Neural Network Course Changing and Track Keeping Controller for a Submarine

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ABSTRACT

This paper presents the performance of ANN (Artificial Neural Networks) technique for the development of controller for heading motions of submarine. A MLP (Multi-Layer Preceptron) FFNN (Feed-Forward Neural Network) is used for development of controller. Supervised type of learning is used for training of network by using back-propagation Algorithm. The training is performed by providing a nonlinear sliding mode controller as a supervisor. The development of controller is based on nonlinear decoupled heading model of a submarine without consideration of external environmental disturbances. To demonstrate the robustness of controller the performance of controller is tested in different operating conditions: course changing, track keeping and under the influence of sea currents. Simulations results show that in all cases, the heading error comes to zero, which indicates that the actual heading converges to the desired heading in finite time.

The maximum error is observed 0.5^o for 45^o command angle, in presence of sea currents. The result demonstrates that the performance neural network controller has been robust.

Key Words: Feed-Forward Neural Network, Sliding Mode, Autopilot, Submarine, and Sea Currents.

1. INTRODUCTION

According to IFAC (International Federation of Automatic Control), submarine control problem is one of the IFAC benchmark problems [1-2]. Submarine control is a difficult control problem because the dynamics of this vehicle is nonlinear and coupled with hydrodynamics like radiation induced forces, viscous damping forces and propulsive forces and moments.

The parameters of submarine also vary with operating conditions like depth of water and speed of vehicle; additionally the effects of environmental disturbances like wind, waves and ocean currents also affects the maneuvering of a submarine.

Generally PID (Proportional Integral and Derivative) control system is used for control of marine vehicles [3]. A PID is linear and provides optimal performance only at some fixed operating conditions. Apart from PID controller, other nonlinear control techniques like sliding mode [4-10] H_2/H_∞ controller [11], back-stepping and Lyapunov method [12] and MPC (Model Predictive Control) [13] are also employed for submarine control.

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Though the performance of nonlinear control techniques proved to be satisfactory, but the shortcoming of these techniques is that they require an accurate model of system for designing a controller. The dynamics of submarine is nonlinear and complex enough; it is not possible to obtain an accurate model of submarine. Therefore, many assumptions are made for developing such traditional controllers for submarine. Because of these limitations, it becomes beneficial to investigate for some advanced control strategies like artificial neural networks and fuzzy logic.

Various authors worked on neural network for under-water vehicle. Yuh, [14] applied neural network for control of an underwater robotic vehicles. Fujii, et. al. [15] implemented the combination of fuzzy and neural network for pitch control of an autonomous underwater vehicle. Ishii et al. [16-18] developed a SONIC (Self-Organizing Neural Network Controller) for the underwater vehicles. Li, et. al. [19-21] proposed a NN (Neural Network) based controller for the depth control of underwater vehicles, the training of network was based on linear feedback. Lin, et. al. [22] also worked on fuzzy logic in combination with neural network for submarine depth and pitch control. The proposed scheme called FCMAC (Fuzzy logic Cerebellar Model Arithmetic Computer). Labonte, [23] used ADALINE model for online control of underwater vehicles. Lin [24] developed an autopilot for tracking control of an autonomous underwater vehicle. In this scheme the outputs of ANN are separated into two subnets, the ASN (Associate Search Element) and ACN (Adaptive Critic Element). Moattari, et. al. [25] also worked on NN for diving control of underwater vehicle. Xu, et. al. [26] used the ANN for modeling as well as control of an autonomous underwater vehicle. The MENN (Modified Elman Neural Network) was used as multi-step prediction model and Generalized Predictive control, known as Model Predictive Control strategy. The scheme used to control yaw velocity of autonomous underwater vehicle.

The training of network in specific applications found in research papers is based on linear controllers, however, for this work the training of network is carried out by using nonlinear sliding mode control scheme. After training the ANN controller possesses all the properties of its supervisor. A linear controller is optimal only at some fixed operating conditions. However, a nonlinear sliding mode controller proved to be robust under varying operating conditions [8]. The literature review reveals that only the depth of vehicle is considered as a manipulated variable. However trajectory tracking is one of most important aspect for autonomous maneuvering of a submarine. Further the real environment of submarine encounters randomly varying disturbances like waves and sea currents. In given literature no evidence is found for testing the performance of controller in presence of sea currents.

2. MATHEMATICAL MODEL OF SUBMARINE

The application used for development of neural networks controller involves a tenth order model of military submarine approximately 100m length. Like all underwater vehicles, submarine also maneuvers within rectangular coordinate system, resulting in six degrees of freedom motion (i.e. in each translational and rotational orientation). The co-ordinates of motions are defined as surge, sway and heave (linear velocities along x-y-z axes respectively and roll, pitch and yaw (angular velocities about x-y-z axes respectively).

The mathematical model of submarine is represented by set of equations; the model describes complete motion of submarine through water. McGookin has worked well on this model [7-9]. These equations are known as standard equation of motion. In state space form they represented by Equation (1) [27-28].

$$\underline{\dot{x}} = \underline{Ax} + \underline{Bu} \tag{1}$$

where the x=[u v w p q r ϕ θ ψ z] is state vector (Table 1), u=[δb δr δs] is input vector, A is system matrix and B is input matrix. (see the Appendix for model values [7]).

where δb is bow_plane defection, δr is rudder deflection and δs stern_plane deflection.

2.1 Heading Motion of Submarine

For a submarine the states which are generally need to be controlled are its heading (direction), diving (depth), submarine speed and submarine roll motion. For this work it is intended to design an autopilot to control heading motions of submarine. Heading refers to direction or angle ψ of the vehicle's longitudinal axis with respect to earth fixed inertial axes, which occurs due to rudder deflection δr of the submarine.

The states which significantly change during this motion are sway 'v' (the velocity along y-axis), yaw 'r' (angular velocity about z-axis) and psi 'ψ' (the angle about z-axis) and thus reduces the system third order system model consisting of state vector x=[v, r,ψ] and input u=[δr].

$$\dot{x} = Ax + Bu \tag{2}$$

The heading subsystem described by Equation (2) represents the horizontal motion generally called course keeping. The course keeping control mode involves control of heading angle and manipulation of rudder deflection. By taking consideration of mass and inertia of vehicle it is propose to develop course changing and track keeping controller for submarine. The main requirement of this control system is that the submarine should attain the desired course and follow predefined track with reasonable accuracy even in presence of sea currents and system remains stable.

TABLE 1. STATES DEFINING THE MOTION OF MARINE VEHICLE

DOF	Motion Components	Linear and Angular Velocities	Position and Angles
1	Motion in x-direction (surge)	u	x
2	Motion in y-direction (sway)	v	y
3	Motion in z-direction (heave)	w	z
4	Rotation about x-axis (roll)	p	ϕ
5	Rotation about y-axi (pitch)	q	θ
6	Rotation about z-axis (yaw)	r	ψ

3. ARTIFICIAL NEURAL NETWORKS

ANN is a branch of AI (Artificial Intelligence), whose functionality is based on principle of biological NNs. It provides a methodology to develop a computational model by using the structural and functional features of human brain processing.

Mathematically a simple artificial neuron model consists of single node having one or more inputs 'x'. Each input has its associated weight 'w'. All weighted inputs are sum up. Typically the sum of weighted input is added with bias 'b', then the resulting output come across some activation function 'f ' and results the output 'y'.

$$y = f\left(\sum_{i=1}^{p} w_i x_i + b\right) \tag{3}$$

An ANN is combination of various neurons in the form of layers. In each layer various neurons are connected in parallel. The output of each neuron of a layer is interconnected to every neuron of next layer having different strengths (weights) forming a matrix of weights depending on size of network.

The essence of getting the desired output from a particular network lies in continuously changing the values of weights and biases on basis of training of network. Once the training phase is completed the configuration of such network remains fixed. The resulting networks have more predictable characteristics than those, which are found in many forms of traditional self-adaptive control systems [2].

Based on flow of signals the ANNs are categorized as FFNNs and feed-back NNs. For this work a FFN is used.

4. METHODOLOGY FOR DEVELOPMENT OF NEURAL NETWORK CONTROLLER

In this paper MLP network is used to design course changing and track keeping controller of a submarine.

Rumelhart, et. al. [29-30] worked well on MLP networks and their applications. A MLP is a FFN. Back-propagation algorithm is used for training. The back propagation algorithm is supervised type learning algorithm. The algorithm adjusts the values of weights and biases of network to minimize the square of error of network. This is done by continuously adjusting the values of weights and biases in direction of steepest descent with respect to error.

For training of network a pair of input and target data set is generated by a closed loop system in conjunction with submarine model and sliding mode controller as shown in Fig. 1.

The algorithm developed for training of network consists of reference model, submarine model, sliding mode controller and neural network. For reference model a second order differential equation is used. A network with tagent-sigmoidal function for hidden layer and purlin function for output layer selected.

From reference model, desired states consisting of desired heading ψ_d and desired yaw velocity r_d are generated; from the model of submarine the actual heading ψ_{ac} and actual yaw velocity r_{ac} are fed back to compare with desired states and thus generating the error vector x_{error}=[r_{error}, and ψ_{error}]. These errors are fed to neural network as an input. However the output δr from sliding mode controller is continuously fed to network as desired target making pair of input and target data set. By developing a secondary closed loop the desired target is continuously compared with actual targeted output from network to achieve a goal.

For obtaining the optimal performance for a wide range of commands, the data for training is generated by series of control commands (ranging from -45^o to 45^o).

The development of network started with trial and error basis. Training started with three neurons for hidden layer and one neuron in the output layer. By gradually increasing the number of hidden neurons, finally the network represented by Equation (3), having 2 inputs, 5 hidden neurons and 1 output neuron provided satisfactory performance.

$$u_k = f_2(\Sigma f_1(\Sigma x_i . w_{ij} + b_j) \text{ x } w_{jk} + b_k \quad (4)$$

where i is number of inputs, j is the number on neurons in hidden layer, k in number of neurons in output layer, w is weight matrix, b is bias vector, x is input vector, f_1(.) is hidden layer activation function and f_2(.) is output layer activation function and u is output of network, which is input of model of system. Hence the Equation (1) has become function of output of ANN controller.

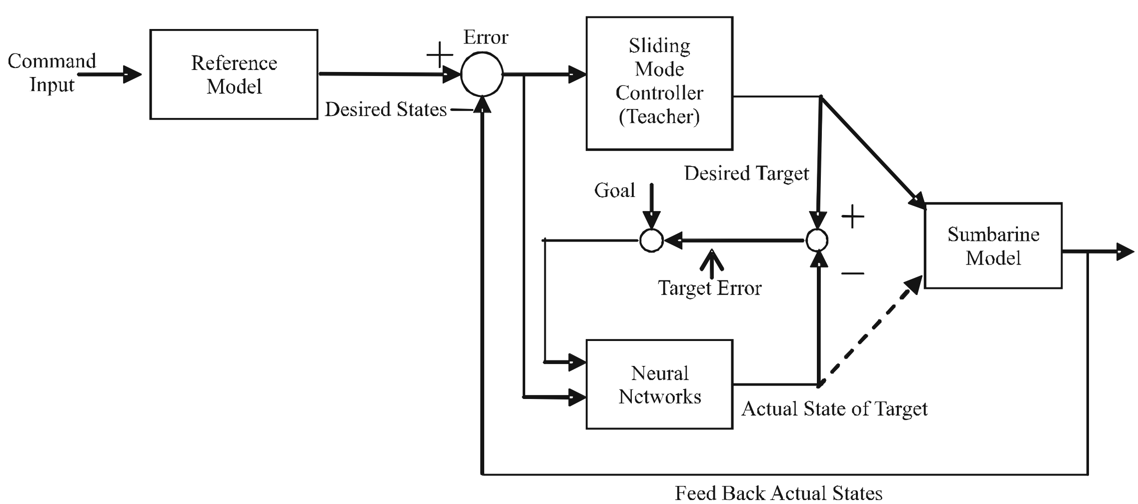

FIG. 1. DIAGRAMMATIC VIEW FOR TRAINING OF NEURAL NETWORK

For this submarine control system the values are taken as:

input state vector = x_i.=[ψ_error, r_error]

output = u_k=δr
number of input = i = 2
number of neurons in hidden layer = j = 5
number of neurons hidden output layer = k=1
size of hidden layer weight matrix = ($i \times j$) = (2×5)
size of output layer weight matrix = (j×k) = (5×1)
hidden layer activation function = f_1 = 1/(1+exp(-(w.x+b)
output layer activation function = f_2 = $w.x+b$

After successful training the controller provided the exact mapping of output of the network to its trainer as shown in Fig. 2, where graph 1 represents output of sliding mode

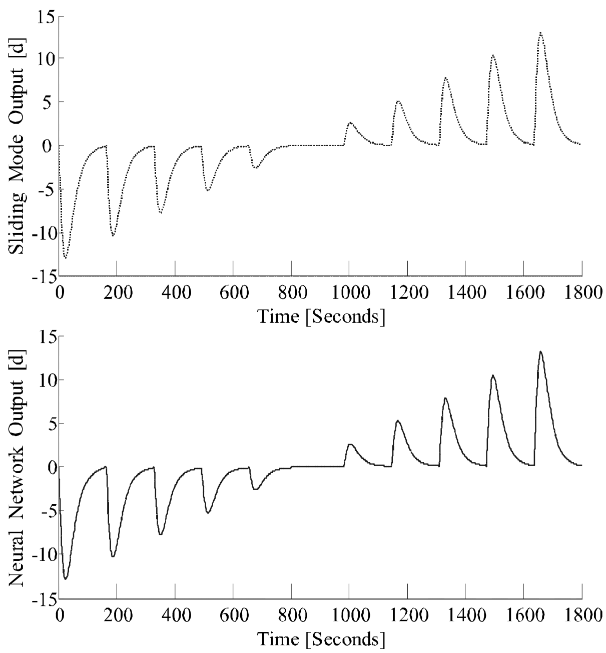

FIG. 2. TRAINING OF MLP NN WITH NETWORK FOR SERIES OF COMMAND HEADINGS

and graph 2 shows the output from NN, which exactly follows the nonlinear controller.

5. COMPLETE SYSTEM MODEL

After getting a trained network, the controller is incorporated in closed loop system consisting of desired system model, NN controller and submarine model as shown in Fig. 3. From the desired state model the desired states are generated and by feedback path the actual states which influences the heading motion of submarine feedback and errors (i.e. the difference between the actual sate and the desired state) are generated The errors fed to the controller and on the basis of deviations/errors the controller directs the submarine to regulate to the desired direction.

The purpose of this investigation is to design and test the performance NN controller for heading motions that yields satisfactory performance for any reference heading (from +3° to +45° to for heading) not only in ideal conditions but also at varying operating conditions (in presence of environmental disturbance i.e. sea currents). The performance index is that the error should not increase +3° and the control signal should not reach the maximum value of rudder angle +35°.

6. SIMULATIONS RESULTS UNDER VARIOUS OPERATING CONDITIONS

The three operating conditions to test the performance of controller involves the course changing, track keeping and effects of sea currents.

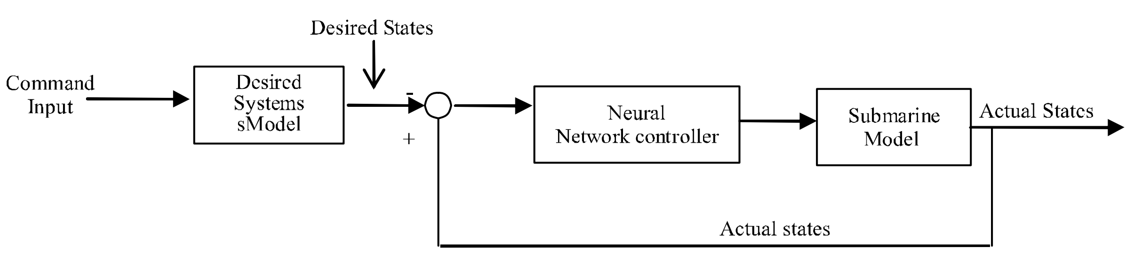

FIG. 3. COMPLETE SYSTEM MODEL

6.1 Course Changing Controller

The course changing controller is designed in such a way that controller changes its direction continuously provided by the step commands from helmsman. It continuous to change the course till the steady state is achieved. The time to achieve the steady state depends upon the mass and inertia of the vehicle. Due to inertia and mass the vehicle is not be able to exactly follow the changes in course provided by step commands. Therefore the desired states responses are developed by critically damped second order system to copy the actual responses.

Simulations of closed loop system are carried out by using MATLAB Version 7. Results are shown in Figs. 4-5. The controller exhibits the performance in ideal conditions. In the indicated figures the first graph of first row represents the desired (by dashed lines) and actual heading (by solid lines), where the second graph of first row shows the error between actual and desired heading. The first graph of second row indicates the behaviour of rudder deflection, the second plot of second row represents the sway velocity and the last graph shows yaw velocity (angular velocity about z-axis).

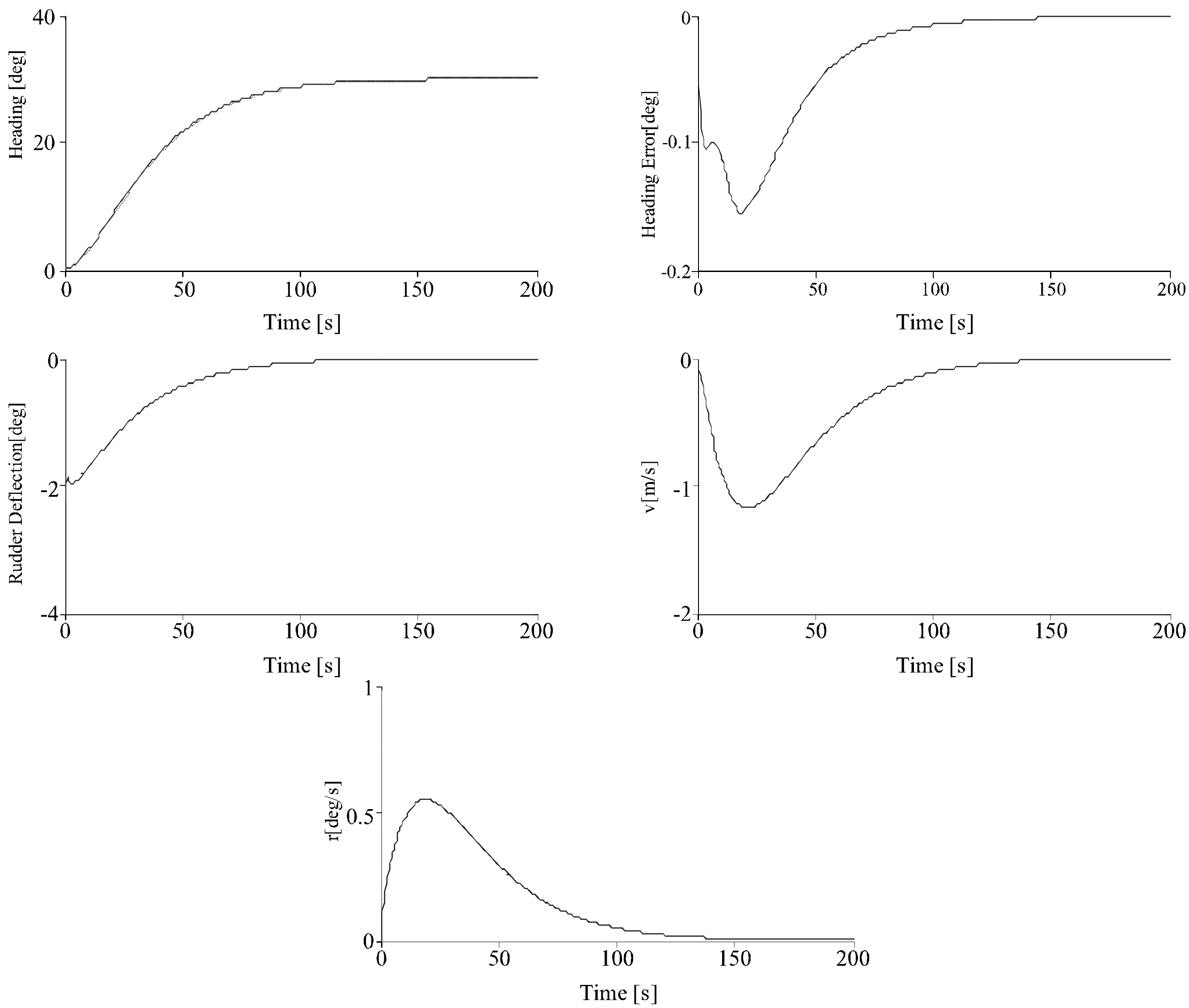

FIG. 4. SIMULATION RESULTS AT 30^{O} COMMAND ANGLE

6.2 Track Keeping Controller

For track keeping mode condition, a predefined track has been developed by an additional loop in control system by a series of command heading angles for specified time intervals

In this application the sequence of heading angles are chosen as to turn 10^o and remain there for 200 sec, then further turning at 20^o from it initial position and remain at that position for next 300 seconds. Finally to turn at -5^o from its initial position.

7. CONTROLLER IN PRESENCE OF SEA CURRENTS

Sea currents are the forceful changing velocities which continuously change both in direction and magnitudes because of atmospheric wind and heat over the sea surface.

The model used in this paper shall represent this disturbance as time varying linear velocity which acts along submarine's body fixed axes.

The current induced force and moments yields as [27]:

$$f = A_{cur}.\ T(\theta,\phi,\psi).T_{cur}(\alpha,\beta).V \tag{5}$$

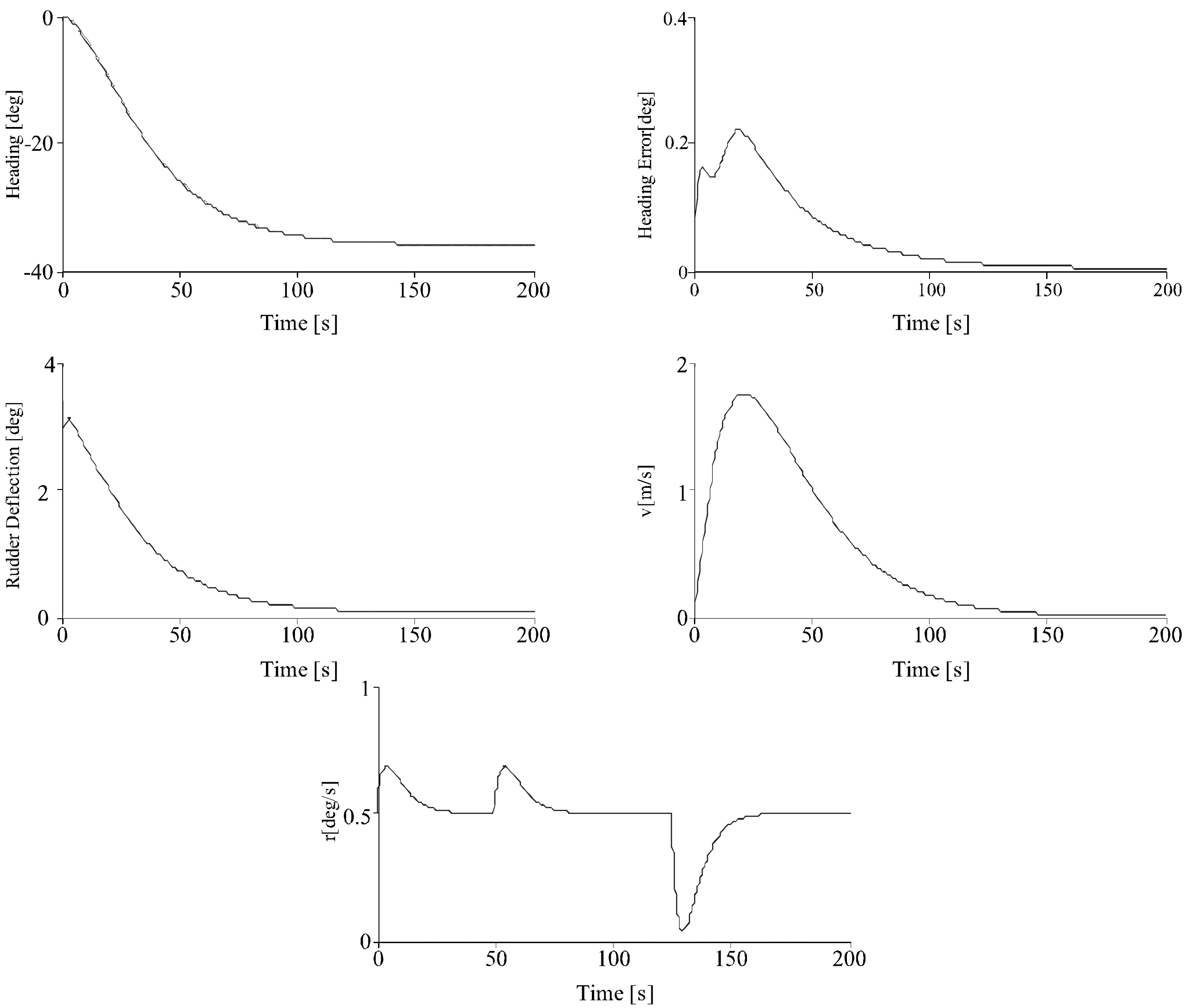

FIG. 5. SIMULATION RESULTS AT -45^O COMMAND ANGLE

where A_{cur} is current induced system matrix, $T(\theta,\phi,\psi)$ is the transformation matrix relating current axes to body fixed axes, V is magnitude of velocity and $T_{cur}(\alpha,\beta)$ transformation matrix as function of angle of attack (α) and angle of side slip (β).

Using the principle of superposition, the model of sea currents Equation (5) is integrated into model of vehicle hence the Equation (2) yields as:

$$\dot{x} = Ax + Bu + f\left(\alpha, \beta, V\right) \tag{6}$$

Simulations are carried out by close loop system by taking the model given by Equation (5). where the limits of magnitude of velocity is taken randomly varying form 0-1 m/sec, while the limits for angle of attack and angle of side slip are taken randomly varying from 0-360 degrees.

Results are shown in Figs. 6-8. In Figs.6-8 the graphs of first row represent the headings (actual and desired) and error respectively. The second row graphs show rudder deflection and sway velocity, the first graph of third row shows yaw velocity, while the rest of three plots show the states of sea currents (i.e. the angle of attack 'alpha', angle of side slip 'beta' and the randomly varying velocity).

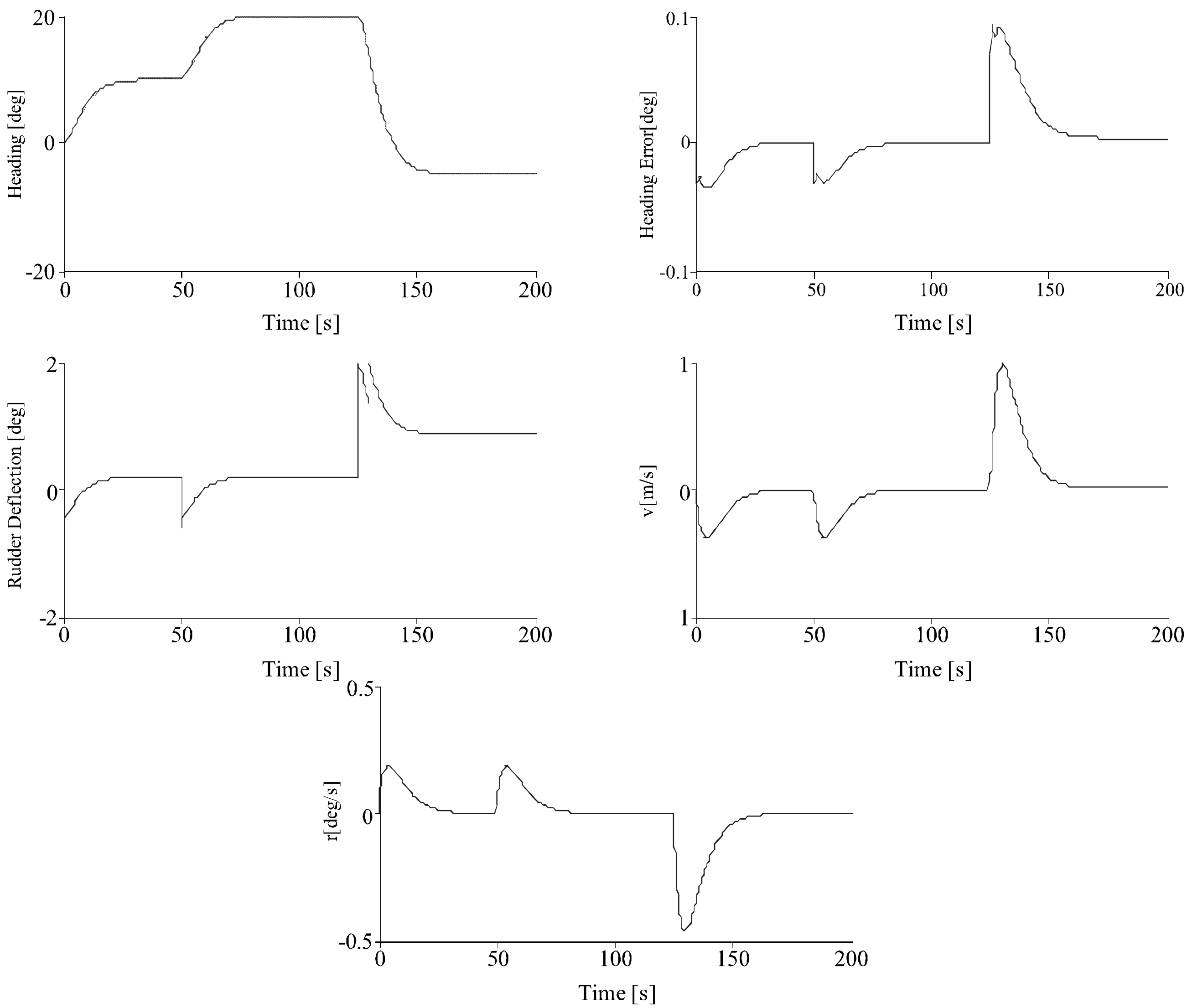

FIG. 6. SIMULATION RESULTS OF TRACK KEEPING CONTROL SYSTEM

8. RESULTS AND DISCUSSION

Graphical results show the performance of controller for different operating conditions. In ideal conditions, for 30^o command angle the error is 0.15^o, however, for 45^o command angle the error increases to 0.2^o. In case of sea currents, for 45^o command angle the error is 0.5^o and some oscillations are observed in performance of controller. This is because of randomly varying parameters, however overall the performance of controller remained within limits.

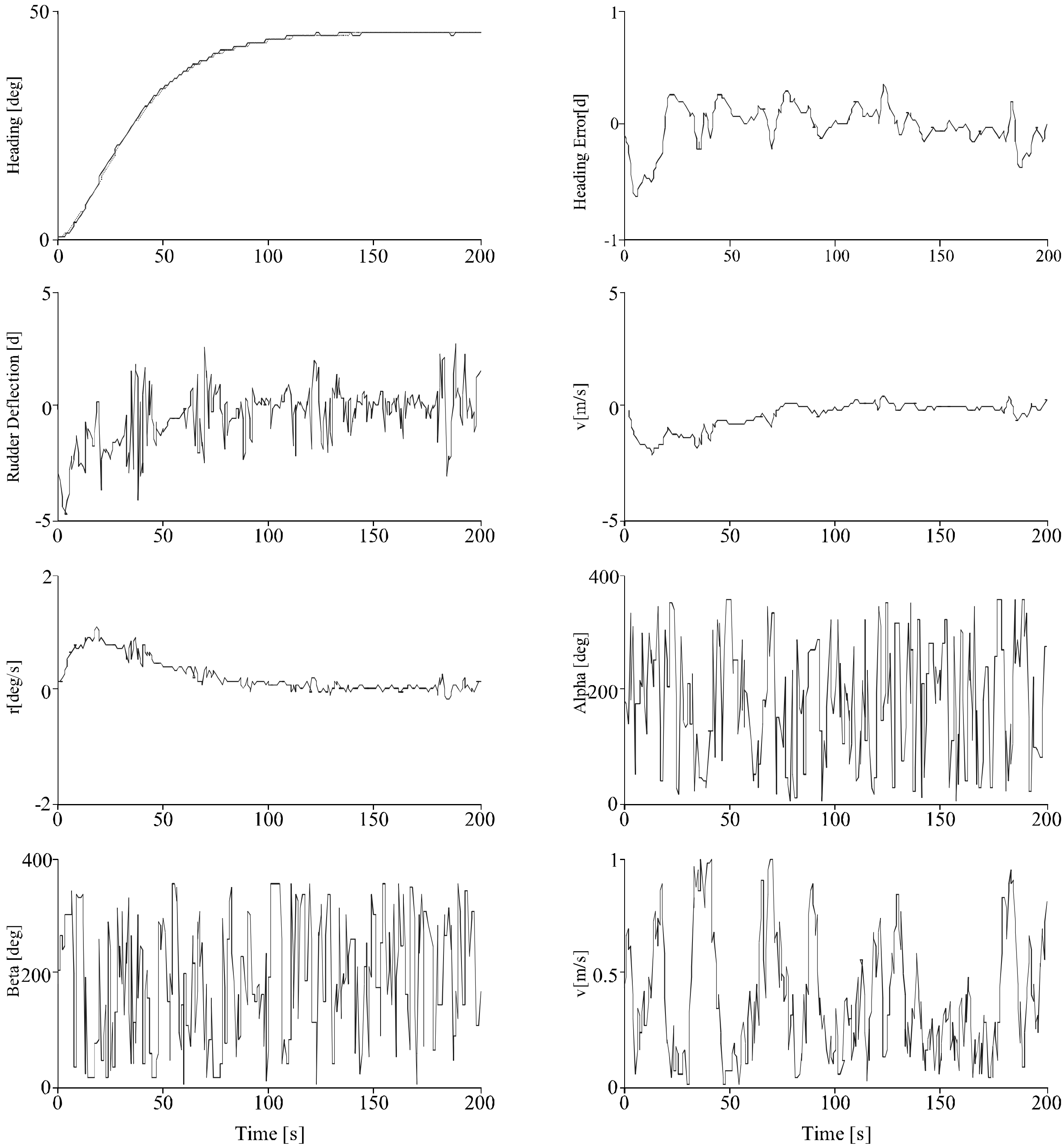

FIG. 7. SIMULATION RESULTS AT 45^O COMMAND ANGLE

9. CONCLUSION

In this paper ANN control system is applied for course changing and track keeping motions of a submarine. The development of controller is based on model of submarine without incorporating the external environmental disturbances, but the performance controller proved to be satisfactory not only in ideal conditions but in presence of randomly varying sea currents. This proves that once

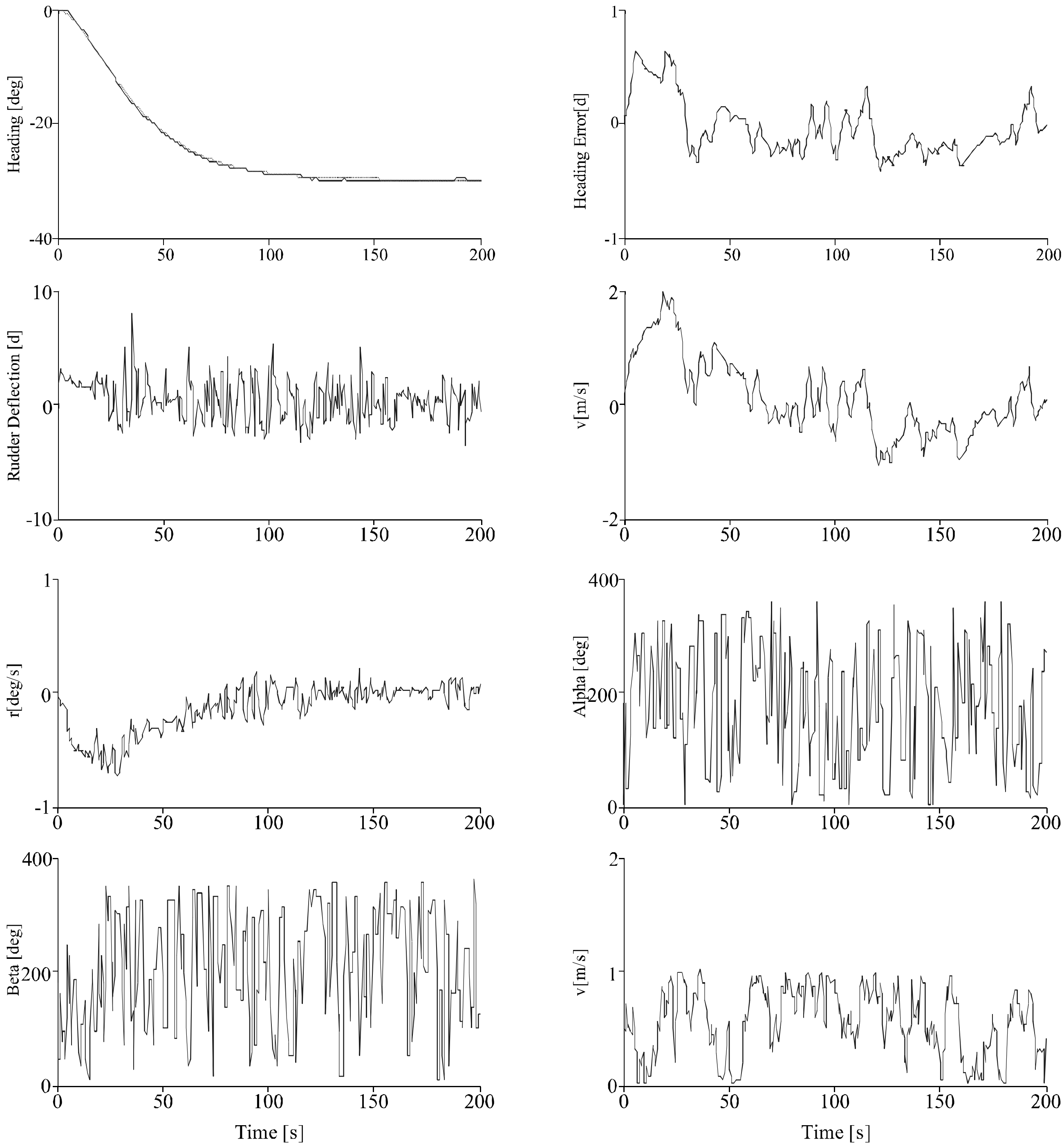

FIG. 8. SIMULATION RESULTS AT -30° COMMAND ANGLE

the training phase of ANN is completed, the configuration of NN remains fixed but resulting control systems have capability to cope with unpredictable characteristics of system.

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