A Novel Methodology for Robust Dynamic Positioning of Marine Vessels: Theory and Experiments*

Vahid Hassani1, Asgeir J. Sørensen2 and António M. Pascoal3

Abstract—The paper proposes a novel robust adaptive solution for Dynamic Positioning (DP) of marine vessels. The proposed Robust Multiple Model Adaptive Dynamic Positioning (RMMADP) structure consists of a bank of robust controllers designed using the Mixed-μ methodology and an identification unit. The latter is composed by a bank of (steady-state) Kalman filters (KFs) that generate online the output estimation errors (residuals) that are used to generate appropriate monitoring signals. At each sampling time, the monitoring signals are assessed to decide which controller should be selected from the bank of the controllers. The proposed adaptive structure of the RMMADP enables the DP system to operate in different operational conditions and hence, it is a step forward to a so-called all-year marine DP system. Numerical simulations, carried out with a high fidelity nonlinear DP simulator, illustrate the efficacy of the RMMADP techniques proposed. To bridge the gap between theory and practice, the results are experimentally verified by model testing a DP operated ship, the Cybership III, under different sea conditions in a towing tank equipped with a hydraulic wave maker.

I. INTRODUCTION

The first generation of DP systems came to existence in the 1960s for offshore drilling applications, due to the need to drill in deep waters and the realization that Jack-up barges and anchoring systems could not be used economically at such depths. The first vessel equipped with a Dynamic Positioning (DP) system was launched in 1961 [1]. The vessel, named Eureka, was property of the Shell Oil Company. Nowadays DP systems are used with a wide range of vessel types and in different marine operations such as hydrographic surveying, marine construction, wreck investigation, underwater recovery, site surveying, underwater cable and pipe laying, and inspection and maintenance. In particular, in the offshore, oil, and gas industries many applications are only possible with the use of DP systems for service vessels, drilling rigs and ships, shuttle tankers, cable and pipe layers, floating production off-loading and storage units (FPSOs), crane and heavy lift vessels, geological survey vessels, and multi-purpose supply and intervention vessels.

Early dynamic positioning systems were implemented using PID controllers. In order to restrain thruster trembling caused by the wave-induced motion components, notch filters in cascade with low pass filters were used with the controllers. An improvement in performance was achieved by exploiting more advanced control techniques based on optimal control and Kalman filter theory, see [2]–[4]. A simpler set-up based on nonlinear passive observers (to replace Kalman filters) were introduced in [5], [6]. Further developments in recent years have led to the use of nonlinear control [7], robust control [8], [9], adaptive control [10] and hybrid control [11] theories in the design of DP systems. The literature on ship DP is vast and defies a simple summary. See for example [12], [13] and the references therein for a short presentation of the subject and its historical evolution.

Most of current DP systems are designed to operate up to a certain limit of weather conditions. However, in practice the sea state may undergo large variations and therefore the controller should adapt to the sea state itself. To meet this challenge, different techniques have been proposed. Among them, supervisory control techniques were exploited in [11] to design a hybrid DP controller. A distinctive feature of the controller developed was the use of spectral techniques to estimate the wave spectrum in surge, sway, and yaw from position and heading measurements. The results were used to identify the sea state, based on which the appropriate controller was selected from a pre-defined bank of controllers. However, this approach is sensitive to measurement noise and may have latency problems because it requires that the samples acquired be buffered to estimate the Power Density Spectrum of the measurement time series.

In this paper, availing ourselves of previous results obtained by the authors in [8], [9], [14], [15], we propose a new type of DP control law that we will henceforth be referred to as a Robust Multiple Model Adaptive Dynamic Positioning (RMMADP) system. A bank of individual robust DP controllers for different sea conditions (calm, moderate, high and extreme) are designed using mixed-μ techniques [16]. In the new structure proposed, a bank of Kalman filters are designed based on a finite number of models of the vessel when it undergoes operations under different sea conditions. Multiple model identification tools are used to identify the sea state and to select the appropriate (locally) robust DP controller from a pre-defined bank of the controllers. The main objective of this paper is to integrate a bank of appropriate robust DP controllers into a state-of-the-art robust adaptive DP architecture yielding good performance.
in varying operational conditions, from calm to extreme seas. The proposed structure extends the so-called weather window operational availability of the DP system without the need for spectral identification techniques (which exhibit latency and are very sensitive to measurement noise).

Numerical simulations, carried out in a high fidelity non-linear DP simulator, illustrate the efficacy of the RMMADP techniques proposed. To bridge the gap between theory and practice, the results are experimentally verified by model testing of a DP operated ship, the Cybership III, under different simulated sea conditions in a towing tank equipped with a hydraulic wave maker.

The structure of the paper is as follows. In section II we present the main issues that arise in the design of the RMMADP. In Section III we present the results of numerical Monte-Carlo simulations with stochastic signals, carried out in the Marine Cybernatics Simulator, that illustrate the performance of developed DP controller in calm to extreme sea conditions. In section IV, a short description of the model-test vessel, Cybership III, and experimental results of model-tests are presented. Conclusions and suggestions for future research are summarized in Section V.

II. THE ROBUST MULTIPLE-MODEL ADAPTIVE DYNAMIC POSITIONING

In what follows, the vessel model that is by now standard is presented. See for example [7], [17], [18]. The model admits the realization

\[
\dot{x}_W = A_W(x_W)\xi_W + E_Ww_W \quad (1) \\
\eta_W = R(\psi_L)C_W\zeta_W \quad (2) \\
b = -T^{-1}b + E_b w_b \quad (3) \\
\hat{\eta}_L = R(\psi_L)\nu \quad (4) \\
M\dot{\nu} + D\nu = \tau + R^T(\psi_{tot})b \quad (5) \\
\eta_{tot} = \eta_L + \eta_W \quad (6) \\
\eta_y = \hat{\eta}_{tot} + \nu, \quad (7)
\]

where (1) and (2) capture the 1st-order wave induced motions in surge, sway, and yaw; equation (3) represents the 1st-order Markov process approximating the unmodelled dynamics and the slowly varying environmental forces (in surge and sway) and torques (in yaw) due to waves (2nd order wave induced loads), wind, and currents. The latter are given in earth fixed coordinates but expressed in body-axis. In the above, \(\eta_W \in \mathbb{R}^3\) is the vessel’s WF motion due to 1st-order wave-induced disturbances, consisting of WF position \((x_W, y_W)\) and WF heading \(\psi_W\) of the vessel; \(w_W \in \mathbb{R}^3\) and \(w_b \in \mathbb{R}^3\) are zero mean Gaussian white noise vectors, and

\[
A_W = \begin{bmatrix}
0_{3 \times 3} & \Omega_{3 \times 3} \\
-\Omega_{3 \times 3} & -A_{3 \times 3}
\end{bmatrix}, \\
E_W = \begin{bmatrix}
I_{3 \times 1} \\
0_{3 \times 1}
\end{bmatrix}, \\
C_W = \begin{bmatrix}
I_{3 \times 3} \\
0_{3 \times 3}
\end{bmatrix},
\]

with

\[
\Omega = \text{diag}\{\omega_0^2, \omega_0^2, \omega_0^2\}, \\
A = \text{diag}\{2\xi_{\text{11}}, 2\xi_{\text{22}}, 2\xi_{\text{33}}\},
\]

where \(\omega_0 = [\omega_{01}, \omega_{02}, \omega_{03}]^T\) and \(\xi_i\) are the Dominant Wave Frequency (DWF) and relative damping ratio, respectively. Matrix \(T = \text{diag}(T_x, T_y, T_v)\) is a diagonal matrix of positive time constants and \(E_r \in \mathbb{R}^{3\times3}\) is a diagonal scaling matrix. Vector \(\eta_L \in \mathbb{R}^3\) consists of low frequency (LF), earth-fixed position \((x_L, y_L)\) and LF heading \(\psi_L\) of the vessel relative to an earth-fixed frame, \(\nu \in \mathbb{R}^3\) represents the velocities decomposed in a vessel-fixed reference, and \(R(\psi_L)\) is the standard orthogonal yaw angle rotation matrix (see [20] for complete details). Equation (5) describes the vessel’s LF motion at low speed (see [20]), where \(M \in \mathbb{R}^{3\times3}\) is the generalized system inertia matrix including zero frequency added mass components, \(D \in \mathbb{R}^{3\times3}\) is the linear damping matrix, and \(\tau \in \mathbb{R}^3\) is a control vector of generalized forces generated by the propulsion system, that is, the main propellers aft of the ship and thrusters which can produce surge and sway forces as well as a yaw moment. Vector \(\eta_{tot} \in \mathbb{R}^3\) describes the vessel’s total motion, consisting of total position \((x_{tot}, y_{tot})\) and total heading \(\psi_{tot}\) of the vessel. Finally, (7) represents the position and heading measurement equation, with \(\nu \in \mathbb{R}^3\) a zero-mean Gaussian white measurement noise.

From (1)-(6), using practical assumptions, a linear model with parametric uncertainty was obtained in [8] as follows:

\[
\dot{\xi}_W = A_W(\omega_0)\xi_W + E_Ww_W \quad (8) \\
\hat{\eta}_L = C_W\xi_W \quad (9) \\
\hat{b}^p = -T^{-1}b^p + \theta_1 S b^p + w_b^f \quad (10) \\
\hat{\eta}_L^f = \theta_1 S \hat{\eta}_L^f + \nu + \theta_2 S \nu \quad (11) \\
M\dot{\nu} + D\nu = \tau + \nu \quad (12) \\
\eta_y^f = \eta_L^f + \eta_y^b + n \quad (13)
\]

where \(\hat{\eta}_L^b\) are WF components of motion on the body-coordinate axis, \(\hat{\eta}_y^b\) and \(\hat{\eta}_L^b\) are a new modified disturbance and a modified measurement defined by \(w_b^f = R^T(\psi_L)E_bw_b\) and \(\eta_L^f = R^T(\psi_L)\eta_{tot} + n\), respectively, \(n \in \mathbb{R}^3\) is the measurement noise, \(\omega_0\), \(\theta_1\), and \(\theta_2\) are parametric uncertainties given in Table II, and the matrix \(S\) is given by

\[
S = \begin{bmatrix}
0 & 1 & 0 \\
-1 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}.
\]

The equations describing the kinematics and the dynamics of the vessel can be represented in the following standard form for multiple-input-multiple-output (MIMO) linear plant models:

\[
\dot{x}(t) = A(\omega_0, \theta_1, \theta_2)x(t) + Bu(t) + Lw(t), \\
y(t) = Cx(t) + v(t),
\]

where \(x(t) = [\xi_w^T \hat{b}^p]^T \hat{\eta}_L^T \hat{\nu}^T]^T \in \mathbb{R}^{15}\) denotes the state of the system, \(u(t) = M^{-1}\tau \in \mathbb{R}^3\) its control input, \(y(t) = \eta_y^f \in \mathbb{R}^3\) its measured noisy output, \(w(t) = \)
An input plant disturbance that cannot be measured, and \(v(t) = n \in \mathbb{R}^3\) is the measurement noise. The equations in (14) are simply a compact way of presenting equations in (8)-(13); \(A(\omega_0, \theta_1, \theta_2), B, L\) and \(C\) are defined in the obvious manner. Vectors \(w(t)\) and \(v(t)\) are zero-mean white Gaussian signals, mutually independent with intensities \(E\{w(t)w^T(\tau)\} = Q\delta(t - \tau)\) and \(E\{v(t)v^T(\tau)\} = R\delta(t - \tau)\). The initial condition \(x(0)\) of (14) is a Gaussian random vector with mean and covariance given by \(E\{x(0)\} = 0\) and \(E\{x(0)x^T(0)\} = \Sigma(0)\), respectively. Matrix \(A(\omega_0, \theta_1, \theta_2)\) contains unknown constant parameters indexed by \(\omega_0, \theta_1, \text{ and } \theta_2\). The parametric uncertainty interval of \(\theta_1\) and \(\theta_2\) is very small\(^1\) and the main parametric uncertainty in the model given by (14) is the DWF, \(\omega_0\). Table I shows the definition of the sea conditions characterized by the DWF. The sea conditions are associated with the particular model of offshore supply vessel that is used in our study. We assume that DWF lies in the interval \([0.48, 0.63, 0.92, 1.18]\) (rad/s). Each selected value represents one of the sea states, calm, moderate, high and extreme. The bank of the Kalman filters is designed based on the selected nominal values for the dominant wave frequency (DWF); see [23] for details on the design of a Kalman filter for DP systems and [24] for details on the selection of the nominal design models. Each steady state KF has the following realization [25]:

\[
\dot{x}_i(t + 1) = A(\omega_0, \theta_1, \theta_2)\dot{x}_i(t) + B(u(t) + H_{\theta_i}(y(t) - \hat{y}_i(t))),
\]

\[
\hat{y}_i(t) = C\hat{x}_i(t),
\]

\[
H_{\theta_i} = A(\omega_0, \theta_1, \theta_2)P_iC^T[CP_iC^T + R]^{-1},
\]

where \(P_i\) is the solution of the discrete Riccati equation

\[
P_i = A(\omega_0, \theta_1, \theta_2)P_iA(\omega_0, \theta_1, \theta_2)^T + LQL^T - A(\omega_0, \theta_1, \theta_2)P_iC^T[CP_iC^T + R]^{-1}CP_iA(\omega_0, \theta_1, \theta_2)^T.
\]

It is assumed that \([A(\omega_0, \theta_1, \theta_2), L]\) and \([A(\omega_0, \theta_1, \theta_2), C]\) are controllable and observable, respectively for all admissible values of \(\omega_0, \theta_1, \text{ and } \theta_2\). The symmetric positive definite matrices \(Q\) and \(R\) were defined before as covariance matrices of the plant disturbance and measurement noise, respectively.

The output estimation errors \((\hat{y}_i(t) - y(t) - \hat{y}_i(t))\) and error covariances of all the Kalman filters \((S_i = CP_iC^T + R)\) are used to compute a performance signal that can be viewed as a gaussian maximum likelihood ratio. This signal is called a “monitoring signal” \(\mu_i(t)\), and is defined as

\[
\mu_i(t) := \frac{1}{t} \sum_{k=1}^t \frac{1}{2} \hat{y}_i(k)^T S_i^{-1} \hat{y}_i(k) + \ln \left((2\pi)^{\frac{1}{2}} \sqrt{S_i}\right).
\]

For more details on definition and concept of the monitoring signals see [14]. The monitoring signals are then used to select one of the local controllers (the one associated with Kalman filter with the smallest monitoring signal).

Fig. 1 shows the architecture of the RMMADP system. The RMMADP, in Fig. 1, consists of: i) the monitoring signal evaluator, ii) a bank of \(N\) KFs, where each local estimator is designed based on one of the representative parameters, and iii) a bank of \(N\) robust DP controllers which are switched in the feedback loop based on the values of monitoring signals. A dwell-time switching policy is used to prevent chattering.

\[\text{TABLE I} \quad \text{DEFINITION OF SEA STATES FROM [21]}\]

<table>
<thead>
<tr>
<th>Sea Status</th>
<th>DWF (rad/s)</th>
<th>Significant Wave Height (H_s) (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calm Seas</td>
<td>&gt; 1.11</td>
<td>&lt; 0.1</td>
</tr>
<tr>
<td>Moderate Seas</td>
<td>[0.74, 1.11]</td>
<td>[0.1, 1.60]</td>
</tr>
<tr>
<td>High Seas</td>
<td>0.53, 0.74</td>
<td>[1.69, 6.0]</td>
</tr>
<tr>
<td>Extreme Seas</td>
<td>&lt; 0.53</td>
<td>&gt; 6.0</td>
</tr>
</tbody>
</table>

\[\text{TABLE II} \quad \text{INTERVAL OF PARAMETRIC UNCERTAINTIES}\]

<table>
<thead>
<tr>
<th>Sea Status</th>
<th>(\omega_0) (rad/s)</th>
<th>(\theta_1) (rad/s(^2))</th>
<th>(\theta_2) (rad/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calm Seas</td>
<td>[1.11, 1.8]</td>
<td>Int*</td>
<td>[-0.038, 0.038]</td>
</tr>
<tr>
<td>Moderate Seas</td>
<td>[0.74, 1.11]</td>
<td>Int</td>
<td>[-0.04, 0.04]</td>
</tr>
<tr>
<td>High Seas</td>
<td>0.53, 0.74</td>
<td>Int</td>
<td>[-0.042, 0.042]</td>
</tr>
<tr>
<td>Extreme Seas</td>
<td>0.39, 0.53</td>
<td>Int</td>
<td>[-0.04, 0.04]</td>
</tr>
</tbody>
</table>

\(*\text{Int}=[-5 \times 10^{-4}, 5 \times 10^{-4}]\)

The validity of [39, 1.8] that covers calm, moderate, high and extreme sea conditions.

In the RMMADP design methodology we divide the parametric uncertainty region into smaller regions and we design robust controllers \(K_i\) for each subregion using the \(\mu\)-synthesis method [16], [22]. Here, we borrow from the work in [8], [9] where four (locally) robust DP controllers, for calm, moderate, high and extreme sea conditions, were designed and their performance evaluated both through numerical simulations (in the Marine Cybernetics Simulator - MCsim), and experimentally, using model test experiments. Moreover, the performance of the designed robust DP controllers for different sea conditions is compared with the ones of LQG and PID controllers in [23] showing the satisfactory performance of robust DP controllers in different sea conditions; in particular, superior performance of robust DP controllers in extreme sea condition is shown in [23].

In a RMMADP system a bank of KFs are used in order to select the correct controllers from the bank of the controllers. Each KF is designed based on a selected value of the unknown parameter, \(\omega_0\). The residuals of all the KFs are analyzed in a block called Monitoring Signal Evaluator (MSE). The MSE assigns a performance index (monitoring signal) to each KF (and the corresponding controller). Then, the monitoring signals \(\mu_i\) (to be defined shortly) are associated with the \(i\)th KF (and \(i\)th controller, i.e. \(K_i\), in the bank of the controllers). These monitoring signals are used to select the best local controller from the bank of robust DP controllers. Four selected values for \(\omega_0\) are chosen as \([0.48, 0.63, 0.92, 1.18]\) (rad/s). Each selected value represents one of the sea states, calm, moderate, high and extreme. The bank of the Kalman filters is designed based on the selected nominal values for the dominant wave frequency (DWF); see [23] for details on the design of a Kalman filter for DP systems and [24] for details on the selection of the nominal design models. Each steady state KF has the following realization [25]:

\[
\mu_i(t) := \frac{1}{t} \sum_{k=1}^t \frac{1}{2} \hat{y}_i(k)^T S_i^{-1} \hat{y}_i(k) + \ln \left((2\pi)^{\frac{1}{2}} \sqrt{S_i}\right). \tag{17}
\]

For more details on definition and concept of the monitoring signals see [14]. The monitoring signals are then used to select one of the local controllers (the one associated with Kalman filter with the smallest monitoring signal).
III. NUMERICAL SIMULATIONS

In what follows we test the performance of our controller using the Marine Cybernetics Simulator (MCSim), later on upgraded to the Marine System Simulator (MSS). The MCSim is a modular multi-disciplinary simulator based on Matlab/Simulink. It was developed at the department of marine technology of the Norwegian University of Science and Technology (NTNU). The MCSim incorporates high fidelity models, denoted as process plant model or simulation model in [18], at all levels (plants and actuators). It captures hydrodynamic effects, generalized coriolis and centripetal forces, nonlinear damping and current forces, and generalized restoring forces. It is composed of different modules such as environmental module, vessel dynamics module, thruster and shaft module, and Vessel control module. For more details on the MCSim see [26], [27].

The results of Monte-Carlo simulations aimed at assessing the performance of the RMMADP controller are presented below. In these simulations, the different environment conditions from calm to extreme seas are simulated using the spectrum of the Joint North Sea Wave Project (JONSWAP).

In this architecture, the identification module (that relies on monitoring signal evaluator) computes the smallest monitoring signal \( \mu_i \); \( i \in \{1, 2, \ldots, N\} \) and switches the controller \( K_i \) associated with that monitoring signal, after which it dwells on that selection for a predefined time, called dwell-time. See [14] for details on dwell-time and how to compute it.

We stress that the performance of any adaptive system must be evaluated not only for constant unknown parameters but also, for time-varying parameters which undergo slow or rapid time-variations. In practice, the sea state may experience large variations and therefore adaptation is necessary in the dynamic positioning. Fig. 3 shows the results of the simulation where the sea state changes in time. In this experiment, during the first 300 seconds the moderate sea state is simulated and for the next 300 seconds the sea state changes to high condition. Fig. 3 represents the time evolution of the switching signal and the position of the vessel. The first sub-figure shows the switching signal in a moderate sea condition. The switching signal in high sea condition is shown in the third sub-figure and finally the switching signal in extreme sea state is depicted in the last (lowest) sub-figure of Fig. 2.

Fig. 3 shows the results of Monte-Carlo simulations aimed at assessing the performance of the RMMADP controller. For time varying case, 2 monitoring signals are computed for each observer. The monitoring signals reset every 40 seconds (with 20 seconds time difference between resetting time of monitoring signals associated to each observer) and at each time only one of these monitoring signals (for each observer) goes to the supervisor. This means that when a monitoring signal, which is fed to supervisor, resets its value, the other monitoring signal whose value was rest 20 seconds ago and by now reached to its steady state value, will be fed to the supervisor.

All the results in the paper are presented in full scale.

Fig. 2. Simulation result: Switching signals in different sea conditions; from top to bottom: calm, moderate, high, and extreme sea condition.

[28]. Throughout the paper, four different environment conditions from calm to extreme seas are considered. Table I shows the definition of the sea condition associated with a particular model of supply vessel that is used in the MCSim. The sampling time of \( T_s = 0.25 \) (sec) is used to implement the RMMADP system throughout the simulation and experimental tests.

Fig. 2 shows the results of a simple simulation\(^4\). In this experiment we examine the performance of the RMMADP system in different sea conditions. The first (upper) sub-figure shows the switching signal in a calm sea condition. The second sub-figure shows the switching signal in a moderate sea condition. The switching signal in high sea condition is shown in the third sub-figure and finally the switching signal in extreme sea state is depicted in the last (lowest) sub-figure of Fig. 2.

\(^3\)In this architecture, the identification module (that relies on monitoring signal evaluator) computes the smallest monitoring signal \( \mu_i \); \( i \in \{1, 2, \ldots, N\} \) and switches the controller \( K_i \) associated with that monitoring signal, after which it dwells on that selection for a predefined time, called dwell-time. See [14] for details on dwell-time and how to compute it.

\(^4\)All the results in the paper are presented in full scale.

\(^5\)For time varying case, 2 monitoring signals are computed for each observer. The monitoring signals reset every 40 seconds (with 20 seconds time difference between resetting time of monitoring signals associated to each observer) and at each time only one of these monitoring signals (for each observer) goes to the supervisor. This means that when a monitoring signal, which is fed to supervisor, resets its value, the other monitoring signal whose value was rest 20 seconds ago and by now reached to its steady state value, will be fed to the supervisor.
A Robust Multiple Model Adaptive Dynamic Positioning (RMMADP) system was described. The RMMADP system can operate in time-varying operational conditions, from calm to extreme seas, thus making it a good candidate for all-year operations. Furthermore, the system dispenses with the need for spectral techniques (which have delay and are very sensitive to measurement noise). The proposed RMMADP design built upon recent developments on robust adaptive techniques using multiple model structure. The

with onshore PC through a WLAN. The PC onboard the ship uses QNX real-time operating system (target PC). The control system is developed on a PC in the control room (host PC) under Simulink/Opal and downloaded to the target PC using automatic C-code generation and wireless Ethernet. The motion capture unit (MCU), installed in the MCLab, provides Earth-fixed position and heading of the vessel. The MCU consists of 3 onshore cameras mounted on the towing carriage and a marker mounted on the vessel. The cameras emit infrared light and receive the light reflected from the marker.

To simulate the different sea conditions, a hydraulic wave maker system is used. It consists of a single flap covering the whole breadth of the basin, and a computer controlled motor, moving the flap. It is able to produce regular and irregular waves with different spectrums. We have used JONSWAP spectral for simulating the different sea conditions for our experiment.

Fig. 5 shows the results of the experiment where the wave maker system simulates different sea state conditions during the time. Since the robust DP controllers are designed for a linearized system, a simple PI controller is used as an initializer to bring the vessel to the desired point (the origin) in the basin. The first (upper) sub-figure shows the wave elevation profile recorded by a probe installed five meters away from the wave maker. The second sub-figure shows the switching signal. As in the case of simulations, the RMMADP system keeps track of the sea state. However, we should stress that we have tuned the RMMADP during a few tests and Fig. 5 shows the final tuned system. We also should highlight that the wave profiles generated by the wave maker for high and extreme seas were very close due to the limited capacity of the wave maker. Therefore, identifying the high and extreme sea conditions proved to be more difficult than identifying the other conditions. The remaining sub-figures in Fig. 5 shows the time evolution of the position and heading of the vessel.

V. CONCLUSIONS AND FUTURE RESEARCH

A tunnel thruster and an azimuth thruster are installed in the bow. It has a mass of $m = 75$ (kg), length of $L = 2.27$ (m) and breadth of $B = 0.4$ (m). Main parameters of the model is presented in Table III. The internal hardware architecture is controlled by an onboard computer which can communicate

Cybership III is equipped with two pods located at the aft. A tunnel thruster and an azimuth thruster are installed in the bow. It has a mass of $m = 75$ (kg), length of $L = 2.27$ (m) and breadth of $B = 0.4$ (m). Main parameters of the model is presented in Table III. The internal hardware architecture is controlled by an onboard computer which can communicate

TABLE III

<table>
<thead>
<tr>
<th>Model main parameters</th>
<th>Model</th>
<th>Full Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Length</td>
<td>2.275 m</td>
<td>68.28 m</td>
</tr>
<tr>
<td>Length between perpendiculars</td>
<td>1.971 m</td>
<td>59.13 m</td>
</tr>
<tr>
<td>Breadth</td>
<td>0.437 m</td>
<td>13.11 m</td>
</tr>
<tr>
<td>Breath at water line</td>
<td>0.437 m</td>
<td>13.11 m</td>
</tr>
<tr>
<td>Draught</td>
<td>0.153 m</td>
<td>4.59 m</td>
</tr>
<tr>
<td>Draught front perpendicular</td>
<td>0.153 m</td>
<td>4.59 m</td>
</tr>
<tr>
<td>Draught aft. perpendicular</td>
<td>0.153 m</td>
<td>4.59 m</td>
</tr>
<tr>
<td>Depth to main deck</td>
<td>0.203 m</td>
<td>6.10 m</td>
</tr>
<tr>
<td>Weight (full)</td>
<td>17.5 kg</td>
<td>Unknown</td>
</tr>
<tr>
<td>Weight (normal load)</td>
<td>7.42 kg</td>
<td>22.62 tons</td>
</tr>
<tr>
<td>Longitudinal center of gravity</td>
<td>100 cm</td>
<td>30 m</td>
</tr>
<tr>
<td>Vertical center of gravity</td>
<td>19.56 cm</td>
<td>5.87 m</td>
</tr>
<tr>
<td>Propulsion motors max shaft power (6% gear loss)</td>
<td>81 W 3200 HP</td>
<td></td>
</tr>
<tr>
<td>Funnel thruster max shaft power (6% gear loss)</td>
<td>27 W 550 HP</td>
<td></td>
</tr>
<tr>
<td>Maximum Speed</td>
<td>Unknown</td>
<td>11 knots</td>
</tr>
</tbody>
</table>

$^6$For technical reasons in this experiment the tunnel thruster was deactivated.
RMMADP consists of a bank of robust controllers designed using Mixed-μ methodology and an identification unit. The identification unit uses a bank of (steady-state) Kalman filters (KF) that generates online appropriate monitoring signals. At each sampling time, the monitoring signals are processed to select which controller should be selected from the bank of controllers. Numerical simulation, carried out with a high fidelity nonlinear DP simulator illustrated the efficacy of the RMMADP techniques proposed. The results were experimentally verified by model testing a DP operated ship, the Cybership III, under different simulated sea conditions in a towing tank with a hydraulic wave maker. The experimental data confirms that the method developed holds promise for practical applications.

ACKNOWLEDGMENT

We thank our colleagues A. Pedro Aguiar, J. Hespanha and Michael Athans for many discussions on adaptive control. We would also like to thank T. Wahl, Øyvind Smogeli, M. Etemaddar, E. Peymani, M. Shapouri, and B. Ommani for their great assistance during the model tests at MCLab.

REFERENCES


Fig. 5. Experimental results: evolution of the wave profile, the switching signal and the position of the vessel in time varying scenario (data is scaled from model to full scale).