costing horizon

N_u is the control horizon

y_m is predicted output of the neural network

y_r is reference trajectory

ρ is the control input weighting factor.

u is control signal

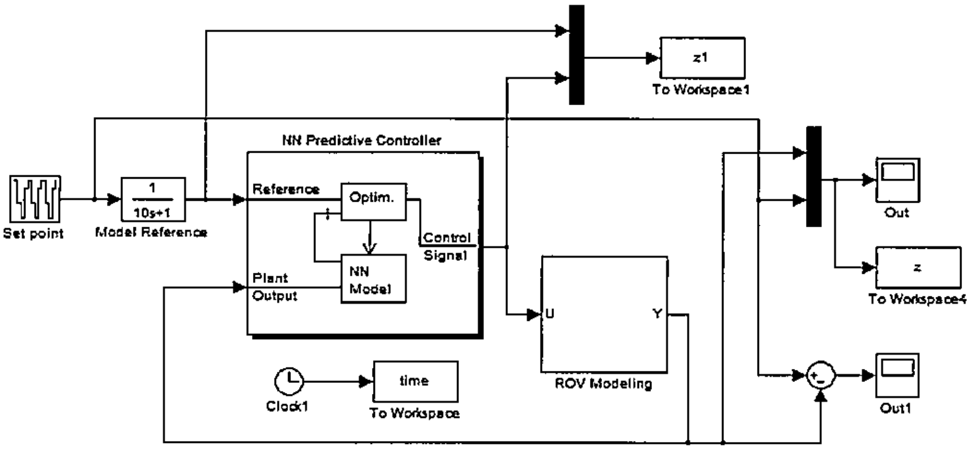

Fig. 3: Block Diagram Neural Network Predictive Control for the ROV

Neural network predictive control is a control method that finds the control input by optimizing a cost function subject to constraint. The cost function used to calculates the desired control signal by using a model of the plant to predict future plant output [5],[6]. A fundamental part of this method is the actual optimization problem that obtains future control inputs by minimizing a cost function subject to constraints on the system. Typically, the cost function, J consists of the error between the reference trajectory r and the predicted outputs y in addition to the control effort, u. A.S.M Nor et al using NNPS for control deep submergence rescue vehicle (DSRV) [1]. In [7],[8] used the DSRV model to design an intelligent controller that called single input fuzzy logic controller. Based on [1], the NNPC will used to control the ROV that was develop by Underwater Technology Research Group (UTeRG) from faculty of electrical engineering Universiti Teknikal Malaysia Melaka. The model of ROV obtained from system identification technique as can referred to [9],[10],[11]. The parameter for NNPC almost the same just varied on number of data samples (e.g. 1000, 5000 and 10,000).

2. Neural Network Predictive Control (NNPC)

This section illustrates a simple way of controlling a nonlinear and 4th order system using neural network predictive control. The design procedure utilizes MATLAB® Neural Network Predictive Control toolbox and was implemented using SIMULINK® version 7.6.A Neural Network Predictive Control (NNPC) was designed to control the ROV as shown in Fig. 3. A neural network was designed to be used as the predictive model of the MPC. The NNPC will then be compared with conventional controllers such as PI, fuzzy logic Controller, and LQR controllers to determine its performance and characteristics. Control design methods based on MPC was found to be widely used in many industrial applications [12]. The ability of MPC in handling constraints contributes to a significant advantage in a context of the overall operating objectives of many process industries. The optimization determines the control signal that optimizes plant behaviour over the time horizon [13]. Fig. 4 shows the window for designing the model predictive controller. Fig. 5 shows the Neural Network algorithm in MATLAB. From this figure the number of layer for NN can be seen and also the progress of neural network performances can be obtained. Fig. 6 shows the input and output of the system based on 5000 data samples. This input and output system based on model ROV that used for open loop system. Fig. 7 shows then validation data and training data for NN Predictive Control based on 5000 data samples while Fig. 8 shows the regression plot of the train and valid data.

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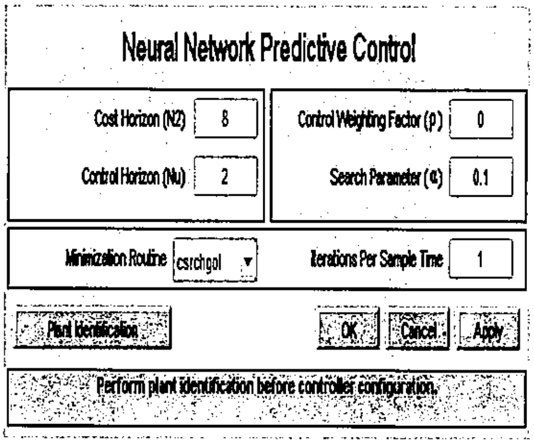
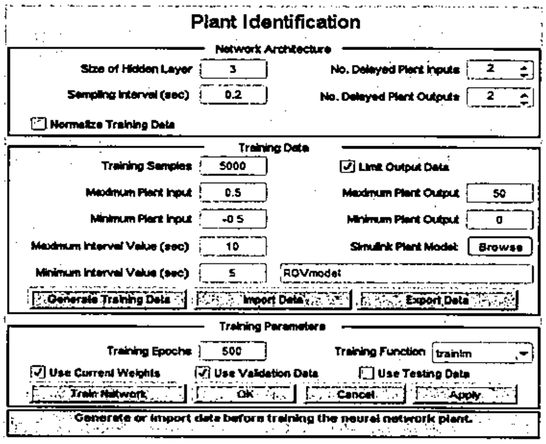


(a) Neural Network Predictive Control



(b) Plant Identification

Fig. 4: Neural Network Predictive Control Block

3. Result and Analysis

The results based on three data samples (e.g. 1000, 5000, 10,000) as shown in Fig. 8. Fig. 8 shows the results for each data samples, respectively. Based on this results, the number of data samples doesn't not affect the performances of NNPC. The results of three data samples are almost the same. Fig. 9 shows the different set point based on the best data samples (5000 data samples).

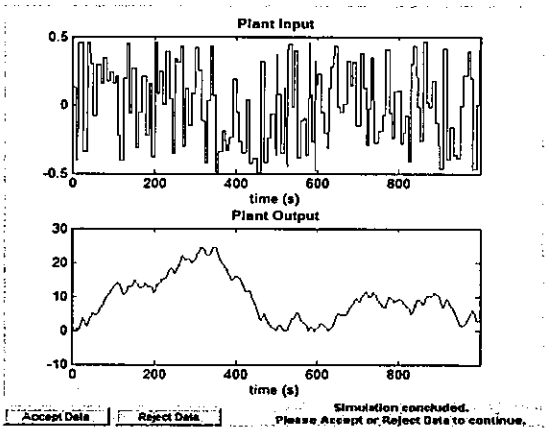


Fig. 5: Input and Output of the system based on 5000 data samples

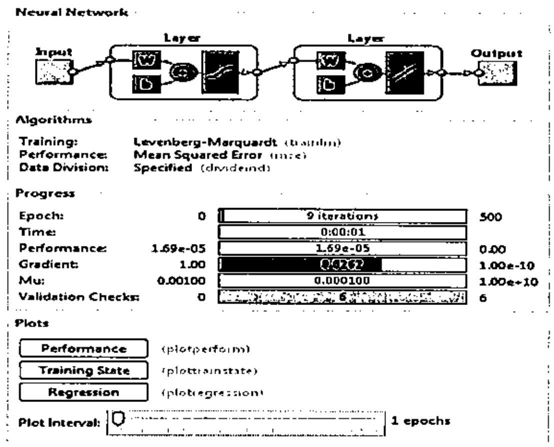
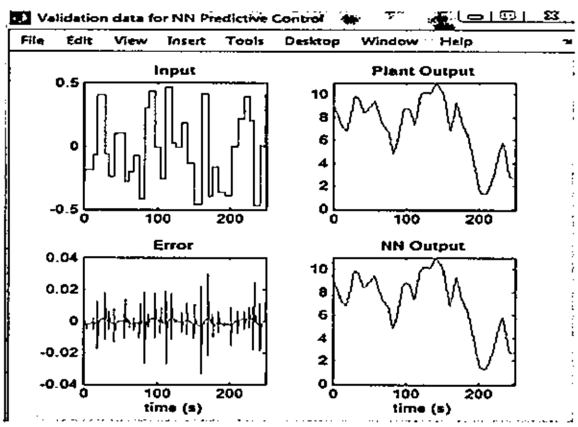
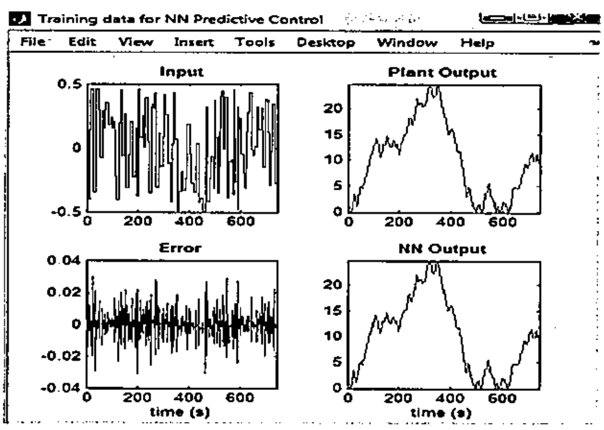


Fig. 6: Neural Network Toolbox



(a)



(b)

Fig. 7: Validation data and Training Data for NN Predictive Control

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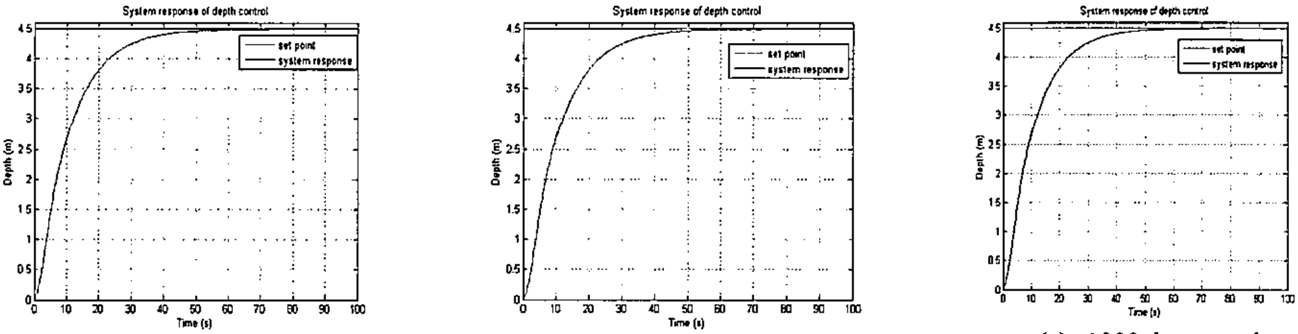

(a) 10,000 data samples

(b) 5000 data samples

(c) 1000 data samples

Fig. 8: System response of depth control

3.1. Comparison Controller

The comparison system response other controllers (e.g. PI controller, FLC controller, and Observer based on output feedback control). Fig. 10 shows all simulation system response results for ROV vertical trajectory. The set point is varied for a given time of 100 seconds. The simulation shows that, all five controllers give a zero steady-state error and zero overshoot. However, neural network predictive control gives a better performance in terms of the transient response. As can be seen in Fig. 10, neural network predictive control gives a faster settling time and rise time, followed by LQR, PI controller, and FLC controller. The simulation results expressed the steady-state performance. The steady-state performance indexes are summarized in Table 1. From the table, the depth response of the neural network predictive control achieved a better transient and steady-state performance than an improved SIFLC, LQR, PI controller, and SIFLC. An advantage of an improved SIFLC over other controllers is, the computation time, which is the time required to compute the simulation. Table 2 shows the comparison of computational time between the neural network predictive controller, LQR controller, PI controller, and single input fuzzy logic controller. It can be observed that an improved SIFLC is faster than LQR and PI controller and neural network predictive controller is the slowest among them. The NNPC cannot meet the requirement of rapid response. Here it can conclude that an NNPC is better for the system need accuracy and precision task where the task doesn't care about computational time. The reason is why NNPC more suitable for forecasting and prediction application. For underwater application, NNPC more suitable for recognition of images on underwater and prediction of underwater environments where the important issues should be covered when implemented in real time system especially in the ocean. The research of NNPC is not end, because a lot of parameter can be studied to give better results (e.g. Neural Network predictive Block). To many parameter can be changes to improved the performances of system response.

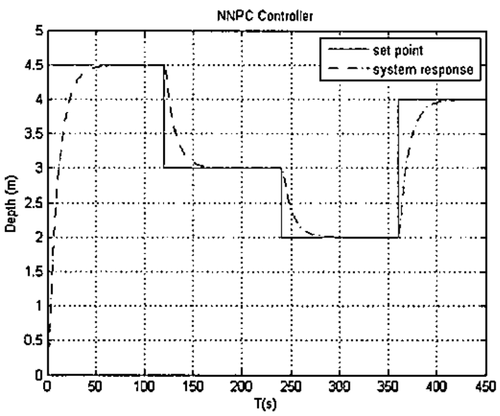

Fig. 9: Neural Network Predictive Controller system response

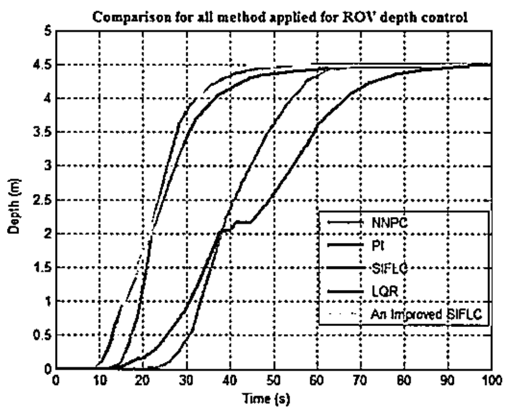

Fig. 10: Comparison for all method applied for ROV depth control

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Table 1: Comparison controller techniques for depth control

	SIFLC	PI	NNPC	LQR	Improved SIFLC
Peak Time, Tp (s)	100	80	65	75	70
Rise Time, Tr (s)	90	70	50	70	60
Settling Time, Ts (s)	110	80	65	75	70
Overshoot (%)	0.1	0.1	0.1	0.7	0
Steady state error ess	0	0	0	0.2	0

Table 2: Execution Time

Controller Method	Computation time
NNPC	452.10 s
PI	58.33 s
SIFLC	14.05 s
LQR	11.87 s
Improved SIFLC	10.45 s

4. Conclusion

The NNPC is applied to control the depth of the ROV. The system was simulated using MATLAB/Simulink and NNPC toolbox. The simulation reveals that the NNPC has the better performance, and it exactly resembles the an improved SIFLC in terms of its response, but the execution time will be higher than others. The main advantage of NNPC is the fastest system response on depth control but execution time for simulation take longer time. A lot of parameter can be studied to give better results (i.e. Neural Network predictive Block) where many parameter can be changes to improved the performances of system response. For future recommendation applied this NNPC to real time system by using Microbox 2000/2000C where Microbox 2000/2000C is an XPC target machine device to interface between an ROV with the MATLAB 2009 software.

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