# Disturbance Estimation for Unmanned Surface Vehicles using a Nonlinear Disturbance Observer

Emilta Friska Juniar[1] and Tahiyatul Asfihani[2]

***Abstract*—An Unmanned Surface Vehicle (USV) is a maritime transportation system designed to operate autonomously. However, in complex marine environments, the vessel is subjected to external disturbances such as wind, ocean currents, and waves that can affect the stability and robustness of its motion control system. This study aims to estimate these disturbances in real time using a Nonlinear Disturbance Observer (NDO) and to utilize the estimated disturbances to update the predictive model in a Disturbance Compensating–Nonlinear Model Predictive Control (DC-NMPC) framework. The estimation considers two types of disturbances: constant disturbances representing steady wind and current forces, and periodic disturbances representing wave effects modeled as sinusoidal functions. These disturbances affect the sway velocity ($v$) and yaw velocity ($r$) of the vessel. Simulation results show that the NDO is capable of reconstructing the actual disturbances with bounded and consistent estimation errors. This is indicated by RMSE values of 0.0070 for $d_1$ and 0.0605 for $d_2$ under the tested disturbance scenario. The estimation performance remains consistent under variations of the observer gain matrix, indicating observer stability. Increasing the gain improves the estimation response speed but slightly increases the error, revealing a trade-off between responsiveness and estimation accuracy. Furthermore, the observer is able to track time-varying sinusoidal disturbances, demonstrating robustness against dynamic environmental disturbances. These results indicate that NDO-based disturbance estimation can enhance the robustness of USV motion control under environmental disturbances.**

***Index Terms* - Unmanned Surface Vehicle, Maritime, Disturbance Estimation, Nonlinear Disturbance Observer**

## I. INTRODUCTION

An Unmanned Surface Vehicle (USV) is a type of maritime transportation designed to move autonomously towards a specific destination. USVs can operate automatically because they use the Global Positioning System (GPS), allowing the vessel to determine its own direction of movement [1]. With the advancement of technology, USVs have been utilized in various sectors, both military and commercial, such as environmental inspections, geophysical exploration, ocean data collection, and search and rescue operations at sea [2]. However, when operating in the complex marine environment, USVs face challenges such as nonlinearity, model uncertainty, and external disturbances that can impact the stability and robustness of the vessel's motion control system [3].

*This work was not supported by any organization

[1]Emilta Friska Juniar is a student at Department of Mathematics, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia emiltaworkspace@gmail.com

[2]Tahiyatul Asfihani is a lecturer at Department of Mathematics, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia t_asfihani@matematika.its.ac.id

Manuscript received April 7, 2025; accepted April 27, 2026.

External disturbances are an inevitable part of a vessel's dynamic system. One significant disturbance to the vessel's movement is the sea state, which refers to the condition of the sea influenced by wind, waves, and ocean currents. Sea state is used to measure the roughness of the sea in a particular area at a specific time, without considering the effects of swell (wave propagation) from surrounding areas [4]. The behavior of disturbances in USV systems is often unknown and difficult to measure, posing a significant challenge in designing an effective control system for trajectory tracking missions. Various methods have been developed to estimate disturbances in such systems, including disturbance estimators, perturbation observers, Extended State Observers (ESO), Disturbance Observers (DO), and others. Mathematically, disturbance estimation based on the Disturbance Observer (DO) can be integrated with various control approaches. The key advantage of DO-based control systems lies in their ability to estimate disturbances and compensate for their effects without compromising controller performance [5]

The Disturbance Observer (DO) has been widely used in control design to enhance system performance in the presence of external disturbances. Chen et al. [2] developed a Sliding Mode Controller (SMC) based on DO for ship trajectory tracking, while in the following year, [3] integrated DO with a Radial Basis Function Neural Network (RBFNN) to improve model uncertainty estimation and external disturbance rejection. To address nonlinear systems with complex disturbances, Nonlinear Model Predictive Control (NMPC) based on Nonlinear Disturbance Observer (NDO) has been proposed. Yang et al. [6] demonstrated that integrating NDO into NMPC can reduce tracking errors to nearly zero, while Tang et al. [7] introduced an Improved NDO (INDO) based on super-twisting control to enhance disturbance estimation and rejection in NMPC. Simulation results from these studies show that using NDO in control strategies significantly improves system response, tracking accuracy, and control stability.

In addition to marine systems, NDO has also been widely applied in Multi-Input-Multi-Output (MIMO) systems such as quadrotors and robotic manipulators. Subchan et al. [8] applied NDO-NMPC to a quadrotor and demonstrated that NDO can effectively estimate and compensate for disturbances, thereby improving system stability. Similar applications are found in quadrotor UAV trajectory control [9], where NDO is used to estimate external disturbances caused by wind model uncertainties and is incorporated into a nonlinear backstepping controller to stabilize the system. In robotics, Chen et al. [10] showed that NDO can be used to address disturbances such as joint friction and unknown payloads in robotic manipulators.

Numerous studies have shown that integrating a Nonlinear Disturbance Observer (NDO) with advanced control methods can improve disturbance compensation and system stability. In USV systems, disturbance estimation is essential due to nonlinear hydrodynamic behavior, environmental uncertainty, and the difficulty of directly measuring forces caused by waves and ocean currents. The Nonlinear Disturbance Observer (NDO) offers a practical advantage because it can estimate disturbances in real time without requiring a fully accurate system model. By reconstructing unknown external disturbances and model uncertainties as an equivalent disturbance, NDO enables disturbance compensation within the control framework, thereby enhancing robustness and trajectory tracking performance under varying sea conditions.

However, previous studies have largely been limited to theoretical models or small-scale platforms, and the application of NDO-based disturbance estimation to full-scale USV motion models, particularly the SIGMA-class corvette, remains limited. Therefore, this study aims to develop an NDO-based disturbance estimation method for the motion model of a SIGMA-class USV and to compare the estimated disturbances with actual disturbances modeled as constant disturbances and periodic disturbances in sinusoidal form. In addition, this study analyzes the effect of observer gain selection on estimation performance and control robustness.

## II. MATHEMATICAL MODEL OF USV

The mathematical model of unmanned surface vessel (USV) motion used in this study is adopted from the mathematical model of the extended corvette SIGMA (Ship Integrated Geometrical Modularity Approach) which includes both dynamic and kinematic models [11]. The dynamic model is based on the Davidson-Schiff formulation, considering two degrees of freedom (DOF) is sway and yaw motions. This model assumes a constant surge velocity [12]. The state variables in the dynamic model include sway velocity ($v$) and yaw velocity ($r$) with the control input represented by the rudder angle ($\delta$). Meanwhile, the kinematic model describes the vessel's position in the x-axis ($x$), position in the y-axis ($y$), and yaw angle ($\psi$). Therefore, the nonlinear USV system can be defined as follows

$$\begin{aligned}
\dot{v} &= a_{11}v + a_{12}r + b_1\delta \\
\dot{r} &= a_{21}v + a_{22}r + b_2\delta \\
\dot{x} &= u_0\cos\psi - v\sin\psi \\
\dot{y} &= u_0\sin\psi + v\cos\psi \\
\dot{\psi} &= r
\end{aligned} \tag{1}$$

Before applying the NDO methods, the vessel's motion model is discretized using the forward finite difference method. The resulting discretized model is presented as follows:

$$\boldsymbol{\eta}(k+1) = \boldsymbol{F}(\boldsymbol{\eta}(k)) + \boldsymbol{B}\boldsymbol{u}(k) \tag{2}$$

Next, the discretized model in Equation (2) is updated to account for disturbances that affect the sway velocity ($v$) and yaw velocity ($r$). These velocities are part of the vessel's dynamic motion model, influenced by lateral forces and rotational moments caused by external disturbances, such as wind, waves and ocean currents. These disturbances can cause the vessel to deviate from the desired trajectory and alter its heading direction during turns. The discretized vessel motion model, considering the presence of disturbances is presented as follows:

$$\boldsymbol{\eta}(k+1) = \boldsymbol{F}(\boldsymbol{\eta}(k)) + \boldsymbol{B}\boldsymbol{u}(k) + \boldsymbol{B_d}\boldsymbol{d}(k) \tag{3}$$

with $\boldsymbol{\eta}$ is the state vector and $\boldsymbol{F} : \mathbb{R}^5 \to \mathbb{R}^5$ is the nonlinear system matrix for the vessel's motion, which is expressed as follows:

$$\boldsymbol{\eta}(k+1) = \begin{bmatrix} v(k+1) \\ r(k+1) \\ x(k+1) \\ y(k+1) \\ \psi(k+1) \end{bmatrix} \tag{4}$$

$$\boldsymbol{F}(\boldsymbol{\eta}(k)) = \begin{bmatrix} (1+a_{11}\Delta t)v(k) + (a_{12}\Delta t)r(k) \\ (a_{21}\Delta t)v(k) + (1+a_{22}\Delta t)r(k) \\ x(k) + u_0\Delta t\cos\psi(k) - v(k)\Delta t\sin\psi(k) \\ y(k) + u_0\Delta t\sin\psi(k) + v(k)\Delta t\cos\psi(k) \\ \psi(k) + r(k)\Delta t \end{bmatrix} \tag{5}$$

Control input $\boldsymbol{u}$, represented by the rudder angle ($\delta$) and $\boldsymbol{B}$, is the matrix that represents the influence of the control input $\boldsymbol{u}$, on the system's changes, as shown below:

$$\boldsymbol{B} = \begin{bmatrix} b_1\Delta t & 0 \\ 0 & b_2\Delta t \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{6}$$

while $\boldsymbol{d}$ is the vector of external forces or deterministic disturbances affecting the system, and $\boldsymbol{B_d}$ is the matrix that represents the influence of the disturbances $\boldsymbol{d}$ on the vessel's motion dynamics, as shown below:

$$\boldsymbol{d} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}, \ \boldsymbol{B_d} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{7}$$

where $d_1$ represents the disturbance in the sway velocity ($v$) and $d_2$ represents the disturbance in the yaw velocity ($r$).

Meanwhile, the measurement model in discrete form is given as follows:

$$\boldsymbol{\zeta}(k) = \boldsymbol{H}\boldsymbol{\eta}(k) \tag{8}$$

where ($\boldsymbol{\zeta}$) is the output vector that includes the ship's position along the x-axis ($x$), the ship's position along the y-axis ($y$), and the ship's heading angle ($\psi$). Additionally, $\boldsymbol{C}$ is the measurement matrix, given as follows:

$$\boldsymbol{C} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

## III. Nonlinear Disturbance Observer Algorithm

The design of the Nonlinear Disturbance Observer (NDO) aims to estimate unknown disturbances in a nonlinear system. The disturbance estimates will later be used to design the control system. The block diagram of NDO for system (3) is given by Fig.1 [13].

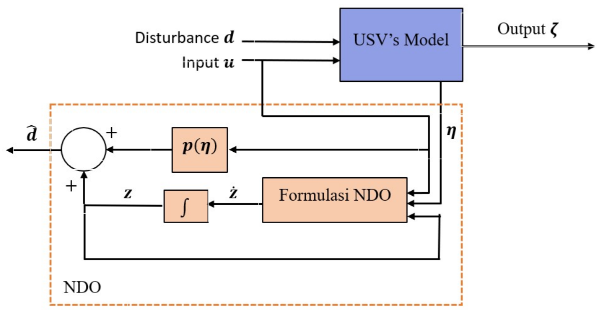


Fig. 1. Block Diagram of The Nonlinear Disturbance Observer

The first step in disturbance estimation using NDO is to select the observer gain matrix $\boldsymbol{l(\eta)}$ as a constant matrix, such that the system $\dot{\boldsymbol{e_d}} = -\boldsymbol{l(\eta)B_d e_d}$ is asymptotically stable. The following observer gain matrix $\boldsymbol{l(\eta)}$ is chosen to be consistent with $\boldsymbol{B_d}$ to represent the influence of disturbances on the sway velocities ($v$) and yaw velocities ($r$), as follows

$$\boldsymbol{l(\eta)} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{9}$$

so

$$\dot{\boldsymbol{e_d}} = -\boldsymbol{l(\eta)B_d e_d} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \boldsymbol{e_d} \tag{10}$$

Let $\boldsymbol{A} = -\boldsymbol{l(\eta)B_d}$, the eigenvalues of matrix $\boldsymbol{A}$ are calculated as follows

$$|\boldsymbol{A} - \lambda \boldsymbol{I}| = 0$$

$$\begin{vmatrix} -1-\lambda & 0 \\ 0 & -1-\lambda \end{vmatrix} = 0$$

$$(-1-\lambda)^2 = 0$$

Thus, the eigenvalues obtained are negative, $\lambda_1 = \lambda_2 = -1$ meaning that system (10) asymptotically stable. This indicates that the disturbance estimation error converges to zero, i.e., $\boldsymbol{e_d} \to 0$ for $t \to \infty$.

Next, the nonlinear system matrix $\boldsymbol{p(\eta)}$ to be designed, is determined by

$$\boldsymbol{l(\eta)} = \frac{\partial \boldsymbol{p(\eta)}}{\partial \boldsymbol{\eta}} \tag{11}$$

By integrating $\boldsymbol{l(\eta)}$ with respect to the variable $(\boldsymbol{\eta})$ based on Equation (11), we obtain

$$\boldsymbol{p(\eta)} = \boldsymbol{l(\eta)\eta} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v \\ r \\ x \\ y \\ \psi \end{bmatrix} = \begin{bmatrix} v \\ r \end{bmatrix} \tag{12}$$

Next, the NDO equation is formulated as follows

$$\dot{\boldsymbol{z}} = -\boldsymbol{l(\eta)B_d z} - \boldsymbol{l(\eta)}[\boldsymbol{B_d p(\eta)} + \boldsymbol{F(\eta)} + \boldsymbol{Bu}] \tag{13}$$

$$\hat{\boldsymbol{d}} = \boldsymbol{z} + \boldsymbol{p(\eta)} \tag{14}$$

By substituting Equations (4) - (9) and (12) into the Equation (13), we obtain

$$\dot{z}_1 = -z_1 - v - a_{11}v - a_{12}r - b_1\delta \tag{15}$$

$$\dot{z}_2 = -z_2 - r - a_{21}v - a_{22}r - b_2\delta \tag{16}$$

Equations (15) and (16) are solved using the Euler method, yielding

$$z_1(k+1) = -z_1(k) - \Delta t\big[v(k) + a_{11}v(k) + a_{12}r(k) + b_1\delta(k)\big] \tag{17}$$

$$z_2(k+1) = -z_2(k) - \Delta t\big[r(k) + a_{21}v(k) + a_{22}r(k) + b_2\delta(k)\big] \tag{18}$$

Next, substituting Equations (17) and (18) into the Equation (14), yielding the disturbance estimation value as follows:

$$\hat{\boldsymbol{d}} = \begin{bmatrix} \hat{d}_1 \\ \hat{d}_2 \end{bmatrix}$$

## IV. Numerical Results

The simulation in this study was conducted for 50 seconds with a sampling time of 0.1 seconds, resulting in $k = 1, 2, ..., 500$ iterations. The initial state variable values are $\boldsymbol{\eta(0)} = [0\ 0\ 0\ 0\ 0]^T$. The ship's hydrodynamic parameters and coefficients used in the simulation are listed in Table I.

The surge velocity is assumed constant at $\boldsymbol{u_0} = 1$ m/s. The control input is the rudder angle $\delta$, which is set to $10^\circ$ to generate the reference trajectory. External disturbances are applied to the sway and yaw dynamics. The constant disturbance magnitude is set to 0.004, while the periodic disturbance is modeled as $\boldsymbol{d} = 0.01\sin(0.1k)$. The NMPC prediction horizon and control horizon are both set to 10. The weighting matrices are selected as $\boldsymbol{Q} = 10^{-3}\boldsymbol{I}$ and $\boldsymbol{R} = 10^{-5}$.

TABLE I
Non-Dimensional Hydrodynamic Parameters and Coefficients

| Parameter dan Coefficient | Value |
|---|---|
| $m'$ | $4.6 \times 10^{-3}$ |
| $x'_G$ | $5.19 \times 10^{-2}$ |
| $I'_z$ | $1.239 \times 10^{-4}$ |
| $Y'_v$ | $-8.4 \times 10^{-3}$ |
| $Y'_r$ | $2.1 \times 10^{-3}$ |
| $N'_v$ | $-2.5 \times 10^{-3}$ |
| $N'_r$ | $-1.3 \times 10^{-3}$ |
| $Y'_{\dot{v}}$ | $-5.5 \times 10^{-3}$ |
| $Y'_{\dot{r}}$ | $-1.9182 \times 10^{-4}$ |
| $N'_{\dot{v}}$ | $1.1643 \times 10^{-5}$ |
| $N'_{\dot{r}}$ | $-3.3443 \times 10^{-4}$ |
| $Y'_\delta$ | $12.3068$ |
| $N'_\delta$ | $-6.1534$ |

The actual disturbance (reference) refers to the disturbance added to the system to evaluate whether the system or observer can accurately estimate it. The simulation considers two types of disturbances are constant and periodic disturbances. The constant disturbance represents the thrust force exerted by wind and ocean currents in a specific direction. Meanwhile, the periodic disturbance represents the effect of ocean waves in the form of a sinusoidal function. These disturbances affect the system's sway ($v$) and yaw velocities ($r$).

The constant disturbance is assumed to be the thrust force from wind and ocean currents with a magnitude of $d = 0.004$. The estimation of this disturbance is performed by selecting a varying observer gain matrix $\boldsymbol{l}(\boldsymbol{\eta})$ to analyze its effect, as shown below:

$$\boldsymbol{l_1}(\boldsymbol{\eta}) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$\boldsymbol{l_2}(\boldsymbol{\eta}) = \begin{bmatrix} 5 & 0 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 & 0 \end{bmatrix}$$

$$\boldsymbol{l_3}(\boldsymbol{\eta}) = \begin{bmatrix} 15 & 0 & 0 & 0 & 0 \\ 0 & 15 & 0 & 0 & 0 \end{bmatrix}$$

The results of estimating the constant disturbance using different observer gain matrices are shown in Fig. 3 - Fig. 7. The graphs indicate that the estimated disturbance is very close to the actual disturbance, as seen from the low RMSE value. This means the observer is working well in estimating the disturbance. However, there is a small difference at the 100th iteration, likely caused by changes in the selected gain matrix $\boldsymbol{l}(\boldsymbol{\eta})$. The results also show that when the gain value increases, the RMSE tends to increase as well. This suggests that while a higher gain makes the observer respond faster, it can also reduce accuracy by making the estimation more sensitive to noise or causing oscillations. Therefore, choosing the right gain value is important to maintain both accuracy and stability in the estimation process.

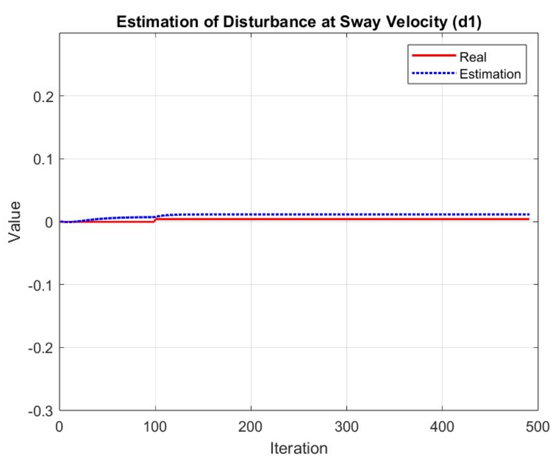


Fig. 2. Estimation of Constant Disturbance $d_1$ with Gain Matrix $\boldsymbol{l}_1(\boldsymbol{\eta})$

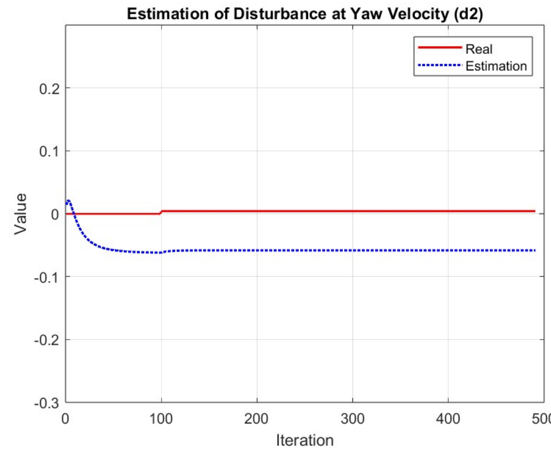


Fig. 3. Estimation of Constant Disturbance $d_2$ with Gain Matrix $\boldsymbol{l}_1(\boldsymbol{\eta})$

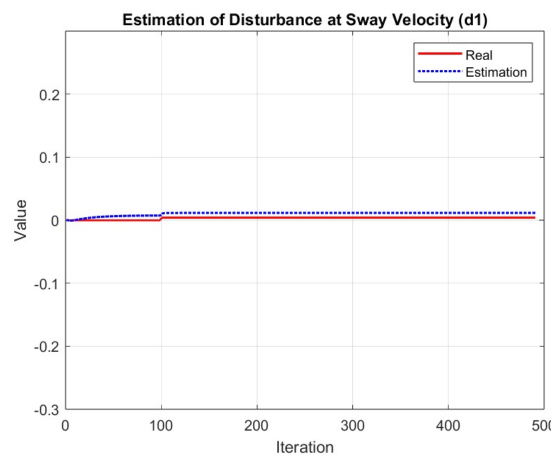


Fig. 4. Estimation of Constant Disturbance $d_1$ with Gain Matrix $\boldsymbol{l}_2(\boldsymbol{\eta})$

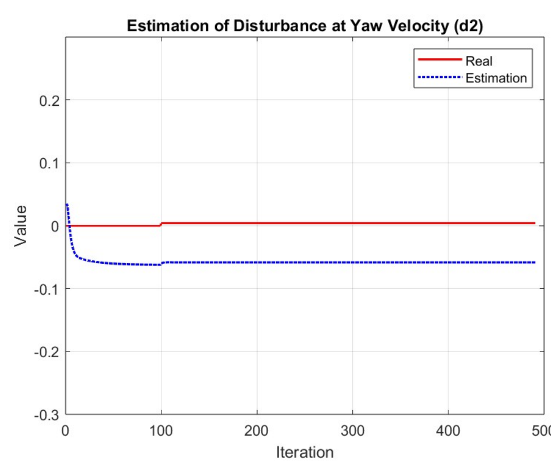


Fig. 5. Estimation of Constant Disturbance $d_2$ with Gain Matrix $\boldsymbol{l}_2(\boldsymbol{\eta})$

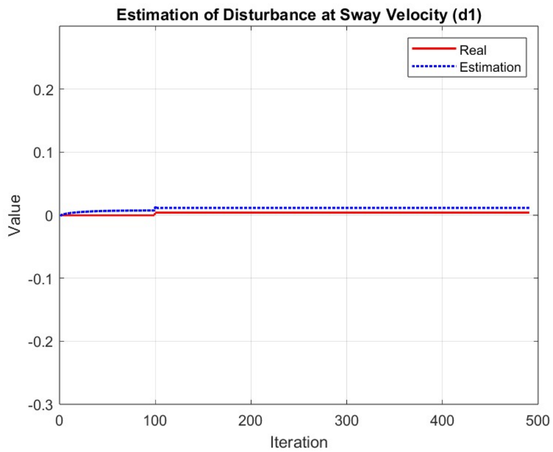


Fig. 6. Estimation of Constant Disturbance $d_1$ with Gain Matrix $\boldsymbol{l}_3(\boldsymbol{\eta})$

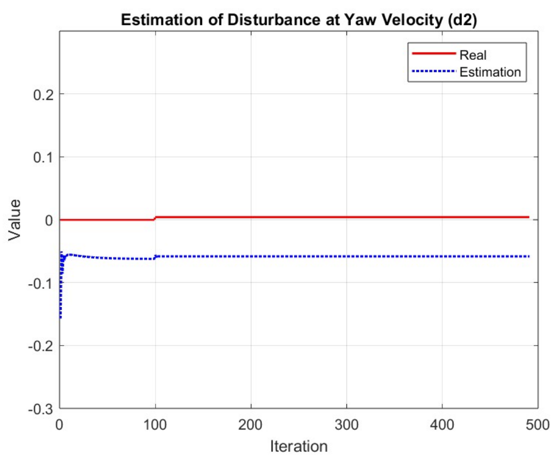


Fig. 7. Estimation of Constant Disturbance $d_2$ with Gain Matrix $\boldsymbol{l}_3(\boldsymbol{\eta})$

Therefore, selecting an appropriate gain is crucial to achieving accurate disturbance estimation. The RMSE values for the constant disturbance estimation with varying gain matrices are provided in Table II.

TABLE II
RMSE OF CONSTANT DISTURBANCE ESTIMATION

| Gain Matrix | RMSE $d_1$ | RMSE $d_2$ |
|---|---|---|
| $\boldsymbol{l_1}(\boldsymbol{\eta})$ | 0.0070 | 0.0605 |
| $\boldsymbol{l_2}(\boldsymbol{\eta})$ | 0.0072 | 0.0614 |
| $\boldsymbol{l_3}(\boldsymbol{\eta})$ | 0.0073 | 0.0624 |

Disturbance estimation performance is evaluated using the Root Mean Square Error (RMSE), which quantifies the average estimation error over the simulation period. The RMSE values indicate that the estimation error remains bounded and consistent under the tested disturbance conditions. The influence of observer gain is further analyzed through the eigenvalues of the disturbance estimation error dynamics. Larger observer gains shift the eigenvalues further into the stable region, resulting in faster convergence of the estimation error. However, excessively large gains increase sensitivity to noise and may lead to larger RMSE values. This behavior explains the observed trade-off between estimation speed and accuracy.

Additional simulations were conducted with increased disturbance magnitude to evaluate the robustness of the NDO. The results show that the estimation RMSE remains small, indicating that the NDO can still accurately estimate the disturbance. However, the vessel trajectory becomes significantly degraded under larger disturbances. This indicates that accurate disturbance estimation alone is insufficient to maintain trajectory tracking when disturbance magnitude exceeds the compensation capability of the controller.

Next, the periodic disturbance is assumed to represent the effect of ocean waves in the form of a sinusoidal function, given by $d = 0.01\sin(0.1k)$. The observer gain matrix used is the same as in the constant disturbance estimation, namely $\boldsymbol{l_1}(\boldsymbol{\eta})$. The estimation results for the periodic disturbance are presented in Fig. 8 and Fig, 9 .

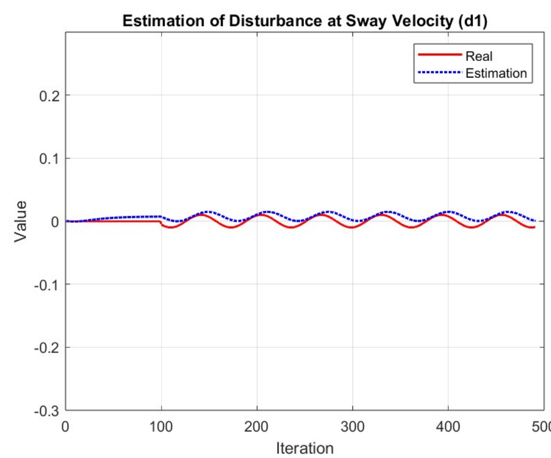


Fig. 8. Estimation of Periodic Disturbance at Sway Velocity ($d_1$)

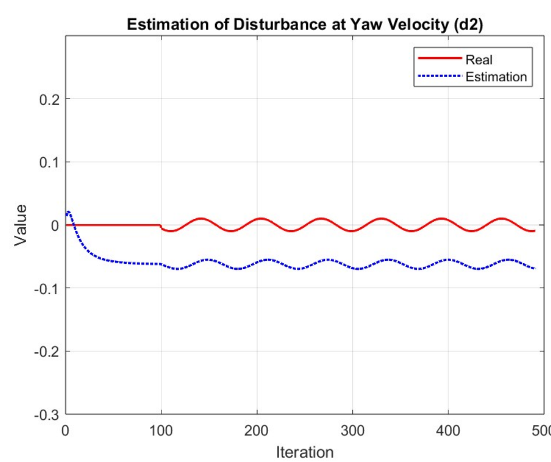


Fig. 9. Estimation of Periodic Disturbance at Yaw Velocity ($d_2$)

The graph shows that the periodic disturbance estimates are close to the actual disturbances, with low RMSE values. The RMSE of the periodic disturbance estimates at sway speed is 0.0083 and the RMSE of the periodic disturbance estimates at yaw speed is 0.0605.

## V. CONCLUSIONS

This study aimed to develop and evaluate a Nonlinear Disturbance Observer (NDO) for real-time disturbance estimation in the motion control of an unmanned surface vehicle. Simulation results under constant and periodic disturbances demonstrate that the NDO provides bounded and consistent disturbance estimation performance, as indicated by low RMSE values. The selection of observer gain significantly influences estimation behavior, where higher gains accelerate convergence but may increase estimation error, indicating a trade-off between speed and accuracy. Robustness analysis with increased disturbance magnitude shows that although the estimation error remains bounded, trajectory tracking performance degrades when disturbances exceed the controller's compensation capability.

Future work will focus on experimental validation, evaluation under larger and more realistic sea-state disturbances, and comparison with alternative disturbance estimation methods to further assess the advantages of the proposed approach.

## REFERENCES

[1] Fauzi, R., Jaya, I., & Iqbal, M. (2021, December). Unmanned Surface Vehicle (USV) performance test in Bintan Island Waters. In IOP Conference Series: Earth and Environmental Science (Vol. 944, No. 1, p. 012013). IOP Publishing.

[2] Chen, Z., Zhang, Y., Zhang, Y., Nie, Y., Tang, J., & Zhu, S. (2019). Disturbance-observer-based sliding mode control design for nonlinear unmanned surface vessel with uncertainties. Ieee Access, 7, 148522-148530.

[3] Chen, Z., Zhang, Y., Nie, Y., Tang, J., & Zhu, S. (2020). Adaptive sliding mode control design for nonlinear unmanned surface vessel using RBFNN and disturbance-observer. Ieee Access, 8, 45457-45467.

[4] BMKG Maritim. (2024). Keadaan laut. Retrieved from https://maritim.bmkg.go.id/glossaries/3/Keadaan-Laut [Accessed: 3-Sep-2024]

[5] Kaldmäe, A., & Kotta, Ü. (2020). A brief tutorial overview of disturbance observers for nonlinear systems: application to flatness-based control. Proceedings of the Estonian Academy of Sciences, 69(1), 57-73.

[6] Yang, H., Deng, F., He, Y., Jiao, D., & Han, Z. (2020). Robust nonlinear model predictive control for reference tracking of dynamic positioning ships based on nonlinear disturbance observer. Ocean Engineering, 215, 107885.

[7] Tang, L., Wang, L., Wang, Y., & Zhang, Y. (2022). An enhanced trajectory tracking control of the dynamic positioning ship based on nonlinear model predictive control and disturbance observer. Ocean Engineering, 265, 112482.

[8] Subchan, S., Amalia, L. R., Asfihani, T., & Purnawan, H. (2023, September). Reference Tracking of Quadrotor Using Modified Nonlinear Model Predictive Control Based on Nonlinear Disturbance Observer. In International Conference on Mathematics: Pure, Applied and Computation (pp. 87-104). Singapore: Springer Nature Singapore.

[9] Chen, F., Lei, W., Zhang, K., Tao, G., & Jiang, B. (2016). A novel nonlinear resilient control for a quadrotor UAV via backstepping control and nonlinear disturbance observer. Nonlinear Dynamics, 85, 1281-1295.

[10] Mohammadi, A., Tavakoli, M., Marquez, H. J., & Hashemzadeh, F. (2013). Nonlinear disturbance observer design for robotic manipulators. Control Engineering Practice, 21(3), 253-267.

[11] Asfihani, T., Adzkiya, D., Rosyid, D. M., Purnawan, H., & Kamilah, R. (2017, August). Estimation of the corvette SIGMA motion in missile firing mission. In 2017 5th International Conference on Instrumentation, Control, and Automation (ICA) (pp. 203-207). IEEE.

[12] Davidson, K. S., & Schiff, L. I. (1946). Turning and course keeping qualities. Stevens Institute of Technology, Experimental Towing Tank, Hoboken, New Yersey, Presented at the Society of Naval Architects and Marine Engineers, SNAME Transactions.

[13] Li, Shihua, Jun Yang, Wen-Hua Chen, and Xisong Chen. Disturbance observer-based control: methods and applications. CRC press, 2014.

[14] Clarke, D., Gedling, P., & Hing, G. (1983). The application of manoeuvering criteria in hull design using linear theory.