A New Method of Ship Weather Routing Using Neural Network

A New Method of Ship Weather Routing Using Neural Network

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ABSTRACT

This paper describes a new approach to the strategic weather routing problem using neural network which is known as a powerful tool of pattern recognition. The 5-day mean 500hPa heights over the North Pacific Ocean for the first 5 days and the latter 5 days during the voyage were input to a neural network. The teacher signals were prepared by simulating the navigations of a container ship on the various routes from San Francisco to Tokyo using the analyzed wave data and calculating the passage times of these routes.

Learning of a neural network was performed for 105 voyages in 5 winter seasons. To verify the generalization ability, a new set of 5-day mean 500hPa heights in the different winter seasons were input to a trained neural network. As a result, a trained neural network could provide the optimum or sub-optimum routes for most of the voyages.

1. INTRODUCTION

At present, numerical weather forecast is carried out up to 10 days ahead on a daily operational basis. However, it can not retain sufficient accuracy beyond 3 or 4 days forecast period. Since it takes about 10 days even for the high-speed container ships to cross the North Pacific Ocean, the use of reliable wind and wave data for the period beyond 3 or 4 days from the departure time is essential to perform effective weather routing.

The research group on ship weather routing established in the Tokyo University of Mercantile Marine found that the 5-day mean wave distribution over the North Pacific in winter was closely related with the corresponding 5-day mean upper-air circulation pattern. They used the "zonal index" as a simple measure to represent the upper-air circulation pattern, and prepared 8 kinds of 5-day mean wave distribution models classified by 5-day mean zonal index. (The zonal index represents the difference between mean 500hPa height on the 40°N parallel and mean 500hPa height on the 60°N parallel in the longitudinal range of the North Pacific Ocean.)

Then the research group developed a simple weather routing method based on the zonal index./1//2/ The procedure of the method is as follows:

① Assume the combinations of 5-day mean zonal indexes for the first 5 days and the latter 5 days during the voyage. (The number of combinations is $8 \times 8 = 64$.)

② Using wave distribution models corresponding to these combinations, perform the minimum time route simulations to obtain 64 recommended routes.

③ At the departure time, predict the combination of 5-day mean zonal indexes for the first and the latter 5 days of the voyage, and adopt the recommended roure corresponding to that combination.

An example of the recommended routes calculated for a container ship (41,144 G/T, 244.8m L_{OA}) for the westbound voyage from San Francisco to Tokyo is shown in Fig.1.

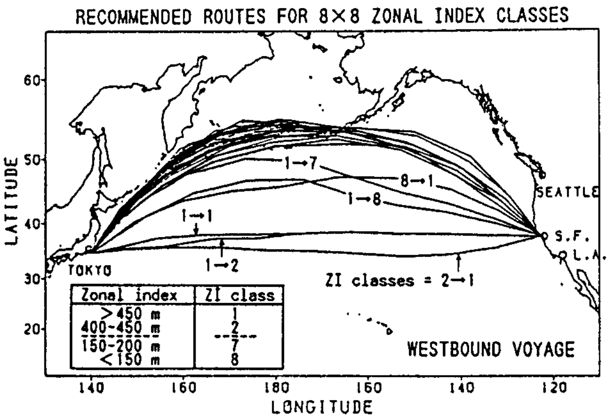

Fig.1 Recommended routes for 8x8 zonal index classes (S.F.→Tokyo)

From Fig.1, it is found that most of the recommended routes based on the zonal index pass through the Bering Sea. Only in the case that both 5-day mean zonal indexes during the voyage are very high (ZI>400m), the recommended routes pass through the vicinity of the rhumb line from San Francisco to Tokyo.

It has been verified by the simulations that this weather routing method is very effective for the strategic route selection at the departure time. /3/ However, since the zonal index is an extremely simplified index, it can not represent the details of the upper-air circulation pattern. For instance, when an upper-air trough or ridge is largely deviated from the mean location in some zonal index class, the development and movement of a surface depression can be largely different from the mean condition. In such a case, the recommended route by this routing method may become disadvantageous.

In this study, a new approach to the above mentioned strategic routing problem is described using the neural network which is known as a powerful tool of pattern recognition. By inputting the distribution pattern of 500hPa heights over the North Pacific, this neural network outputs the scores of 18 routes from San Francisco to Tokyo. It is expected that this neural network can recognize the difference between the distribution patterns of 500hPa heights that can not be distinguished by the zonal index, which leads to the selection of more advantageous route.

In the followings, the structure of weather routing neural network as well as the preparing method of input signals and teacher signals are described. After showing the learning algorithm of the neural network and the result of the learning, the generalization ability of the network is tested to verify the effectiveness of the proposed weather routing method.

2. WEATHER ROUTING NEURAL NETWORK

2.1 Structure of neural network

The proposed neural network for weather routing (WRNN: Weather Routing Neural Network) consists of 3 layers, i.e. input, hidden and output layers. The structure of WRNN is shown in Fig.2.

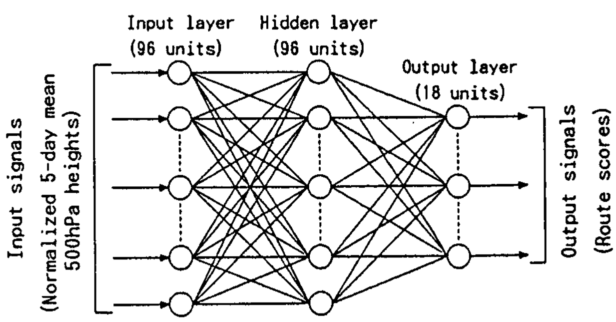

Fig.2 Structure of the WRNN

The numbers of input units and output units are 96 and 18 respectively, corresponding to the numbers of input signals and output signals. In general, we can choose the arbitrary number of hidden units. When the number of hidden units is too small, the learning can not be sufficiently achieved and the errors of output signals become large. On the other hand, when the number is too large, a network learns the unnecessary noises in the input signals, making also large errors of the output signals. For the WRNN, we tried to use as small number of hidden units as possible to achieve sufficient learning. Based on some learning trials, the number of hidden units was decided to be 96, being the same number as that of the input units.

2.2 Input signals of WRNN

Assuming 10-day voyage period, the 5-day mean 500hPa heights on the 30°N, 40°N, 50°N and 60°N parallels for the first 5 days and the latter 5 days during the voyage were used as the input signals to the WRNN. The longitudinal range of these data were chosen to cover the North Pacific Ocean, i.e. between 140°E and 110°W. These 5-day mean 500hPa heights were compiled from the daily 500hPa height analysis data of the Northern Hemisphere issued by the Numerical Forecast Division of Japan Meteorological Agency. The grid interval of these data is 10 degrees for both latitudinal and longitudinal directions. The number of 5-day mean 500hPa height data contained in the above longitudinal range is 48 (4×12), thus total number of the data becomes 96 for 10-day voyage.

Since these 500hPa heights approximately range from 4,800 m to 6,000 m and this range is relatively small compared with the height values, the raw 500hPa heights are not suitable as the input signals to the WRNN. In order to emphasize the height differences, the 500hPa height data in 1978-1991 were normalized by letting the lowest height 4,844 m be zero and the highest height 5,935 m be one. These normalized 5-day mean 500hPa heights ranging from 0 to 1 were input to 96 units of the input layer.

As an example of the input signals, the three-dimensional views of the normalized 5-day mean 500hPa heights for the period from Jan.1 until Jan.20 in 1979 are shown in Fig.3.

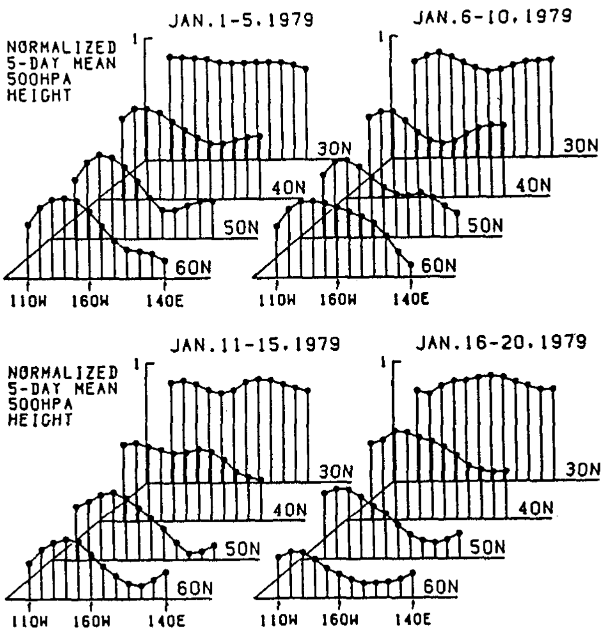

Fig.3 Example of input signals to the WRNN (Jan.1-20, 1979)

From Fig.3, the followings can be found; (1) The 500hPa heights in high latitudes are lower than those in low latitudes; (2) The 500hPa heights in the Western Pacific are lower than those in the Eastern Pacific; (3) The time-changes of the distribution pattern of 500hPa heights are considerably large. For example, 96 normalized 5-day mean 500hPa heights for Jan.1-5 and Jan.6-10 are input to the WRNN for the voyage departing on Jan.1, 1979.

2.3 Teacher signals of WRNN

In order to prepare the teacher signals of WRNN, the navigations of a container ship were simulated on 18 routes from San Francisco to Tokyo for 105 voyages in the winter seasons of 1978-1983 using analyzed wave data. These 18 routes are shown in Fig.4, being numbered 1 to 18 in the order from the north to the south.

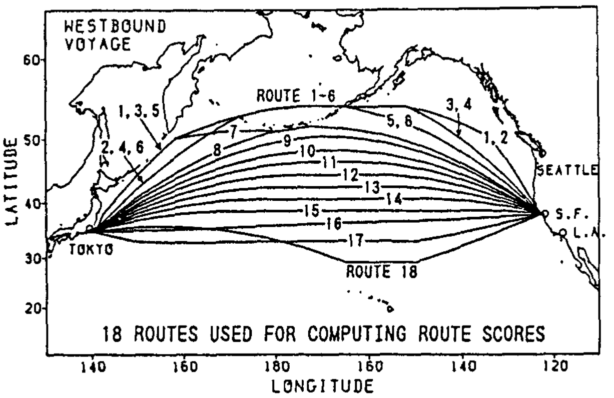

Fig.4 18 routes used for computing route scores, i.e. teacher signals

A score of each route was then computed based on the passage time so as to range from 0.1 to 0.9. The highest score 0.9 and the lowest score 0.1 were allocated to the minimum time route and the maximum time route, respectively. The score S of a particular route is given by

$$S = 0.8(T_{MAX}-T)/(T_{MAX}-T_{MIN})+0.1 \qquad (1)$$

where T_{MIN}, T_{MAX} and T are passage times of the minimum time route, the maximum time route and a particular route, respectively. Hereafter we call this score S the "route score".

Using the route scores determined by (1) as the teacher signals, the learning of WRNN was performed so as to let the output signals from 18 units of the output layer coincide with the teacher signals. The reason why the route scores were set between 0.1 and 0.9 is that the output signals of WRNN are produced by using logistic functions. The logistic function takes the value of 0/1 when the activation value of a unit reaches $-\infty/+\infty$. So, in order to produce all output signals with the finite activation values of the units, the values between 0.1 and 0.9 were allocated to the route scores./4/

3. LEARNING OF WEATHER ROUTING NEURAL NETWORK

3.1 Learning algorithm

For the before mentioned 105 voyages in the winter seasons of 1978-1983, inputting the normalized 5-day mean 500hPa heights for the first and the latter 5 days during the voyage to the WRNN, the learning of WRNN was carried out so as to let the output signals coincide with the teacher signals, i.e. the route scores. For the learning of WRNN, half of the sum of square errors of the output signals over all learning patterns (i.e. voyages) was used as a criterion function:

$$E = (1/2)\sum_{c=1}^{p} \{\sum_{j=1}^{m} (y_{j,c}-\hat{y}_{j,c})^2\} \qquad (2)$$

where $y_{j,c}$: output signal of the j-th unit in output layer for the c-th learning pattern

$\hat{y}_{j,c}$: teacher signal for the j-th unit in output layer for the c-th learning pattern

p : number of learnings (p=105)

m : number of units in output layer (m=18)

The output signal $y_{j,c}$ in (2) is generated by the following logistic function:

$$y_{j,c} = 1/\{1+\exp(-a_{j,c})\} \qquad (3)$$

$$a_{j,c} = \sum_{k=1}^{r} (w_{jk}\, z_{k,c}) - h_j \qquad (4)$$

where $a_{j,c}$: activation value of the j-th unit in output layer for the c-th learning pattern

w_{jk} : connecting weight from the k-th

unit in hidden layer to the j-th unit in output layer
$z_{k,c}$: output signal of the k-th unit in hidden layer for the c-th learning pattern
h_j : threshold value of the j-th unit in output layer
r : number of units in hidden layer (r=96)

The output signal $z_{k,c}$ in (4) is generated by the following logistic function:

$$z_{k,c} = 1/\{1+\exp(-a_{k,c})\} \tag{5}$$

$$a_{k,c} = \sum_{i=1}^{n} (w_{ki}\, x_{i,c}) - h_k \tag{6}$$

where $a_{k,c}$: activation value of the k-th unit in hidden layer for the c-th learning pattern
w_{ki} : connecting weight from the i-th unit in input layer to the k-th unit in hidden layer
$x_{i,c}$: input signal to the i-th unit in input layer for the c-th learning pattern
h_k : threshold value of the k-th unit in hidden layer
n : number of units in input layer (n=96)

Learning of the neural network is performed by correcting the connecting weights w_{jk}, w_{ki} and the threshold values h_j, h_k so as to decrease a criterion function E to zero. To achieve this process, regarding a criterion function E as the function of parameters w_{jk}, w_{ki} and h_j, h_k, these parameters are corrected in the opposite direction of the gradient vector of E. The corrections of the connecting weights and the threshold values are given by

$$\Delta w_{jk} = -\varepsilon \frac{\partial E}{\partial w_{jk}} = -\varepsilon \sum_{c=1}^{p} \{(y_{j,c}-\hat{y}_{j,c})\, y_{j,c}(1-y_{j,c})\, z_{k,c}\} \tag{7}$$

$$\Delta h_j = -\varepsilon \frac{\partial E}{\partial h_j} = -\varepsilon \sum_{c=1}^{p} \{(y_{j,c}-\hat{y}_{j,c})\, y_{j,c}(1-y_{j,c})(-1)\} \tag{8}$$

$$\Delta w_{ki} = -\varepsilon \frac{\partial E}{\partial w_{ki}} = -\varepsilon \sum_{c=1}^{p} \{ \sum_{j=1}^{m} [(y_{j,c}-\hat{y}_{j,c})\, y_{j,c}(1-y_{j,c})\, w_{jk}\, z_{k,c}(1-z_{k,c})\, x_{i,c}]\} \tag{9}$$

$$\Delta h_k = -\varepsilon \frac{\partial E}{\partial h_k} = -\varepsilon \sum_{c=1}^{p} \{ \sum_{j=1}^{m} [(y_{j,c}-\hat{y}_{j,c})\, y_{j,c}(1-y_{j,c})\, w_{jk}\, z_{k,c}(1-z_{k,c})(-1)]\} \tag{10}$$

Formulae (7)-(10) are called the error back-propagation algorithm, and ε in (7)-(10) is a positive constant called the learning rate which determines the magnitude of correction. Learning of the WRNN was carried out by the following procedure:

① Give an uniform random number between -1 and +1 to each weight and threshold as an initial value.
② For 105 voyages in which the teacher signals were computed, input the normalized 5-day mean 500hPa heights for the first and the latter 5 days of the voyage to the WRNN, and compute the output signals.
③ Using all teacher signals and output signals, calculate a criterion function (2); and if its value is less than 0.5, finish the calculation.
④ Calculate the correcting values of weights and thresholds by the formulae (7)-(10), and add these values to the present weights and thresholds.
⑤ Repeat the above process ②～④.

3.2 Result of the learning

Learning of the WRNN was executed following the above mentioned procedure. During the learning process, when the sum of square errors of the output signals fluctuated largely, the learning rate ε was decreased. The value of ε was set to 0.005, 0.004, 0.003 and 0.002 for the learning iterations of 1-10,000, 10,000-20,000, 20,000-90,000 and more than 90,000, respectively.

The change of the sum of square errors of the output signals during the learning process is shown in Fig.5.

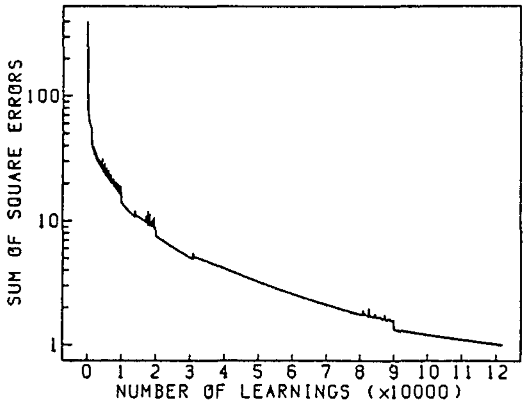

Fig.5 Change of the error of output signals during the learning process

From Fig.5, it is found that although the sum of square errors decreases largely at the beginning stage of the learning, decreasing rate becomes small fast. About 121,800 iterations of the learning were necessary to let the sum of square errors be less than 1.0. The reason for such many iterations is that in addition to the many learning patterns (105), there existed several cases that the teacher signal pattern for some input signal pattern differed largely from that for similar input signal pattern.

A part of the comparison of the output signals with the teacher signals at the completion of learning is shown in Fig.6. In Fig.6, both the signals (OUTPUT and TEACHER) on 18 routes for 18 voyages departing every 5 days from Nov.2, 1978 until Jan.26, 1979 are represented by the lengths of the vertical bars. As shown in Fig.4, the route 1 is the most northern one and the route 18 is the most southern one; the route 10 is the great circle route. From Fig.6, it can be seen that through an iterative learning, the WRNN could possess the ability to provide almost the same output signals as the teacher signals.

4. EVALUATION TEST OF WEATHER ROUTING NEURAL NETWORK

The WRNN trained as mentioned above

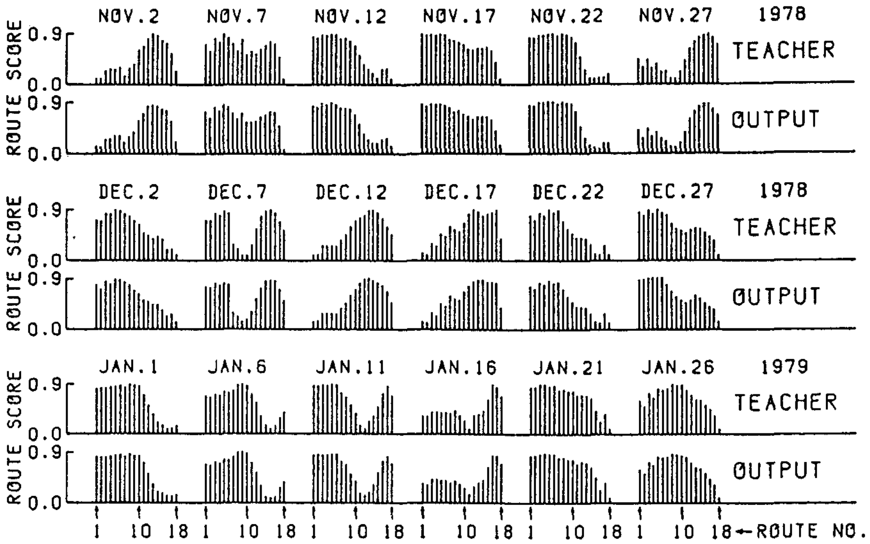

Fig.6 Comparison of the output signals with the teacher signals at the completion of learning

should provide the correct output signals for the input signals other than those used for the learning. In general, this ability of a neural network is called the generalization ability. A test to evaluate the generalization ability of the WRNN was performed for 36 voyages in two winter seasons of 1989-1991. The normalized 5-day mean 500hPa height data for the first and the latter 5 days of the voyages were input to the trained WRNN, and the route scores of 18 routes were output.

In each voyage, by simulating the navigation of a container ship on 18 routes using the analyzed wave data, the correct route scores of 18 routes were computed by (1). Hereafter these correct route scores are called the "target signals".

A part of the comparison of the output signals from the WRNN with the target signals is shown in Fig.7. In Fig.7, both the signals (OUTPUT and TARGET) on 18 routes for 18 voyages departing every 5 days from Nov.2, 1989 until Jan.26, 1990 are represented by the lengths of the vertical bars. From Fig.7, it can be found that when the route scores of the output signals are high on the northern routes and gradually become low as going to the south, the distribution pattern of the output signals almost coincides with that of the target signals. The distribution patterns for the voyages departing on Dec.12, Dec.22, Dec.27 and Jan.1 correspond to this case. In other cases, the distribution patterns of both signals do not always coincide well. However, concerning the voyages departing on Nov.12, Jan.6, Jan.21 and Jan.26 for instance, the rough shapes of the distributions of both signals can be regarded as the same.

In each voyage, let the route with the highest score of the output signal be the route based on the WRNN. On the other hand, let the route with the highest score of the target signal be the minimum time route (among 18 routes).

Concerning 36 voyages in two winter seasons (1989-1991), the comparison of route numbers of the routes based on the WRNN with those of the minimum time routes is shown in Fig.8. In Fig.8, the triangles and the circles denote the route numbers provided by the WRNN and those of the minimum time

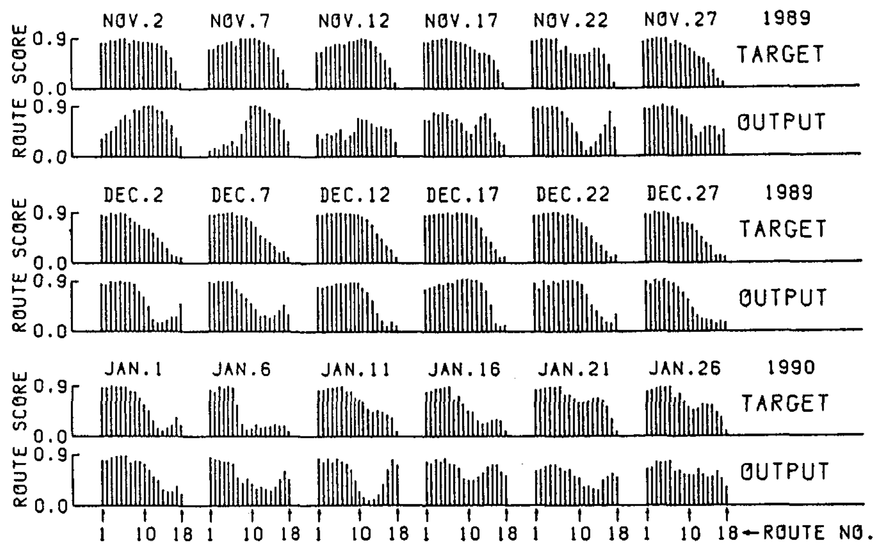

Fig.7 Comparison of the output signals from the trained WRNN with the target signals

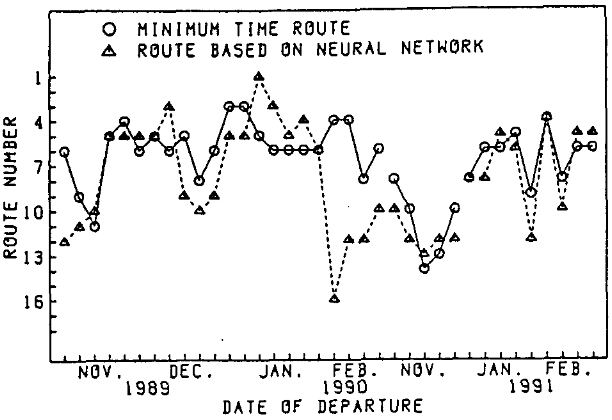

Fig.8 Comparison of route numbers of the routes based on the WRNN with those of the minimum time routes

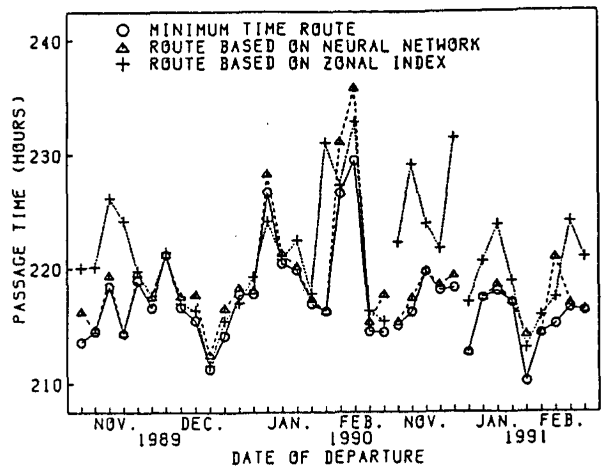

Fig.9 Comparison of passage times on the routes based on the WRNN with those based on the zonal index and those of the minimum time routes

routes, respectively.

From Fig.8, it can be found that the route numbers of both routes coincide well for most of the voyages except a few voyages. In 36 voyages, there are 5 voyages in which the route numbers of both route completely coincide; there are 20 voyages in which the difference between route numbers of both routes is 1 or 2. So, it can be said that the WRNN could provide the optimum or sub-optimum routes for most of the voyages.

Concerning 36 voyages, the comparison of passage times on the routes based on the WRNN with those based on the zonal index and those of the minimum time routes is shown in Fig.9. The passage times on the routes based on the zonal index were calculated by simulating the navigations of a container ship on the recommended routes corresponding to the combinations of 5-day mean zonal indexes shown in Fig.1 using the actual wave data. In Fig.9, the triangles, the crosses and the circles denote the passage times on the routes based on the WRNN, those based on the zonal index and those of the minimum time routes, respectively.

In most of the voyages, the passage times on the routes based on the WRNN were not so different from those of the minimum time routes; on the average over 36 voyages, the difference between the passage times of both routes was only 1.2 hours. In many voyages, the routes based on the WRNN were more advantageous than those based on the zonal index. There were 12 voyages in which the former routes could shorten the passage times more than 4 hours compared with the latter routes. The passage time of the route based on the WRNN was 14.8 hours shorter than that based on the zonal index in the maximum case, and 2.5 hours shorter on the average.

5. CONCLUSIONS

In this paper, the structure of the proposed WRNN (Weather Routing Neural Network) was shown and the methods of producing the input signals and the teacher signals for the WRNN were described. After showing the learning algorithm of the WRNN, the result of the learning performed for 105 voyages in 5 winter seasons (1978-1983) was presented. Finally, the result of evaluation test of a trained WRNN carried out for 36 voyages in the different winter seasons (1989-1991) was described.

In the evaluation test, the WRNN could achieve a better result compared with the routing method based on the zonal index. This is because the WRNN could recognize the difference between distribution patterns of the 500hPa heights which was not distinguishable by the zonal index. It can be concluded that the proposed WRNN is a very effective method for the strategic ship weather routing at the departure time or the beginning stage of the voyage.

In this study, the evaluation test of the WRNN was executed assuming that the 5-day mean 500hPa heights for the first and the latter 5 days of the voyage could be accurately predicted. Although the prediction of these 5-day mean 500hPa heights is much easier than that of the daily surface wind and ocean waves for 10-day period, the accuracy of predicted 5-day mean 500hPa heights should be thoroughly investigated when this WRNN is applied to the actual voyage.

In a practical use of the WRNN, it is expected that by comparing the route computed based on the predicted wind/wave data with the route based on the WRNN, a very reliable recommended route can be provided to the ship-master at the departure time. As the further research, the evaluation test of a trained WRNN will be performed for many other voyages and a new method of producing the input signals will be developed to improve the generalization ability of WRNN.

In addition to the application to the strategic ship weather routing, the neural network theory is applicable to many fields of marine navigation, such as optimum track keeping, collision avoidance, lookout support, damage-reducing manoeuvres in rough seas, etc.. The use of properly trained neural network for such navigational fields will greatly improve the safety and economy of ship operations.

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