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Estimation of Dry Docking Maintenance Duration using Artificial Neural Network

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Abstract— Maintenance duration is a substantial part of dry docking activities. Maintenance duration estimation is needed to prepare a ship maintenance schedule in a dockyard. Unfortunately, the dockyard operators have not yet own any standard in estimating duration of the maintenance. This research aims to obtain a mathematical model of dry docking maintenance duration estimation using Artificial Neural Network, by considering volume and dry docking type of activity as the input.

Keywords—Decision Tree, Dry Docking, Genetic Algorithm, Neural Network

I. INTRODUCTION

TRANSPORTATION holds a significant role in accelerating economic condition of a country. Shipping industry is one of the strategic industries which is very essential to be developed [1]. Routine periodic maintenance and repair are required to maintain the quality and condition of a ship during operation.

In ship maintenance activities, *docking* duration estimation becomes very substantial. Based on field observation, it is found that there is no standard model used by the dockyard operator in estimating ship maintenance duration. Whereas, Srdoc et al. found the use of data mining method in estimating ship maintenance duration, that is by looking for any pattern from maintenance duration data based on volume classification from several types of maintenances [2]. Neural Network has often been used to carry out estimation problems, such as: disease classification time series forecasting [3], web classification under the field of Information technology [4], weather forecast [5] and cost estimation [6].

Literature study also shows that Neural Network forecasting method with backpropagation algorithm can upgrade the forecasting accuracy level [7]. The objective of this study is to model Dry Docking duration by using Neural Network with back propagation algorithm.

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II. METHODS

Referring to the satisfaction note data, there are 29 types of work in dry docking maintenance activities which are used as Input Variables of the estimation model, as can be seen in Table I.

Model limitation is specified as an indicator of how far the iterations (optimal value search) in the model should be done. The learning parameter used in the model are learning rate, number of neuron within the hidden layer, and momentum. Specifying the limit value and learning parameter is done using *trial and error* until the least error value obtained. These limit and parameters further become the indicator used in generating estimation model

The *trial and error* phase gave the following limit and learning parameters that will be used in the model :

Maximum Number of Neural Network iteration	: 1000
Learning rate value	: 0.04
Number of neuron within the hidden layer	: 8
Momentum	: 0.06

TABLE I
INPUT VARIABLES OF THE FORECASTING METHOD

Variables	Specification
Tank Scraping, sandblasting, cuci, cat	Volume (m^3) Area (m^2)
Zinc, Sealprop, Ringprop, packingprop, chrome, ringkem, packingkem, sealkem, chest, valve, scrupper, ut, las	Amount (point)
Plate, grease, propeller, porosprop, kemudi, poroskem	Mass (kg) A = no maintenance, B = recondition, C = balancing, D = change, E = recondition and balancing, F = change and balancing, G = change and recondition, H = change, recondition, and balancing
Bantalanprop, bantalankem	A = no maintenance, B = recondition, C = change, D = balancing
Shaftseal	Options (YES, NO)
Panjanglas	Length (m)

In the process of generating the model, several assumptions are used as follows:

- Neural Network algorithm used in the learning process is back propagation with signoid binary activation function
- Maximum number of hidden layer within the neural network : 1 layer
- Error value (RMSE) in Neural Network learning process : 1 day

Learning algorithm for the one hidden layer network with binary sigmoid activation function are as follows :

Step 0 : Initialization all weights with small random numbers

Step 1 : If the stopping condition has not been fulfilled, proceed to step 2 – 9

Step 2 : For each pair of learning data, do step 3 – 8

Phase 1 : Forward propagation

Step 3 : Each input unit receives signal and forward it to the hidden unit above them

Step 4 : Compute all output in hidden unit z_j (j=1,2,...,p)

$$z\_net_j = v_{j0} + \sum_{i=1}^{n} x_i v_{ji} \quad (1)$$

$$z_j = f\left(z_{net_j}\right) = \frac{1}{1+e^{-z\_net_j}} \quad (2)$$

Step 5 : Compute all network output in unit y_k (k=1,2,...,m)

$$y\_net_k = w_{k0} + \sum_{j=1}^{p} z_j w_{kj} \quad (3)$$

$$y_k = f(y\_net_k) = \frac{1}{1+e^{-y\_net_k}} \quad (4)$$

Phase 2: Backward propagation

Step 6 :Calculate factor δ output unit based on error in each output unit y_k (k=1,2,...,m)

$$\delta_k = (t_k - y_k) f'\left(y_{net_k}\right) = (t_k - y_k) y_k (1 - y_k) \quad (5)$$

δ_k is the error unit that will be used within the change of layer weight below it (step 7)

Compute the weight alteration rate w_{kj} (which will be used later to modify weight w_{kj}) with acceleration rate α

$$\Delta w_{kj} = \alpha\, \delta_k z_j\, ; k = 1,2,\dots,m\, ; j = 0,1,\dots,p \quad (6)$$

Step 7 :Compute factor δhidden unit based on error in each hidden uit z_j (j=1,2,...,p)

$$\delta\_net_j = \sum_{k=1}^{m} \delta_k w_{kj} \quad (7)$$

Factor δ hidden unit :

$$\delta_j = \delta_{net_j} f'\left(z_{net_j}\right) = \delta\_net_j z_j (1 - z_j) \quad (8)$$

Compute the alteration rate of weight v_{ji} (which will be used to modify weight v_{ji})

$$\Delta v_{ji} = \alpha\, \delta_j\, x_i\, ; j = 1,2,\dots,p\, ; i = 0,1,\dots,n \quad (9)$$

Phase 3 : Weight alteration

Step 8 : Calculate all the weight alteration

Modification of line weight towards the output unit:

$$w_{kj}(\text{new}) = w_{kj}(\text{old}) + \Delta_{w_{kj}}\ (k = 1,2,\dots,m\, ; j = 0,1,\dots,p) \quad (10)$$

Modification of line weight towards the hidden unit:

$$v_{ji}(\text{new}) = v_{ji}(\text{old}) + \Delta v_j i\ (j = 1,2,\dots,p\, ; i = 0,1,\dots,n) \quad (11)$$

As the learning process has been executed, network can be used to recognize the pattern. In this case, forward propagation is used to assign the network output. *Netbeans IDE* version 7.2 software is used in this research to assist the model generating process above.

III. Results and Analysis

146 data were used in this study, composed of 103 training data, 21 testing data and 21 validation data. Training data were used to train the Neural Network, while testing data were used to test the trained model. A validation was also done to the model.

Table II shows that the estimation gives 11 ships with quite accurate forecasted value, that is with the error value of 0 to 1 day. Twenty three ships indicates error value of 2 to 4 days, and the rest of the 8 ships have error value of 5 to 11 days, so that the average error value is 5.99 days. Less accurate forecasts are caused by the unsimilar or unrepresented data pattern in the training data that lead to the inability of the model to recognize the pattern well (i.e., during the testing and validation process). The high level of variance may be caused by weather factor, material availability and the number of workers.

TABLE II
ESTIMATION RESULT

Testing		Validation	
Actual Duration	Neural Network Forecasting Result	Actual Duration	Neural Network Forecasting Result
6	9	6	9
7	9	7	8
7	10	7	9
7	8	8	9
7	9	8	11
8	10	8	10
8	18	9	11
8	13	9	13
8	10	10	11
8	9	10	6
8	11	10	12
8	10	10	10
9	11	10	10
9	5	11	15
9	8	12	15
9	11	13	9
9	13	15	11
10	5	16	14
10	9	16	11
10	11	17	21
10	11	30	40

Weather is a natural factor which is not easy to be predicted. If the weather is considered *not supporting* for the dry docking activities, then the dry docking duration will be longer by few days.supply of material might also cause the variance level. Ship owners tend to buy materials by themselves, and this impedes dockyard operators to finish the works, because when materials are not available, idle time exists.

The last problem is the availability of workers. If the number of workers disproportionate with the number of works, or volume of the works, then the dry docking duration will be even longer and harder to predict as it is related to the human behavior factor.

IV. CONCLUSIONS

The result of this study gives an estimation model of Dry Docking duration with average error value of 5.99 days. Inaccurate estimations of some ships may be caused by weather factor, supply of material and number of workers, making the high variance of duration. For future research, ship characteristics can be used as one of the input variables in estimating Dry Docking duration, such as life and type of the ships. Furthermore, Neural Network combined with Genetic Algorithm can be considered as methods used for future research regarding its capability to eliminate the *trial and error* phase, as the optimal learning parameters are specified using genetic algorithm operations, thus the model generating process will be more efficient.

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