Journal of Engineering Science and Technology
Vol. 15, No. 2 (2020) 1455 - 1465

APPLICATION OF KALMAN FILTER TO THE UNCERTAINTY OF MODEL RESISTANCE DATA OBTAINED FROM EXPERIMENT

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Abstract

Standard deviation is the correct way to characterise the spread of the data and as the uncertainty associated with measurement the value of the standard deviation may be refined. The aim is to quantify the level of uncertainty in the resistance data of a model tanker obtained from towing tank tests. Kalman Filter (KF) was used to correct the standard deviation of the data, which is composed of the state-space model and least-squares method. Results of the simulations showed that KF could decrease the standard deviation of the resistance for a range of speeds (1,029-1.543 m/s). The standard deviation of filtered data is much smaller (1.3%-4.2%) than that of unfiltered data (14.7%-28.4%). The proposed filter method can therefore reduce the uncertainty of the model experiment.

Keywords: Kalman filter, Least-squares, Resistance, State-space, Uncertainty.

1. Introduction

Random errors arise from uncontrollable factors that simultaneously affect an experiment. There are assorted resources of error or noise which induce random uncertainty in resistance experiments in towing tanks. Noise in the carriage velocity is the main source of random error in resistance of a ship model [1]. The resistance data is a realisation of a stationary random process. The mean value and the standard deviation of stationary data are constant. As in most experiments, the mean value of a measured signal used for further analysis. It is essential to identify the magnitude of uncertainty.

Various attempts of uncertainty analysis have been made to find an appropriate estimator for random uncertainty of the resistance ship model. Dang et al. [2] presented preliminary of the autocovariance method that has been used to designate as variance analysis on stationary measurements to compare the quality of quasi-steady measurement methods. Brouwer et al. [3] proposed a new technique called the 'Transient Scanning Technique" to verify the stationarity of a signal and uncertainty analysis of finite length measurement time series. Steen et al. [1] quantifying the uncertainty by proposing a method Multiple Time Windows (MTW) technique. A comparison of simulated and measured towing force allowed us to conclude that the noise in the carriage speed is the main contributor to the noise in the resistance data. Brouwer et al. [4] presented a new power spectrum-based method was developed to define the contribution of spectral to the uncertainty of the resistance data.

Measurements of resistance ship model obtained from the physical system. The Kalman filter, a linear recursive filter generates an optimal estimate of the state of a dynamic system from noisy data set collected at a discrete-time interval [5]. The system noise is assumed to be uncorrelated between signals and has a zero-mean Gaussian distribution. The Kalman filter requires two system models: the dynamic model and the observation/measurement model. The system being model is described by a set of state-space equations. The state of a system is defined by state variables. Kalman filter used in the experiment of ship model. Liggins et al [6] proposed tracking the motion of the model ship is achieved with a predictive extended Kalman filter. The EKF is used because it can readily integrate and filter multiple noisy data sets, as well as generate an optimal estimate of relative pose (position and orientation) of the ship model.

Shi et al [7] established a nonlinear model of ship maneuvering originate on the Extended Kalman Filter algorithm to account the parameters of turning circle tests and Zig-zag tests. The errors found in the measurement process are eliminated. Comparisons have been made to the simulated and measured data. The results show that the ship maneuvering model can represent the real motion of ship, and the parameter estimation procedure and algorithms are efficient. Radhakrishnan [8] presented a Kalman filter for estimating the sway velocity and the effects of its cross-coupling between roll and yaw. The roll reduced without sway velocity feedback for the ship speed up to 13 m/sec. if the sway velocity used for rudder control, the high-frequency does not seriously affect the heading.

The objective of this paper is to propose a Kalman filter to eliminate the standard deviation of resistance data. The difference has been made to the simulated and experimental data. The outcomes show that parameter estimation and algorithms are practical.

2. Method

The resistance (or drag) is the horizontal component of the force opposing the steady forward motion of the model hull through the water. The resistance is determined by measuring the towing force. Data were acquired on 1unit PSC 8115 Strain Gauges and 2 units PSC 8025 DSP, controlled by NI PCI DAQ Card 6024E desktop computer. Two data channels were scanned and sampled, namely carriage speed and resistance dynamometer TF-R56. The data used as an example are as shown in Fig.1.

The measurement of resistance at a range of speed (1.029-1.534m/s) obtained by averaging the time history of the signal from the DAS in an interval of time. $\Delta t = N/fs$, data acquisition made through the collection of N=1.500 samples, Δt is over 30 seconds, fs = 50 Hz, and data are not filtered. All data is assumed to be stationary. An average of the signal resistance and the standard deviation of a range speed are defined for time series, as shown in Table 1. Tests were conducted at the Indonesian Hydrodynamics Laboratory towing tank. The tank is 234.5 m long (including the loading dock) and 11 m wide and water depth 5.5 m.

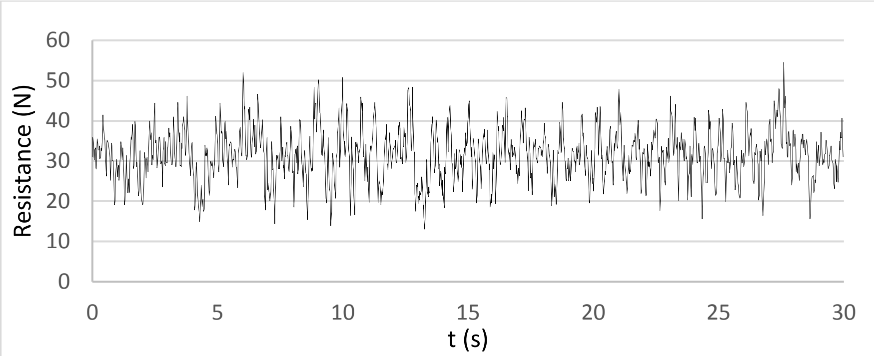


Fig. 1. Time series of resistance.

Table 1. The measurement of resistance at range of speed.

V_m (m/s)	R (N)	s(N)
1.029	18.913	5.353
1.132	22.461	5.730
1.235	27.533	6.061
1.338	31.637	6.331
1.440	37.856	6.151
1.543	46.412	6.827

The total resistance at each speed is obtained by averaging the time history can be written as [9]:

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i \quad (1)$$

The standard deviation of time history for single measurement can be obtained [9-10]:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_i - R)^2} \quad (2)$$

The standard uncertainty of any single resistance tests can be estimated by standard deviations [9]:

$$u(R) \approx s \tag{3}$$

The process of filtering is to process out the noise in the measurement values and give an optimal estimate for the state. Consider the Autoregressive (AR) model. The AR (2) in state-space form is as follows**:**

$$y[k] = \phi_0 + \phi_1 y[k-1] + \phi_2 y[k-2] \tag{4}$$

$$y[k] = \phi_0 + \phi_1 x_1[k] + \phi_2 x_2[k]$$
$$x_1[k] = y[k-1] \tag{5}$$
$$x_2[k] = y[k-2]$$

The parameters of the AR (2) model are estimated using the least square method [11-13], allowing to decompose a time series into relevant components and to infer the best historical estimates.

$$\mathbf{y} = \mathbf{X\Phi} \tag{6}$$

$$\boldsymbol{y} = \begin{bmatrix} y[1] \\ y[1] \\ \vdots \\ y[n] \end{bmatrix} \quad \boldsymbol{X} = \begin{bmatrix} 1 & x_1[1] & x_2[1] \\ 1 & x_1[2] & x_2[2] \\ \vdots & \vdots & \vdots \\ 1 & x_1[n] & x_2[1n] \end{bmatrix} \boldsymbol{\Phi} = \begin{bmatrix} \boldsymbol{\Phi_0} \\ \boldsymbol{\Phi_1} \\ \boldsymbol{\Phi_2} \end{bmatrix} \tag{7}$$

$$\widehat{\boldsymbol{\Phi}} = (\mathbf{X^T X})^{-1} \mathbf{X^T} \boldsymbol{y} \tag{8}$$

Equation (4) can be discretized and transformed into the following discrete linear state function

$$x[k] = \boldsymbol{A} x[k-1] + \boldsymbol{F} \tag{9}$$

$$\begin{bmatrix} y[k] \\ y[k-1] \end{bmatrix} = \begin{bmatrix} \phi_1 \phi_2 & \\ 1 & 2 \end{bmatrix} \begin{bmatrix} y[k-1] \\ y[k-2] \end{bmatrix} + \begin{bmatrix} \phi_0 \\ 0 \end{bmatrix} \tag{10}$$

$$z[k] = \boldsymbol{H} x[k] + \epsilon[k-1] \tag{11}$$

$$z[k] = [1 \quad 0] \begin{bmatrix} y[k] \\ y[k-1] \end{bmatrix} + \epsilon[k-1] \tag{12}$$

By Eq. (9), the following KF recursive equations:

Time update:

Prediction on the state

$$\hat{x}_k^- = A z_{k-1} + \boldsymbol{F} \tag{13}$$

Prediction error covariance

$$P_k^- = A \boldsymbol{H}_{k-1} A^T + \boldsymbol{Q} \tag{14}$$

Measurement update:

Calculate Kalman gain

$$K_k = P_k^- H^T (H P_k^- H^T + \boldsymbol{R})^{-1} \tag{15}$$

Update estimation measurement

$$\hat{x}_k = \hat{x}_k^- + K(z_k - H\hat{x}_k^-) \tag{16}$$

Update error covariance

$$P_k = (1 - K_k H) P_k^- \quad (17)$$

The treatment is assumed that these are uncorrelated Gaussian stationary white noise with zero means. Process noise *Q* and measurement noise *R* are an important parameter. *Q* and *R* decides the estimation closeness to the true value. The study of the various values of *Q* and *R* effects on the mean value of resistance and standard deviations was carried out by changing *Q* with a fixed *R*, and vice versa. It will have consequences on the Kalman gain regarding the result of the Kalman filter.

3. Results and Discussion

The value of the parameter ϕ estimated using the previously described technique are as follows:

$$\Phi = \begin{bmatrix} \phi_0 \\ \phi_1 \\ \phi_2 \end{bmatrix} = \begin{bmatrix} 1.0429 \\ -0.0121 \\ 0.0065 \end{bmatrix}$$

Substituting ϕ into Eq. (4) gives:

$$y[k] = 1.0429 - 0.0121 y[k-1] + 0.0065 y[k-2]$$

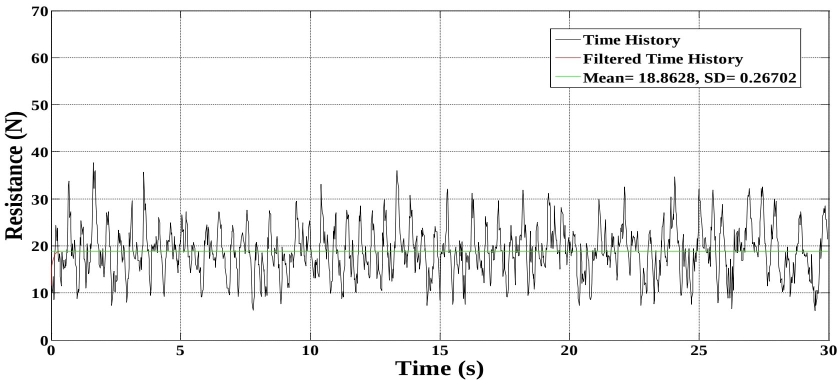
The matrices system used to calculate the steady state Kalman Filter are as follows:

$$A = \begin{bmatrix} -0.0121 & 0.0065 \\ 1 & 0 \end{bmatrix} \quad F = \begin{bmatrix} 1.0429 \\ 1 \end{bmatrix} \quad H = [1 \quad 0]$$

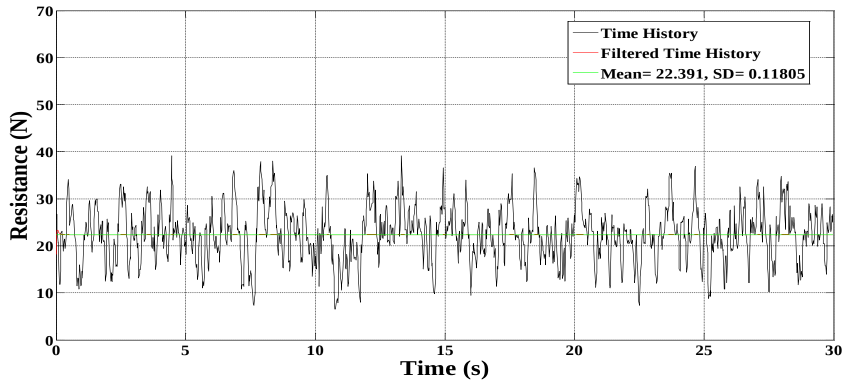
$$\hat{x}_{k-1}^- = \begin{bmatrix} 0 \\ 0 \end{bmatrix} P_{k-1}^- = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.0001 & 0 \\ 0 & 0.0001 \end{bmatrix} \quad R = 0.01$$

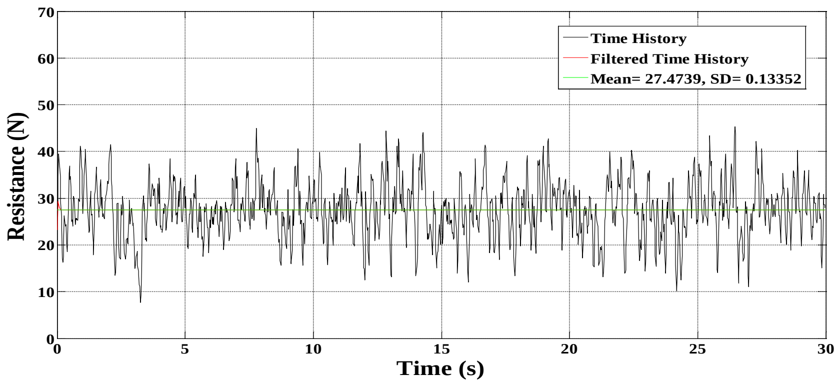
Figures 2(a)-(f) show the results of the simulation of the steady-state KF in MATLAB. The plots show the mean and standard deviation value of the model ship tanker resistance at the speed range (1.029-1.543 m/s). The graph shows that KF can produce an almost noise-free estimate, and the two algorithms work well for estimating the parameters and states of this state-space system.



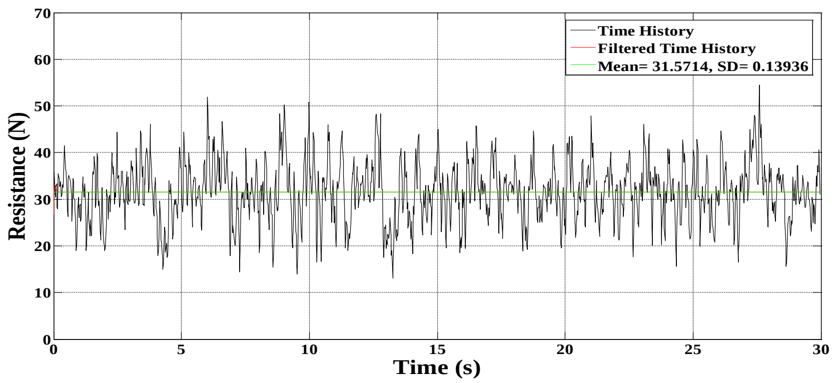
(a). Resistance at 1.029 m/s.



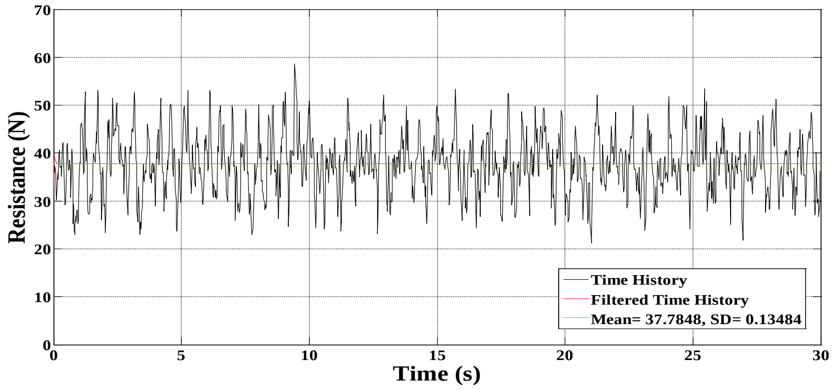
(b). Resistance at 1.132 m/s.



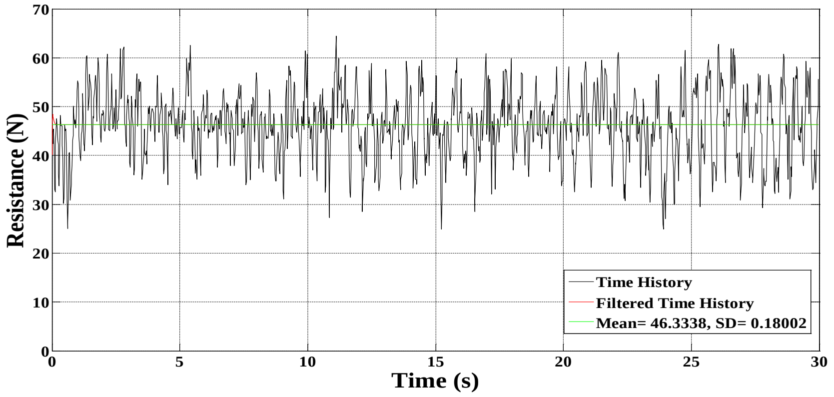
(c). Resistance at 1.235 m/s.



(d). Resistance at 1.338 m/s.



(e). Resistance at 1.440 m/s.



(f). Resistance at 1.543 m/s.

Fig. 2. The simulation of KF in MATLAB.

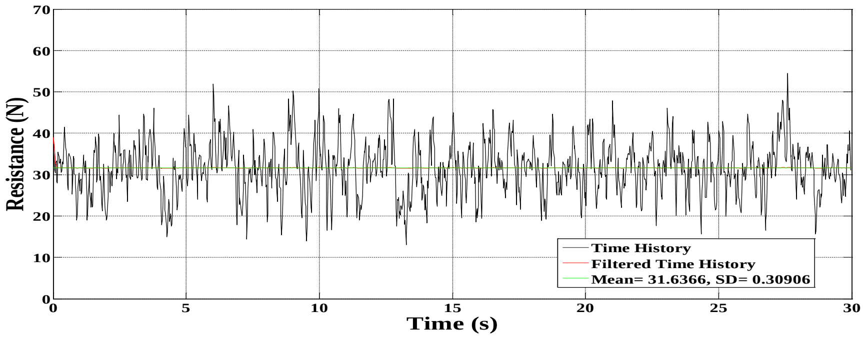
The performance of the Kalman filter is shown in Fig. 2. The results show that significant improvement to the predictions can be achieved with a decrease in the fluctuation of time series. The fit to data is plotted versus before filtered. The mean value is stable and the standard deviation is minimised. This implies all the information from the data has been extracted and what remains is pure random 'white' noise. This can happen only when the model and the measurement structures are proper, the parameters in them have been obtained after the numerical optimisation algorithm has converged properly.

Table 2 presents the performance of the Kalman filter based on the AR parameter estimates and the least square method. The standard deviation of a filtered time history is about 1.3%-4.1%**.** The results show that significant improvement to the predictions can be achieved. In the full range of the speed, the corresponding the standard deviation is close to zero suggesting that the main goal of a Kalman-type filter is fulfilled.

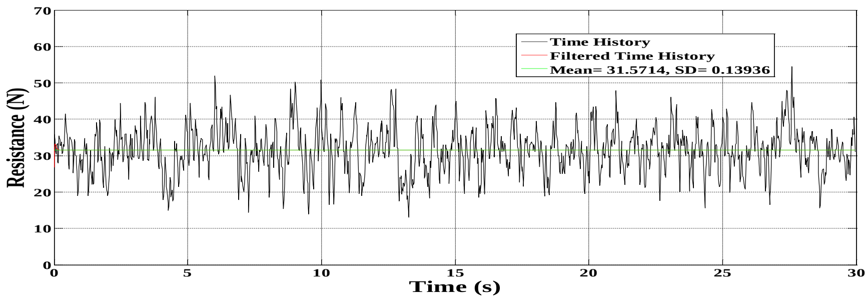
Table 2. Resistance data tanker 17.500 DWT after filtered.

V_m (m/s)	R (N)	s (N)
1.029	18.913	0.140
1.132	22.461	0.287
1.235	27.533	0.239
1.338	31.637	0.309
1.440	37.856	0.388
1.543	46.412	0.384

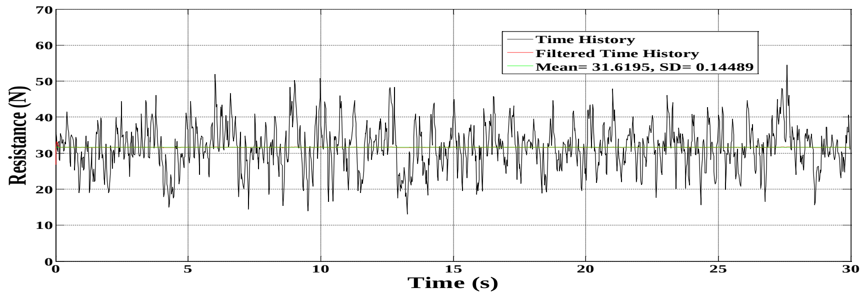
The identification of the estimates of the noise covariance matrices for resistance data at speed 1.338 m/s as shown in Fig. 3. The complete optimal estimation of the sample means value and standard deviation of resistance data.



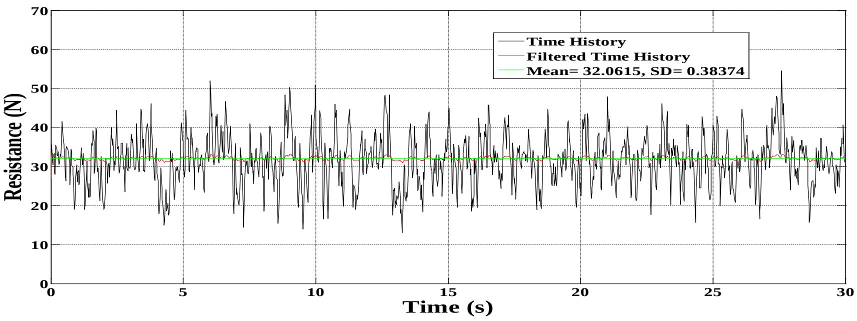
(a). *Q*=0.000001, *R*=0.001.



(b). Q=0.000001, *R*=0.01.



(c). *Q*=0.00001, *R*=0.01.



(d). *Q*=0.0001, *R*=0.01.

Fig. 3. The estimates of the noise covariance matrices *Q* and *R*.

Based on these results, the Kalman filter was proven to eliminate the noise of resistance predictions. The consistency of the performance of this optimum filter by assessed the noise covariance matrices *Q*, and *R*. Fig. 3 focus on the variation of the standard deviation of the resistance sample

Table 3 shows simulation results for the four different *Q* and *R* parameter scenarios outlined above and different values of standard deviation. In particular, the table displays the relative efficiency of the KF estimator that the corrected resistance data, which are assumed more accurate. The standard deviation is small the predicted uncertainty is likely to be smaller as well as prescribed by the ITTC [9].

Table 3. Estimation summary.

Q	*R*	*s*
0.000001	0.001	0.309
0.000001	0.01	0.139
0.00001	0.01	0.145
0.0001	0.01	0.384

4. Conclusions

A practical and successful way to address resistance estimation using a Kalman filter has been presented. Using a standard Kalman filter algorithm to post-process the raw data of resistance tests the standard deviation of measurement is minimised.

The parameter model has been proposed in the form of a Kalman filter and in the simulation study performed useful techniques for tuning of noise covariance matrices are presented.

Future developments can be done in on-line detection schemes to predict the resistance of a ship model. This work will extend the ideas presented to other data types such as seakeeping tests.

Nomenclatures

A	Discrete system matrix, $k \times\times k$
F	Matrix input with update state, $k \times k$
Fs	Sampling rate, Hz

H	Matrix update state with measurement, $k \times k$
K	Kalman gain
N	Number of samples
P_k^-	Prior state covariance matrix at time index k given data up to k-1, $k \times 1$
P_k	Posterior state covariance matrix at time index k given data up to k, $n \times 1$
$\boldsymbol{Q}$	Covariance proses noise, $k \times 1$
R	Mean of resistance, kg
$\boldsymbol{R}$	Covariance measurement noise, $k \times 1$
R_i	Data point
s	Standard deviation, kg
Δt	Interval of time, s
$u(R)$	Uncertainty of resistance, kg
$\hat{x}_k^-$	State estimate before the measurement at time k is taken into consideration, $k \times 1$
$\hat{x}_k$	State estimate after the measurement at time k is taken into consideration, $n \times 1$
$y[k]$	Measurement value, i = 1,2,3…….n
$y[k$-1], $y[k$-2]	The past series values

Greek Symbols

ϕ	Parameter model

Abbreviations

AR	Autoregressive
DAS	Data Acquisition System
DWT	Dead Weight Tonnage
EKF	Extended Kalman Filter
EUA	Experiment Uncertainty Analysis
ITTC	International Towing Tank Conference
KF	Kalman Filter

Acknowledgment

The first author expressed her gratitude to The Ministry of Research, Technology and Higher Education (Kemristekdikti) of The Republic of Indonesia which funded her Ph.D. program at ITS Surabaya under contract number 07/S3/D/PTB/XI/2015. The second author expressed his gratitude to the Ministry of Research, Technology and Higher Education (Kemristekdikti), which funded the research under a scheme known as World Class Professor (WCP) program at ITS under-contract number of 2019/PKS/ITS/2018. The authors would like to thank the staff members of Indonesian Hydrodynamic Laboratory for their support during the experiment.

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