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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