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Predicting Velocity and Direction of Ocean Surface Currents using Elman Recurrent Neural Network Method

Eka Alifia Kusnanti [1], Dian Candra Rini Novitasari [2]*, Fajar Setiawan [3], Aris Fanani [4], Mohammad Hafiyusholeh [5], Ghaluh Indah Permata Sari [6]

[1)2)4)5)] *Universitas Islam Negeri Sunan Ampel Surabaya, Indonesia*
Jl. Ahmad Yani No 117, Surabaya
[1)]ekaalifia2@gmail.com, [2)]diancrini@uinsby.ac.id, [4)]ekaalifia2@gmail.com, [5)]hafiyusholeh@uinsby.ac.id

[3)] *Badan Meteorologi, Klimatologi, dan Geofisika Maritim Tanjung Perak Surabaya, Indonesia*
Jl. Kalimas Baru no 97B, Surabaya
[3)]geomaritim@bmkg.go.id

[6)] *National Taiwan University of Science and Technology, Taiwan*
No.43, Keelung Rd., Sec.4, Da'an Dist., Taipei City
[6)]ghaluhips@gmail.com

Abstract

Background: Ocean surface currents need to be monitored to minimize accidents at ship crossings. One way to predict ocean currents—and estimate the danger level of the sea—is by finding out the currents' velocity and their future direction.
Objective: This study aims to predict the velocity and direction of ocean surface currents.
Methods: This research uses the Elman recurrent neural network (ERNN). This study used 3,750 long-term data and 72 short-term data.
Results: The evaluation with Mean Absolute Percentage Error (MAPE) achieved the best results in short-term predictions. The best MAPE of the U currents (east to west) was 14.0279% with five inputs; the first and second hidden layers were 50 and 100, and the learning rate was 0.3. While the best MAPE of the V currents (north to south) was 3.1253% with five inputs, the first and second hidden layers were 20 and 50, and the learning rate was 0.1. The ocean surface currents' prediction indicates that the current state is from east to south with a magnitude of around 169,5773°-175,7127° resulting in a MAPE of 0.0668%.
Conclusion: ERNN is more effective than single exponential smoothing and RBFNN in ocean current prediction studies because it produces a smaller error value. In addition, the ERNN method is good for short-term ocean surface currents but is not optimal for long-term current predictions.

Keywords: MAPE, ERNN, ocean currents, ocean currents' velocity, ocean currents' directions

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I. INTRODUCTION

Ocean surface currents are the movement of seawater horizontally and vertically to reach equilibrium. Such movement occurs due to the forces that affect the sea [16], such as the wind stress on the surface that pushes water in its direction [17]. The value of the moving current can indicate the direction of wind movement. U currents move from east to west on the x-axis. If the current is positive, the current moves east, and if the value is negative, the current moves west. Likewise, V currents move from north to south on the y-axis. If the magnitude of the direction is positive, the current moves north, and if it is negative, the current moves south [18].

Studies have been conducted to predict the ocean's currents' velocity using the exponential smoothing Holt-Winters method with a case study in the Bali Strait. The MAPE value was 49.837% for the U ocean current velocity and a MAPE value of 60.976% for the V ocean current velocity [10]. Another research applied the radial basis function neural network (RBFNN) using 308 data obtained by randomly selecting centres. The result shows an average MAPE value of 34% and an accuracy of 66% for training data using 35 centres, an average MAPE value of 53% and an

*Corresponding author

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accuracy of 47% for test data using five centres [11]. Previous research has used a backpropagation neural network algorithm to predict ocean surface currents' velocity. The number of the input data used was 308 data—the current velocity data in 2015. This prediction obtained a Root Mean Square Error (RMSE) value of 0.01601839 using a 0.9 learning rate and five hidden layers [12].

Previous research has also used the Elman recurrent neural network (ERNN) method with digital voice recognition. One thousand data were tested in two modes: multi-speaker mode and speaker independent mode, resulting in high accuracy of approximately 99.30% [13]. Meanwhile, another research using ERNN to predict cavitation signals produced the smallest Root Mean Square Error(MSE) value of 0.0936 [14]. Other research on financial problems using time series patterned data applied Elman recurrent random neural network and forecast models of BPNN, STNN, ERNN, and ST-ERNN. ERNN achieved the smallest MAPE of 0.5191 [15]. Some of these studies show that using the ERNN method results in a relatively good accuracy value, so this method is suitable for predicting time series data.

Based on the reviews from various studies regarding ocean current prediction and the advantages of the ERNN method for predicting time series pattern data, this study predicts the velocity and direction of ocean surface currents. There are many ships crossing and fishermen passing through the strait. The results of this research can anticipate and reduce the rate of accidents.

II. Literature Review

A. Fill-missing

Blank data is a problem that often occurs in a study. This can be caused by various things, such as insufficient sampling or errors when measuring data. Research that uses time series data requires continuous data, so blank data problems must be overcome [19]. One way to fill in blank data is by using (1) below [20].

$$f(x) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x - x_0) \quad (1)$$

B. Normalization

Normalization is a pre-processing step that changes the scale of data so that they are in the same range [21]. One of them uses the minmax scaler where there are min and max values, namely a scale of 0 to 1[22]. The algorithm will be de-normalised to return the value after the calculation process. Equation (2) formulates the calculation of the normalization [23].

$$x_i{}' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (2)$$

C. Elman Recurrent Neural Network

The Elman recurrent neural network (ERNN) is a development of the RNN. There are two kinds of RNN, namely the Elman network and the Hopfield network [24]. Language modelling and machine translation use these networks [25]. The ERNN network is commonly called another network/partial repetitive architecture. It is because the existing connections are usually feedforward [26]. The hidden layer in the ERNN architecture has many neurons that can recognize the relationship dynamics between the input layer and the output layer [27]. Fig. 1 is the architecture of ERNN.

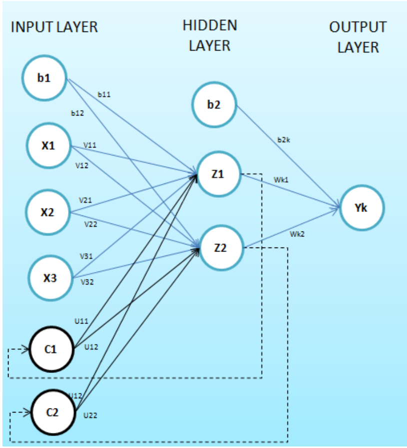

Fig. 1 ERNN network architecture

D. *Mean Absolute Percentage Error*

Mean absolute percentage error or MAPE is one way to calculate the accuracy of a system by using prediction data and observation data. The result of the calculation is in the form of a percentage. The MAPE value can be calculated using (3).

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|Xt-\hat{X}t|}{\hat{X}t} \quad (3)$$

$\hat{X}t$ = actual data
Xt = prediction data
N = the number of data [28].

III. METHODS

The current research is quantitative because the data is numerical. This study used secondary data containing the velocity of ocean surface currents in the Bali Strait for three months (measured every 30 minutes) obtained in collaboration with the Meteorology, Climatology and Maritime Geophysics Agency of Tanjung Perak Surabaya. The Bali Strait is located between Java Island and Bali Island, and it connects the Java Sea with the Indian Ocean in the north [1] [2]. The movement of currents in the Bali Strait makes the area fertile. It becomes a high natural resource of biomass, making it popular among fishermen in the south part of Java and Bali [3] [4]. In addition, the sea provides a large source of potential energy [5]. The occurrence of tidal waves, thermal differences and salinity, as well as ocean surface currents, provides potential sources of marine renewable energy [6]. Nine pressure gauges of outflows have been monitored in Indonesia since 1995 [7] to estimate the average fluctuation at the surface and the geostrophic velocity of the strait [8] [9]. Considering these circumstances, it is very important to know the magnitude of the ocean surface currents in the Bali Strait for the safety of ship crossings and fishermen. The description of ocean current movement is shown in Fig. 2.

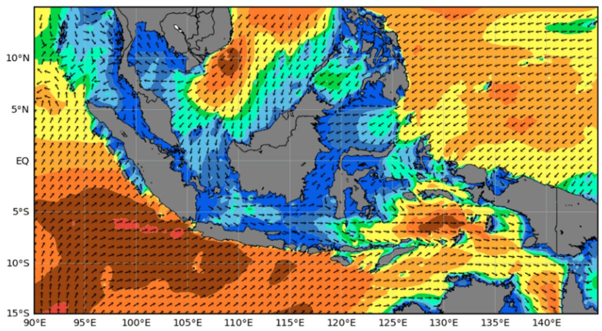

Fig. 2 Ocean surface currents (Source: BMKG)

Past research has shown that the suitable method for time series data such as ocean surface currents is ERNN. Therefore, this study predicts the magnitude and direction of ocean surface currents in the Bali Strait using the ERNN method. Fig. 3 shows the steps carried out in this research.

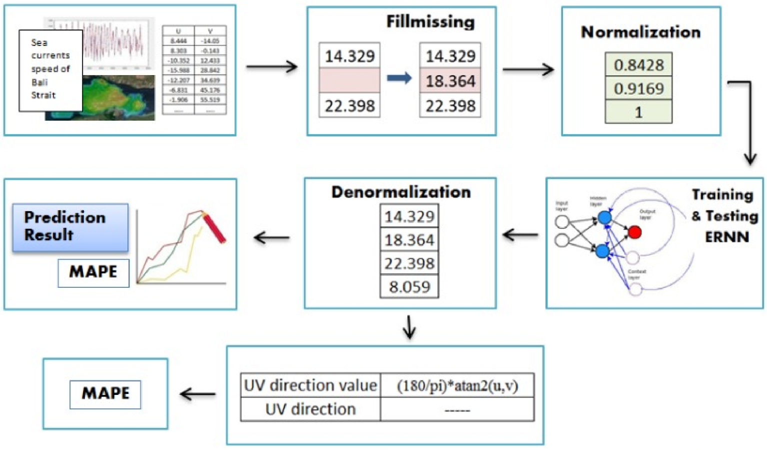

Fig. 3 Theoretical Framework of ERNN

Ocean surface currents data has missed values and a high data range, so fill-missing and normalization processes must turn the data range into 0-1. The training and the testing processes use ERNN data as input, learning rates, and hidden layers. The selection of tuning parameters in ERNN is based on previous research, i.e., how many hidden neurons to use. Similarly, the learning rate is based on previous research. It is an important parameter that controls neural networks' performance [29]. After getting the ocean current velocity prediction, de-normalization returns the value to the initial value range. The ocean surface currents prediction result is used to predict the direction of ocean surface currents. The final evaluation uses MAPE and graphs to compare the predicted data with actual data. The trial was carried out on long-term and short-term data. In the long term, all data were used, while in the short term, 72 sequence data from 18 July at 22.00 to 20 July at 09.30 were used to generate predictions for the next three hours. The algorithm to predict the velocity with ERNN is as follows.

Step 1:
The training was carried out on a vector pattern each time (t) or input as seen on (4)

$$y_k\ (t) = f(net_j\ (t)) \quad (4)$$

using recurrent networks (5):

$$net_j\ (t) = \textstyle\sum_i^n v_{ji}x_i(t) + \sum_h^m u_{jh}y_h(t-1) + \theta_j \quad (5)$$

Step 2:
The output was determined by the context layer and the output with a weight value (w) in (6).

$$y_k\ (t) = g(net_k\ (t)) \quad (6)$$

Furthermore, it was further described in (7).

$$net_k(t) = \textstyle\sum_j^m w_{kj}y_j(t) + \theta_k \quad (7)$$

Step 3:
This network's weight value was always updated, which was calculated from the weight error. The weight was then used to determine the next weight value. Error calculation was carried out using the calculation of MAPE.

Step 4:
At the gradient descent, the value of each weight change is proportional to the negative gradient η is the value of a learning rate as shown in (8).

$$\Delta w = -\eta \frac{\partial C}{\partial w} \quad (8)$$

Step 5:
The calculation was carried out by the derivative rule of the differentiation chain. Equation (9) calculated the weight value associated with the error.

$$\delta_{pk} = -\frac{\partial C}{\partial y_{pk}} \frac{\partial y_{pk}}{\partial net_{pk}} = (d_{pk} - y_{pk}) g(y_{pk}) \quad (9)$$

Meanwhile, the error in the hidden layer is calculated using (10).

$$\delta_{pj} = \sum_{k=1}^{m} \delta_{pk} w_{kj} f'(y_{pj}) \quad (10)$$

Step 6:
Changes in the weighted value at the output uses (11).

$$\Delta w_{kj} = \eta \sum_{p}^{n} \delta_{pk} y_{pj} \quad (11)$$

As for the change in weight on the input in (12).

$$\Delta v_{ji} = \eta \sum_{p}^{n} \delta_{pj} y_{pi} \quad (12)$$

Step 7:
Based on the component of each time (t), the change in the weight value of the recurrent is as shown in (13).

$$\Delta u_{j\hbar} = \eta \sum_{p}^{n} \delta_{pj} y_{p\hbar}(t-1) \quad (13)$$

Step 8: Training/testing only stops if the error value < target error. Description of the equation symbol (1)- (13) is in Table 1.

TABLE 1
SYMBOLS ON THE EQUATION

Symbol	Quantity	Symbol	Quantity
net_j	Hidden layer input	η	Learning rate
v_{ji}	Weight on the hidden layer	θ_k	Output layer bias
x_i	Input	δ_{pk}	Output layer error
y_h	Context layer output	δ_{pj}	Hidden layer error
θ_j	Hidden layer bias	d_{pk}	Actual value
y_k	Output on the output layer	y_{pk}	Predictive value
net_k	Input to the output layer	Δw_{kj}	The term changes in the weight of the output layer
w_{kj}	Weight on the output layer	Δv_{ji}	The term changes in the weight of the hidden layer
y_j	Output on the hidden layer	Δu_{jh}	The term changes in the weight of the context layer

IV. RESULTS

Based on all the calculations and evaluation results in this study, the ERNN method is more effective than the method used in previous ocean current prediction studies [10] [11] because it can produce a smaller error value. In addition, the ERNN method is good for short-term ocean surface currents but is not optimal for long-term current predictions because it produces large MAPE. This is in line with previous studies stating that a lot of data resulted in a larger MAPE [8] than the use of smaller data [11]. Therefore, further research will benefit from using other methods that can be used for long-term predictions by considering the parameters that affect ocean surface currents for better accuracy [12], [30]. Table 2 shows sequential data of this research.

TABLE 2
DATA SET

Dataset	Target
X_1, X_2, X_3, X_4, X_5	X_6
X_2, X_3, X_4, X_5, X_6	X_7
X_3, X_4, X_5, X_6, X_7	X_8
…….	…
$X_{3745}, X_{3746}, X_{3747}, X_{3748}\ X_{3749}$	X_{3750}

Fig. 4 shows the coordinate points of the ocean current velocity data at the Bali Strait. Table II shows the data sample of ocean surface currents in cm/s. Overall, it is shown that the data on ocean surface currents is not stable every 30 minutes. Table 3 shows the data sample on the ocean surface current velocity at Bali.

Fig. 4 Coordinate Point of the Bali Strait

TABLE 3
DATA SAMPLE OF OCEAN SURFACE CURRENT VELOCITY

YYYY_mm_DD_HHMM (utc)	U comp (cm/s)	V comp (cm/s)
2020_01_02_1900	0.906	-15.776
2020_01_02_1930	1.063	-6.786
2020_01_02_2000	-1.677	2.510
2020_01_02_2030	-1.192	5.503
2020_01_02_2100	-1.414	3.364
2020_01_02_2130	0.859	-0.610
2020_01_02_2200	8.484	-6.791

ERNN processes the best results at 9:1 data flow distribution, 90% for training data and 10% for testing data. Training with 2-5 input data, 0.1-0.5 learning rate and a combination of hidden layers of 20 and 50, 50 and 100, and 80 and 150. Table 4 is the result of using ERNN.

Table IV shows the best test results of the U and V currents' data. The results show that U currents are not suitable for long-term predictions. This is in line with previous studies that used 1,344 data [10] which had a greater error value than 308 data [11]. In this study, the use of 3,750 data shows a very large error than the use of 72 data because ocean surface currents are daily periodic data. The best combination of parameters is a short-term prediction on the input for five, with the number of the first hidden layer being 50 and the second hidden layer being 100, and with a learning rate value of 0.3. The prediction accuracy of MAPE during training is 27.1170%, and MAPE during testing is 14.0279%. In line with previous studies, V currents are also not suitable for long-term predictions [10]. The best combination of parameters is the short-term prediction on the input for five, with the number of the first hidden layer being 20 and the second hidden layer being 50, and with a learning rate value of 0.1. The prediction accuracy of MAPE during the training is 20.7519%, and MAPE during testing is 3.1253%.

TABLE 4
THE RESULT OF THE PREDICTION DATA OF U AND V CURRENTS

Input	Parameter			U currents				V currents			
				Short-Term		Long-term		Short-Term		Long-term	
	Hidden Layer-1	Hidden Layer-2	Learning Rate	MAPE training	MAPE testing	MAPE training	MAPE testing	MAPE training	MAPE testing	MAPE training	MAPE testing
5	20	50	0.1	240.811	175.276	1.603.123	1.581.093	207.519	**31.253**	6.394.631	**6.359.569**
			0.2	267.955	172.449	1.620.849	1.587.236	219.889	63.925	6.545.321	6.510.619
			0.3	277.975	176.194	1.605.074	1.613.024	176.306	55.947	6.635.804	6.515.593
			0.4	295.692	149.559	1.602.123	1.561.269	229.947	49.642	6.705.562	6.440.431
			0.5	240.043	158.851	1.642.765	1.626.431	209.453	49.681	6.516.412	6.454.298
	50	100	0.1	321.082	196.433	1.582.545	1.570.715	242.549	72.114	6.845.282	6.477.927
			0.2	302.261	197.182	1.586.770	1.596.252	251.993	68.261	6.921.739	6.453.180
			0.3	271.170	**140.279**	1.596.949	1.599.006	242.030	71.391	6.576.513	6.476.574
			0.4	276.268	177.996	1.578.156	**1.525.681**	228.462	71.434	6.704.929	6.469.754
			0.5	254.057	144.222	1.583.001	1.526.447	244.670	66.638	6.693.001	6.512.709
	80	150	0.1	384.195	246.484	1.591.220	1.580.196	263.468	73.111	6.638.702	6.509.881
			0.2	325.116	208.137	1.579.299	1.559.721	266.234	76.680	6.553.567	6.451.621
			0.3	327.446	235.986	1.584.708	1.549.942	255.171	76.392	6.678.084	6.420.842
			0.4	350.335	216.472	1.584.827	1.538.288	243.782	52.475	6.649.199	6.491.665
			0.5	407.199	258.200	1.592.047	1.572.948	237.956	56.770	6.762.809	6.489.727

In Backpropagation, the best results for both currents are short-term predictions. The best MAPE of U currents is 40.1603% using five sequence input data, with the first hidden layer having 50 nodes, the second layer having 100 nodes, and the learning rate being 0.3. Meanwhile, the best MAPE on the V currents is 3.6274%, with the value of the first hidden layer being 20 and the second hidden layer being 50, with a learning rate of 0.1. The ERNN method produces a smaller MAPE value than the backpropagation method. Fig. 5 is the result on graphs and predictions of the ERNN method.

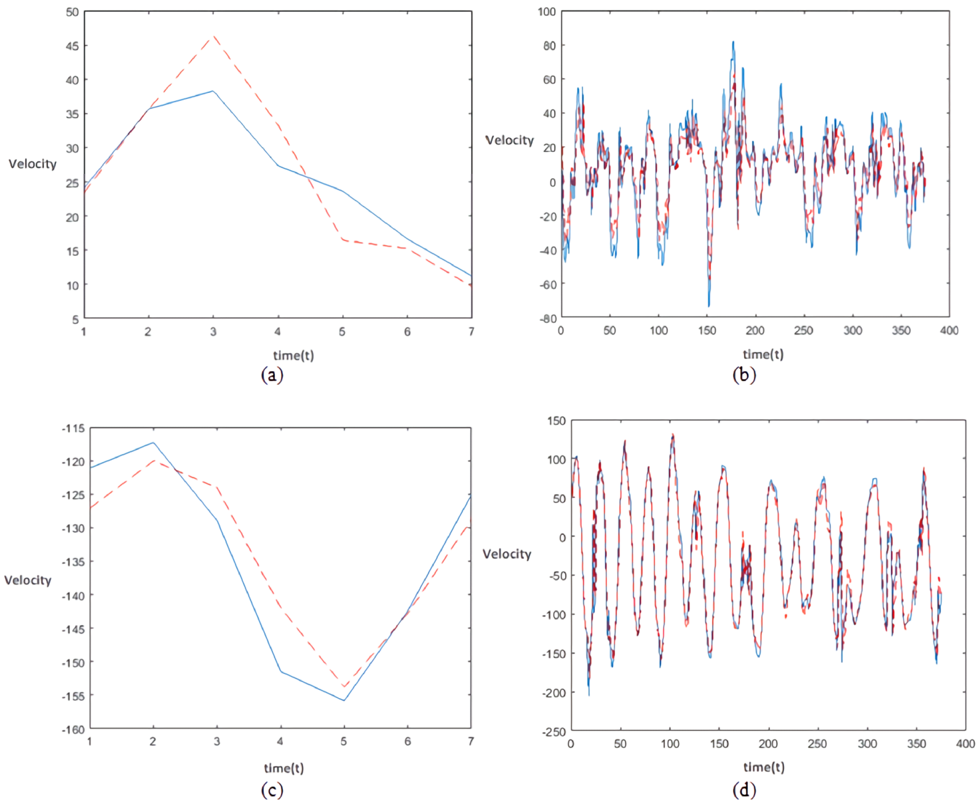

Fig. 5 (a) U short-term prediction results (b) U long-term prediction results (c) V short-term prediction results (d) V long-term prediction results

TABLE 5
SHORT-TERM AND LONG-TERM PREDICTION VALUE OF U AND V

Prediction	Ocean Current	Actual Data	Prediction Data
SHORT-TERM	U	24.059	23.378
		35.649	35.630
		38.280	46.386
		27.337	33.273
		23.631	16.462
		16.625	15.220
		11.176	9.652
	V	-121.114	-127.093
		-117.286	-120.039
		-128.937	-124.049
		-151.472	-141.937
		-155.851	-153.807
		-142.396	-142.787
		-125.094	-127.093
LONG-TERM	U	6.132	20.117
		-27.441	5.340
		-41.988	-24.238
		-47.853	-34.626
		-43.136	-35.945
		-30.082	-28.673
		-37.904	-15.907
	V	55.628	51.946
		71.301	70.568
		86.842	83.044
		99.322	93.700
		102.974	102.192
		102.468	102.172
		55.628	51.942

Fig. 5 shows the short-term and long-term U and V current predictions, whose values are shown in Table 5. The tables of the short-term show the prediction results on 20 July 2020 at 06.30-09.30 per 30 minutes. It can be seen that the prediction results are more accurate or closer to the actual values in the short-term prediction than those in the long-term one. The tables of long-term predictions show the results on 24 August 2020 at 05.00-08.00 per 30 minutes. Table 6 is the magnitude and direction of the UV currents using the ERNN method.

TABLE 6
PREDICTION OF THE MAGNITUDE AND DIRECTION OF UV CURRENTS

U	V	Prediction Direction	Actual Direction	Direction
23.3780	-127.0930	169.5773°	168.7646°	East to South
35.6300	-120.0390	163.4680°	163.0934°	East to South
46.3860	-124.0490	159.4976°	163.4644°	East to South
33.2730	-141.9370	166.8069°	169.7696°	East to South
16.4620	-153.8070	173.8909°	171.3782°	East to South
15.2200	-142.7870	173.9157°	173.3408°	East to South
9.6520	-128.7480	175.7127°	174.8947°	East to South

V. DISCUSSION

From the prediction results of both U and V currents, it can be seen that the error value for the U currents is greater than the V currents. This is in accordance with previous studies because U currents are residual currents that tend to vary and are inconsistent, so it is difficult to predict. Meanwhile, the V currents are the harmonic ones, whose current pattern follows the tidal pattern. Ocean surface currents generally rise due to wind, but tidal changes dominate in ocean surface currents with a narrow area such as a strait so that it has a daily periodic nature. Therefore, the direction of the tidal currents is more dominant, following the shape of Bali Strait, which extends from north to south. After we obtained the results on U and V currents' prediction above, we calculated the magnitude and direction.

The direction is determined by looking at the values of U and V. In Table VI, the predicted U value is positive, so the direction is towards the east. In contrast, the value of V is negative, then the direction is towards the south.

Therefore, the current state was from east to south with a magnitude of around 169.5773°-175.7127°. The prediction on the direction of the ocean surface currents resulted in a MAPE of 0.0668%.

In previous research, the evaluation results show that the ERNN method is more effective than single exponential smoothing and RBFNN. The MAPE value of U and V ocean current velocity prediction using single exponential smoothing are 49.837% and 60.976% [10]. Meanwhile, the RBFNN method's MAPE value is 34%, and accuracy is 66% for training data in 35 centres. The average MAPE value is 53%, and the accuracy is 47% for test data using five centres [11]. From the table [31], the MAPE values are 3.888% (U prediction) and 13% (V prediction), which is a sound prediction system. In addition, the ERNN method is suitable for short-term ocean surface currents but is not optimal for long-term current predictions, as shown by the MAPE values. Previous research has proven that long-term data's MAPE result is more effective than short-term data [11]. Therefore, future research will benefit from using other methods such as LSTM [32] [33], 1d CNN [34], GRU [35], and other variables that affect ocean surface currents [12] [30].

VI. CONCLUSIONS

Based on the study results, it can be concluded that the ERNN network successfully predicts the velocity and direction of ocean surface currents. ERNN is more suitable for predicting ocean surface currents than the other methods based on the MAPE value. Previous studies only predicted the ocean surface currents velocity, but the current study also indicates the direction of these surface currents by considering the MAPE value. The ERNN method generates smaller MAPE in the short term. The best pattern for U currents was with five inputs, the first hidden layers of 50, the second hidden layers of 100 and a learning rate of 0.3, resulting in 27.1170% MAPE in training and 14.0279% in testing. While the best pattern for V current consists of five inputs, 20 first hidden layers, 50-second hidden layers and a learning rate of 0.1 for MAPE 20.7519% in training and 3.1253% in testing. The prediction of the direction indicates that the current state is from east to south with a magnitude of around 169,5773°-175,7127° resulting in a MAPE of 0.0668%.

Author Contributions: *Eka Alifia Kusnanti*: Writing the conceptualization, Formal analysis. *Dian Candra Rini Novitasari*: Writing the conceptualization, Formal analysis, Methodology, Validation. *Fajar Setiawan*: Data collection, Interpretation and Validation. *Aris Fanani*: Formal analysis, Interpretation and Validation. *Moh. Hafiyusholeh*: Formal analysis, Interpretation and Validation. *Ghaluh Indah Permata Sari*: Formal analysis and Methodology.

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Conflicts of Interest: The authors declare no conflict of interest.

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