Where are the North Atlantic fish going, and where should fishermen go?

Chengxin Li1,*, Liangchen Zhao2, Dongyun Li1, Chenyang Chang1, Jiakai Chen3, Chenlu Jiang1

1School of Emergency Management and Safety Engineering, China University of Mining and Technology-Beijing, Beijing, 100083
2School of Energy and Mining Engineering, China University of Mining and Technology-Beijing, Beijing, 100083
3School of Law and Humanities, China University of Mining and Technology-Beijing, Beijing, 100083

*Corresponding author email: chengxinli@cumtb.edu.cn

Abstract. On September 23, 2019, the World Meteorological Organization WMO published the Global Climate Report 2015-2019, which explained the trend of global warming. The phenomenon of rising global ocean temperature in the report is also an issue that needs to be researched. It will make certain marine life be forced to migrate from their habitats, thus affecting the development of economic industries such as fisheries. As consultants to the Scottish North Atlantic Fisheries Management Association, in this work, we have launched a corresponding study on this issue. Corresponding mathematical models have been established, which can well predict the future distribution of fish populations. Questions are essentially predictions of the future distribution of North Atlantic fish stocks and their impact on fishing companies. So our first task is to build an identification and prediction model of future fish habitat space model (IPM-FFHS Model). Because this distribution is caused by changes in ocean temperature, we have established a prediction model for the average sea surface temperature of the North Atlantic region (AMO-BP Model) based on BP neural network to predict future SST. At the same time, other influential factors of the distribution can modify the model. The AMO-BP Model was then combined with the current distribution of the habitat of the fish to draw a predicted spatial image of the future habitat range. At last, we combined the IPM-FFHS Model to obtain the abandonment temperature threshold of the fishery to obtain the duration of fish migration and the survival environment under different effects.

Keywords: Warming oceans, AMO-BP, Prediction of fish distribution.

1. Introduction

In the past 100 years, especially in the last 20 years, the global average surface temperature has increased significantly [1]. Global warming has become the focus of global change research and the focus of international politics. At the same time, the global ocean temperature is rising [2]. The global
ocean temperature is not only a serious environmental problem but also a serious economic problem. It will make some marine habitats forced to change, thus affecting the economic development of fishery related industries [3].

2. Establishment and Solution of Model

2.1. Resolution of problem

A. AMO-BP prediction model of future temperature change in the North Atlantic based on BP neural network:

(1) Data processing

In order to identify the most likely location of these two fishes in the next 50 years, we use the annual data of AMO from 1854 to 2018 to predict.

We try to use time series prediction model, least square linear regression fitting, grey prediction model and other simple prediction models to predict water temperature, and according to the error analysis of the prediction results, we find that the mapping relationship formed by grey prediction and least square regression fitting cannot accurately reflect the changing trend of AMO [4].

In order to get the mapping relationship that can reflect the long-term changes of AMO, we first processed the AMO data with low-throughput filtering.

![AMO history curve:1854-2018](image)

**Figure 1.** AMO history curve:1854-2018

(2) The establishment of neural network model

1) The establishment of neural network structure:

First, set a pair of samples \( (X, Y) \), where \( X \) is the input vector and \( Y \) is the output vector

\[
X = [x_1, x_2, \ldots, x_m]^T, \quad Y = [y_1, y_2, \ldots, y_n]^T
\]

Then set the hidden layer neurons: \( O = [O_1, O_2, \ldots, O_n] \)

The weight matrix between the input layer and the hidden layer is:

\[
w^1 = \begin{pmatrix}
w_{11}^j & w_{12}^j & \cdots & w_{1n}^j \\
w_{21}^j & w_{22}^j & \cdots & w_{2n}^j \\
\vdots & \vdots & \ddots & \vdots \\
w_{m1}^j & w_{m2}^j & \cdots & w_{mn}^j
\end{pmatrix}
\]  \( (1) \)

The weight matrix between the hidden layer and the output layer is:
Threshold of hidden layer is $\theta^1$, threshold of the output layer is $\theta^2$:

$$\theta^1 = [\theta^1_1, \theta^1_2, \ldots, \theta^1_l], \theta^2 = [\theta^2_1, \theta^2_2, \ldots, \theta^2_j].$$

Therefore, the output of the hidden layer is:

$$O_j = f\left(\sum_{i=1}^{n} w^2_{ij} x_i - \theta^1_j\right) = f(n_{et_j})$$

(The $f(x)$ is the transformation function of the hidden layer)

The output of the output layer is the predicted value:

$$z_k = g\left(\sum_{j=1}^{m} w^2_{kj} O_j - \theta^2_k\right) = g(n_{et_k})$$

(The $g(x)$ is the transformation function of the output layer)

2) Error formula between output and original output of network

$$E = \frac{1}{2} \sum_{k=1}^{l} (y_k - z_k)^2$$

$$= \frac{1}{2} \sum_{k=1}^{l} \left[ y_k - g\left(\sum_{j=1}^{m} w^2_{kj} O_j - \theta^2_k\right)\right]^2$$

$$= \frac{1}{2} \sum_{k=1}^{l} \left[ y_k - g\left(\sum_{j=1}^{m} w^2_{kj} f\left(\sum_{i=1}^{n} w^1_{ij} x_i - \theta^1_j\right) - \theta^2_k\right)\right]^2$$

$$w^2_{ij}$$ is the partial derivative between the hidden layer and the output layer.

The partial derivative of the error:

$$\frac{\partial E}{\partial w^2_{ij}} = \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial w^2_{ij}} = -(y_k - z_k) g'(n_{et_k}) O_j = -\delta^2_k O_j$$

$w^1_{ij}$ is the weight of the neuron between the input layer and the hidden layer.

The partial derivative of the error:

$$\frac{\partial E}{\partial w^1_{ij}} = \sum_{k=1}^{l} \sum_{j=1}^{m} \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial O_j} \frac{\partial O_j}{\partial w^1_{ij}} = -\sum_{k=1}^{l} (y_k - z_k) g'(n_{et_k}) w^2_{kj} f'(n_{et_j}) x_i = -\delta^2_k x_i$$
Combining equations (6) and (7) to get the weight adjustment formula (8)

\[
\begin{align*}
w_{kj}^{2}(t+1) &= w_{kj}^{2}(t) + \eta \frac{\partial E}{\partial w_{kj}^{2}} = w_{kj}^{2}(t) + \eta \frac{\partial E}{\partial w_{kj}^{2}}O_{j} \\
w_{ij}^{1}(t+1) &= w_{ij}^{1}(t) + \eta \frac{\partial E}{\partial w_{ij}^{1}} = w_{ij}^{1}(t) + \eta \frac{\partial E}{\partial w_{ij}^{1}}x_{i}
\end{align*}
\]

3) Training of neural network

After establishing the basic structure of neural network, the neural network toolbox in MATLAB is used to substitute the known AMO data for training, and the values of weight matrix and threshold matrix are adjusted continuously, finally the neural network meeting the accuracy requirements is obtained [5].

Eventually, we get the non-linear function fitting based on BP neural network (AMO-BP neural network), and create a suitable multi hidden layer neural network to improve the prediction accuracy of future temperature. Through the optimized AMO-BP Model, the possible changes of temperature in the North Atlantic in the future are predicted [6].

Of course, these prediction positions should be within the maximum moving range of the fish group. Predators, competitors and water quality are also factors that affect the distribution of the fish group, so the AMO-BP prediction model can be modified.

B. A recognition and prediction model for the habitat of fish in the future -- a case study of mackerel and herring

(1) The spatial distribution of fish habitat at present

Based on the data of the annual North Atlantic SST anomaly, the spatial image suitable for fish habitat distribution is drawn through the processing of uniform sampling and quadratic spline interpolation.

![BP neural network training diagram](image-url)
(2) Prediction of future fish habitat

Based on the AMO-BP prediction model and the spatial distribution of fish habitat, we can get the prediction of fish habitat in the next 30 years and 50 years, which shows that our model and method can identify and map the spatial position of fish in the next 50 years.
C. Sensitivity test of model

(1) Test of predictive reliability

In order to test the reliability of BP neural network, we collected amo data of each season from 1854 to 2018, and tested it with the constructed neural network in different seasons. Then we use the error formula to calculate the average error between the actual value and the predicted value.

Table 1. AMO prediction error

| season       | spring | summer | fall  | winter |
|--------------|--------|--------|-------|--------|
| error rate   | 9.397% | 12.66% | 3.097%| 4.131% |

(2) Sensitivity analysis

When constructing neural network, we set the number of neurons in the hidden layer as the parameter k and make k = 6. How will the change of K affect the prediction results? We analyze the effect of changing k on the mean deviation.

Table 2. Result table of Sensitivity test

| parameter | k-2 | k-1 | k+1 | k+2 |
|-----------|-----|-----|-----|-----|
| error rate| 12.33% | 7.6% | 9.92% | 14.58% |

It can be seen from the above table that the effect of K is not significant and is within the acceptable range.

2.2. Results and Analysis

(1) Conclusion for question one

According to the prediction of AMO-BP Model for the future temperature change and the spatial distribution of fish stocks, we know that in the future, the main fishing grounds in the North Atlantic will concentrate on the west coast, and two large-scale fishing grounds may be formed in the north...
central part of the US Coast and the south of Canada, while those on the European side will decrease or disappear.

(2) Conclusion for question two

In order to assess the impact of future sea water temperature changes on small-scale fishing companies in the UK, we first used the fish population spatial distribution model to determine that when the sea water rises 3 degrees Celsius, it will not be suitable for the survival of such fish, that is, to reach the abandonment threshold.

According to the AMO-BP Model, the most likely situation is to preprocess the AMO data of 165 years, filter out the abnormal values, and then predict the most likely time for fish to move to the living environment.

According to the AMO-BP Model, the best situation is the situation that the fish can be caught for the longest time before reaching the abandonment threshold of the fishing ground. That is to say, for the AMO data, only the abnormal value of the negative effect is filtered out, and then the prediction is carried out to get the duration of the survival environment of the fish in the best situation.

According to the AMO-BP Model, the worst case refers to the shortest time to catch fish before reaching the abandonment threshold of fishing ground, that is, only filter out the abnormal value of positive effect for AMO data, and then predict the time for fish to survive in the worst case.

In the end, we get that the most likely situation for small-scale fishing companies to continue to catch these stocks will make small-scale fishing companies unable to harvest, that is, to reach the threshold in the 24th year; the best situation is to reach the threshold in the 30th year; the worst situation is to reach the threshold in the 21st year.

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