ANALYSIS AND PREDICTION OF YELLOWFIN TUNA (*THUNNUS ALBACARES*) CATCH RATES OF LONGLINE FISHERIES IN THE WESTERN INDIAN OCEAN USING A NEURAL NETWORK

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Introduction

Strengthening tuna management is one of the primary tasks for the new Indian Ocean Tuna Commission (IOTC). Stock assessment and the prediction of the dynamics of the tuna resources will become increasingly important research topics because they provide the basic information for the management decision process. Under these circumstances, this paper attempts to develop the stock analyses and prediction techniques using neural networks. As a first step and as a test study, analyses and predictions of catch rates of the Japanese yellowfin tuna longline fisheries are attempted.

Neural networks

Background

Because fisheries data are uncertain in quality, and thus not adequate to fit rigid and logical mathematical models like those used in physics, engineering or chemistry, in recent years Artificial Intelligence (AI) methods have been introduced to fisheries resource analyses. Three major approaches have been applied with the AI techniques in fisheries: fuzzy logic, expert systems, and neutral networks. Fuzzy logic and expert systems are appropriate approaches for handling qualitative and descriptive data (thus, discrete variables) (Appendix A), while the neural network is a suitable method for prediction using the continuous variables that we usually handle, such as catch, effort, and CPUE as the input data.

Neural networks do not require a particular functional relationship and distribution assumptions for the data. Hence, they can be easily applied by non-statisticians and novice users (Cherkassky *et al*., 1994). They conduct parallel processing of all the information by non-linear interaction treatment. Neural networks have two special functions, 'learning' ability and the ability to recognize and classify patterns (Aihara, 1988). They can therefore learn complex non-linear events, then through a 'teaching – learning' process classify new information into a particular pattern. They are thus useful for predictions.

In recent years, a number of studies have been conducted in Japan using neural networks on the prediction analyses. In fisheries, Aoki and Komatsu (1995a) predicted fluctuation of sardine abundance, Hawing *et al* (1996) and Asano *et al* (1996) forecast catch of jack mackerels and Japanese sardine, respectively, and Kusakabe *et al* (1997) predicted recruitment of sand eel. In fisheries oceanography, Komatsu *et al* (1994) predicted the path type and offshore distance of the Kuroshio Current, Aoki and Komatsu (1995b) conducted neural network analyses of zooplankton abundance and long-term climate-ocean fluctuations, and Tameishi *et al* (1986) reported forecasting fishing and oceanographic conditions using a neural network. The predictions resulting from all of these studies were fairly accurate.

We therefore applied a neural network to our yellowfin tuna data to develop a prediction technique for the CPUE of adult fish in the longline fisheries. Appendix A provides more information on fuzzy logic and expert systems. These AI techniques in fisheries and oceanography are still experimental, hence a careful examination is necessary to see if they are feasible for analyses of tuna fisheries resources.

Theory

In the nervous system of living creatures there is a neural network system which is composed of (a) many neurons and (b) the synapses, which exchange the weighted signals among neurons (Figure 1). The neural network system shares the following characteristics with electrical circuits (Azabu, 1988). Neurons receive a stimulus (electrical signals) from other neurons. That stimulus has the accumulated values of the various neurons, and each neuron is weighted by each synapse. If the value of the summed neuron exceeds the threshold value, then that neuron (electrical signal) is re-transferred to other neurons..

There are two types of neural network system, depending upon the bonding structure among neurons (Figure 2): (a) feed-forward (layered) networks, in which the signals are transmitted in only one direction, and (b) a mutual bond networks, in which signals are exchanged in any direction among neurons (Kikuchi, 1988). The former is suitable for developing a pattern recognition technique, while the latter is suitable for solving problems of association, combination, and optimisation. In this study, we applied the first type of neural network because a pattern recognition problem is involved in the study.

A layered neural network has an input layer and an output layer, with several intermediate (hidden) layers in between (Figure 2). The input signal goes through units in the input layer, is transmitted into units in the intermediate layer, and finally becomes an output signal. A layered neural network generally uses the back-propagation technique. This technique has the function of adjusting the weight and threshold values in the units (neurons) in order to minimize errors between output signal values and the correct signal values (or 'teacher' signal values). This process is called 'supervised learning'. Computer software that can perform such processes is called a neural network simulator.

In practice, it has been shown that greater weight values in the neural network, given after completing the 'learning' process, affect the output value greatly, while smaller values affect it less. Based on this relationship, it is possible to find

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out which input data greatly contribute to output values by checking the size of the weight values in the neural network that completes the ‘learning’ process. We used a commercial neural network simulator, RHINE (CRC Inc.), on a personal computer in this study.

Analyses

Data

In this analysis, two types of the data sets are prepared: CPUE of Japanese longline fisheries and catch-at-age of all fisheries. The yellowfin (YFT) stock in the western Indian Ocean is assumed to be as defined by Nishida (1991). It is further assumed that FAO Area F51 is the approximate area of the western stock.

(1) CPUE (Japanese longline)

For a preliminary attempt, Japanese longline data for 1970-92, by 5°x5° areas within FAO Area F51, from the NRIFSF database were used, . Catch and effort (hooks) are primarily used.

(2) Catch-at-age (CAA)

Catch-at-age (CAA) data (1970-95) in the western Indian Ocean estimated by Nishida (IOTC/TWS/98/20) are used in the analyses. In that paper, CAA matrices for 8 gear types (Table 1) are initially estimated, then the global CAA is evaluated by summing up all the gear-specific CAAs.

(3) Environmental data

Annual Southern Oscillation Indices (SOI) are used. Although sea-surface temperature (SST) and other environmental parameters were considered for inclusion, their preparation was not completed before the analyses were initiated.

Model

It is reported that the dynamics of tuna populations are better explained by density-dependent processes, unlike small pelagic fish such as sardines and mackerels which are more affected by density-independent processes (Sugimoto, 1995). Therefore, this model assumes that the dynamics of the CPUE of adult YFT (age 2 or older) is primarily affected by density-dependent processes such as catch, effort and strength of the cohort. In addition, it is further assumed that YFT CPUE is also slightly affected by the density independent process by environmental factors such as the SOI, SSTs and other factors. Based on these assumptions, the model (input variables) are considered.

Figure 3 depicts adult YFT CPUE in the year t and its relevant cohorts in previous five years (*t*-5 to *t*-1). By examining this diagram, catches in the previous five years (*t*-5 to *t*-1) and CPUE in the previous four years (*t*-4 to *t*-1) are defined as the input variables, which are related to the CPUE of adult YFT in year t. In addition, the SOI indices for the previous 4 years (*t*-4 to *t*-1) are also included. The intention was to include SSTs, but there was not enough time to prepare the data before completing this paper. Table 2 lists 14 input variables.

Results

Table 3 and Figure 4 show actual figures of the response variable (YFT CPUE) and 14 input variables. Figures 5 and 6 show the results of the neural network analyses and synapse weights, respectively.

Discussion

To reduce confusion, we define ‘prediction’ as the CPUE trends up to year t reproduced by the learning process of the neural network, and ‘projection’ as the forecast CPUE value for year *t*+1.

Reproducing the dynamics of nominal CPUE

The results indicate that the neural network could reproduce approximate trends of the nominal CPUE. Those for the first half of the period reviewed (1975-84) were especially well reproduced. On the other hand, in the later period (1985-92), the nominal CPUE was not as well reproduced. This is probably due to the fact that catch (mainly purse-seine) and longline CPUE are not well correlated: as catch increased sharply in the period 1985-92, CPUE remained steady (Figure 4). Nishida (1995) pointed this out when studying the influence of purse-seine catch on longline CPUE. We probably need to include more qualified input variables relating to this event in the future.

Synapse weights and evaluation of the input variables

We chose three types of input variables: CPUE, catch and SOI. However, careful study of the synapse weights (Figure 6) shows that only a few input variables (C14(*t*-1), C03(*t*-2), C01(*t*-4) and SOI (*t*-4)) are good contributors for the prediction (reproduction). This is because synapse weights for these input variables showed a consistent sign with higher magnitudes. Therefore, if we re-evaluate the input variable, we may find better and unique variables that can explain the dynamics for the later period. To implement this re-evaluation process, we need to exclude unfavourable input variables and include new data such as SST, economic factors (fish price, demand, *etc.*), and catchability-related information (longline material, composition (deep/regular), *etc*.).

Use of other longline data

In this first attempt of this kind of analysis we used only Japanese longline data. We suggest using Taiwanese and Korean longline data for the same period and comparing the results to see if they are similar. Also, fine-scale data might be useful for this type of neural network analyses because we can include more realistic information.

Projection for t+1

We could reproduce the dynamics of CPUE fairly well because the neural network could learn the mechanisms of the CPUE dynamics from the input variables. Because we can reproduce the dynamics of CPUE to the year t, we can project (forecast) CPUE for year *t*+1. However, due to time constraints, this was not conducted in this paper.

Projection for longer term (after t+1)

Once we have the input information to year t, we can make the projection for year *t*+1. However, it is not possible to make projections for the longer term beyond year t because we have no information beyond year t. However, by setting various scenarios for the input values after *t*+1, we can make projections in the same way as for projections based upon the results of virtual population analysis (VPA). This means that some fixed values need to be set for the input values, *e.g.* average environmental conditions, a certain level of the catch and CPUE, *etc*.

Standardized CPUE

In this study nominal CPUE was used for the analyses and predictions, but standardized CPUE is used for tuning VPAs and should be used for this type of analysis, because nominal CPUE contains biases caused by year, season and area. In this way better prediction (reproduced CPUE) will probably be obtained.

Application to the other fisheries indicators

In this first attempt at neural network analyses of tuna data we analysed the longline data. Although the resulting prediction (reproduction) was not very accurate, we can improve the accuracy by selecting better input variables. In the future, we may attempt the analyses with other fisheries indicators to study their dynamics and predictions such as global catch, recruitment, *etc*. If these analyses and prediction produce reasonable results, we can provide more accurate and concrete suggestions for YFT resource management. Unlike small pelagic fishes like sardines and mackerel, the population dynamics of tuna follow density-dependent process (Sugimoto, 1995). Thus, tuna population are affected mainly by catch and fishing effort. Because IOTC (IPTP) has been building up a database on tuna fisheries (including fishing vessels), the neural network can be applied for other species.

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Table 1. Eight gear types for YFT catch and corresponding countries (from Nishida and Anganuzzi, 1998)

Gear type	**Artisanal**	**Industrial**
(1) **Pole and line (PL)**	Madagascar, Maldives, Sri Lanka	Spain
(2) **Troll (TROLL)**	Comoros, Kenya, Maldives, Mauritius, Seychelles, Sri Lanka, Mozambique, South Africa	France
(3) **Purse seine (PS) (free school)**	Belize, Cayman Islands, Iran, Ivory Coast, Libya, Malta, Seychelles, Sri Lanka	France, Iran, Japan, Panama, Russia, Spain
(4) **Purse seine (PS) (log school)**	Belize, Cayman Island, Iran, Ivory Coast, Libya, Malta, Mauritius, Seychelles, Sri Lanka	France, Japan (nil), Panama, Russia, Spain
(5) **Gillnet (GILL)**	Iran, Maldives, Pakistan, Sri Lanka	Taiwan
(6) **Unclassified (UNCL)**		
(a) Sri Lanka type (gillnet combined)	Sri Lanka	
(b) Yemen type (handline and gillnet)	Yemen	
(c) Oman type (troll, small PS & LL)	Oman	
(7) **Handline (HAND)**	Comoros, Maldives, Seychelles, South Africa, Sri Lanka	
(8) **Longline (LL)**	(small boats) Honduras, India, Kenya, Mauritius, Oman, Pakistan, Seychelles, Sri Lanka, Unknown	(large boats) France, Japan, Russia, Spain, China (Taiwan), Unknown

Table 2. List of 14 input variables used in the neural network analyses. Units: catch in millions of fish, CPUE in fish/1000 hooks. The response variable is CPUE of adult (age 2-5) YFT (fish/1000 hooks) of the Japanese longline fisheries.

Variable	Code	Meaning
Catch	C (age1- 4)(*t*-1)	Total catch (age 1-4) in year *t*-1
	C (age 0-3) (*t*-2)	Total catch (age 0-3) in year t-2
	C (age 0-2) (*t*-3)	Total catch (age 0-2) in year *t*-3
	C (age 0-1)(*t*-4)	Total catch (age 0-1) in year *t*-4
	C age 0 (*t*-5)	Total catch (age 0) in year *t*-5
CPUE	X (age1- 4)(t-1)	CPUE (age 1-4) in year *t*-1
	X (age 0-3)(*t*-2)	CPUE (age 0-3) in year t-2
	X (age 0-2)(*t*-3)	CPUE (age 0-2) in year *t*-3
	X (age 0-1)(*t*-4)	CPUE (age 0-1) in year t-4
SOI	SOI (*t*-1)	Southern Oscillation Index in year *t*-1
	SOI (*t*-2)	Southern Oscillation Index in year *t*-2
	SOI (*t*-3)	Southern Oscillation Index in year *t*-3
	SOI (*t*-4)	Southern Oscillation Index in year *t*-4

Table 3. Response variable (YFT CPUE) and 14 input variables

Year	YFT(*t*) CPUE	Var 1 C1_4(*t*-1)	Var 2 C0_3(*t*-2)	Var 3 C0_2(*t*-3)	Var 4 C0_1(*t*-4)	Var 5 C0(*t*-5)	Var 6 x1_4(*t*-1)	Var 7 x0_3(*t*-2)
	fish/1000 hooks	millions of fish					fish/1000 hooks	
75	8.163	2.351	4.688	3.672	2.765	1.391	8.337	11.7782
76	11.3557	1.841	5.482	4.621	2.824	1.113	12.2266	8.3212
77	16.8408	1.607	4.185	5.396	4.098	1.625	11.7524	12.1193
78	10.8648	1.962	4.376	4.13	5.004	3.197	16.8714	10.7606
79	4.7978	1.792	4.384	4.271	3.761	3.139	12.4617	14.2329
80	11.2406	1.458	3.874	3.954	3.874	2.347	4.7978	11.3863
81	7.7517	1.393	3.926	3.595	3.4	2.785	11.3612	4.6354
82	10.1849	1.957	3.829	3.668	3.182	2.502	8.6974	9.301
83	7.3279	2.044	5.079	3.674	3.414	2.115	11.6789	7.4712
84	8.7512	2.189	4.54	4.89	3.494	2.476	8.3449	11.2164
85	8.8533	3.273	8.947	4.293	4.559	2.468	8.9493	7.5029
86	8.8319	4.982	22.562	8.58	3.435	3.143	9.5112	8.2678
87	7.4367	6.428	18.931	22.072	8.072	2.525	9.6443	8.8617
88	8.7903	6.055	15.829	18.375	21.471	6.814	7.4587	9.3434
89	7.3909	9.114	15.153	15.096	17.748	19.392	8.8938	7.1561
90	10.2775	10.151	23.853	14.251	13.696	14.079	7.6132	8.4375
91	9.4031	10.581	23.468	22.582	12.594	9.474	10.5532	7.0918
92	6.675	9.432	25.689	22.873	20.731	9.166	9.5695	9.9496

Year	YFT(*t*) CPUE	Var 8 x0_2(*t*-3)	Var 9 x0_1(*t*-4)	Var 10 SOI(*t*-1)	Var 11 SOI(*t*-2)	Var 12 SOI(*t*-3)	Var 13 SOI(*t*-4)	Var 14 SOI(*t*-5)
	fish/1000 hooks	millions of fish		index				
75	8.163	13.3807	8.76998	1.01667	0.58333	-0.84167	1.0	0.25
76	11.3557	9.9443	2.42804	1.28333	1.01667	0.58333	-0.84167	1.
77	16.8408	6.754	0.44513	0.08333	1.28333	1.01667	0.58333	-0.84167
78	10.8648	10.6536	2.87573	-1.025	0.08333	1.28333	1.01667	0.58333
79	4.7978	7.0415	4.06361	-0.36667	-1.025	0.08333	1.28333	1.01667
80	11.2406	5.1318	0.40497	-0.10833	-0.36667	-1.025	0.08333	1.28333
81	7.7517	5.8016	0.05354	-0.375	-0.10833	-0.36667	-1.025	0.08333
82	10.1849	1.4213	1.65694	0.025	-0.375	-0.10833	-0.36667	-1.025
83	7.3279	2.8015	0.00406	-1.31667	0.025	-0.375	-0.10833	-0.36667
84	8.7512	2.9182	0.14654	-1.10833	-1.31667	0.025	-0.375	-0.10833
85	8.8533	9.7195	0.96005	-0.125	-1.10833	-1.31667	0.025	-0.375
86	8.8319	4.0544	1.51409	0.04167	-0.125	-1.10833	-1.31667	0.025
87	7.4367	5.1006	1.12721	-0.39167	0.04167	-0.125	-1.10833	-1.31667
88	8.7903	5.559	0.23196	-1.33333	-0.39167	0.04167	-0.125	-1.10833
89	7.3909	6.6253	0.68587	0.725	-1.33333	-0.39167	0.04167	-0.125
90	10.2775	3.9135	0.82245	0.56667	0.725	-1.33333	-0.39167	0.04167
91	9.4031	4.7524	0.02928	-0.39167	0.56667	0.725	-1.33333	-0.39167
92	6.675	3.8404	0.11108	-0.95	-0.39167	0.56667	0.725	-1.33333

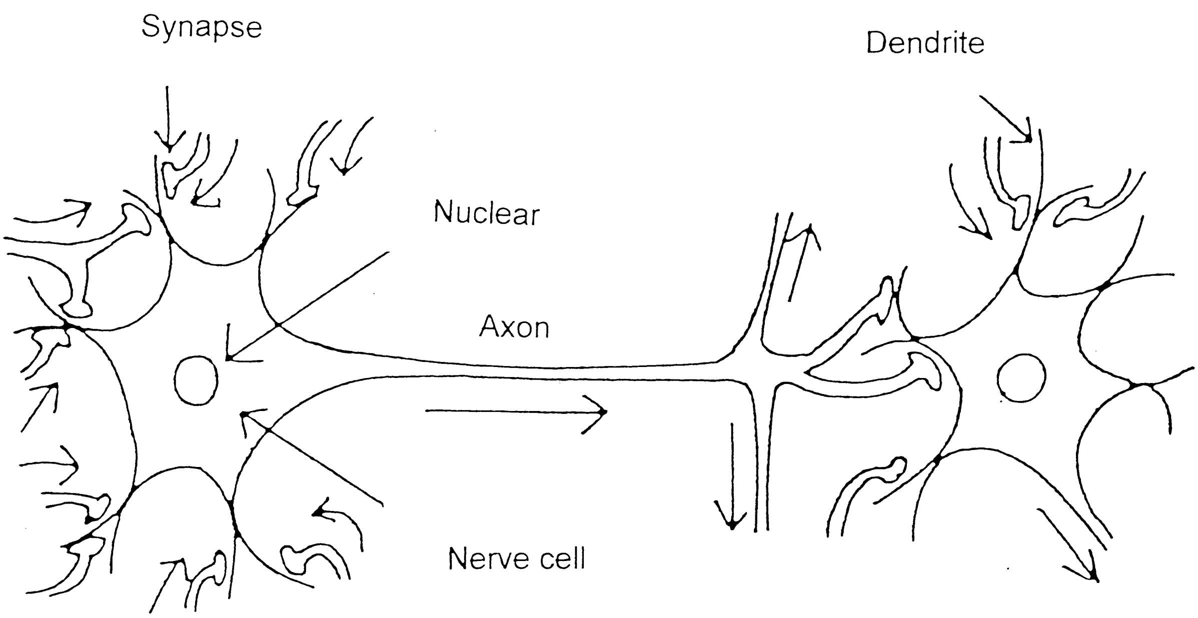

Figure 1. Schematic diagram of the neuron. Signals (data) flow in the direction of the arrows.

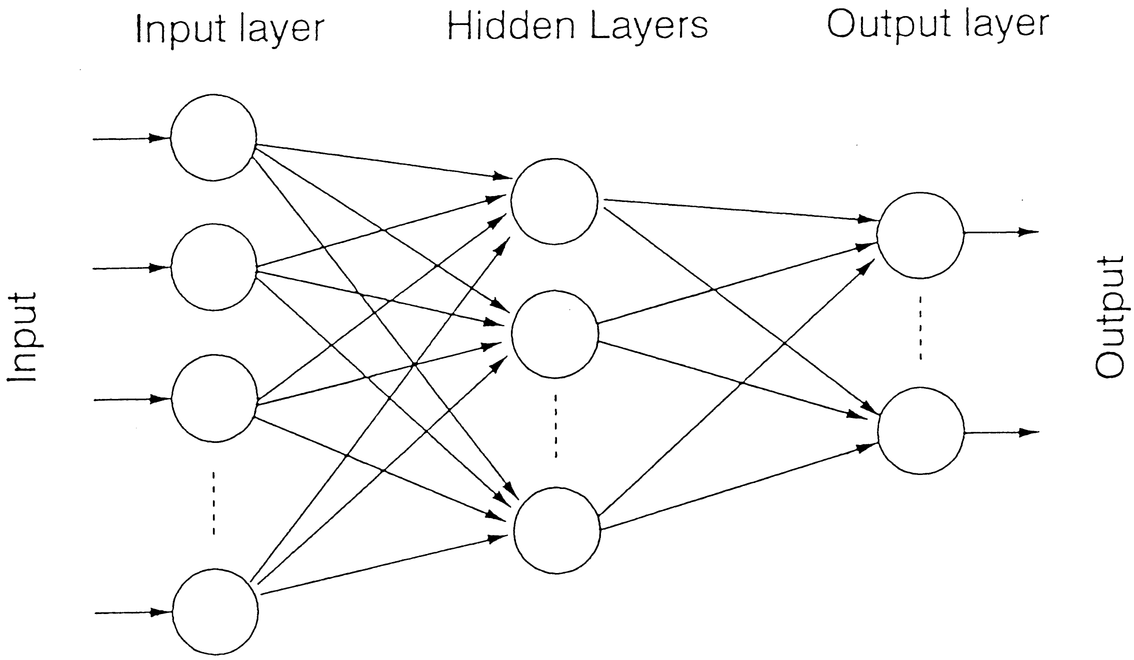

Figure 2. Principle of a feed-forward multi-layered neural network.

Age	Year(t-5)	Year(t-4)	Year(t-3)	Year(t-2)	Year (t-1)	Year (t)
0						
1						(adult YFT ↓)
2						
3						
4						
5						

Figure 3. Adult YFT (*t*) and its related cohorts in (*t*-5) to (*t*-1).

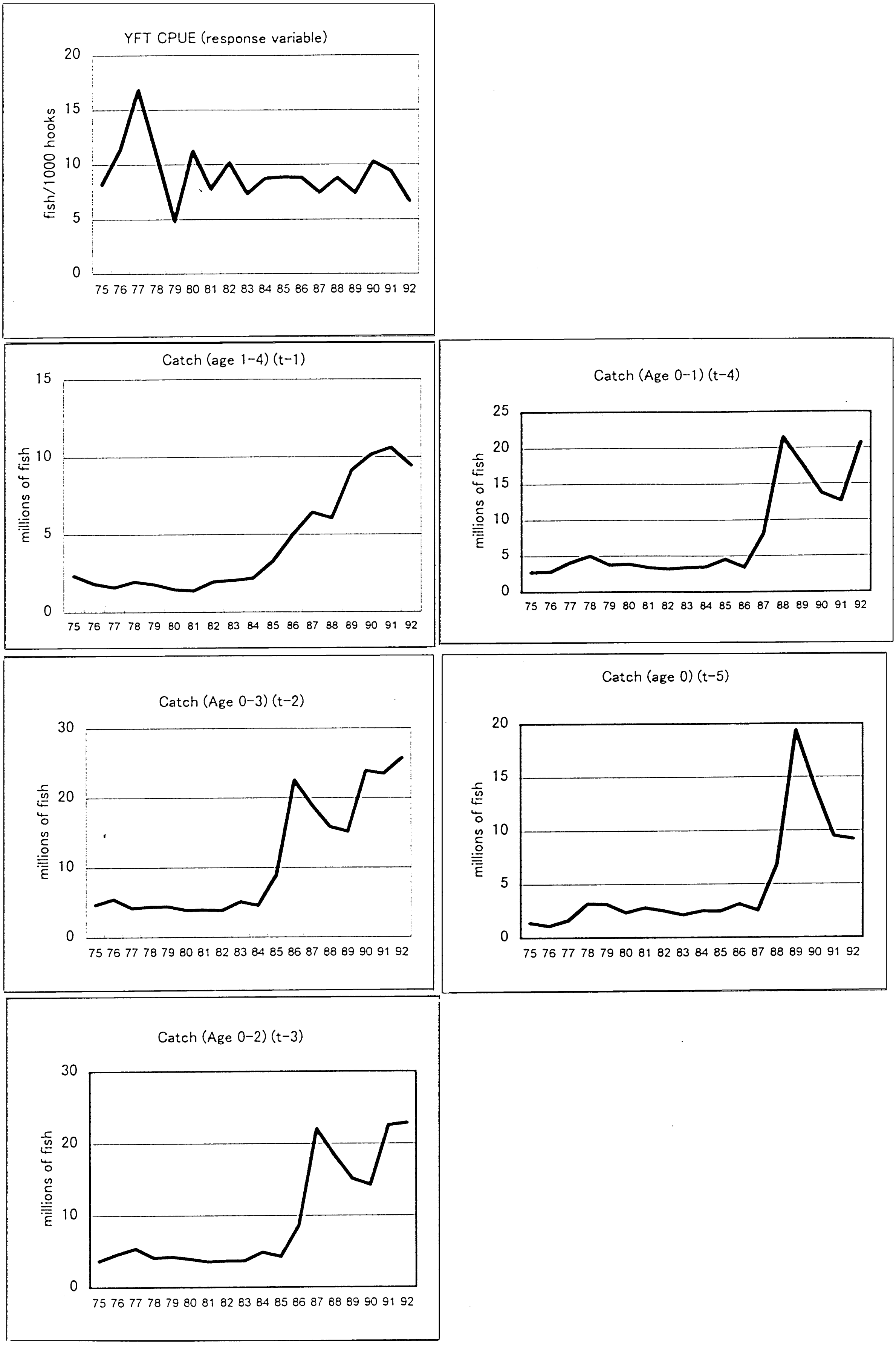

Figure 4 Annual trends of the response variable and 14 input variables (continued on next page)

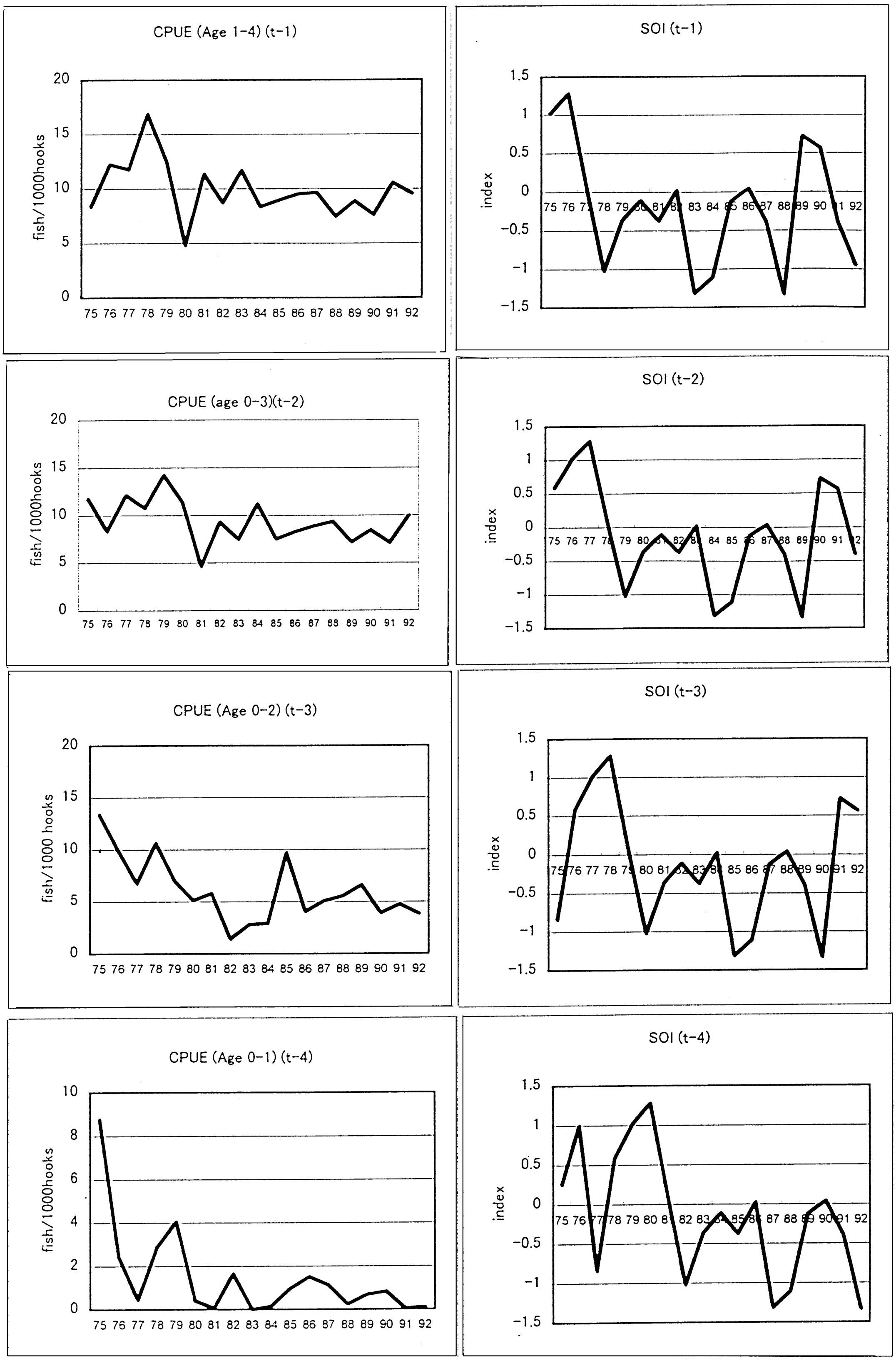

Figure 4 Annual trends of the response variable and 14 input variables (continued from previous page)

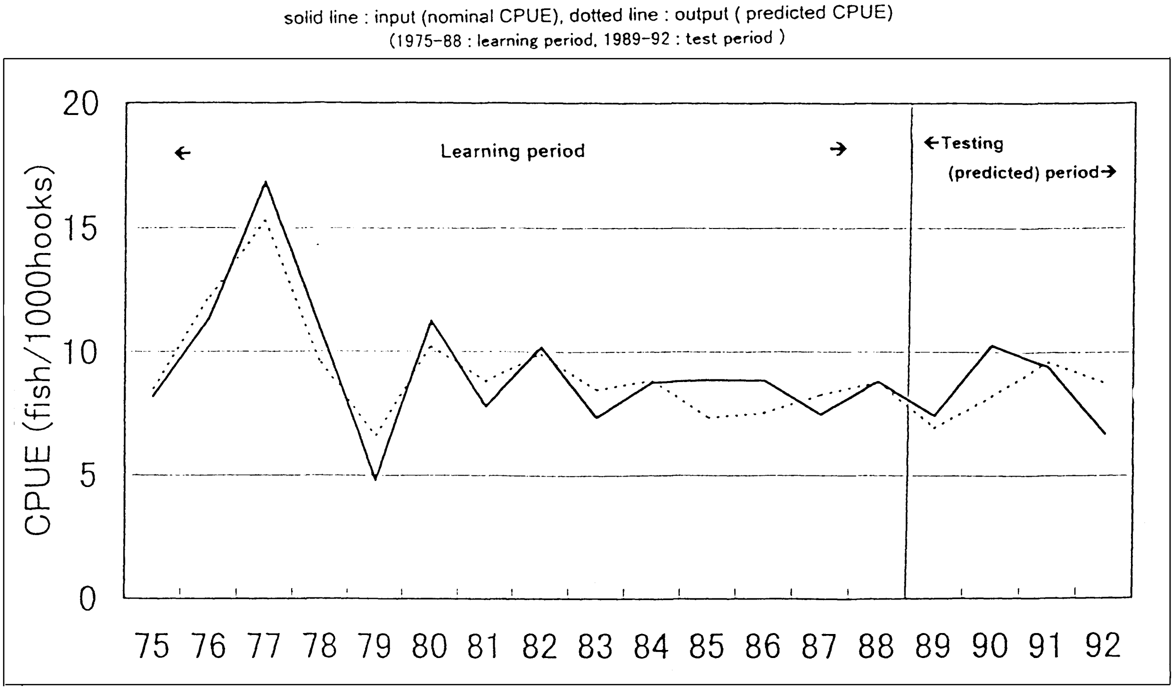

Figure 5 Results of the neural network work analyses.

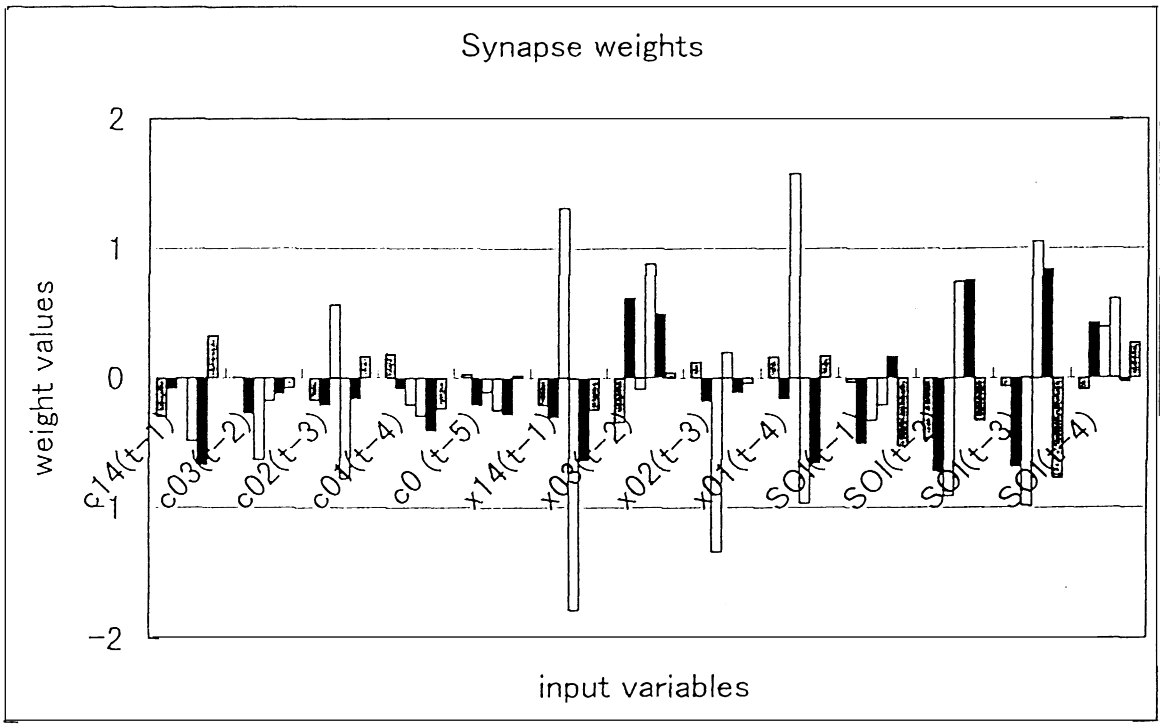

Figure 6 Synapse weights of the connections from each input unit to 6 intermediate units in the supervised learning.

APPENDIX A:

Fuzzy logic and Expert systems in fisheries (From Nishida and Fluharty, 1999)

Fuzzy control theory (Fuzzy logic)

'*The binary logic of modern computers often falls short when describing the vagueness of the real world. Fuzzy logic offers more graceful alternatives'* (Kosko and Isaka, 1993). Fuzzy logic originated from 'Fuzzy set theory' by Professor Zedeh (1965), University of California. Fuzzy control theory is developed by applying fuzzy logic, which is presently applied to various fields such as robotics, water reservoir control, automatic operations of subway and transportation. The original meaning of 'fuzzy' is an unique phenomenon without a clear boundary like a feather. Hence, fuzzy logic can handle vague expression such as 'bright green', 'young', 'very dirty', etc., as input information. The Appendix explains the concept of fuzzy logic in detail.

Fuzzy control theory is likely appropriate and feasible for analysing fisheries data because various types of uncertainties and complexity are involved, e.g., uncertain dynamics of fish stocks, uncertain biological parameters, vague geographic distribution of the stock, unclear relationship between oceanographic conditions and resources, complex quality of catch data due to heterogeneous fishing operations and limited quantity and quantity of fisheries data. Therefore, the fuzzy control theory is potentially effective to overcome some of these uncertainty problems.

Fisheries data are 'rough' and 'approximate' information, hence descriptive data such as 'high' catch, 'good' prediction, etc., might be just as adequate as the existing data to be used as inputs. Recently, qualitative information based fisheries resources analyses known as 'fuzzy control theory' , have been developed and applied for whale and skipjack data in Japan (Sakuramoto, 1991).

Expert systems

The Expert system is a similar technique to fuzzy logic and is also applied for prediction of fishing conditions for young sardines (Aoki *et al.*, 1991) and for forecasting the Kuroshio current (Komatsu *et al.*, 1994). Expert systems can use a computer to process intellectual information based on specialists' experiences and knowledge. It is based on methodology similar to the human thought process, instead of equations and rigid logic. Expert systemsare almost equivalent to fuzzy logic, which are all based on processing of descriptive information (signal or code). The merits of using expert systems in fisheries are that specialized descriptive knowledge from experts such as experienced fishermen, scientists and managers can be utilized as input information.