The estimation of ship resistance using Neuro-fuzzy

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***Abstract*— A ship designer should lay out hull form which has the least resistance so that optimum hull form is created. This would reduce the expense and time to the minimum that you estimate exact relationships between hull form and resistance at an early stage. The existing way of estimating the resistance was either statistical one that didn't consider three-dimensional form or CFD(Computational Fluid Dynamics) that is complicated and hard to be embodied. The study using Neuro-fuzzy has suggested a new way of resistance estimation by predicting the ship resistance expressed as three-dimensional form. Neuro-fuzzy system has four layers and goes through two stages. The first stage is being fuzzification by membership function, and the second is training stage by error back-propagation. We estimated hard-to-expect form factor and wave-making resistance coefficient using the system before a model test. 96 ships for form factor and 52 ships for wave-making resistance coefficient were used as data to estimate, and the result was comparatively precise.**

I. INTRODUCTIONS

The free form that cannot be converted to mathematically typical expressions like ship might enter to input and corresponding output of performance come out. In that case, technological operation is classified as below. First, with expressing the flow field near a ship in 2-ordinary partial differential equation, it is required to handle it analytically or numerically; otherwise, it needs the access of artificial intelligence that considers the relativity between input and output. In this study, we tried to conduct effects of various 3D free forms with Neuro-fuzzy not analytical or numerical methods.

The input range of hull form information does not require entire ship. In the case of the bow, the range is the part of Entrance and in case of the stern, it is the part of Run. Although the hull information is 3D, it is not necessary to input conventional all (x,y,z) values because contrary to a human being, a computer can recognize numerical combinations. For instance, conventional potential-calculation needs all (x,y,z) values; however, computers can divide 3D hull forms into difference by only a combination of characteristic in x, y ,or z values. In this study, we utilize the Breadth(y) that shows the 3D hull form changes in the part of Entrance and Run in (x,y,z) Cartesian coordinates.

The resistance of ship is related with the hull form. Therefore, it is inevitable that accurate resistance should be estimated according to the hull form. In these days, regression analysis or approximate expressions with coefficients such as L/B or C_b are used for early resistance calculation. However, if some parts of hull forms covert locally, this way cannot presume resistance value. Specifically, this is not the resistance estimation with 3D hull forms. According to development of computer technology there are many studies to calculate the resistance using CFD however, it cannot be pragmatic yet.

Ship building plants have made many ships and constructed the data base relation between hull forms and resistance. We can assume that there are nonlinear rules in these data. In this study, we try to find the rules and examine the credibility of Neuro-fuzzy

Ship resistance is divided into wave-making resistance, frictional resistance and form resistance. In the three resistances, the wave-making resistance and form resistance are related with 3D hull form closely. We need to estimate C_W for the wave-making resistance and Form-factor for the form resistance. 31 ships were used for C_W and 96 ships were used for Form-factor.

II. SHIP RESISTANCE

Resistance is expressed as formula (1)

$$R_T = R_W + R_F + kR_F = R_W + (1+k)R_F \tag{1}$$

Here, R_T is total resistance, R_W is wave-making resistance, R_F is frictional resistance and $1+k$ is Form-factor.

A. Wave-making resistance

R_W is resistance which is made by wave and it is expressed as formula (2)

$$C_W = \frac{R_W}{1/2\,\rho S v^2} \tag{2}$$

In formula (2) ρ is water density, C_W is wave making coefficient, v is ship velocity , and S is wetted surface.

After estimating R_T, R_F, and $1+k$ through model-test, we can calculate R_W. Because C_W is various according to C_p, or principle dimensions such as L/B, B/d or C_b, it cannot be expressed into approximate expression like frictional resistance coefficient or form factor. As the fig. 1 shows, we can know the part of Entrance and Run are much more complicated than parallel part.

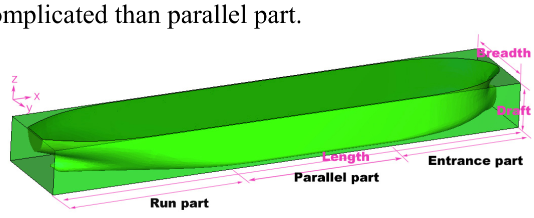


Fig. 1 Hull form

B. Frictional resistance

R_F is calculated by formula (3)

$$C_F(R_N)=\frac{R_F}{1/2\rho S v^2} \tag{3}$$

Here, ρ is water density, C_F is frictional resistance coefficient, v is velocity, and S is wetted surface. According to ITTC-57, C_F is determined by Reynolds function as formula (4).

$$C_F=\frac{0.075}{(Log_{10} R_N-2)^2} \tag{4}$$

C. Form-factor

Frictional resistance is estimated from 2D flat plate so we need to consider it with 3D hull form. This method that considers 3D hull form is k. k is calculated using approximate expressions, and those are same as Table 1.

Table 1 k approximate expression

person	approximate expression
Granville	$k=-0.07+(C_b\frac{B}{L})^2$
Prohaska	$k=1.728-1.512\frac{B}{d}+0.2446\left(\frac{B}{d}\right)^2+5.40\frac{C_b}{L/B}+13.9\left(\frac{C_b}{L/B}\right)^2$
Sasajima-Oh	$k=3r_A^5+0.30-0.035\left(\frac{B}{d}\right)+0.5\left(\frac{T}{L}\right)\cdot\left(\frac{B}{d}\right)$

In Table 1 k approximate expressions, Sasajima-Oh's is accurate comparatively. The reason is that Run coefficient r_A has the hull form information of the part of Run. r_A is expressed as formula (5).

$$r_A=\frac{B/L}{1.3(1-C_b)-3.1l_{cb}} \tag{5}$$

Here, B is the breadth of ship, L is the length of ship, C_b is block coefficient, and l_{cb} is the value that LCB is divided by L.

III. THE NETWORK STRUCTURE

During the past years, there has been a large and energetic upswing in research efforts aimed at synthesizing fuzzy logic with neural networks. There are many ways to synthesize fuzzy logic and neural networks[3][4]. The Neuro-fuzzy we constructed is of 2 stages. Being fuzzification is the first stage, training through backpropagation is the second. Here's the following explanation about it.

A. Fuzzy set and membership function

Let X be a space of points, with a generic element of X denoted by x. Thus, $X=\{x\}$. A fuzzy set A in X is characterized by a membership function $f_A(x)$ which associates with each point in X a real number in the interval [0,1], with the value of $f_A(x)$ at x representing the "grade of membership"of x in A. Thus, the nearer the value of $f_A(x)$ to unity, the higher the grade of membership of x in A [4][5].

Membership function used in the study was the form of trapezoid composed of Fuzzy unit. Figure 1 is showing that trapezoid membership function, which is defined by a, b, c, d is defined by fuzzy unit. Fuzzy unit divides into two fuzzy partition. In other words, two partitions mean unit 1, 3 partitions mean unit 2.

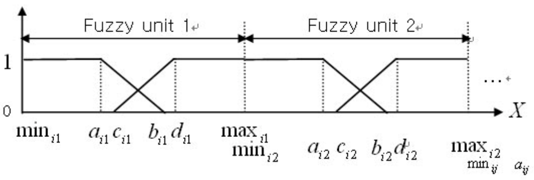


Fig. 2 Relationship of fuzzy partition and fuzzy unit

$$\begin{aligned} a_{ij} &= x_{ij} \\ b_{ij} &= a_{ij}+\alpha_{ij}(\max_{ij}-a_{ij}) \\ c_{ij} &= a_{ij}+\alpha_{ij}(b_{ij}-a_{ij}) \\ d_{ij} &= b_{ij}+\alpha_{ij}(\max_{ij}-b_{ij}) \end{aligned} \tag{6}$$

a_{ij}, b_{ij}, c_{ij}, d_{ij} : from i variable to j fuzzy unit parameter

x_{ij} : from i variable to j fuzzy unit first set value

α_{ij} : 0 to 1 value

B. Back-propagation with one hidden layer

We shall denote by w_{JK} the weight between the hidden unit Z_J and the output unit Y_K; these units are considered arbitrary, but fixed, Z_J. With this notation, the corresponding lowercase letters can serve as summation indices in the derivation of the weight update rules. We shall return to the more common lowercase indices following the derivation.

The derivation is given here for an arbitrary activation function $f(x)$. The derivative of the activation function is denoted by f'. The dependence of the activation on the weights results from applying the activation function f to the net input

$$y\_in_K=\sum_j z_j w_{jK} \tag{7}$$

to find $f(y\_in_K)$.

The error to be minimized is

$$E=.5\sum_k [t_k-y_k]^2 \tag{8}$$

If there is p number of input pattern, the error is

$$E_{rror}=\sum_p E \tag{9}$$

By use of the chain rule, we have

$$\begin{aligned} \frac{\partial E}{\partial w_{JK}} &= \frac{\partial}{\partial w_{JK}}.5\sum_k[t_k-y_k]^2 \\ &= \frac{\partial}{\partial w_{JK}}.5[t_K-f(y\_in_K)]^2 \\ &= -[t_K-y_K]\frac{\partial}{\partial w_{JK}}f(y\_in_K) \\ &= -[t_K-y_K]f'(y\_in_K)\frac{\partial}{\partial w_{JK}}(y\_in_K) \\ &= -[t_K-y_K]f'(y\_in_K)z_J \end{aligned} \tag{10}$$

It is convenient to define δ_K:

$$\delta_K = [t_K - y_K] f'(y\_in_K) \tag{11}$$

For weights on connections to the hidden unit Z_J:

$$\begin{aligned}
\frac{\partial E}{\partial v_{IJ}} &= -\sum_k [t_k - y_k] \frac{\partial}{\partial v_{IJ}} y_k \\
&= -\sum_k [t_k - y_k] f'(y_in_k) \frac{\partial}{\partial v_{IJ}} y_in_k \\
&= -\sum_k \delta_k \frac{\partial}{\partial v_{IJ}} y_in_k \\
&= -\sum_k \delta_k w_{JK} \frac{\partial}{\partial v_{IJ}} z_J \\
&= -\sum_k \delta_k w_{JK} f'(z_in_J)[x_I]
\end{aligned} \tag{12}$$

Define:

$$\delta_J = -\sum_k \delta_k w_{Jk} f'(y\_in_J) \tag{13}$$

Thus, the updates for the weights to the output units (returning to the more common lower case subscripts) are given by:

$$\begin{aligned}
\Delta w_{jk} &= -\alpha \frac{\partial E}{\partial w_{jk}} \\
&= \alpha [t_k - y_k] f'(y_in_k) z_j \\
&= \alpha \delta_k z_j
\end{aligned} \tag{14}$$

and for the weights to the hidden unit:

$$\begin{aligned}
\Delta v_{ij} &= -\alpha \frac{\partial E}{\partial v_{ij}} \\
&= \alpha f'(z_in_j) x_i \sum_k \delta_k w_{jk} \\
&= \alpha \delta_j x_i
\end{aligned} \tag{15}$$

C. Neuro-fuzzy structure

Neuro-fuzzy is composed of 4 layers. The first layer is the input layer, the second layer is the fuzzification, the third layer is hidden layer, the fourth layer is output layer.

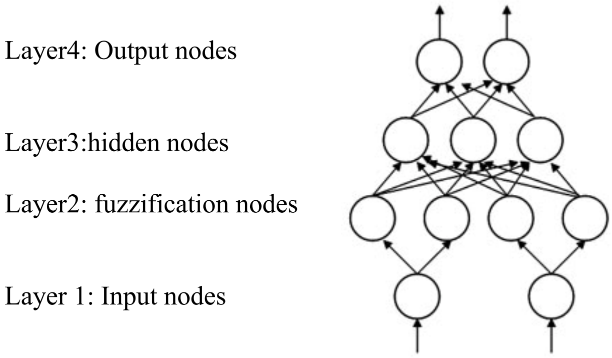


Fig. 3 The network structure

Layer 1: Each node in layer 1 represents an input linguistic variable of the network and is used as a buffer to transmit the input to the next layer, that is to the membership function nodes of its linguistic values.

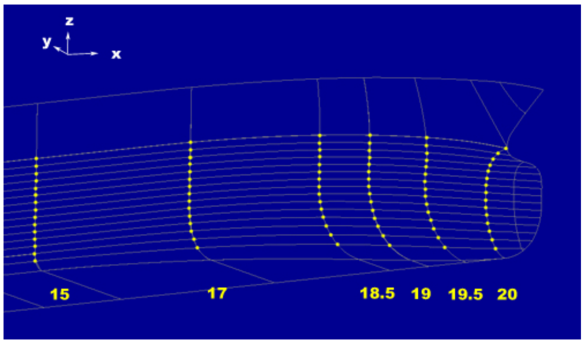
Layer 2: This is the fuzzification layer. Each node in this layer represents the membership function of a linguistic value associated with an input linguistic variable. The output of a layer 2 node represents the membership grade of the input with respect to a linguistic value. We used trapezoid membership function. The node number of layer 2 is changing according to number of input variable and fuzzy partition.

Layer 3: This is the hidden layer. In layer 2 to layer 4, this system is trained by back-propagation[6].

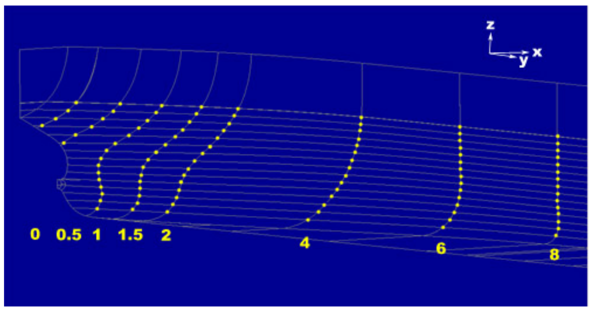
Layer 4: This is the output layer.

IV. EXPERIMENT AND RESULTS

The selection of input data that represent 3D hull form is very important. In this study, 3D hull forms are represented as combination of x, y, and z. As Fig.4(a) shows the hull form information of the part of Entrance is used for C_w prediction. Because C_w is related with the part of Entrance closely. The hull is divided among 20 in the direction of x, and also divided among 15 from the bottom to draft in the direction of z. Then, the y values of the 90 interaction points at section 15, 17, 18.5, 19, 19.5, 20 are used for hull information.



(a) Entrance part for C_w prediction



(b) Run part for Form-factor prediction

Fig. 4 3D expression for Neuro-fuzzy input valuable

Output data is 8 C_w values according to Froude number (Fn=$v/\sqrt{gL}$:0.125, 0.13, 0.135, 0.14, 0.145, 0.15, 0.155, 0.16). As Fig.4(b) shows, the 120 interaction points of the part of Run are used for Form-factor prediction because it is related with the part of Run.

A. C_w prediction

In 31 ships, 27 ships were used for training data and 4 ships were used for validation. For C_w prediction, cross validation was conducted using 31 ships that were classified into 8 groups randomly. The result of this validation were compared with the result of estimation method(Regression) used actually in ship building plants. In addition, we selected one group among 8 groups and compared the result of Neuro-fuzzy with the result of standard back-propagation.

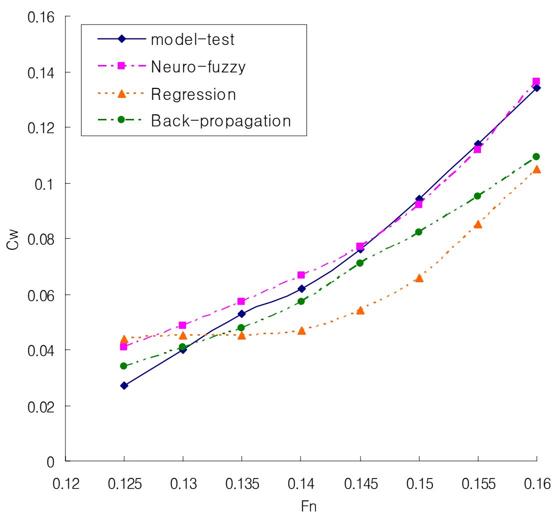
For the cross validation, we conducted experiment in the condition that Epoch number was 2,000, training rate was 0.5 and the number of partition is 3. Table 2 shows that error rate of Neuro-fuzzy was lower than one of Regression.

Table 2 cross validation result

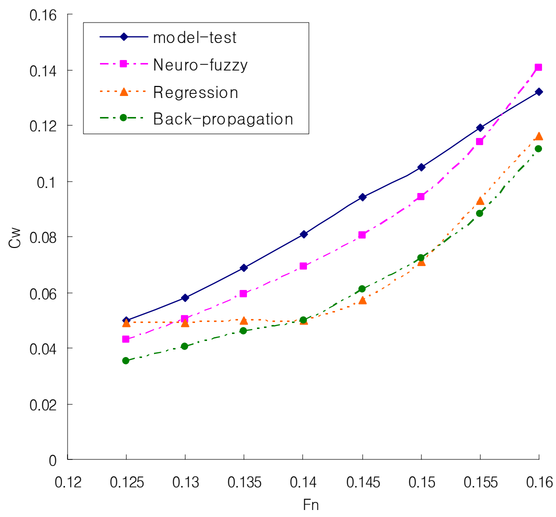
group	Traning error(MSE)	Neuro-fuzzy error(%)	Regression error(%)
1	0.11	16.3	33.0
2	0.09	13.4	22.9
3	0.05	22.5	28.2
4	0.18	18.6	24.6
5	0.15	15.6	24.3
6	0.14	24.4	29.0
7	0.16	19.3	17.3
8	0.14	30.2	26.0

The result of Neuro-fuzzy was compared with one of Standard back-propagation at group 2. In the condition that Neuro-fuzzy Epoch number was 2,000, training rate was 0.5, and Fuzzy partition was 3, MSE(Mean Square Error) was 0.097. In the case of standard back-propagation MSE was 0.0041 in the condition that Epoch number was 50,000, and training rate was 0.5.The result is presented at Table 3.

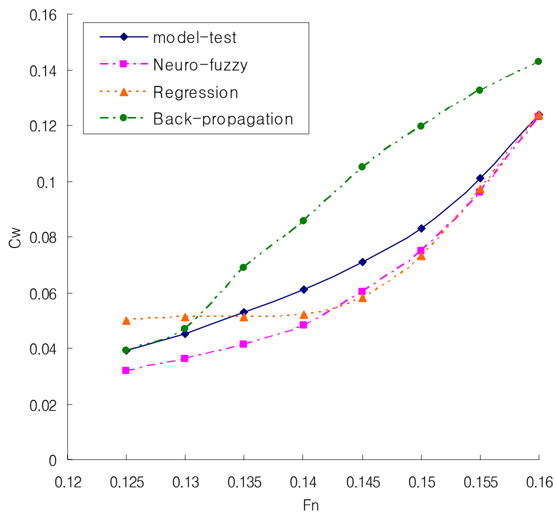
The error rates were 11.8%, 11.4%, 14.0%, 16.5% in order, and the average was 13.4%. On the other hand, the error rates of Regression were 27.57%, 23.63%, 11.80%, 28.88% and these were quite higher than ones of Neuro-fuzzy. The results of Standard back-propagation were 23.3%, 29.9%, 26.5%, 14.1%, and the average error was 20.76%. Fig. 5 represent those results.



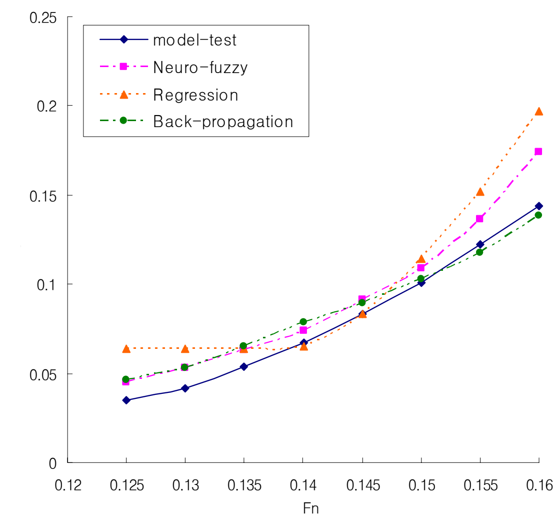
(a) test ship 1



(b) test ship2



(c) test ship3



(d) test ship4

Fig. 5 comparison of C_w prediction result

Table 3 experiment result

classification \ Fn		0.125	0.130	0.135	0.140	0.145	0.150	0.155	0.160
Model-test (target)	Ship1	0.027	0.040	0.053	0.062	0.076	0.094	0.114	0.134
	Ship2	0.050	0.058	0.069	0.081	0.094	0.105	0.119	0.132
	Ship3	0.039	0.045	0.053	0.061	0.071	0.083	0.101	0.124
	Ship4	0.035	0.042	0.054	0.067	0.083	0.101	0.122	0.144
Neuro-fuzzy	Ship1	0.041	0.050	0.058	0.067	0.076	0.093	0.113	0.138
	Ship2	0.044	0.051	0.060	0.070	0.081	0.095	0.115	0.144
	Ship3	0.031	0.036	0.040	0.048	0.060	0.074	0.095	0.121
	Ship4	0.042	0.050	0.060	0.070	0.084	0.102	0.128	0.163
Regression	Ship1	0.044	0.045	0.045	0.047	0.054	0.066	0.085	0.105
	Ship2	0.049	0.049	0.050	0.050	0.057	0.071	0.093	0.116
	Ship3	0.050	0.051	0.051	0.052	0.058	0.073	0.097	0.124
	Ship4	0.064	0.064	0.064	0.065	0.083	0.114	0.152	0.197
Standard back-propagation	Ship1	0.034	0.041	0.048	0.057	0.071	0.082	0.095	0.109
	Ship2	0.035	0.040	0.046	0.050	0.061	0.072	0.088	0.111
	Ship3	0.039	0.047	0.069	0.086	0.105	0.119	0.132	0.143
	Ship4	0.046	0.053	0.065	0.079	0.090	0.103	0.118	0.139

B. Form-factor prediction

88 ships were used for training data and 8 ships were used for validation. Fuzzy partition was 3 and training rate was 0.5 for input, and each Form-factor value was used for output. Training error(MSE) was 0.276 and the prediction result of 8 ships are represented at Table 4.

Table 4 Form-factor prediction result

Test ship	Model test (target)	Neuro-fuzzy (prediction)	Regression
1	1.178	1.197	1.1526
2	1.215	1.243	1.2208
3	1.259	1.200	1.1629
4	1.160	1.180	1.1419
5	1.215	1.261	1.2497
6	1.228	1.262	1.2350
7	1.245	1.254	1.2112
8	1.214	1.254	1.1682

The average error rate of ships which are not used for training at Table 4 is 2.59%.We can know there is little estimation error. This result is better than 2.71% which is the estimating rate using Regression.

V. CONCLUSIONS

It is found from the result that the resistance estimation using Neuro-fuzzy helps hull from designer to produce hull forms. This method can represent hull form more accurately and is more precise than Regression. Moreover, it is less complicated and can identify the result more quickly than CFD. If study about the relation between the number of in-output variables and the number of pattern advances , we can expect the better result.

The following results were obtained:

- To find relation between the relation between hull form and in-output of performance, we use Artificial Intelligence mothod.

- Using breadth values at Entrance and Run part, we diminishes the number of input variables.

- At C_w estimation, it shows that the estimation using Neuro-fuzzy is more accurate through the comparison between the results of Regression and ones of Neural-network. And at $1+k$ estimation, it is possible to get the highly precise results compared with the results of Regression.

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