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Statistical Prediction of Wake Fields on Propeller Plane by Neural Network using Back-Propagation

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Abstract

A number of numerical methods like Computational Fluid Dynamics(CFD) have been developed to predict the flow fields of a vessel but the present study is developed to infer the wake fields on propeller plane by Statistical Fluid Dynamics(SFD) approach which is emerging as a new technique over a wide range of industrial fields nowadays. Neural network is well known as one prospective representative of the SFD tool and is widely applied even in the engineering fields. Further to its stable and effective system structure, generalization of input training patterns into different classification or categorization in training can offer more systematic treatments of input part and more reliable result.

Because neural network has an ability to learn the knowledge through the external information, it is not necessary to use logical programming and it can flexibly handle the incomplete information which is not easy to make a definition clear. Three dimensional stern hull forms and nominal wake values from a model test are structured as processing elements of input and output layer respectively and a neural network is trained by the back-propagation method. The inferred results show similar figures to the experimental wake distribution.

Keywords: ship wake, statistical fluid dynamics, neural network, back-propagation method

1 Introduction

Afterbody shape of a merchant vessel has a big influence on the flow fields on the propeller plane and consequently on the self propulsion factors such as wake factor, thrust deduction factor, relative rotative efficiency as well as resistance characteristics. And this flow field on the propeller plane is directly connected with propeller design and governs its cavitation behavior and propulsive efficiency. So high wake peak or inhomogeneous wake patterns should be avoided by a good qualified hull form design. Every hull form designer try to image or infer flow patterns of his designing hull forms in the course of all design procedure because they want to keep a certain limitation of homogeneity of the flow fields within the given restriction.

CFD tool is one of the good candidates to carry out this kind of estimation or simulation, which adopts numerical approach to solve physical problem with some simplification and assumption, but the results of the CFD show a little bit of skeptical aspect yet even though it requires a very high performance computing machine and also a long computing time as well as a tedious grid generation procedure.

Another emerging approach to predict the flow fields or hydrodynamic behavior is based on the previous experimental experience and systematically accumulated data. Neural networks are today expanding its application ranges and capabilities by adopting new technologies such as fuzzy theory, genetic algorithm and back propagation in comparison with a previous rigid regression method. Even in ship design fields, Neural Network is already being introduced, but it is just in the limited ranges so far. It normally employs artificially formulated parameters (such as L/B ratio, B/d ratio, etc) as input variables and simply draw outputs for the estimation and optimization.

However, we carried out a study to use offset data themselves as input variables which are similar to the input hull form data of CFD computation to predict the wake fields on the propeller plane as output results. The offset datum simply converted to the angle value at a certain point is focused to a certain point to have same height value on the vertical line of the propeller plane. This simple treatment is evaluated that all desired output points on the propeller plane and input offset points over hull surface are well connected to have physical meaning and it is one of the important factors to get better results.

Input and desired output data are constructed from 57 vessels built actually in HHI and measured wake data in Hyundai Maritime Research Institute including the various kinds and ranges from very large full VLCC to high speed slender container carrier.

2 Neural network

2.1 Basic description of neural network

The neural network technique is structured to attempt artificial modeling of the human brain's problem solving capabilities such as calculation, recognition and training. The physical networking transfers a proper signal or stimulus by interaction between biological neurons, which will be referred as a processing element in the artificial system. The processing element(PE) has many input paths and combines, usually by a simple summation. The combined input is then modified by a transfer function. This transfer function can consist of special kinds of mathematical functions like sigmoid, hyperbolic tangent or sine. When input values are connected to each other, the proper weights which correspond to the synaptic strength of neural connection is multiplied and added to reach the desired output processing elements. The output value manipulated by the transfer function is generally passed to the output layer, but some hidden layers can be added between the input and output layer for the improvement of the network accuracy in a certain complex case. The weights are modified continuously through a number of iteration to have appropriate correlation between input and output processing elements.

2.2 Back propagation technique

Back propagation network, which is also sometimes referred to as a multi-layer perceptron, is currently used as a common neural network paradigm. Back-propagation network achieves its generality by the gradient-descent technique that is analogous to an error-minimization process. Error minimization is an attempt to fit a closed-form solution to a set of empirical data points.

The BPN (back propagation network) learns to generate a mapping from the input pattern

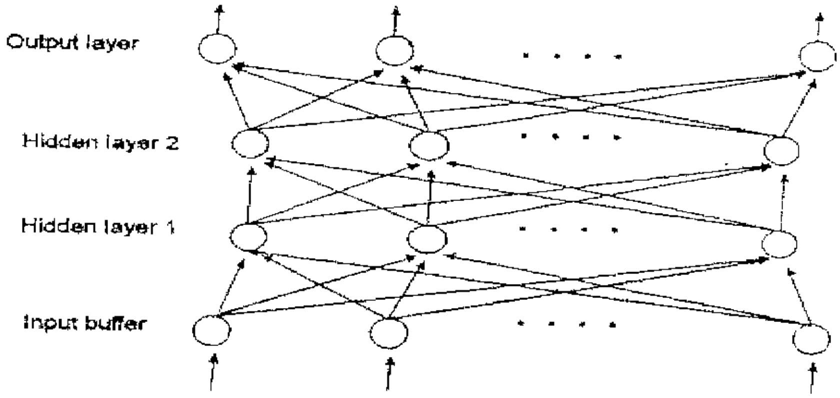

Figure 1: Typical back-propagation processing element

space to the output pattern space by minimizing the error between the actual output produced by network and the desired output. Each unit modifies its input connection weights slightly in a direction that reduces its error signal, and the process is repeated for the next pattern. A back-propagation element transfer its inputs as follows:

$$x_j^{[s]} = f\left(\sum_i (w_{ji}^{[s]} \cdot x_i^{[s-1]})\right) = f(I_j^{[s]}) \tag{1}$$

$x_j^{[s]}$ Current output state of j^{th} neuron in layer s
$w_{ji}^{[s]}$ Weight on connection joining i^{th} neuron in layer $(s-1)$ to j^{th} neuron in layer s
$Ij^{[s]}$ Weighted summation of inputs to j^{th} neuron in layer s

where f is traditionally, the sigmoid function but can be any differentiable function. The sigmoid function is defined as

$$f(z) = (1.0 + e^{-z})^{-1} \tag{2}$$

If some global error function E associated with it which is a differential function of all the connection weights in the network, the critical parameter that is passed back through the layer s is defined by

$$e_j^{[s]} = -\partial E / \partial I_j^{[s]} \tag{3}$$

Using the chain rule twice in succession gives a relationship between the local error at a particular processing element at level s and

$$e_j^{[s]} = f'(I_j^{[s]}) \cdot \sum_k (e_k^{[s+1]} \cdot w_{kj}^{[s+1]}) \tag{4}$$

If f is the sigmoid function as defined in (2), then its derivative can be expressed as a simple function of itself as follows:

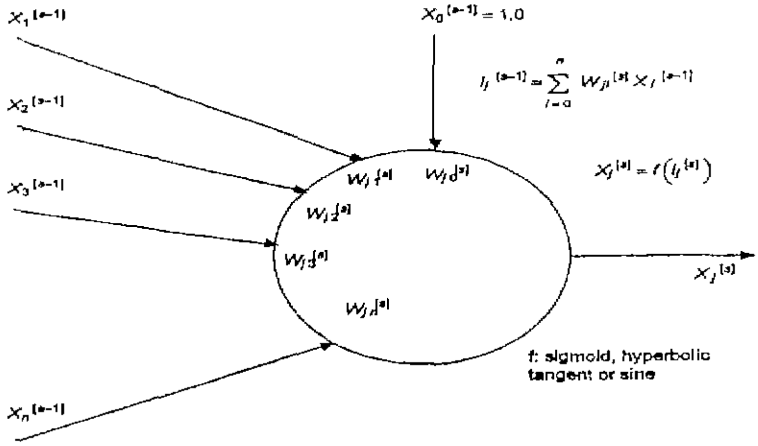

Figure 2: Typical back-propagation proccssing element

$$f'(z) = f(z) \cdot (1.0 - f(z)) \tag{5}$$

Therefore, from (1), equation (4) can be rewritten as

$$e_j^{[s]} = x_j^{[s]} \cdot (1.0 - x_j^{[s]}) \cdot \sum_k (e_k^{[s+1]} \cdot w_{kj}^{[s+1]}) \tag{6}$$

Provided the transfer function is a sigmoid. The summation term in (6) which is used to back-propagate errors is analogous to the summation term in (1) which is used to forward propagate the input through the network. Thus the main mechanism in a back-propagation network is to forward propagate the input to the output layer, determine the error at the output layer, and then propagate the error to the input layer using (6) or more generally (4). The multiplication of the error by the derivative of the transfer function scales the error. The aim of the learning process is to minimize the global error E of the system by modifying the weights. Given the current set of weights $w_{ij}^{[s]}$, increment or decrement of them is determined to decrease the global error. This can be done using a gradient descent rule as follows:

$$\triangle w_{ji}^{[s]} = -C_{\text{learn}} \cdot (\partial E / \partial w_{ji}^{[s]}) \tag{7}$$

where C_{learn} is a learning coefficient. In other words, it changes each weight according to the size and direction of negative gradient on the error surface. The partial derivatives in (7) can be calculated directly from the local error values discussed in the above, because, by the chain rule and (1):

$$\partial E / w_{ji}^{[s]} = (\partial E / \partial I_j^{[s]}) \cdot (\partial I_j^{[s]} / \partial w_{ji}^{[s]}) = -e_j^{[s]} \cdot x_i^{[s-1]} \tag{8}$$

Combining (7) and (8) together gives

$$\triangle w_{ji}^{[s]} = -C_{\text{learn}} \cdot e^{[s]} \cdot x_i^{[s-1]} \tag{9}$$

In the above the existence of a global error function has been assumed without actually specifying it. This function is needed to define the local errors at the output layer so that they can be propagated back through the network. Let o denote the actual output produced by the network with its current set of weights. If a vector i is presented at the input edge layer of the network and the desired output d is specified by a teacher, then the global error in achieving from the desired output is given by

$$E = 0.5 \cdot \sum_k \left((d_k - o_k)^2 \right) \tag{10}$$

Here, the raw local error is given by $d_k - o_k$. From (3), the scaled "local error" at each processing element of the output layer is given by

$$e_k^{(o)} = -\partial E / \partial I_k^{(o)} = -\partial E / \partial o_k \cdot \partial o_k / \partial I_k = (d_k - o_k) \cdot f'(I_k) \tag{11}$$

E in (10) defines the global error of the network for a particular (i, d). An overall global error function can be defined as the sum of all the pattern of specific error functions. Then each time a particular (i, d) is shown, the back-propagation algorithm modifies the weights to reduce that particular component of the overall error function.

3 Hull form description for neural network

In order to embody a real problem well in the network system, it is most important to represent the problem as the appropriate input data to have physical meaning. Offset data of a hull form themselves have a very native physical meaning because it indicates wideness at a certain position and this has a very close connection with flow speed on the propeller plane. Raw and simple representation may simulate the real problem effectively. It's the main reason why the offset data of hull form are simply used as input parameters in this neural network system.

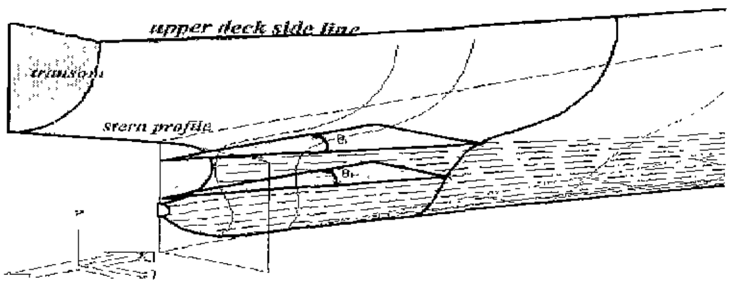

Figure 3: Offset definition by angle value

But there is still one difficulty to make the network system recognize effectively the three dimensional offset data even if they means wideness at a certain point. To overcome this problem, lengthwise and breadthwise values of offset data are converted to an angular value converged horizontally into one vertical line at the propeller plane shown in Figure 3. It gives physical meaning that two dimensional value is expressed by one implicative value.

Furthermore, entire input data are obtained at the particular x and z position because each vessel has different dimensions respectively such as propeller diameter, ship length and breadth. When it is considered wake value is defined as the flow velocity induced on propeller plane, it is a highly meaningful approach to generate newly non-dimensionalized section and water line by propeller diameter size. Six new stations (0.5,1,2,3,4,5 $\times D$, where D is the diameter) and twelve new waterlines (from $0.1D$ level to $1.2D$ level by each $0.1D$ increment) are generated and crossed to get the input data values shown in Figure 4, and it is esteemed good enough to represent after body of the hull.

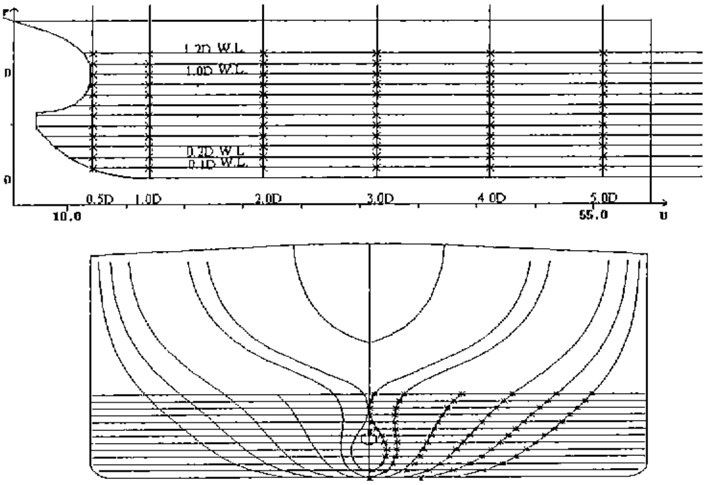

Figure 4: Section and waterline description

According to each angular position and radial direction, measured wake values on the propeller plane are set as a desired output of the system. It can be divided by every 10 degrees over a half side of propeller plane and 19 divisions in clockwise direction. In addition, five radial divisions from $r/R = 0.4$ to 1.0 by 0.15 steps are added and in consequence total 19×5 points of wake values are adopted as output parameters. The wake is of cause non-dimensional value by ship's speed. The basic input and output data consist of hull forms and measured wake data by model tests that cover whole ranges which can be extended to the merchant vessel, whose total number of vessels reach 57. The block coefficient of the collected hull forms is widely dispersed from about 0.55 to more than 0.85 and the ship's speed in Froude number is from 0.14 to 0.26. In general the reliability of the trained neural network system is quite dependent on the number of data group because the correlation between input and output data are more enhanced if more cases are shown to network. The commercial program "NeuralWorks Professional II/PLUS" developed by "NeuralWare, Inc." is used for prediction of the wake field on the propeller plane in this paper.

4 Network training for simulation of wake fields

4.1 Input parameters and hidden layer

Simply converted angle values from crossed offset data by new 6 stations and 12 waterlines, as above stated, are utilized as the basic input parameters for the neural network training. To make a difference between stations, every station is classified and categorized before the training. This categorization can effectively upgrade the training.

4.2 Input data and categorization

The n and m indicate lengthwise and waterlinewise number, respectively. The input data are prepared as: (X_n, Y_m), for $n = 1$ to 6, and $m = 1$ to 12.

(1,1) (1,2) (1,3) (1,4) (1,5) (1,6) (1,7) (1,8) (1,9) (1,10) (1,11) (1,12)
(2,1) (2,2) (2,3) (2,4) (2,5) (2,6) (2,7) (2,8) (2,9) (2,10) (2,11) (2,12)
(3,1) (3,2) (3,3) (3,4) (3,5) (3,6) (3,7) (3,8) (3,9) (3,10) (3,11) (3,12)
(4,1) (4,2) (4,3) (4,4) (4,5) (4,6) (4,7) (4,8) (4,9) (4,10) (4,11) (4,12)
(5,1) (5,2) (5,3) (5,4) (5,5) (5,6) (5,7) (5,8) (5,9) (5,10) (5,11) (5,12)
(6,1) (6,2) (6,3) (6,4) (6,5) (6,6) (6,7) (6,8) (6,9) (6,10) (6,11) (6,12)

Lengthwise division

waterlinewise division

Figure 5: Input data numberings

4.3 Hidden layer

To select an optimum number of hidden layer, variation tests are carried out in the course of the neural network training and 1 hidden layer with 12 processing elements is finally adopted for the training.

4.4 Output parameters

Because the wake data for the tested models are not accumulated in a regular position due to different model sizes, each measured wake data are transferred to have a regular position by interpolation procedure. Every 10 degrees in clockwise direction and 5 radial divisions from $r/R = 0.4$ by 0.15 steps are made over a half side of propeller plane for the description of the wake value as the output parameters. So 19×5 points of the wake values are finally utilized for desired output processing elements in the training, which are produced in orders as: $(r/R_n, \theta_m)$, for $n = 1 \sim 5$ at $r/R = 0.4$,0.55, 0.70, 0.85, 1.0 and $m = 1 \sim 19$ between 0 and 180 degrees.

5 Training results of wake simulations

In the Figure 7, the neural network by back propagation results in 80% correlation and 0.074 RMS (Root Mean Square) errors during 100,000 trainings. Every input and output element shows

(1,1) (2,1) (3,1) (4,1) (5,1)
(1,2) (2,2) (3,2) (4,2) (5,2)
(1,3) (2,3) (3,3) (4,3) (5,3)
(1,4) (2,4) (3,4) (4,4) (5,4)
(1,5) (2,5) (3,5) (4,5) (5,5)
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.
.
(1,15) (2,15) (3,15) (4,15) (5,15)
(1,16) (2,16) (3,16) (4,16) (5,16)
(1,17) (2,17) (3,17) (4,17) (5,17)
(1,18) (2,18) (3,18) (4,18) (5,18)
(1,19) (2,19) (3,19) (4,19) (5,19)

↑ Top
↓ Bottom

0.4 r/R → 1.0 r/R

Figure 6: Output data numberings

its magnitude of correlation strength by symbols and its colors. It is generally found that the input elements which are close to the propeller plane have a strong relationship with the wake values. Especially processing elements in the low waterline level of the hull form and long distance position from propeller give less influence.

After the system training. the additional 4 new stern hull forms which is not used for learning with various kind of dimensions are tested for the confirmation of the level of network learning. An axial wake velocity and it's harmonic wake distribution of a VLCC are shown as one example in the Figure 8, the harmonic wake distribution of a Cape size Bulk carrier and a slender high speed large container carrier are shown in the Figures 9 and 10, respectively. It is estimated that the predicted results are so analogous to measured original wake fields, that it is good enough to be applied in the design stage before the model tests. Moreover, a very precise depiction of local vortices on the full afterbody hull forms can be stated very prospective application in the stern hull form design. Considering that even a very advanced CFD tool is suffering from difficulty to simulate the vortex flow correctly on the propeller plane, it can be esteemed that this new approach by the neural network technique may produces more reliable results.

To make a comparison of the wake predictions between neural network and CFD methods, very recent CFD results by KRISO(Korea Research Institute of Ships & Ocean Engineering), which have simulated relatively realistic hook-like vortex shape, is introduced here in Figure 12. The same computation on the KRISO VLCC is carried out by the neural network in this paper and its result is shown in Figure 11. It is very difficult to be directly stated better or worse between two methods. Figures 11 and 12 show that the present statistical approach method by neural network is unlikely inferior to the CFD in the simulation of wake fields for stern hull form design quantitatively as well as qualitatively.

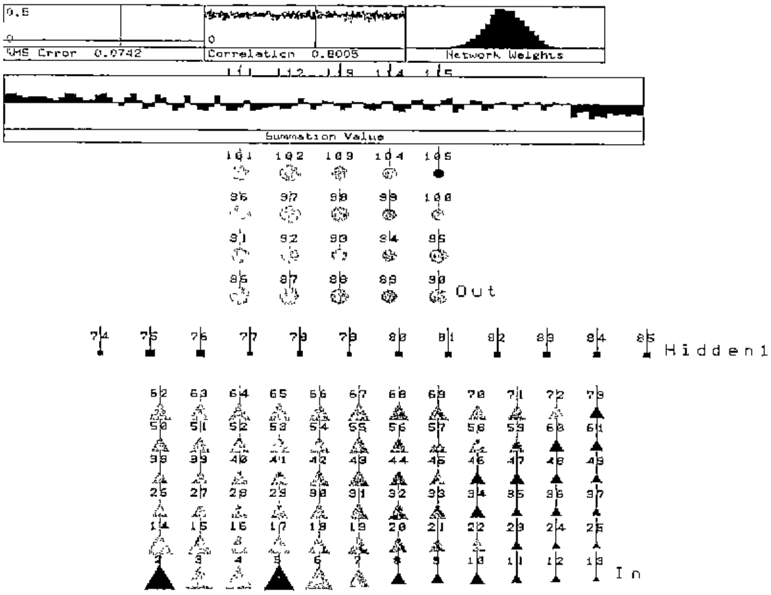
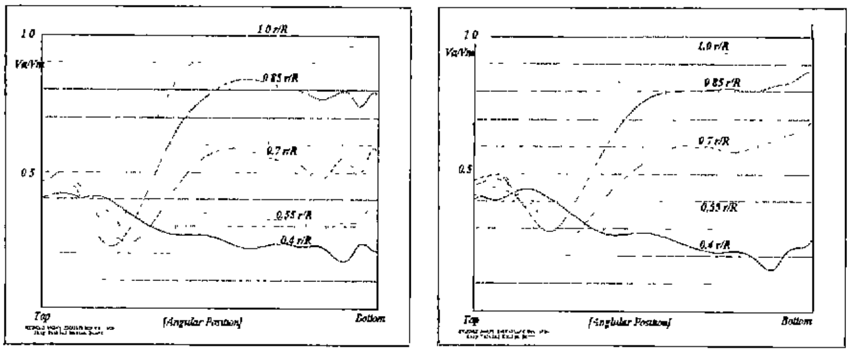
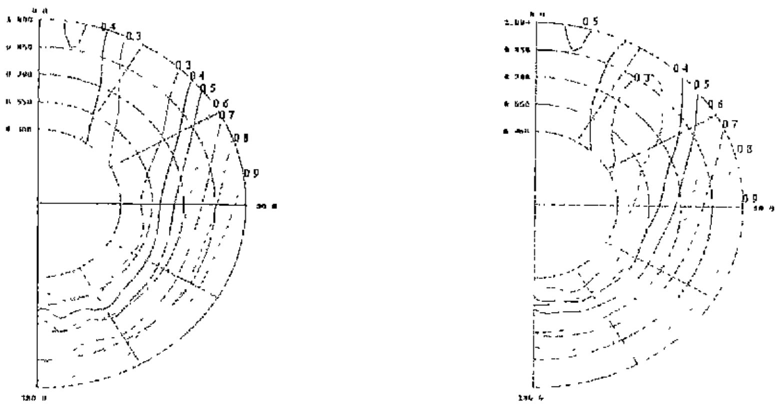


Figure 7: Trained network simulation



(a) Axial wake distribution



(b) Harmonic wake distribution

Figure 8: Measured(left) and predicted(right) wake fields for VLCC

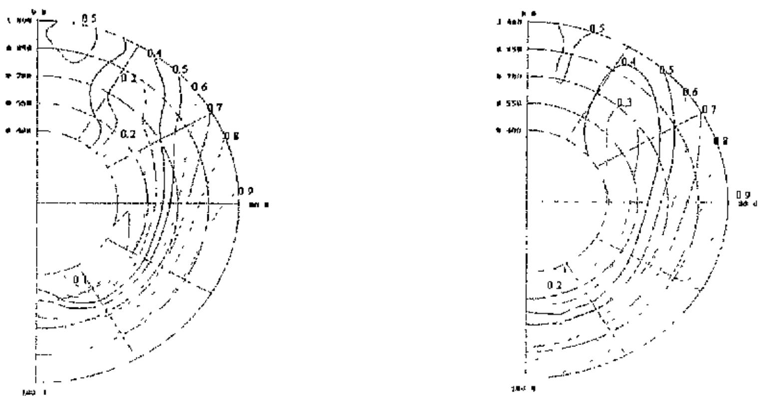


Figure 9: Measured(left) and predicted(right) wake fields for Cape size Bulk carrier

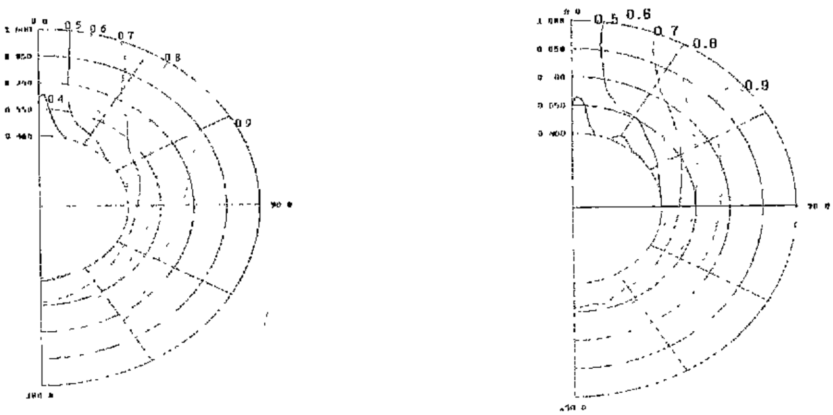


Figure 10: Measured(left) and predicted(right) wake fields for high speed large container

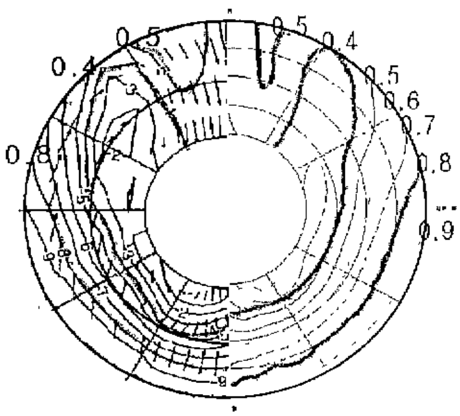


Figure 11: Measured(left) and predicted wake fields by neural network(right)

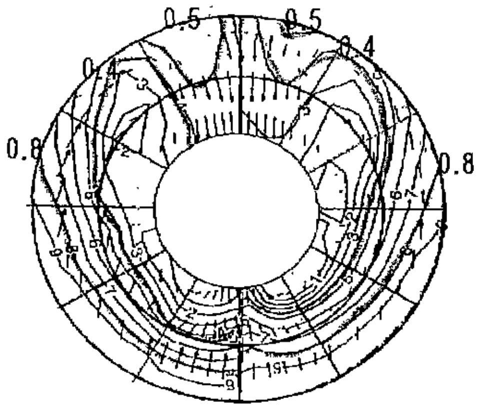


Figure 12: Measured(left) and calculated wake fields by CFD(right)

6 Conclusion

Simulation of the wake fields by a new statistical approach using neural network is carried out and prospective results, which show that inferred wake field on the propeller plane is very similar to the measured data, are obtained. Former neural network using fuzzy theory and genetic algorithm have been applied in a very limited fields of the ship design, while the flow fields prediction by back-propagation method of neural network in this paper may be a novel method to evaluate and optimize the stern hull form by prediction of a ship's wake distribution.

Although the offset data are used as input parameters like CFD computation, but it is not needed to take a lot of time-consuming processing for obtaining target values, and once the learning of system is finished, additional time consumption is not necessary for the wake field predictions of another new vessels. Furthermore, if the learning data are conglomerated more, the reliability of the system will be upgraded.

Even though the training and basic theory of the system itself have no physical sense of the flow pattern but the simulation results after the training indicates that flow pattern is physically connected with the stern hull form as good as imagination, of which results also hint the reliability of the method.

In this paper, training is made up to 100,000 times iterations and achieved 80% correlation results between input data and output data, and according to these it is expected to have obtained considerably similar results compared to measured data, but if further additional reinforcement, for instance by increasing the number of case of input, output data or further precise adjustment of hidden layer and processing elements can be done, the neural network may produce the much enhanced results with a more accurate correlation.

This method can be extended to predict and simulate all kinds of hydrodynamic matters. The form factor, wave resistance and all self-propulsion factors can be predicted through the neural network system with basic input parameters of offset data. It is regarded this system will be further developed to the entire optimization routine for the hull form design, which will be approached easily by anyone who wants to find something optimized.

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