

RECONFIGURABLE CONTROL SYSTEM FOR SHIP COURSE-CHANGING/KEEPING

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Abstract: This paper presents reconfigurable control system for ship course-changing/keeping. Adaptive neuro-fuzzy inference system (ANFIS) is used to identify a steering gear subsystem (actuator) in order to build an accurate reference model for the fault detection in this non-linear component. The proposed control system uses a compensator for reducing the loss of the control performance produced by faults in the steering gear subsystem. It is shown that the proposed control system is robust to faults in steering gear subsystem. *Copyright © 2002 IFAC*

Keywords: Fault Detection, Fault Tolerant System, Non-linear System Identification.

1. INTRODUCTION

Faults in steering gear subsystems produce serious problems for ship control. The consequence can be the degradation in control performance and increasing of the risk of safety. Fault-tolerant control (FTC) is an emerging area in automatic ship control, where several disciplines and techniques are combined to obtain a unique functionality. FTC provides a mechanism to monitor behaviour of components and function blocks and to take appropriate remedial action in order to keep manoeuvre capability of ship and prevent the loss of the control performance (Blanke, *et al.*, 2001).

The main goal is the design of a reconfigurable control system (RCS), which has built in an element of automatic reconfiguration, once a fault in the actuator has been detected and isolated. A basic RCS for ship course-changing/keeping, tolerant to faults in the steering gear subsystem, is proposed in this paper. Reconfiguration is based on a heuristic approach for the design of fault tolerant control. (Noriega and Wang, 1998) have previously used a similar approach for the design of a fault tolerant control of an unknown non-linear system using neural networks (NW system). A key part of the proposed RCS is an accurate mathematical model of the actuator. An analytical model based FDI approach for the rudder servo system was explored in (Vukic, *et al.*, 1999). In this paper an adaptive

neuro-fuzzy inference system (ANFIS) is applied to non-linear identification of steering gear subsystem (actuator). ANFIS identification is used to estimate residual, defined as difference between actual and estimated output of the steering gear subsystem. The compensator uses residuals to generate signals for compensation for the change in actuator dynamics, produced by faults.

2. STEERING GEAR SUBSYSTEM

The steering gear subsystem considered is the “two-loop” electro-hydraulic steering subsystem, common on many ships. The non-linear steering gear model is shown in Fig. 1 and parameters are given in Table 1.

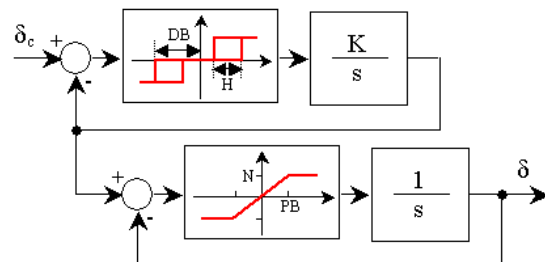


Fig. 1. “Two-loop” steering gear subsystem for ship.

Table 1 Parameter values for steering gear subsystem.

Parameter	Value
DB	1°
H	0.8°
K	4°/s
PB	7°
N	5°/s

3. ANFIS IDENTIFICATOR

This section applies ANFIS to the non-linear identification of steering gear subsystem (actuator). The input to the actuator is the command rudder angle $u = \delta_c$ and the output is the actual rudder angle $y = \delta$. System identification using ANFIS generally involves two top-down steps:

1. *Structure identification*: selection of the number and type of inputs and membership functions, partitioning of input space, selection of FIS order etc.
2. *Parameter identification*: ANFIS structure is known and fixed; optimisation techniques (for example, hybrid method) need to be applied to determine the optimal vector of premise and consequent parameters.

ANFIS performs static non-linear mapping from input to output space but without modification it cannot be used to represent dynamic systems. In order to identify dynamic systems, a combination of ANFIS with some time delay units and feedback is required. Hence, non-linear dynamic system can be modelled by ANFIS combined with some time delay units. Therefore, the main question in input selection is: *How many time delay units are needed to obtain the best model?* An excessive number of inputs not only impair the transparency of the underlying model, but also increase the complexity of computation necessary for building the model. Therefore, it is necessary to do input selection that finds the priority of each candidate inputs and uses them accordingly.

In order to predict the output $y(t)$ of the actuator, there are four candidate inputs in a group $G_y = \{y(t-1), y(t-2), y(t-3), y(t-4)\}$ and four candidate inputs in a group $G_u = \{u(t-1), u(t-2), u(t-3), u(t-4)\}$. In the first approximation, if non-linearity is omitted, the steering gear subsystem in Fig. 1. behaves as if it were a second-order system and for this reason two inputs are expected from both groups. An efficient method of input selection is presented in (Jang, *et al.*, 1997). A similar approach is used in this paper and gives an ANFIS identifier with four inputs $[y(t-1), y(t-2), u(t-1), u(t-2)]$ and one output $y(t)$ as the best candidate for further parameter-level fine-tuning (see Fig. 2.).

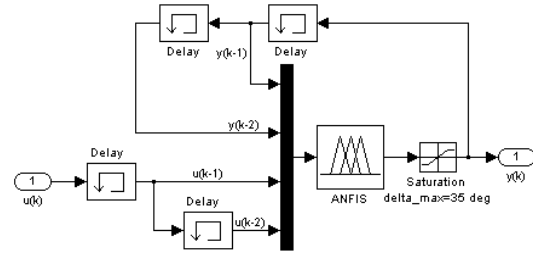


Fig. 2. ANFIS identifier of steering gear subsystem.

The selection of input signals for training data generation is very important. Data distribution in input 4-D space should be homogenous, but cannot be reached, because it is dictated by system dynamics. Hence, some regions in input space are not reachable by input data, but reachable regions should be homogeneously covered by input data. For these reasons and after some experimentation, it was decided to use only the training data set, without checking data. Signals $u(t)$ and $y(t)$ that form training data set are shown in Fig. 3.

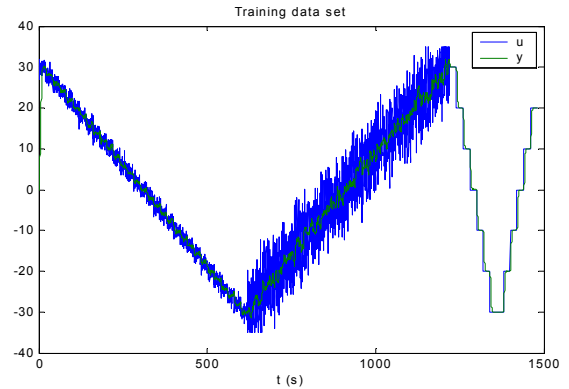


Fig. 3. Signals that form training data set.

Table 2 Characteristics of ANFIS identifier.

FIS type	First order
# Inputs	4
# Outputs	1
AND operator	prod
OR operator	max
# Epochs	500
# Linear parameters	80
# Non-linear parameters	24
# Training data pairs	5919
# MF per input	2
# Fuzzy rules	16

ANFIS characteristics are given in Table 2. Vectors $u(t)$ and $y(t)$ have a dimension of 5921×1 . The training data set M is a matrix with dimensions of 5919×5 and a format of the training data point (row of M) is $[y(t-1), y(t-2), u(t-1), u(t-2), y(t)]$. Fig. 4 (a) and (b) show the initial and final membership functions, respectively.

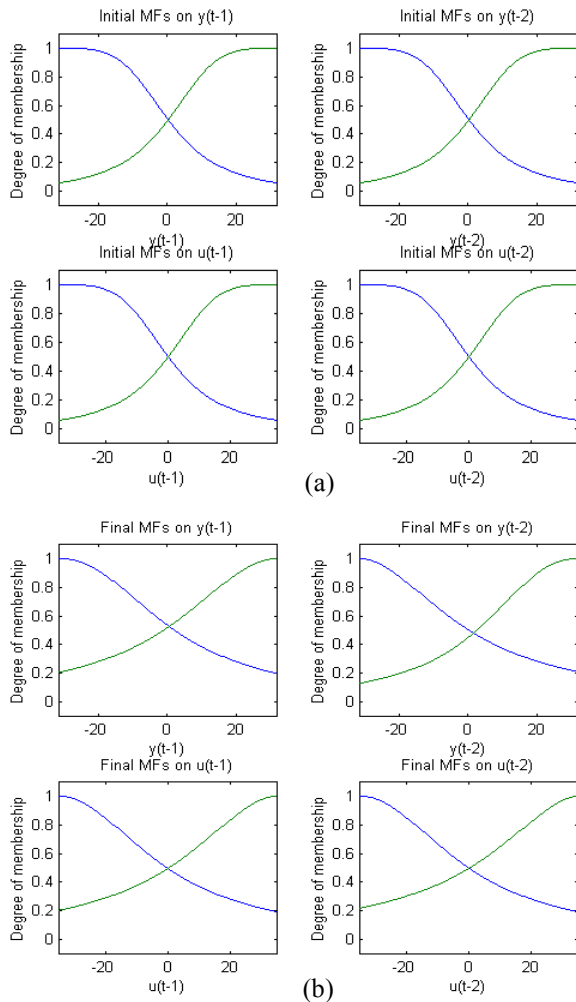


Fig. 4. (a) Initial membership functions (grid partition); (b) Final membership functions.

Fig. 5. shows the result of training the ANFIS identifier for 500 epochs. In particular, Fig. 5 (a) shows the change in step size through epochs; Fig. 5 (b) displays the training error curve; Fig. 5 (c) displays the desired curve from the training set and the output of the ANFIS identifier. Fig. 5 (d) shows an identification error between desired and ANFIS output.

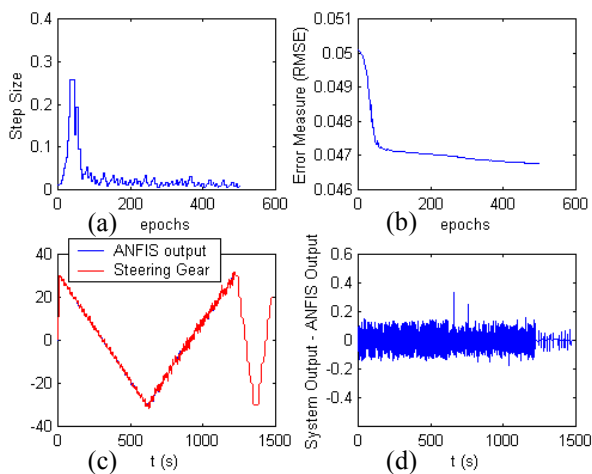


Fig. 5. (a) Change in step size; (b) Training error curve; (c) Performance of the ANFIS identifier; (d) Identification error.

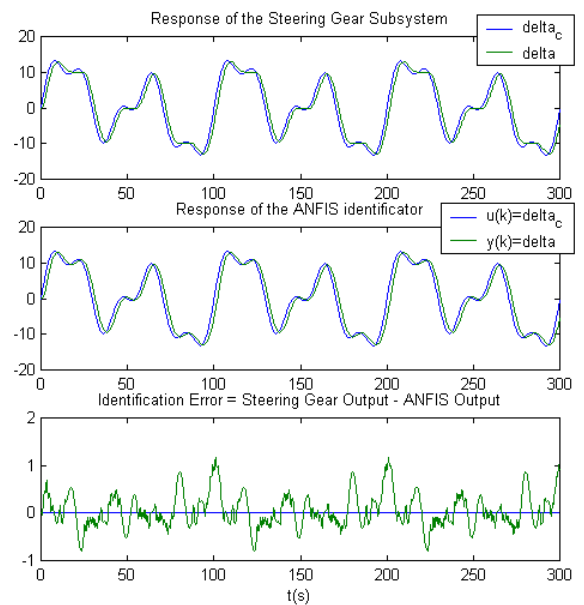


Fig. 6. Performance testing of ANFIS identifier.

Time responses of the actuator, ANFIS identifier and identification error are shown in Fig. 6. Sum of sinusoid signals was used as common input signal. Size of the identification error is acceptable. Peaks are due to “dead zone” type of non-linearity in the actuator.

3. FAULTS IN ACTUATOR

It is assumed that fault diagnosis system produces information about the type and time t_i of the occurrence of a particular fault. For this reason, faults in actuator are simulated by a switch. Fig. 7. shows the switch realisation in the case of a fault in an actuator. The steering gear subsystem has two feedback loops and two gains ($K_1 = 4$ and $K_2 = 5/7$) in a direct path. Faults in the actuator are simulated by abrupt reductions of these gains. This is achieved by multiplication of the gain K_i with a factor $f_i < 1$ after time instant t_i , so that a nominal value of the gain is reduced for $(1 - f_i) \cdot 100\%$. For example, if $f_i = 0.6$, then for $t > t_i$ gain K_i has a value $0.6K_i$, that is reduced for $(1 - 0.6) \cdot 100\% = 40\%$ of its nominal value.

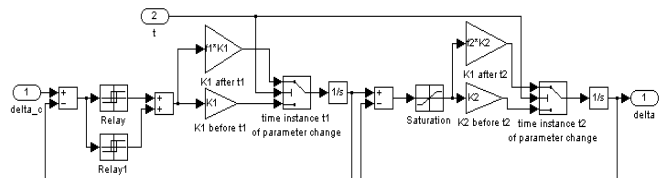


Fig. 7. Simulation of faults in an actuator.

Fig. 8. shows the time response of a steering gear subsystem in the case of consecutive simultaneous changes in parameters K_1 and K_2 for 40% and 70% at $t = 100$ and $t = 200$, respectively.

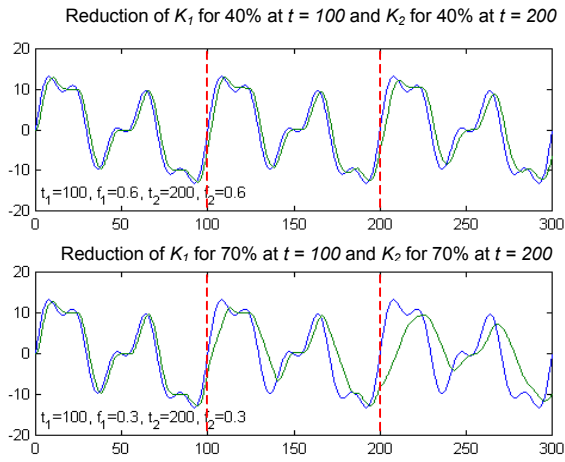


Fig. 8. Simulation of faults in an actuator.

It can be seen that system dynamics change dramatically, but it is still possible to steer the ship with appropriate reconfiguration, in order to reduce the loss of the control performance. In this case reconfiguration is performed by the introduction of an additional signal to compensate for changes in system dynamics.

4. RECONFIGURABLE CONTROL SYSTEM

Reconfiguration is based on a heuristic approach for the design of fault tolerant control. The basic architecture of the system proposed in this paper is similar to the NW system: at first, non-linear identification of the system is performed. After that, the residual signal $d(t)$, defined as a difference between system output $y(t)$ and model output $\hat{y}(t)$, is used to generate a compensation signal $c(t)$ (Fig. 9). A mathematical form of compensator block is obtained using a combination of the heuristic approach and experimentation.

Two forms of compensator have been proposed:

$$c(t) = c(t-1) + k \cdot d(t) \quad (C_1) \quad (1)$$

$$c(t) = c(t-1) + k \cdot \text{sgn}(d(t)) \cdot [d(t) - d(t-1)]^2 \quad (C_2) \quad (2)$$

where the value of constant k can be found experimentally. As yet, there is no analytical proof of stability for the proposed control system.

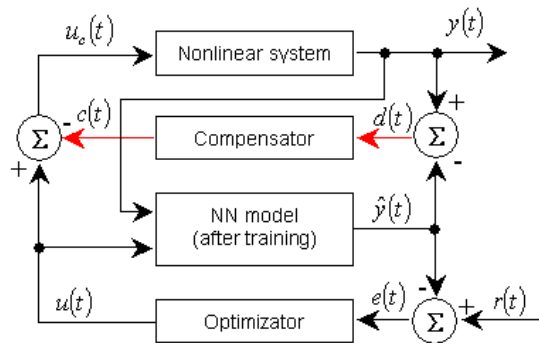


Fig. 9. Noriega-Wang's RCS (NW system).

Fig. 10. shows RCS for ship course-changing in the case of faults in the actuator. RCS consists of two loops: upper (real ship) and lower (reference model). A fuzzy controller FC1 (FC2) produces a command signal for rudder angle in the upper (lower) loop. Both controllers have an identical structure, described in (Omerdic, *et al.*, 2002). Residual d is the difference between the real rudder angle and its estimate (output of ANFIS identifier). The block "Compensator" (realized as C_1 or C_2) produces a signal c , which is added to command signal u . Its purpose is to compensate for a change in actuator dynamics, produced by faults. In the absence of faults, the residual is near zero due to unmodelled noise and identification error. When a fault occurs in the actuator, the residual notably deviates from zero. In order to compare the performance of the basic RCS in the case with and without using compensator, another switch is added to the basic configuration, so it is possible to turn on/off the compensator with a switch "Compensator on/off" and to select the compensator with a switch "Compensator Selector" (see Fig. 11.).

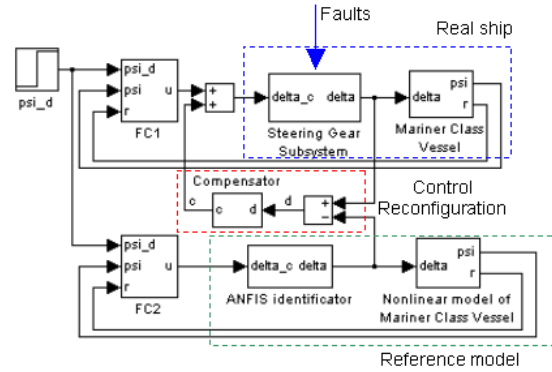


Fig. 10. Basic RCS for course-changing/keeping (tolerant to faults in the actuator).

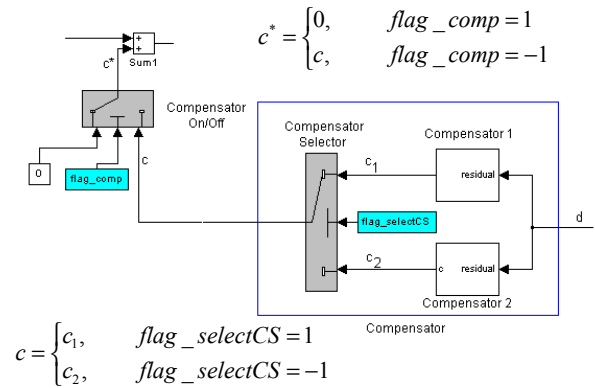


Fig. 11. Switches for compensator selection and turning on/off.

5. SIMULATION RESULTS

In this section performance of the basic RCS is tested for different fault conditions in the actuator. The non-linear model of Mariner Class Vessel, described in (Fossen, 1994), is used for simulation. Fig. 12. displays time response of heading and rudder signals in the case of healthy system without disturbances. It shows the high performance of the proposed fuzzy logic controller in the lack of faults. Heading time

response is without overshoot. Command rudder signal is similar to signal performed by an experienced helmsman. Fig. 13., 14. and 15. show simulation results in the case of faults in actuator (consecutive simultaneous changes in parameters K_1 and K_2 for 70% at $t=20$ and $t=80$, respectively). In particular, Fig. 13 shows the performance without using compensator. Command rudder signal has oscillatory character, because of change in dynamics of the steering gear subsystem. Fig. 14. and 15. display performance when compensator C_1 and C_2 were used. Oscillatory character of command signal is attenuated in both cases. Comparison of compensation signal c^* shows that C_1 is more sensitive than C_2 to change in parameter values.

6. CONCLUSION

This paper described basic reconfigurable control system for ship's course-changing/keeping problem. A heuristic approach was used in the design of fault tolerant control system. An adaptive neuro-fuzzy inference system was applied to non-linear identification of steering gear subsystem (actuator). Simulation results show that the proposed basic RCS is robust to faults in actuator. Command signals, produced by fuzzy autopilot and experienced helmsman, are very similar in all cases. Proposed RCS is used as basic control scheme for building advanced RCS, robust to faults in actuator, gyrocompass and GPS in presence of disturbances (Omerdic, *et al.*, 2002).

REFERENCES

- Blanke, M., M. Staroswiecki and N. E. Wu (2001). Concepts and Methods in Fault-tolerant Control. *Invited tutorial lecture at American Control Conference*, Washington, USA, 22-24 June 2001. 15 p.
- Fossen, T.I. (1994). *Guidance and Control of Ocean Vehicles*, John Wiley&Sons, Chichester.
- Jang, J.-S.R., C.-T. Sun and E. Mizutani (1997). *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice Hall, Upper Saddle River, NJ 07458.
- Noriega, J.R., H. Wang (1998). A Heuristic Approach to Fault Tolerant Control of Unknown Nonlinear System Using Neural Networks. *IFAC Algorithms and Architectures for Real-Time Control*, Cancun, 1998, pp. 229-233.
- Omerdic, E., G. Roberts and Z. Vukic (2002). Advanced Reconfigurable Control System for Ship Course-changing/keeping and Track-keeping. Submitted for presentation at *The 8th Mechatronics Forum International Conference: Mechatronics 2002*, 24-26 June 2002, Enschede, Netherlands
- Vukic, Z., H. Ozbolt and D. Pavlekovic (1999). Improving fault handling in marine vehicle course-keeping systems. *IEEE Robotics & automation magazine*. 6 (1999), 2; pp. 39-53

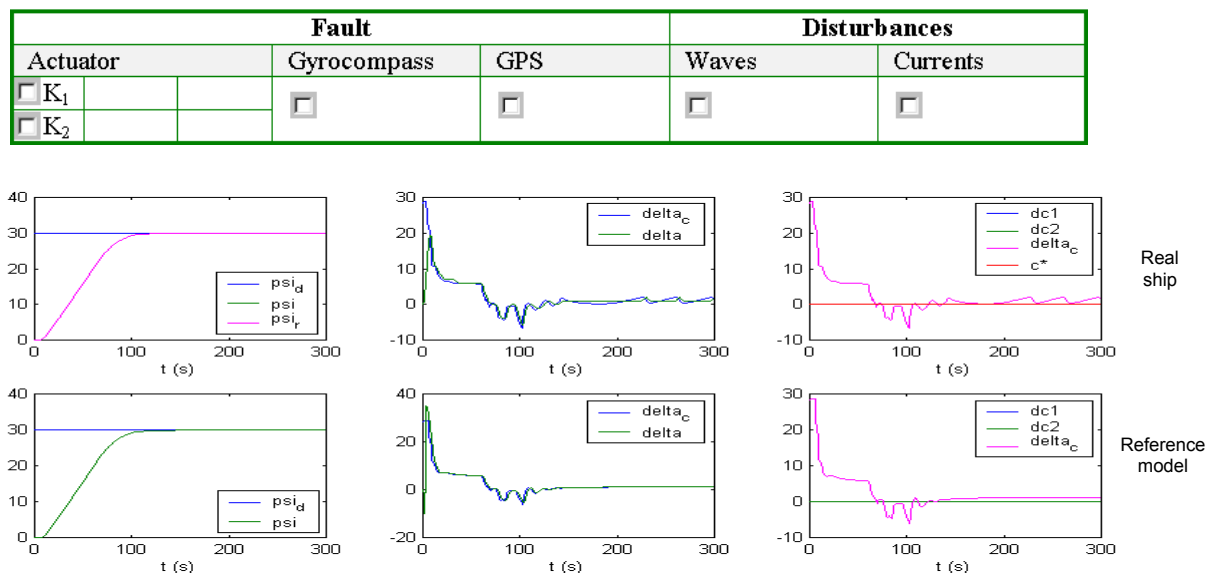


Fig. 12. Simulation A1-1 (Course changing problem, $\Psi_d = 30^\circ$, without compensator).

Fault			Disturbances			
Actuator			Gyrocompass	GPS	Waves	Currents
<input checked="" type="checkbox"/> K_1	$\downarrow 70\%$	$t_1=20$	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<input checked="" type="checkbox"/> K_2	$\downarrow 70\%$	$t_2=80$				

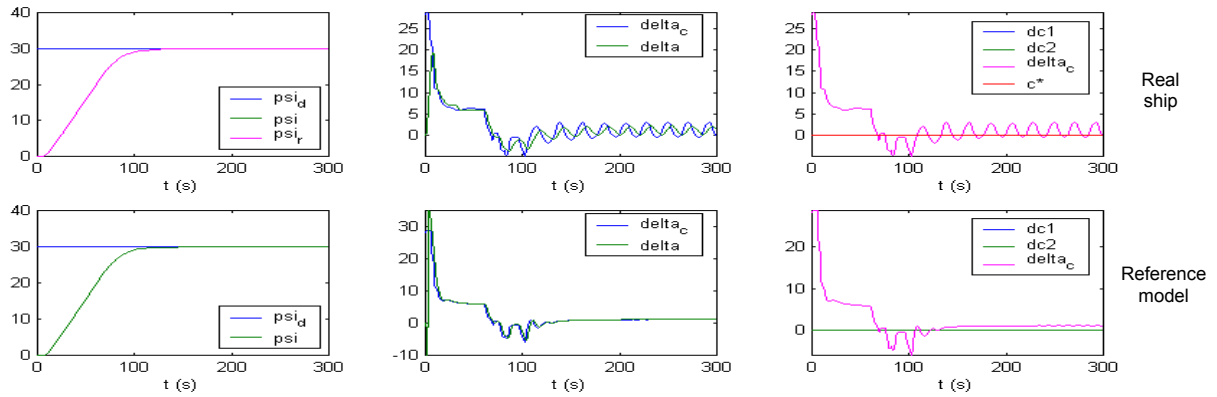


Fig. 13. Simulation B6-1 (Course changing problem, $\Psi_d = 30^\circ$, without compensator).

Fault			Disturbances			
Actuator			Gyrocompass	GPS	Waves	Currents
<input checked="" type="checkbox"/> K_1	$\downarrow 70\%$	$t_1=20$	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<input checked="" type="checkbox"/> K_2	$\downarrow 70\%$	$t_2=80$				

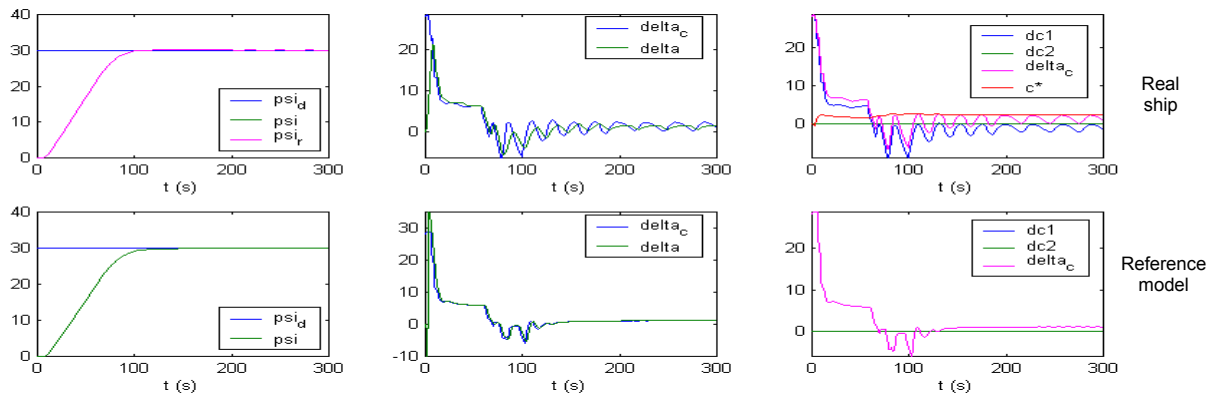


Fig. 14. Simulation B6-2 (Course changing problem, $\Psi_d = 30^\circ$, Compensator 1).

Fault			Disturbances			
Actuator			Gyrocompass	GPS	Waves	Currents
<input checked="" type="checkbox"/> K_1	$\downarrow 70\%$	$t_1=20$	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<input checked="" type="checkbox"/> K_2	$\downarrow 70\%$	$t_2=80$				

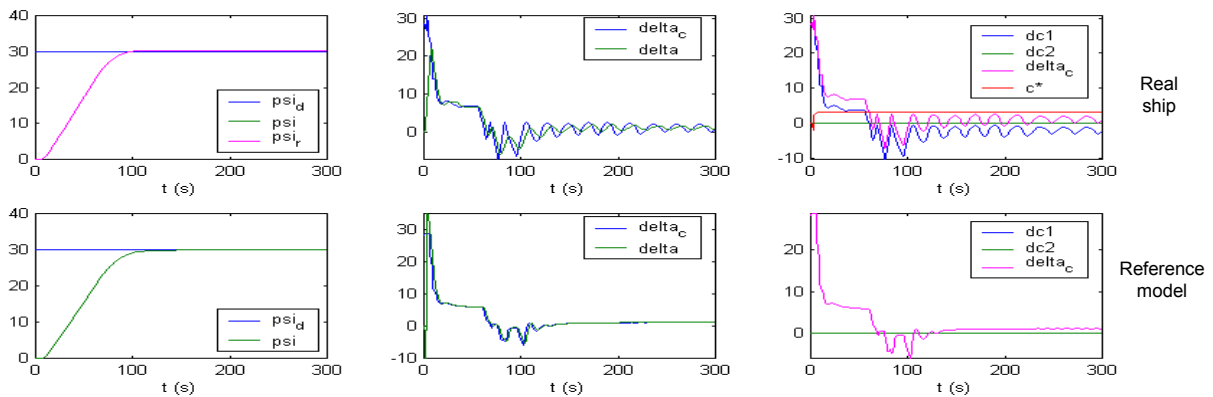


Fig. 15. Simulation B6-3 (Course changing problem, $\Psi_d = 30^\circ$, Compensator 2).